Doctoral theses at NTNU, 2021:288

Eivind Kristoffersen

Towards a Smart Circular Economy

How digital technologies can support the adoption of circular economy

Doctoral thesis

NTNU
Norwegian University of Science and Technology
Thesis for the Degree of Philosophiae Doctor
Faculty of Information Technology and Electrical Engineering
Department of Computer Science

NTNU
Norwegian University of Science and Technology

Eivind Kristoffersen

Towards a Smart Circular Economy

How digital technologies can support the adoption of circular economy

Thesis for the Degree of Philosophiae Doctor

Trondheim, September 2021

Norwegian University of Science and Technology
Faculty of Information Technology and Electrical Engineering
Department of Computer Science

NTNU
Norwegian University of
Science and Technology

NTNU
Norwegian University of Science and Technology

Thesis for the Degree of Philosophiae Doctor

Faculty of Information Technology and Electrical Engineering
Department of Computer Science

ISBN 978-82-326-6505-1 (printed ver.)
ISBN 978-82-326-5669-1 (electronic ver.)
ISSN 1503-8181 (printed ver.)
ISSN 2703-8084 (online ver.)

Doctoral theses at NTNU, 2021:288

Printed by NTNU Grafisk senter

Pessimism of the intellect,
optimism of the will.

Antonio Gramsci - Letter from prison, 1929

Abstract

The digital transformation holds much potential for solving some of society's grandest and most pressing challenges, such as climate change and resource depletion. Specifically, digital technologies (DTs) represent a major opportunity to accelerate the circular economy (CE) transition. However, effectively managing this joint transformation is challenging, and firms struggle to understand how DTs support circular strategies and which business analytics (BA) resources and capabilities they should target. Addressing this gap, the thesis first establishes a reference framework for circular strategies along with a digital CE framework, enabling researchers, practitioners, and policymakers to better align their activities across boundaries in the information systems and CE fields. Next, drawing on the resource-based view and the resource orchestration view of the firm, the thesis investigates which BA resources are essential for CE and how to leverage them towards a firm-wide BA capability for CE. Finally, a conceptual model summarizes the mechanisms of how BA improves firms' CE implementation, resource orchestration capability, and firm performance.

The thesis followed a sequential mixed methods research design, starting from an exploratory approach to uncover key concepts and their relationships, followed by a confirmatory study to examine effects. Both qualitative and quantitative cross-sectional data were sought to empirically examine the conceptual model. In total, one in-depth case study, 15 expert interviews, and a quantitative survey of 125 European firms were performed.

The resulting contributions add new knowledge to both the CE and information systems fields by detailing how DTs can increase the efficiency and enhance the effectiveness of circular strategies. First, by two reference frameworks and a process methodology providing systematic support from the strategic level of CE and digital objectives to the operational level of data science processes. Second, by a conceptual model and associated BA resources and capability of how firms manage this transition to improve their corporate reputation and environmental, financial, and competitive performance. Third, by detailing the mechanisms and effects of DTs on circular strategies and performance effects. In closing, research, practice, and policy implications are discussed, along with avenues for future research.

Preface

This doctoral thesis was submitted to the Norwegian University of Science and Technology (NTNU) for partial fulfilment of the requirements for the degree of philosophiae doctor. Associate Professor Jingyue Li (NTNU) was the main supervisor, and Associate Professor Patrick Mikalef (NTNU) and Junior Professor Fenna Blomsma (University of Hamburg) were the active co-supervisors. Guidance was also provided by Associate Professor Mariusz Nowostawski (NTNU) as a co-supervisor and Associate Professor Lillian Røstad (University of Oslo) as a mentor and in the early phases of the PhD.

The thesis was funded as part of the CIRCit[1] research project (grant number: 83144). It was carried out between 2017-2021 as part of the Nordic Green Growth Research and Innovation Programme financed by NordForsk, Nordic Energy Research, and Nordic Innovation. The project was led by the Technical University of Denmark together with the Research Institutes of Sweden, NTNU, Innovation Center Iceland, and Technology Industries of Finland.

The aim of the project was to develop science-based tools and approaches to support the Nordic industry in its transition to a circular economy in six main areas (or work packages): (1) sustainability impact assessment for CE, (2) circular business modeling, (3) development of circular products and services, (4) circular product operation by the use of intelligent assets, (5) closing the product cycle, and (6) cross-sectoral collaboration and networking in supply chains. The project followed action research as the overall research framework. This meant that close collaboration was kept with the companies throughout the duration of the project. A total of 144 companies were engaged in the form of company visits, workshops, webinars, interviews and/or questionnaires. The scope of this thesis was to produce the main contributions for work package 4.

As the leader of work package 4, I aided in a multitude of administrative and communication tasks such as company recruitment and engagement, organization of a series of workshops and webinars, reporting, and dissemination of findings in popular news articles, industry clusters, and global conferences. During the whole of my PhD period, I worked part-time in industry, first as a solutions architect for

[1]CIRCit stands for Circular Economy Integration in the Nordic Industry for Enhanced Sustainability and Competitiveness. See here for more information: http://www.circitnord.com/

Sopra Steria and then as a research scientist for SINTEF. At NTNU, I assisted as a master's thesis examiner, guest lecturer, and journal reviewer.

The impact and importance of this research have far surpassed all my expectations. At the time of writing, the research has been picked up and used by both the World Bank and the Circular Economy Roadmap for Germany.

Acknowledgements

This has been a long one... I am glad that I did not know what I was getting myself into when I first started a PhD. Sometimes, ignorance is truly bliss. Yet, this journey has transformed my life in ways I could not imagine and would definitely not be without. Importantly, this PhD would not have been possible without the support from a few key people.

First, I would like to thank my supervisor, Jingyue Li, who gave me this opportunity. It has been an honor to be your PhD student and work with you for the past few years. Thank you for your guidance and support throughout this process. Second, I am especially thankful to Patrick Mikalef for jumping on board the ship to help steer this PhD towards land. Your experience and knowledge of the information systems field have truly been of great help to make this PhD come together. I am also very grateful to Fenna Blomsma for teaching me the ropes of circular economy, concept by concept, and strategy by strategy. Thank you for both challenging and supporting me in times of need. Your contributions and knowledge of the circular economy have truly raised the quality and impact of this research.

I am honored to have been part of the CIRCit project and would like to thank all colleagues from the CIRCit consortium for your collaboration, shared experiences, and inspirational work. It has been great fun! I would also like to thank Lillian Røstad and Mariusz Nowostawski for their guidance and support in the early phases of the PhD.

This PhD is the culmination of years of studying, even going back to the early years in primary school. I would like to thank my parents, Laila and Trond, for your support throughout all these years and for teaching me about hard work, persistence, and how to stay positive when things get tough.

Lastly, I reserve my most intimate acknowledgment for my partner and fiancée, Blerina. I would never have started, let alone finished, this PhD if it was not for you. Thank you for your unconditional love, encouragement, and simply always believing in me. For that, I am forever grateful. Te dua.

Eivind Kristoffersen
15th September 2021

Contents

List of Figures

List of Tables

Abbreviations

BA Business Analytics

BAC Business Analytics Capability

CE Circular Economy

COI Circular-oriented innovation

DT Digital Technology

ICT Information and Communications Technology

IS Information Systems

RBV Resource-based view

ROC Resource orchestration capability

ROV Resource orchestration view

PLS Partial Least Squares

SDG Sustainable Development Goal

SEM Structural Equation Modelling

Part I

1 Introduction

This chapter provides an introduction to the thesis subject area and problem statement. To this end, it describes the research motivation, questions, papers, key contributions, and overall outline of the thesis.

1.1 Problem Statement

Over the past 200 years, we have developed an immense industrial global economy, providing unprecedented prosperity. However, following the linear model of 'take-make-dispose' has caused our consumption to massively overshoot the earth's carrying capacity. If we are not to be overwhelmed by negative environmental and social impact, we are in dire need of systemic change.

Sustainability has been a topic of extensive debate ever since the Brundtland report in 1987 (Commission on Environment and Development, 1987), yet solutions have been lacking in scale, arguably due to challenges with profitability. Recently, the concept of circular economy (CE) has gained increasing prominence among organizations, policymakers, and researchers as a way to promote sustainable development while increasing economic development (Geissdoerfer et al., 2017; Ghisellini et al., 2016). By addressing root causes, the CE articulates a global economy where value creation is decoupled from the consumption of finite resources by leveraging a range of restorative, efficiency, and productivity-oriented strategies that keep materials, components, and products in use for longer (Blomsma et al., 2020; Ellen MacArthur Foundation, 2013). The advantages of such an approach are substantial and, for Europe alone, estimated to create a net benefit of €1.8 trillion by 2030 while addressing mounting resource-related challenges, creating jobs, spurring innovation, and generating substantial environmental benefits (Ellen MacArthur Foundation, 2015; Stahel, 2010).

In fact, the CE is one of the key elements in the European Green Deal (European Commission, 2020b) and holds great potential for contributing to many of the UN Sustainable Development Goals (SDGs) (Schroeder et al., 2019). This is for two reasons. First, CE proposes that negating or reducing structural waste decreases the demand for virgin finite material. That is, through the application of circular strategies, the otherwise underused capacity of resources[1] can be applied to deliver value (Ellen MacArthur Foundation, 2013; Ellen MacArthur Foundation, 2015). Second, CE promotes moving away from using the natural environment as a 'sink' to dump used resources (Irani et al., 2018). CE is attributed with the ability to avoid, reduce, and negate value loss and destruction through, for instance, lower emissions, reduced pollution levels, and loss of biodiversity and habitats associated with resource extraction (Ellen MacArthur Foundation, 2013; S. Kumar et al., 2008).

So far, the adoption of circular strategies in industry is modest, and minor improvements are seen in the decoupling from linear consumption of resources (Circle Economy, 2020; Haas et al., 2015; Planing, 2015; Sousa-Zomer et al., 2018). There are multiple reasons for this. For one, CE is a relatively new and emergent concept, which implies that there is a lack of tools for conducting circular-oriented innovation (COI), (Blomsma et al., 2017; Brown et al., 2019). Second, the link between CE and possible enabling technologies is not yet well established (Alcayaga et al., 2019; Jabbour et al., 2019a; Jawahir et al., 2016; Nobre et al., 2017; Okorie et al., 2018; Zeiss et al., 2020). This includes digital technologies (DTs) such as the Internet of Things (IoT), big data, and data analytics as part of Information Systems (IS) research. DTs are highlighted as critical enablers of CE by tracking the flow of products, components, and materials and making the resultant data available for improved resource management and decision-making across different stages of the industrial life cycle (Antikainen et al., 2018; Bressanelli et al., 2018b; de Sousa Jabbour et al., 2018; Lacy et al., 2020; Nobre et al., 2017; Pagoropoulos et al., 2017).

By positioning information flows that enable resource flows to become more circular, DTs may enable a step change that goes beyond incremental efficiency gains towards a more sustainable CE (Wilts et al., 2018). For instance, IoT can enable automated location tracking and monitoring of natural capital (Ellen MacArthur Foundation, 2016). Big data facilitates several aspects of circular strategies, such as improving waste-to-resource matching in industrial symbiosis systems via real-time gathering and processing of input-output flows (Bin et al., 2015; Low et al., 2018). Moreover, data analytics can serve as a tool to predict product health, reduce production downtime, schedule maintenance, order spare parts, and optimize energy consumption (Conboy et al., 2020; Lacy et al., 2020; Porter et al., 2014; Shrouf et al., 2014). These examples illustrate that DTs' contribution to the CE includes a range of circular strategies and business processes: from recycling to reuse and designing new offerings to managing maintenance.

Although there are real and theorized examples of information flows enabling circularity, there remains a gap between the expected and largely unrealized potential to use DTs to leverage circular strategies (Nobre et al., 2020; Rosa et al., 2020). So far, the questions of *in what areas* and *in which ways* DTs support the implementation of circular strategies for companies have been insufficiently researched. As such, a comprehensive understanding of the relationship between CE and DTs is still

[1] Here, we refer to physical resources, or assets, such as materials, components, and products.

missing, leaving a gap in our understanding of the underlying mechanisms and inhibiting firms' ability to accelerate their CE transition through DTs (Ellen MacArthur Foundation, 2016; Ellen MacArthur Foundation, 2019; Nobre et al., 2017). A Gartner survey of 1374 supply chain leaders supports this premise (Gartner, 2020b). The results show that 70% of the respondents are planning to invest in the CE; however, only 12% have so far linked their digital and circular strategies. In other words, there is a lack of guidance on how to leverage DTs in a targeted way to support circular strategies operationally and find new CE opportunities. There is also a gap in practitioners' and researchers' conceptual understanding of how to leverage DTs in a targeted way to support circular strategies operationally and find new CE opportunities.

1.2 Research Motivation

Acknowledging the difficulties faced by organizations pursuing sustainability in an increasingly competitive business landscape, the main motivation and aim of our research is to provide knowledge of how companies can better manage their digital and CE transformation. Various sources have reported the need for research linking these two fields, corroborating the value of effectively managing this joint transformation. For instance, Chauhan et al. (2019), the European Policy Centre (2020), European Commission (2020b), Ellen MacArthur Foundation (2016; 2019), and Zeiss et al. (2020) aim to raise awareness of DT's potential for the CE and support further development through research and innovation. Other authors have investigated how DTs relate to servitized business models and CE value drivers (Alcayaga et al., 2019; Bressanelli et al., 2018a; Pham et al., 2019), and the type of DTs needed within the various categories of well-known CE frameworks, such as the ReSOLVE (regenerate, share, optimize, loop, virtualize, exchange) framework (de Sousa Jabbour et al., 2018; Jabbour et al., 2019a; Nobre et al., 2020). Policy initiatives are also underway, such as the Circular Economy Action Plan, which includes a call for creating an architectural and governance infrastructure in the form of a dataspace for smart circular applications (European Commission, 2020a). In addition, several countries specifically target the digital CE in their national strategies, such as Germany (Circular Economy Initiative Deutschland, 2021) and Norway (Deloitte, 2020; Meld. St. 13, 2021).

Nevertheless, there is a gap between theory and practice (Rosa et al., 2020), and research remains in a pre-paradigmatic stage with mostly anecdotal evidence (Zeiss et al., 2020). Unsurprisingly, there is limited empirical work grounded on established IS and CE theories (Lahti et al., 2018). Previous studies have presented novel insights into the value of leveraging DTs for CE and different perspectives on how to understand these two fields, mainly by high-level integrative frameworks and strategies (Askoxylakis, 2018; Bianchini et al., 2018; de Sousa Jabbour et al., 2018; Ellen MacArthur Foundation, 2016; Ingemarsdotter et al., 2019; Jabbour et al., 2019a; Nobre et al., 2020; Okorie et al., 2018; Rosa et al., 2020; Ünal et al., 2018) or enablers and barriers (Antikainen et al., 2018; Chauhan et al., 2019; Pagoropoulos et al., 2017; Rajput et al., 2019; Wilts et al., 2018).

However, none of the frameworks provides the necessary support for systematically searching, analyzing, and advancing such digital circular strategies with details of their underlying technical mechanisms and the business analytics (BA) needed to operationalize them.

Similarly, few studies have systematically investigated the link between BA and CE. Notwithstanding the number of studies on BA for general business operation and supply chain management (Akter et al., 2016; G. Wang et al., 2016), these are all rooted in the linear economic model and way of thinking. Hence, they lack alignment with more holistic information management and sustainable principles core to the CE (S. Gupta et al., 2019). This applies both to strategic and operational CE activities such as reinventing and reconfiguring business models and value chains, reducing raw material sourcing and manufacturing impacts, and recirculating products and materials to additional use cycles. Present BA research streams in IS have put considerable efforts into defining the organizational resources of firms' BA capabilities (BACs) through the resource-based view (RBV) (M. Gupta et al., 2016; Wamba et al., 2017). However, little is known about the orchestration process required to leverage these BA resources into a firm-wide BAC (Mikalef et al., 2018). Specifically, a gap exists in explicitly addressing managers' roles and actions in effectively structuring, bundling, and leveraging organizational resources through the framework of resource orchestration view (ROV) (Sirmon et al., 2011). The motivation for choosing RBV and ROV as the theoretical groundings is that the former presents a solid foundation whereupon all organizational resources can be identified, while the latter provides a lens to examine how these resources are managed and turned into capabilities to leverage circular strategies for increased firm performance.

Furthermore, efforts in BA research have primarily focused on the mechanisms through which it generates competitive performance while mostly disregarding the impact in areas of CE and sustainability. The review by Rialti et al. (2019) advocates for future research to explore the additional effects of BAC apart from competitive performance. Despite interest in the role of BA for sustainable supply chain management (Dubey et al., 2016; Hazen et al., 2016; Jabbour et al., 2020; K.-J. Wu et al., 2017; P.-J. Wu et al., 2018; Zhao et al., 2017), circular supply chain management (S. Gupta et al., 2019), and environmental impact (Ramanathan et al., 2017; Zhang et al., 2019), there has been significantly less research on its role in leveraging a broader range of circular strategies. Hence, it needs to be established which BA resources companies implementing circular strategies should invest in and how to leverage them into a firm-wide BAC for CE.

1.3 Research Questions

Answering the calls and addressing the gaps in related works, the main research question (MRQ) investigated by this thesis is:

> ***MRQ:*** *How can companies leverage DTs for CE implementation and firm performance?*

To structure its inquiry, the thesis is rooted within the IS field and examines DTs' contribution to CE through the lens of BA. Furthermore, considering the current gap between IS and CE research and the efforts needed to close it, the main research question was broken down into three sub-questions:

> ***RQ1:*** *How can the relationship between DTs and circular strategies be conceptualized?*

> ***RQ2:*** *What are the BA resources and processes required for implementing DTs for circular strategies and firm performance?*

> ***RQ3:*** *How are BA capabilities developed and through what mechanisms do they enable circular strategies and firm performance?*

The research questions (RQs) follow a sequential order in which the study of one relies upon the results of the former. First, RQ1 aims to ground the research by developing a framework and structured approach for understanding how DTs and circular strategies relate at a conceptual, technical, and strategic level. Following this, RQ2 aims to narrow the scope by focusing on BA resources and the data science process. Lastly, RQ3 targets unpacking how these BA resources are leveraged into capabilities and the mechanisms through which they promote CE implementation and firm performance.

1.4 Research Outcomes

Five main and five secondary research papers published in peer-reviewed conferences and journals were produced. Building on the results reported in these papers, a body of knowledge regarding the research questions in the fields of IS and CE has been developed.

1.4.1 Research Papers

The research questions are addressed in the following main research papers (see Table 1.1 for a mapping of their connection to the research questions):

P1 Blomsma, F., Pieroni, M., Kravchenko, M., Pigosso, D., Hildenbrand, J., Kristinsdottir, A. R., Kristoffersen, E. et al. (2019) **'Developing a circular strategies framework for manufacturing companies to support circular economy-oriented innovation.'** *Journal of Cleaner Production, p.118271.*

My contribution: I was a co-author and contributed with framework design and conceptualization in the main activities of the prescriptive studies, including workshop participation, company engagement, and paper writing.

Relevance to the thesis: This paper presents a comprehensive CE framework (the Circular Strategies Scanner) and taxonomy of circular strategies for manufacturing companies. The Circular Strategies Scanner addresses shortcomings of previous CE frameworks, particularly the lacking ability of these frameworks to support companies in the early stages of COI. The paper contributes to RQ1 by rooting the thesis within the CE school of thought and lays a solid foundation for conceptualizing the relationship between DTs and circular strategies.

P2 Kristoffersen, E., Blomsma, F., Mikalef, P. and Li, J. (2020) **'The Smart Circular Economy: A digital-enabled Circular Strategies Framework for Manufacturing Companies.'** *Journal of Business Research, 120, 241-261.*

My contribution: I developed the main research findings, including research design and conceptualization, literature and practice review, framework and knowledge base development, and paper writing, in close collaboration with Blomsma. Mikalef and Li contributed by exchanging ideas and providing comments on the draft.

Relevance to the thesis: This paper presents a digital CE framework (the Smart CE framework) and a knowledge base of example cases from literature and practice. First, the paper synthesizes the findings from two systematic literature reviews of digital frameworks and digital CE frameworks together with the Circular Strategies Scanner from paper 1 to develop the Smart CE framework. Following this, the Smart CE framework and Circular Strategies Scanner were used to organize and map cases from a systematic literature and practice review into a knowledge base of 100 example strategies. The paper contributes to RQ1 and RQ2 by conceptualizing the relationship between DTs and circular strategies and providing a means to support the BA gap analysis.

P3 Kristoffersen, E., Aremu, O. O., Blomsma, F., Mikalef, P. and Li, J. (2019) **'Exploring the Relationship Between Data Science and Circular Economy: An Enhanced CRISP-DM Process Model.'** In Conference on e-Business, e-Services and e-Society and Lecture Notes in Computer Science, 11701, 177-189.

My contribution: I was the leading author and developed the main research findings, including research design and conceptualization, data collection and analysis with case company, process model development, and paper writing. Aremu contributed with paper writing on structuring of data for predictive maintenance. Blomsma, Mikalef, and Li contributed by exchanging ideas and providing comments on the draft.

Relevance to the thesis: This paper presents a data science process model and explores how it connects to the CE. The new process model adds a new phase of data validation and integrates the concept of analytic profiles to address shortcomings in the data science process for CE. The paper contributes to RQ2 by providing an in-depth case study analysis of the underlying data science process required to advance smart circular strategies.

P4 Kristoffersen, E., Mikalef, P., Blomsma, F. and Li, J. (2021) **'Towards a Business Analytics Capability for the Circular Economy.'** *Technological Forecasting and Social Change, 171, 120957.*

My contribution: I was the leading author and developed the main research findings, including research design and conceptualization, interview guide design, data collection, respondent sampling and execution of interviews, data analysis, research model and BAC design, and paper writing. Blomsma contributed by exchanging ideas and comments on the draft and Mikalef and Li provided ideas, cross-validation of analysis results, and wi comments on the draft.

Relevance to the thesis: This paper explores the factors necessary for deploying BA for CE. Through a conceptual model, the paper proposes eight essential BA resources that, when combined, form a BAC for CE. Second, it unpacks the mechanisms through which DTs enable CE by detailing how managers structure, bundle and leverage BA for CE and competitive performance. The results are based on 15 semi-structured expert interviews employing the RBV and ROV theories for data analysis and identification of themes. The paper contributes to RQ2 and RQ3 by detailing the core BA resources that build a BAC for CE and the mechanisms through which managers orchestrate these resources into capabilities.

P5 Kristoffersen, E., Mikalef, P., Blomsma, F. and Li, J. (2021) **'The Effects of Business Analytics Capability on Circular Economy Implementation, Resource Orchestration Capability and Firm Performance.'** *International Journal of Production Economics, 239, 108205.*

My contribution: I was the leading author and developed the main research findings, including research design and conceptualization, questionnaire and instrument design, data collection, respondent sampling and follow-up, data analysis, research model and BAC design, and paper writing. Blomsma contributed by exchanging ideas, Mikalef provided ideas, data collection, cross-validation of analysis results, and comments on the draft, and Li provided ideas and comments on the draft.

Relevance to the thesis: This paper empirically validates the conceptual model and findings from paper 4. The study analyzes quantitative survey data from 125 top-level managers from firms across Europe using partial least squares structural equation modeling (PLS-SEM). The results show that firms with a strong BAC have an increased resource orchestration capability (ROC) and improved ability to excel in CE and, as a result, enhance their organizational performance in an increasingly competitive business landscape. The paper contributes to RQ2 and RQ3 by empirically validating the underlying structure of the BAC for CE along with the mechanisms and effects of this capability on CE and firm performance.

Table 1.1: Mapping of main research papers and research questions.

	P1	P2	P3	P4	P5
RQ1	•	•			
RQ2		•	•	•	•
RQ3				•	•

Furthermore, five secondary papers were produced:

SP1 Gupta, S., Justy, T., Shampy, K., Kumar, A., and Kristoffersen, E. (2021) **'Big Data and Firm Marketing Performance: Findings from Knowledge-Based View.'** *Technological Forecasting and Social Change, 171, 120986.*

SP2 Li, Z., Kristoffersen, E., and Li, J. **'A taxonomy and survey of deep learning driven approaches for predictive maintenance.'** *Manuscript complete*

SP3 Li, Z., Kristoffersen, E., and Li, J. **'Using Deep Transfer Learning to Predict Failures with Insufficient Data.'** *Manuscript complete*

SP4 Kristoffersen, E., Li, Z., Li, J., Jensen, T. H., Pigosso D. C. A., and Mcaloone, T. C., **'Smart Circular Economy: CIRCit Workbook 4.'** *Technical University of Denmark.*

SP5 Berg, H., Blévennec, K. L., Kristoffersen E., Strée, B., Witomski, A., Stein, N., Bastein, T., Ramesohl, S., and Vrancken, K. **'Digital circular economy as a cornerstone of a sustainable European industry transformation.'** *Global Sustainable Technology and Innovation Community Conference 2020.*

Table 1.2: Mapping of secondary research papers and research questions.

	SP1	SP2	SP3	SP4	SP5
RQ1				•	•
RQ2		•	•	•	•
RQ3	•				

All the secondary papers provided complementary perspectives to this thesis. First, secondary paper 1 attempts to identify how firms can enhance their strategic and operational decisions for improved big data marketing performance in sustainable Industry 4.0 applications. The study employs the knowledge-based view for qualitative analysis of 10 semi-structured interviews. The paper's scope is complementary to the topic of this thesis due to the close relationship between circular strategies and sustainable Industry 4.0 applications and firms' big data marketing performance with the effects of BAC. Second, secondary papers 2 and 3 extend the findings in paper 3 by providing an in-depth analysis of how to implement predictive maintenance using deep learning methods. The papers are relevant to this thesis under the topics of predictive maintenance, a good example of a circular strategy relevant to both Industry 4.0 and sustainable manufacturing. Specifically, the papers provide detail to the modeling phase of the enhanced CRISP-DM process model (from paper 3). Secondary paper 2 provides a taxonomy of the five most-used deep learning approaches for predictive maintenance and summarizes the strengths and weaknesses of each. Secondary paper 3 provides an example of how to conduct deep transfer learning, addressing the challenge of collecting enough quality data to train the data-driven models needed for predictive maintenance, a challenge many firms face. Finally, secondary papers 4 and 5 both provide different perspectives on the Smart CE. Secondary paper 4 summarizes the Smart CE tools, frameworks, and use cases developed in the CIRCit project and presents this in an easy-to-follow format for practitioners. Secondary paper 5 expands on the idea of a Smart CE and discusses this in light of recommendations for EU policy development and research and innovation agendas.

For the first, second, and third secondary papers, I contributed with ideas, paper writing, and comments to the draft. For the fourth secondary paper, I was the leading author and developed the main parts of the frameworks, tools, and paper writing in close collaboration with the second and third authors. Finally, in the fifth secondary paper, I contributed with core parts of the report, including conceptualization, framework design, writing, and comments on the draft. However, as these papers only contribute indirectly to the research questions, they are left out of the main narrative of this thesis. See Table 1.2 for their connection to the research questions.

1.4.2 Research Contributions

The IS research field has a long tradition of drawing on theories from other disciplines such as economics, computer science, psychology, and general management (Wade et al., 2004). Therefore, despite being rooted within the IS field, this thesis is highly interdisciplinary and also make contributions to the field of CE (see Figure 1.1 and Table 1.3 for an overview). The work improves the state-of-the-art and adds novel contributions to the body of knowledge of how the implement CE by appropriately leveraging DTs. Accordingly, this thesis establishes a much needed and underexplored link between the two emerging fields. To this end, the thesis proposes the concept of *Smart CE*. For scholars, the concept can be thought of as a joint research stream linking the fields of IS and CE. For firms, the Smart CE may serve as a single-point-of-reference for aligning people and activities across departments and disciplines. For policymakers, the research may be useful to align digital market policies and regulations for improving the adoption of DTs with efforts needed to enable sustainable circular business models. At large, the Smart CE aims to exemplify the link between IS and CE, address the gap of past studies by detailing the mechanisms through which DTs enable circular strategies, and provide a reference framework for identifying which BA resources and capabilities firms should develop how, and the potential benefits. In short, the research questions add to the following contributions:

Table 1.3: Mapping of contributions and research questions.

	C1	C2	C3	C4
RQ1	•	•	•	
RQ2		•	•	•
RQ3			•	•

C1: *Improved understanding of the reciprocal relationship between DTs and the CE.* This represents findings, future avenues of research, and lessons learned derived from the field of experience of the author when researching the concept of a *Smart CE*.

C2: *A new common framework for aligning activities across the boundaries of disciplines in the IS and CE fields.* This integrates CE principles with common DT techniques and taxonomies and BA requirements through the Smart CE framework.

C3: *New knowledge and tools for improving firms' ability to leverage DTs for circular strategies.* This includes a structured approach in bridging the strategic and operational aspects of smart circular strategies. Specifically, the Smart CE framework can be used for creating roadmaps, prioritizing strategic initiatives, setting targets, and facilitating gap analysis of BA resources and capabilities needed for leveraging smart circular strategies. The enhanced CRISP-DM process model can be used to facilitate the analytics implementation process of these strategies by structuring the collection, integration, validation, and analysis of data.

C4: *New knowledge and model of how BA improves firms' CE implementation and firm performance.* This describes which BA resources companies should acquire, how to structure and bundle them into a firm-wide BAC, and the effects this capability has on CE implementation, ROC, and firm performance.

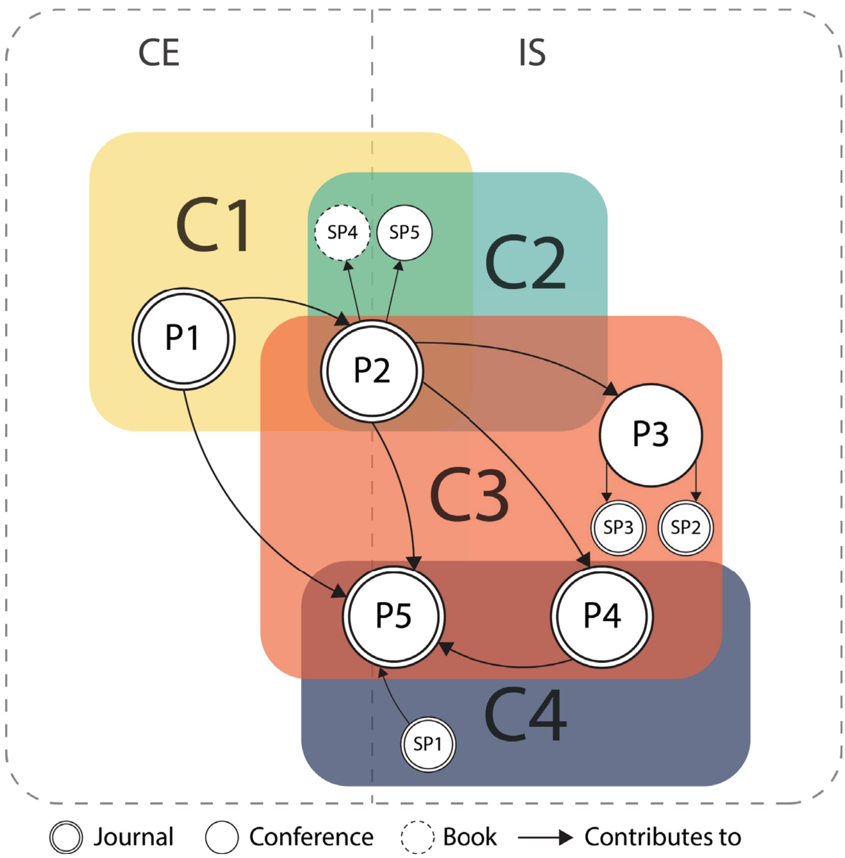


Figure 1.1: A schema of the research papers, contributions, and domains

1.5 Structure of the Thesis

The thesis is composed of two parts. Part I presents an introduction to the research work and provides an overview of the background theories, methods used, results achieved and the contributions made by the thesis. Part II contains the five main research papers in full length and abstracts of the secondary papers.

The rest of Part I is organised as follows:

- **Chapter 2** gives background to relevant concepts in CE and IS.
- **Chapter 3** depicts the research method and approach followed.
- **Chapter 4** summarises and evaluates the results of the research questions and contributions made.
- **Chapter 5** discusses the results of the research questions in terms of research, practice, and policy implications along with limitations and avenues for future research.
- **Chapter 6** concludes the thesis with final remarks.

2 Theoretical Background

This chapter provides an introduction to the concepts discussed in this thesis and a discourse of gaps in the related works. First, we introduce the concept of CE and background on circular strategies and associated frameworks. Next, we present definitions of the DTs relevant to this work, followed by BAC as a concept unifying these technologies from the perspective of the firm. Finally, we present the RBV and the ROV, two theories fundamental to strategic management literature and used as our theoretical underpinning to examine the BAC for CE.

2.1 Circular Economy

Our current, linear economy of 'take-make-dispose' is frequently characterized by the presence of structural waste: instances where components, products, or materials reach their end-of-use/life prematurely or where their capacity for value creation is underutilized. To address this, the concept of CE emerged in the 2010s as an approach to contribute to sustainable development (Blomsma et al., 2017). It encompasses a range of activities for narrowing, slowing, and closing material and energy flows (N. M. Bocken et al., 2016; Ellen MacArthur Foundation, 2013) as a means of addressing structural waste. Although the CE concept continues to grow and gain attention, it remains in an early stage of development, with international standards only recently starting to be developed (ISO, 2020). Therefore, a detailed definition of CE is still missing in the literature (Geng et al., 2008; Jabbour et al., 2019a; Kirchherr et al., 2017; Lieder et al., 2016). In their analysis of 114 definitions, Kirchherr et al. (2017) provide the following meta-definition: *"A CE describes an economic system that is based on business models which replace the 'end-of-life' concept with reducing, alternatively reusing, and recycling [...] materials in production/distribution and consumption processes, [...], with the aim of accomplishing sustainable development, which implies creating environmental quality, economic prosperity and social equity, to the benefit of current and future generations"*. As such, CE may best be understood as an umbrella concept in which various frames exist (Blomsma et al., 2017). As an umbrella concept, it groups a range of sub-concepts and imbues them with a new meaning by highlighting a shared feature of the sub-concepts. This new meaning revolves around the notion that through the application of circular strategies, both more value can be created (Ellen

MacArthur Foundation, 2013) and value loss and destruction reduced (Murray et al., 2017).

Although CE has widely been recognized for its potential economic, environmental, and social merits, the adoption of circular strategies by industry, so far, is modest (Circle Economy, 2020; Haas et al., 2015). This is in line with the progression of umbrella concepts: when the transformative potential of an idea has been recognized, the attention then turns to operationalizing it through frameworks, tools, methods, and approaches. This, in turn, allows for further examination of the concept. For CE, this means that there is currently a focus on developing CE transition methodology. This is taking place in a number of aspects relevant for COI (Brown et al., 2019), such as in business models (N. M. Bocken et al., 2018; Pieroni et al., 2019; Rosa et al., 2019), metrics and assessment (Kravchenko et al., 2019; Moraga et al., 2019; Saidani et al., 2019), product design (Den Hollander et al., 2017; Moreno et al., 2016; Shahbazi et al., 2020), and the creation of organizational capabilities such as experimentation, value chain innovation, and other human factors (Jabbour et al., 2019b; Weissbrod et al., 2017; Zeng et al., 2017).

Previous academic works have focused on answering *what* or *how* to promote COI (Guzzo et al., 2019; Mendoza et al., 2017). However, the question of *why* to perform COI has so far achieved relatively little scholarly attention. As a result, support is lacking in the early stages of COI for establishing a CE vision. Answering the *why* and establishing a CE vision requires understanding the type of structural waste in the system, which can be accomplished with a systemic analysis across life cycle stages and various business processes and knowledge areas. This requires various actors within and across businesses to define and explore problem and solution spaces together (Brown et al., 2019). Specifically, in COI, a high-level conceptual understanding of CE needs to be translated into a useful and meaningful vision on the level of decision-making (Boons et al., 2009; Hoffman, 2003; Lindkvist et al., 2014). The importance of a shared vision in innovation projects has long since been acknowledged (Bititci et al., 2004; Pearce et al., 2004), and it has been posited to be relevant for both inter and intra organizational COI efforts (Brown et al., 2019).

Currently, there is a range of frameworks that could potentially be drawn from to support CE visioning. These take the form of circular strategies frameworks, such as the ReSOLVE framework (Ellen MacArthur Foundation, 2015), the Performance Economy (Stahel, 2010), Cradle-to-Cradle™ (McDonough et al., 2010), and the Waste Hierarchy (EC, 2008). Importantly, these frameworks can be seen as the visual representations of a vision for how to operate in a CE since they select, name, and organize circular strategies seen as relevant, such that their relationship becomes apparent.

However, Blomsma (2018), Mendoza et al. (2017), and Reike et al. (2018) observed that such circular strategies frameworks could identify or emphasize different (groups of) circular strategies, which can be linked to addressing different types of structural waste. As such, there is a risk that they do not include circular strategies with transformative potential for a particular context. Moreover, Blomsma (2018) points out that little work has been done with regard to ensuring that frameworks are seen as relevant and useful by their intended audiences. For these reasons, there is scope to develop these frameworks further to support visioning in COI. Blomsma (2018), Mendoza et al. (2017), and Niero and Hauschild (2017) therefore call for the development of such frameworks within academia.

2.2 Digital Technologies

The term *digital technologies* encompasses several related technological trends such as IoT, big data, data analytics, cloud computing, cyber-physical systems, and distributed ledger technologies (Kagermann et al., 2013; Lasi et al., 2014; Liao et al., 2017). For the purpose of this thesis, we limit our scope of DTs to IoT, big data, and data analytics. DTs are transforming operations management in fields such as automation and industrial manufacturing, supply chain management, agile and lean production, and total quality management (Agrifoglio et al., 2017). For instance, DTs can give production systems the capacity to use historical data to improve quality by detecting abnormal behavior and adjusting performance thresholds accordingly (Aruväli et al., 2014). Furthermore, the improved sharing of information throughout the value chain helps to control and make real-time adjustments of operations according to varying demand (Moeuf et al., 2018). This increases operational efficiency and provides insights into the potential for new products, services, and business models (Kagermann et al., 2013).

Nonetheless, DTs are still an emerging field (Van den Bossche, 2016) in which support for effective implementation in industries such as manufacturing is lacking (Buer et al., 2018; Frank et al., 2019; Hermann et al., 2016; Hofmann et al., 2017; Rüttimann et al., 2016). A possible explanation of this is the hampering effect of ambiguous definitions without clear descriptions of the key constituent elements (Moeuf et al., 2018). In Table 2.1, we illustrate the breadth of DT definitions in the extant literature and clarify our use of these terms in this thesis. In a recent study of 161 manufacturing firms, three key barriers to using DTs to support circular strategies were identified: lack of interface design (e.g., challenges with compatibility, interfacing, and networking), difficulties in technology upgradation (e.g., bringing data analytics and IoT implementation to (near) state of the art), and outdated automated synergy models (e.g., collaborative models, process digitalization, and automation) (Rajput et al., 2019). Acknowledging these barriers, this thesis limits its scope of DTs to focus on aspects of technology upgradation and synergy models.

As discussed in Section 1.2, a gap exists in conceptual understanding and framework support for linking DTs and CE. While existing frameworks (Askoxylakis, 2018; Bianchini et al., 2018; de Sousa Jabbour et al., 2018; Ellen MacArthur Foundation, 2016; Ingemarsdotter et al., 2019; Jabbour et al., 2019a; Nobre et al., 2020; Okorie et al., 2018; Rosa et al., 2020; Ünal et al., 2018) provide novel insights into the value of leveraging DTs for circular strategies, they lack a more detailed structure required to systematically support companies in operationalizing such strategies. Specifically, the frameworks do not allow for unpacking technical architectures, integrations, or implementations on their different potentials to improve resource productivity

Table 2.1: Overview of DT terms and definitions in extant literature and those adapted for this study.

Internet of Things		
Example 1	"The worldwide network of interconnected objects uniquely addressable based on standard communication protocols"	(Gubbi et al., 2013)
Example 2	"Things having identities and virtual personalities operating in smart spaces using intelligent interfaces to connect and communicate within social, environmental, and user contexts"	(Bassi et al., 2008)
Example 3	"[...] Smart and dynamic objects with emergent behavior, embedded intelligence and knowledge functions as tools and become an (external) extension to the human body and mind. [...]"	(Minerva et al., 2015)
Used within this research	The Internet of Things is a dynamic global network infrastructure with self-configuring capabilities based on standards and interoperable communication protocols. It merges the physical and virtual worlds through uniquely identifiable objects, or "things," with sensing and actuating capabilities, enabling data and the state of the thing to be collected and changed from anywhere, anytime, and by anything.	Adapted from: (Atzori et al., 2010; Al-Fuqaha et al., 2015; Kortuem et al., 2009; S. Li et al., 2015; Miorandi et al., 2012; Ray, 2018; Yick et al., 2008)
Big Data		
Example 1	"The broad range of new and massive data types that have appeared over the last decade or so."	(Davenport, 2014)
Example 2	"A term describing the storage and analysis of large and or complex datasets using a series of techniques including, but not limited to: NoSQL, MapReduce, and machine learning"	(Ward et al., 2013)
Example 3	"The ability of society to harness information in novel ways to produce useful insights or goods and services of significant value and [...] things one can do at a large scale that cannot be done at a smaller one, to extract new insights or create new forms of value."	(Mayer-Schönberger et al., 2013)
Used within this research	Big data is high-volume, high-velocity and high-variety datasets that require advanced techniques for processing, storage, distribution, and management in order to turn data into information.	Adapted from: (Gartner, 2020a; Laney, 2001)
Data Analytics		
Example 1	"An overarching concept that is defined as data-driven decision making."	(Van Barneveld et al., 2012)
Example 2	"The processes of data assessment and analysis that enable us to measure, improve, and compare the performance of individuals, programs, departments, institutions or enterprises, groups of organizations, and/or entire industries."	(Norris et al., 2009)
Example 3	"A set of Business Intelligence technologies that uncovers relationships and patterns within large volumes of data that can be used to predict behavior and events."	(Eckerson, 2007)
Used within this research	Data analytics is the process of deriving knowledge and actionable insights from data and information, predominantly involving a series of methods and techniques including, but not limited to Data Mining, Artificial Intelligence, Knowledge Discovery in Databases, Big Data Analytics, Machine Learning, and Deep Learning.	Adapted from: (Cooper et al., 2012; Siow et al., 2018)

and efficiency. As such, the frameworks do not effectively support bridging the gap between an organization's CE objectives and the operational alignment required to achieve them. This alignment is an essential step in COI (Brown et al., 2019) and the continuous improvement processes within companies. See paper 2 in Part II for a detailed review and tables of existing frameworks.

2.3 Business Analytics Capability

The term intelligence was first used by artificial intelligence researchers back in the 1950s, later spurring the concept of business intelligence in the 1990s, closely followed by BA in the 2000s (Chen et al., 2012). While numerous definitions exist, BA is frequently referred to as the collection of technologies, methodologies, practices, and applications that enable the analysis of critical business data to make more sound and evidence-based business decisions (Chen et al., 2012; J. J. J. M. Seddon et al., 2017). Recently, the term *big data analytics* has emerged to describe the culmination of data analytics and big data (defined in Table 2.1) as a set of techniques and applications in which the (big) data sets are too large and complex for traditional data analytics methods (Chen et al., 2012). For the purpose of this thesis, we treat BA and big data analytics as a unified term and draw on the systematic literature review by Mikalef et al. (2018). As highlighted in their review, many data characteristics exist; however, the attributes of volume, velocity, and variety are highlighted as key to underpinning the notion of BA (McAfee et al., 2012). Recent studies have extended this with characteristics such as veracity (Abbasi et al., 2016; Akter et al., 2016), visualization (J. J. J. M. Seddon et al., 2017), and variability (P. B. Seddon et al., 2017).

Nevertheless, effectively leveraging and transforming data into business value and actionable insights requires companies to go beyond the technical aspects of data characteristics (Vidgen et al., 2017). Becoming a data-driven organization is a complex and multifaceted task requiring the transformation of multiple organizational resources with attention from several levels of managers. To address these challenges and provide guidelines for practitioners, scholars have introduced the concept of a BAC to indicate an organizations' ability to leverage data for increased strategic and operational insight (Mikalef et al., 2018). Mikalef et al. (2018) define BAC as a firm's proficiency in capturing and analyzing data towards the generation of insights by effectively managing its data, technology, and talent.

Studies show that companies with a strong BAC are better positioned to identify emerging opportunities and threats and transform their operation accordingly (Wamba et al., 2017). Specifically, BACs help companies expand the locus of decision-making by providing previously unavailable insight and options (Abbasi et al., 2016; Drnevich et al., 2011), improving response time, effectiveness, and efficiency when dealing with environmental changes (Popovič et al., 2018). Acknowledging the role of BA to help solve key societal challenges, an increasing number of studies have noted its positive relationship to Sustainable Development and CE (Chen et al., 2012; Del Giudice et al., 2020; A. Gupta et al., 2018; S. Gupta et al., 2019;

Hashem et al., 2016; Patwa et al., 2020; Rajput et al., 2019; Singh et al., 2019; Song et al., 2017; Zhang et al., 2019). BA has the potential to connect the material and information flows by helping firms understand and enact circular material flows, intensify and extend the use of products and components, and recycle waste materials (Zeiss et al., 2020). The tracking of data and information flow play an important role when transitioning to a more sustainable economy (Jabbour et al., 2019a), providing essential insights for enabling CE adoption and evolution for both large (Geng et al., 2013) and emerging economies (Patwa et al., 2020). Nevertheless, transforming the current modes of business operation requires firms to go beyond focusing solely on technology itself (Janssen et al., 2017). For instance, Raut et al. (2019) find that management and leadership style, supplier and customer integration, and internal business processes have a significant influence on firms' BAC and their ability to support sustainable practices. Chauhan et al. (2019) support this and highlight top-level management as essential actors for enablement.

Therefore, when confronted with the need to support the leveraging of a circular strategy—such as tracking stocks of natural capital, supporting industrial symbiosis matchmaking, and monitoring and managing product health—BACs required to satisfy the need must be established. For any data-driven business, and within the CE, this entails leveraging the full strategic potential of information flows by assembling, integrating, and deploying analytics-related resources (Shuradze et al., 2016). This includes both tangible and intangible organizational resources such as data governance, the existence of a data-driven culture, the presence of appropriate managerial and technical skills, and processes for data-driven organizational learning (Mikalef et al., 2018). However, the CE sets greater demand for firms to collect, integrate, analyze, and share data across organizational boundaries, both upstream and downstream in the value chain, and understand how individual business decisions and activities impact the broader economic, environmental, and social issues. Consequently, adopting circular strategies imposes different BA resources and capabilities compared to previous BAC research. With lacking BAC research for circular strategies, firms are hampered in their ability to transition towards the CE, restructure organizational resources, and fully capitalize on their BA investments. Therefore, to obtain relevant theoretical and practical insights for researchers and practitioners alike, it is essential to identify the core artifacts of BA pertinent to CE and how they are structured, bundled, and leveraged within organizations.

2.4 Resource-Based and Resource Orchestration View

Developing and sustaining a competitive advantage is fundamental to strategic management literature (Amit et al., 1993; Wernerfelt, 1984). To date, RBV is considered to be one of the most rigorous theories to explain firm performance through the resources[1] they own and control (J. B. Barney, 2001). The theory

[1] Here, we refer to organizational resources as data, culture, and human skills, not physical resources such as materials, components, and products under the CE.

has also gained considerable scholarly attention under the notion of IT capabilities (Bharadwaj, 2000). RBV proposes that a firm generates a competitive advantage by collecting tangible and intangible resources, specifically the ones that are valuable, rare, inimitable, and nonsubstitutable (known as VRIN) (J. Barney, 1991). Despite decades of empirical work and recent meta-analysis supporting the importance of these resources for competitive performance, scholars argue that the theory requires additional specification to explain differences among firms' outcomes (Crook et al., 2008; Kraaijenbrink et al., 2010; Sirmon et al., 2011). The core assumptions of VRIN also pose a challenge when applied to the context of BA, as the core resource, data, is often not rare, but an open and shared resource (Braganza et al., 2017).

Amit and Schoemaker (1993) define organizational resources as stocks of tradable and nonspecific assets in the firm, and capabilities as the firm's specific and nontradable ability to deploy such resources, through organizational processes, to effect a desired end. As a result, one can distinguish between the notion of resource-picking (identifying resources of strategic value) and capability-building (orchestrating these resources into useful assets) (Makadok, 2001). Much attention from IS research has been paid to the resource-picking aspects of firms' BAC, but less to capability-building (Mikalef et al., 2018). To this end, (Sirmon et al., 2011) propose the ROV to extend the understanding of RBV by explaining the role of managers in transforming resources into capabilities.

The research stream of ROV builds on RBV and dynamic capabilities through the complementary integration of the resource management framework by Sirmon et al. (2007) and the asset orchestration framework by Helfat et al. (2009). The ROV has received significant attention in recent years and represents a promising area of research to understand how firms should best manage their resources (Gong et al., 2018; Teece, 2014; Wales et al., 2013; J. Wang et al., 2020). The integrated framework provides a more robust perspective of managers' specific role in structuring, bundling, and leveraging capabilities across differences in firm characteristics (i.e., scope, life cycle stage, and levels in the managerial hierarchy). Each process includes several sub-processes with varying relative importance depending on the firm's characteristics, suggesting variance in the type and significance of managerial actions in orchestrating the firm's resources (Sirmon et al., 2011).

Recent studies have demonstrated the importance of a strong ROC for improving innovation when adapting to changing market conditions (Chadwick et al., 2015; Sirmon et al., 2007; Wales et al., 2013; Wong et al., 2018). For instance, Teece (2014) highlights that resource orchestration is essential to decrease internal conflict and improve resource complementarities in the firm, supporting the dynamic capabilities needed to facilitate green innovation (J. Wang et al., 2020). According to the ROV framework, firms can only attain the full potential and value of their resources when deployed in a complementary manner with capabilities and managerial acumen (Helfat et al., 2009; Sirmon et al., 2011). As a result, the theory posits that the ROC is one of the most important competencies a firm can internalize, particularly those organizations prone to suffering from resource-related liabilities, as within the CE. The capability can be seen as the proficiency of a firm to maximize performance by effectively structuring, bundling, and leveraging existing and new resources (Choi et al., 2020; J. Wang et al., 2020). We believe this theory proposes a novel perspective on the orchestration of BA that other theories do not.

While studies have applied the ROV framework to identify IT resources and capabilities for innovation (Ahuja et al., 2017), investigate the nature of e-commerce adoption (Cui et al., 2015), and understand how ambidexterity and IT competence can improve supply chain flexibility (Burin et al., 2020), resource orchestration remains understudied in the context of BA and CE. Therefore, we utilize the joint strengths of both the RBV and the ROV as the theoretical underpinnings to build a solid foundation for the empirical exploration of a BAC for CE.

3 Research Methodology

This chapter presents the methodologies and tactics employed to answer the research questions of the thesis.

3.1 Research Overview

Given the pre-paradigmatic stage of this research field, there is a need for conceptual theory and empirical investigation. To organize the investigation of the research questions and inform the choice of research methodologies and techniques, each question was detailed in corresponding research objectives (ROs):

RQ1: *How can the relationship between DTs and circular strategies be conceptualized?*

- RO1.1: Develop a CE framework and taxonomy of circular strategies that support mapping of current and future strategies along with the business processes they affect within organizations.
- RO1.2: Develop a digital CE framework that supports the systematic identification of BA requirements needed to advance different smart circular strategies.
- RO1.3: Consolidate and further advance the digital CE framework through the development of a knowledge base that can be used for BA gap analysis and the creation of roadmaps for the application of smart circular strategies within organizations.

RQ2: *What are the BA resources and processes required for implementing DTs for circular strategies and firm performance?*

- RO2.1: Identify which BA resources support firms in developing holistic information management and sustainable principles core to the CE.
- RO2.2: Explore and demonstrate how organizations can structure their data understanding and preparation to better align with overall business and CE goals.

RQ3: *How are BA capabilities developed and through what mechanisms do they enable circular strategies and firm performance?*

- RO3.1: Identify how managers structure, bundle, and leverage their BA resources into a BAC for CE.
- RO3.2: Develop a conceptual model detailing the effect of BAC on ROC, CE implementation, and firm performance.

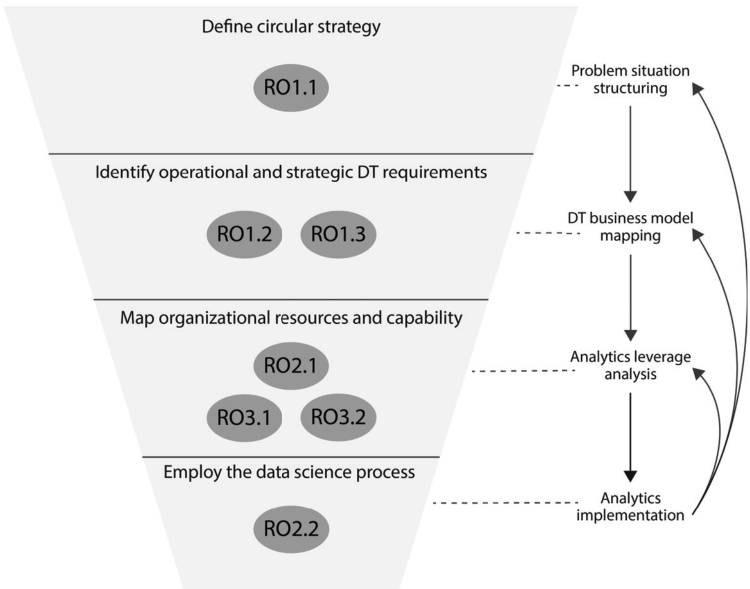


Figure 3.1: Research objectives and BA methodology (Hindle et al., 2018) alignment

Rooted in the philosophical paradigm of positivism, a sequential mixed method research design was followed, analyzing both qualitative and quantitative cross-sectional data. The research started from an exploratory approach to uncover key concepts and their relationships, followed by a confirmatory study to examine effects. Johnson et al. (2007) define mixed method research as an intellectual and practical synthesis of qualitative and quantitative research combining their techniques, methods, approaches, and concepts into a single study. It recognizes the importance of both the qualitative and quantitative viewpoints and tries to combine the strengths and minimize the weaknesses of each inherent method to provide informative, complete, balanced, and useful research results (Creswell et al., 2017; Greene et al., 1989). Following the guidelines of Venkatesh et al. (2013), the thesis started with a literature review and qualitative investigation of the research questions and finished with a large-scale quantitative survey. The goal of the exploratory study was to map the current state of the art, generate hypotheses, and provide deep insights with transferability to a broader set of contexts and strategies for firms. The goal of the confirmatory study was to empirically investigate the relationships of the previously identified hypotheses and provide insights with generalizability to a larger population of companies.

The links shown in Figure 3.1 draw on the BA methodology by Hindle and Vidgen (2018). Addressing how organizations can align their BA development with their business goals, the methodology provides a logical structure and precedence to guide the practice of BA. The BA methodology details a four-stage approach of (1) problem situation structuring, (2) DT business model mapping, (3) analytics leverage analysis, and (4) analytics implementation. The research objectives of this thesis target distinct challenges in each respective stage, as can be seen in Figure 3.1 and detailed in the below sections.

Addressing the first two stages, RQ1 aims to build an understanding and conceptual theory to ground the further exploration of RQ2 and RQ3. For this purpose, we employed the design research methodology for RO1.1 to further develop an existing CE framework and gauge the broad CE expertise from the CIRCit consortium. For RO1.2 and RO1.3, no dominant digital CE framework existed, and the expertise within the CIRCit consortium was limited. Therefore, instead of the design research methodology, we employed a systematic literature and practice review to systematize relevant principles and example strategies from industry and academia. RQ2 targets the two latter stages of the BA methodology, namely analytics leverage analysis and implementation. For RO2.1, we started by conducting a literature review to identify relevant BA resources for CE. Following this, we employed a series of semi-structured expert interviews to detail further the identified factors and a quantitative survey to validate their relevance. For RO2.2, on the other hand, we employed a single case study to provide deep insights and demonstrate how firms can leverage their data science process towards CE. RQ3 targets the third stage of the BA methodology and builds specifically on the identified BA resources from RO2.1. Similar to RO2.1, both RO3.1 and RO3.2 first employed semi-structured expert interviews to detail how managers leverage these BA resources into capabilities, and their effects on CE implementation, ROC, and firm performance. Finally, these insights and the overall conceptual model were validated in a quantitative survey.

3.2 Application Domain

The CIRCit research project focused specifically on manufacturing companies in the Nordics. Although the research outputs can be useful for a broader set of companies, the scope was kept intentionally 'narrow' to ensure consistency and compatibility between the different work packages' methods and tools. Furthermore, since the project followed action research in other work packages, a high degree of relevance and practical implications for each firm was needed. In line with the CIRCit project, we first focused strictly on manufacturing companies for papers 1 to 3 before broadening the scope for papers 4 and 5 to include a more comprehensive set of public and private companies such as IT and financial services, consultancy, retail and consumer goods, transportation, service providers and so on.

3.3 Research Activities

This part details the activities performed during the thesis and the author's main company engagement activities instantiated as part of the CIRCit project. A timeline of the activities is provided in Figure 3.2.

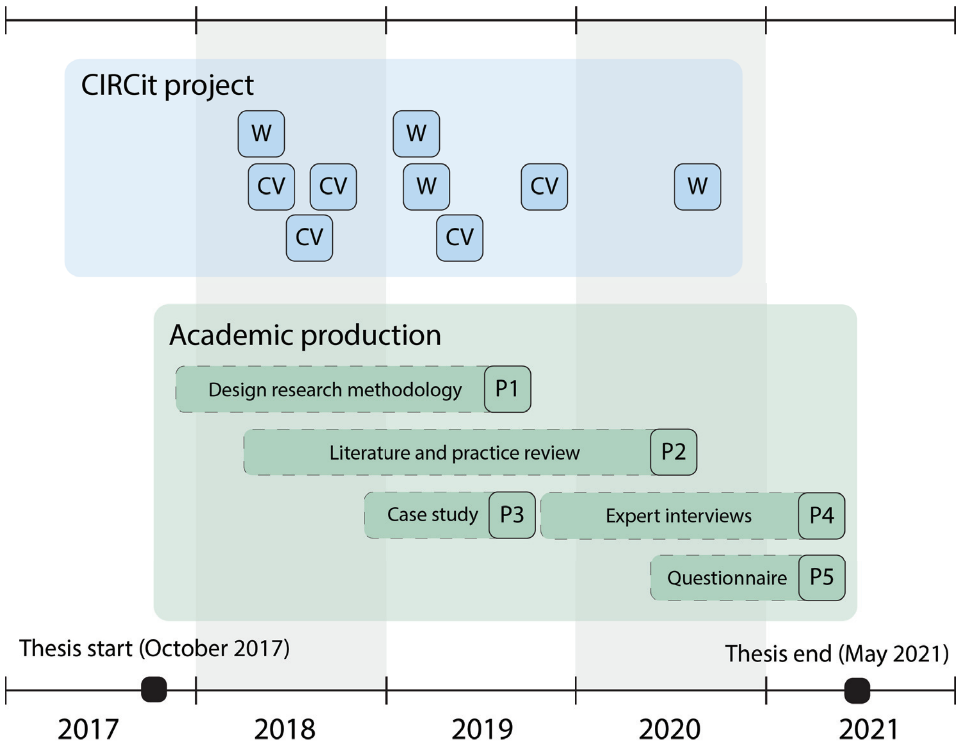


Figure 3.2: Timeline of research activities (W = workshop, CV = company visit)

3.3.1 Design Research Methodology

The first BA methodology stage of problem situation structuring translates to defining a circular strategy of strategic importance to the firm. To support companies conducting CE visioning and extend previous CE frameworks as part of RO1.1, we employed the design research methodology. The design research methodology is particularly suited for iterative improvements of methods and tools (Blessing et al., 2009). The methodology consists of four stages: research clarification, descriptive study I, prescriptive study I, descriptive study II.

The first stage of research clarification aims to explain the research problem at hand and formulate a clear and realistic overall research plan. In this stage, we identified the need for a CE framework specifically for manufacturing companies. Descriptive study I intended to increase the understanding of the research problem identified in the previous stage by describing the research phenomenon and the existing situation. First, a list of circular strategies to be included in the framework was compiled. Second, criteria that could guide the development process of the new framework were articulated, which, third, were used to choose an existing framework as the basis for the development of the new framework. A series of workshops and meetings were held for this purpose. Prescriptive study I aims to address the research problem by leveraging the findings from previous stages for problem-solving and empirical development. A series of workshops and follow-up meetings were held to conceptualize and develop a first version of the circular strategies framework along with corresponding clarifications and elaborations on strategies and the relationship between them. Descriptive study II focuses on evaluating the proposed solutions from the prescriptive study and clarifies the actual applicability and usability of the empirical developments. In this phase, the applicability and usefulness of the framework in the context of the manufacturing sector were evaluated, and improvement opportunities were sought. Workshops were performed with three manufacturing companies from the heavy machinery, electronics, and furniture sectors. For the purpose of our study, we added a fifth stage of prescriptive study II with additional empirical development to further refine the framework. A series of meetings were held to discuss the implementation of improvement opportunities based on insights from the previous phases. A second version of the framework and a final list of strategies and definitions were developed during this phase. See Figure 3.3 for an overview of each respective stage and paper 1 in part II for more details.

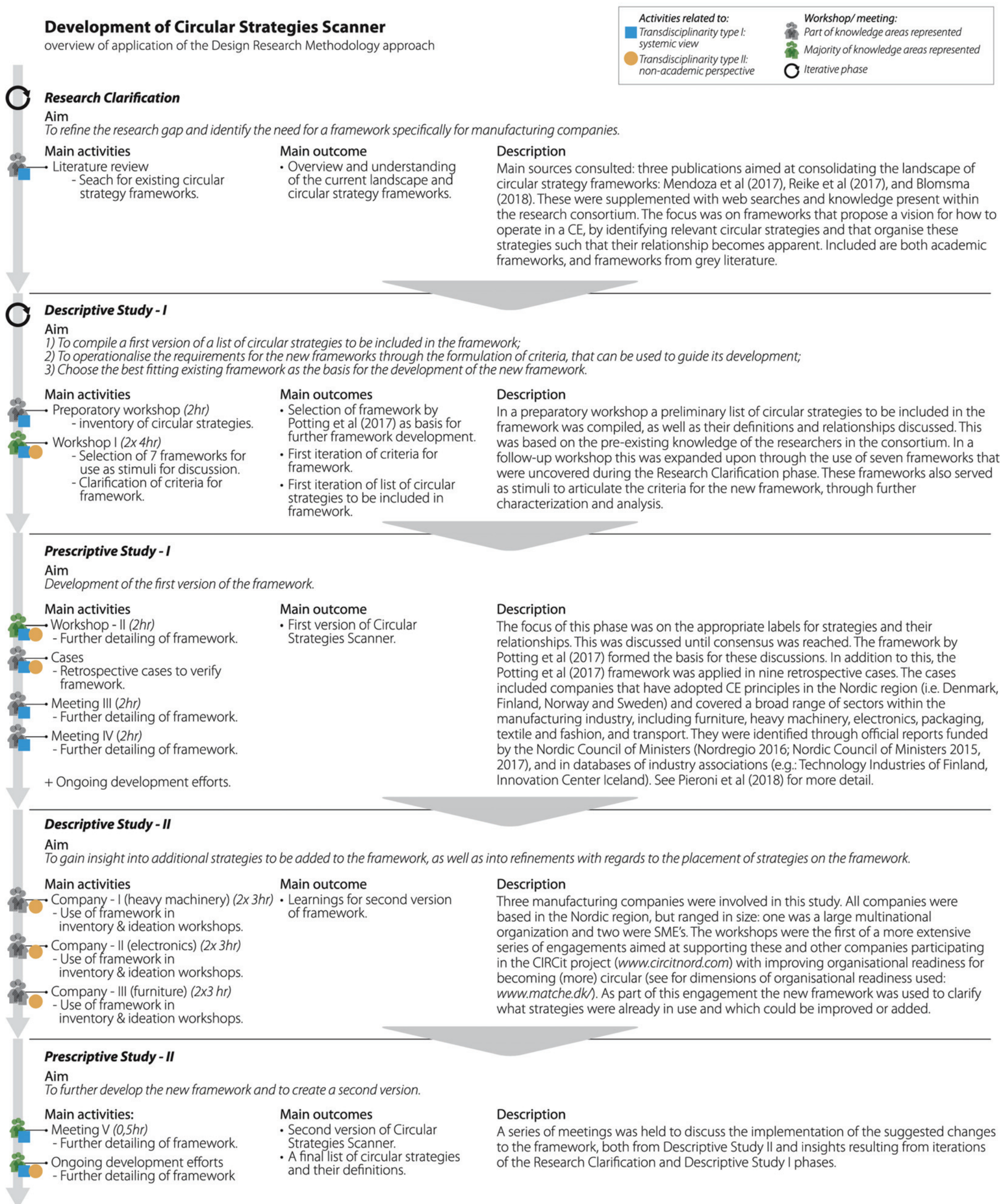


Figure 3.3: Schematic illustration of the design research methodology followed for RO1.1

3.3.2 Literature and Practice Review

In the second BA methodology stage of business model mapping, we focused on identifying the operational and strategic requirements needed to leverage digital circular, or smart circular, strategies. As detailed in RO1.2 and RO1.3, we aimed to develop a digital CE framework and knowledge base to support companies in conducting BA gap analysis and to create roadmaps for implementation. Given the emerging and burgeoning characteristics of the domain, we investigated not only academic sources but also case study examples from practice and 'grey literature' (i.e., published material that has not been subject to a peer-review process (Adams et al., 2017)). We followed the methodology used by Bocken et al. (2014), who detail three iterative phases for a practice and literature review: (1) identification of themes and categorizations by literature review, (2) synthesis by developing an integrative framework, and (3) identification and mapping of examples from practice to validate and further develop the framework. In addition, we adhered to the guidelines for reviewing academic literature by Kitchenham and Charters (2007) and for grey literature by Adams et al. (2017). Furthermore, we built on the previous evaluation and review of CE frameworks conducted for RO1.1. See Figure 3.4 for an overview of the steps involved and paper 2 in part II for more details.

3.3.3 Expert Interview and Questionnaire

In the third BA methodology stage of analytics leverage analysis, we focused on mapping the organizational resources and capabilities needed to leverage BA for CE effectively. Detailed as RO2.1, RO3.1, and RO3.2, the aim was to identify BA resources necessary for CE and understand how managers structure, bundle, and leverage them into capabilities for improved firm performance. Utilizing the RBV and the ROV as the grounding theoretical frameworks, we first employed a literature review in combination with semi-structured interviews (see Figure 3.5 for the steps involved). Provided no previous measures of BAC for CE exist, it was necessary to conduct an exploratory qualitative study before any confirmatory quantitative studies could proceed. This was done in order to explore key concepts and their associations to ensure that no important concepts were omitted from further studies. It is also argued by several method studies that exploratory research should precede confirmatory quantitative studies, in order to explore the construct space and the intricacies of the concept being examined (Sarker et al., 2013).

The literature review focused with on the critical aspects and organizational resources of a CE-specific BAC. The purpose of the review was to identify the main underlying concepts from related research streams in both BAC theory and CE theory. Based on this, we developed the first version of a theoretically guided conceptual model and the resources of the BAC. Following the literature review, a gap remained in understanding how firms leverage BA for CE. To address this, we employed a series of semi-structured interviews, following the guidelines of Bogner et al. (2009) and Patton (1990), with experts from key positions in industry, such as CEOs and directors of IT service, shipping, and retail companies. In this context, experts are defined as someone with privileged knowledge about the topic of interest

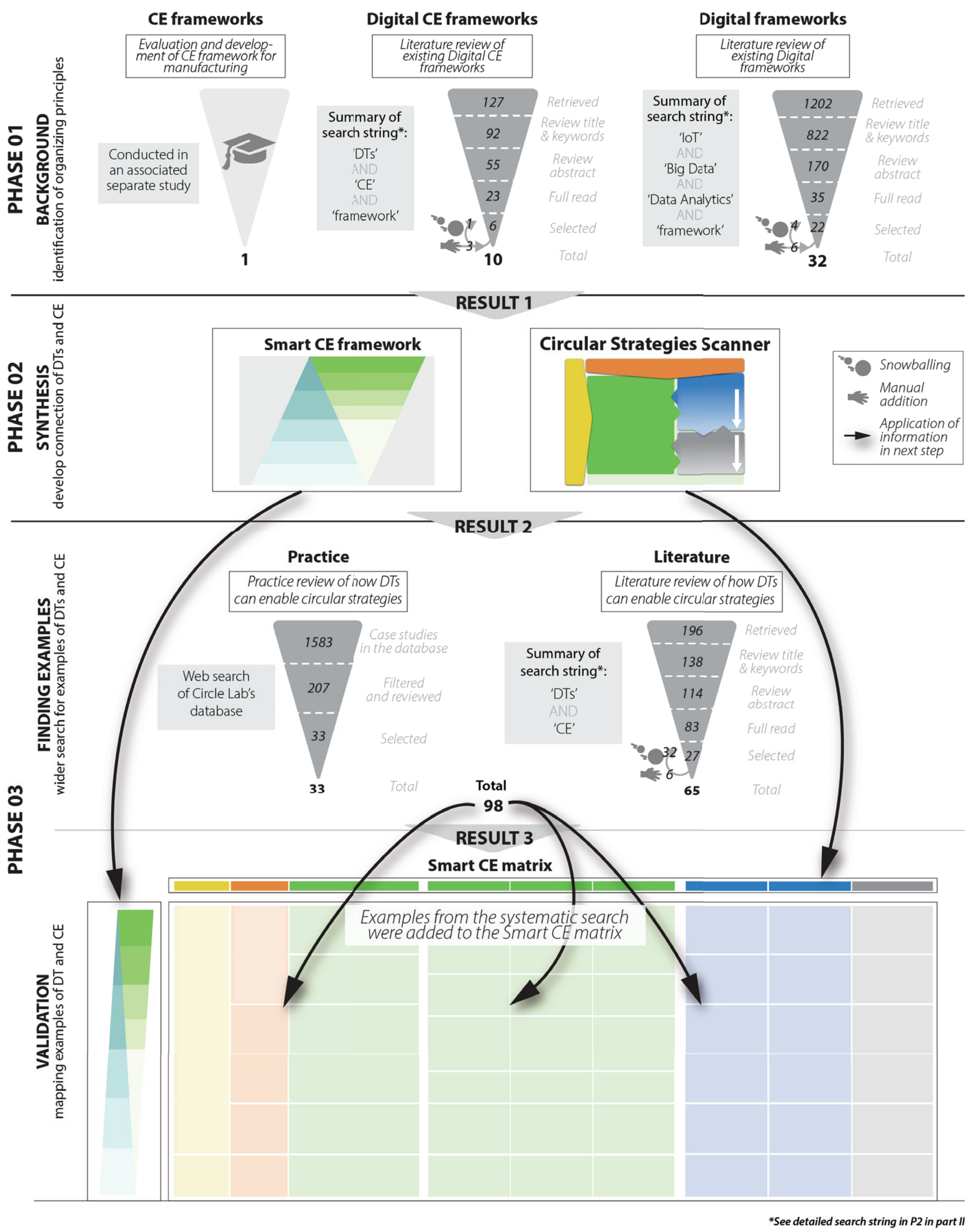


Figure 3.4: Schematic illustration of the research approach followed for RO1.2 and RO1.3

(Bogner et al., 2009). The interviews were supported by an interview guide (see the appendix of paper 4 in part II) in accordance with the recommendations of Myers and Newman (2007). Semi-structured interviews represent an effective way to elicit rich data (Alshenqeeti, 2014; Kvale et al., 2009), understand why some resources are more important than others, and under which conditions they are used for capability-building activities. The benefit of this approach, in contrast with structured interviews or quantitative approaches, is that it allows for thematic analysis and the discovery of new perspectives and relationships between topics that were previously not conceptualized (Savin-Baden et al., 2013). This enabled, after the interviews, updating the initial constructs, definitions, and relationships in the conceptual model and through this the core organizational resources or building blocks of BACs. See paper 4 in part II for information on data collection and analysis along with details of respondents and thematic support.

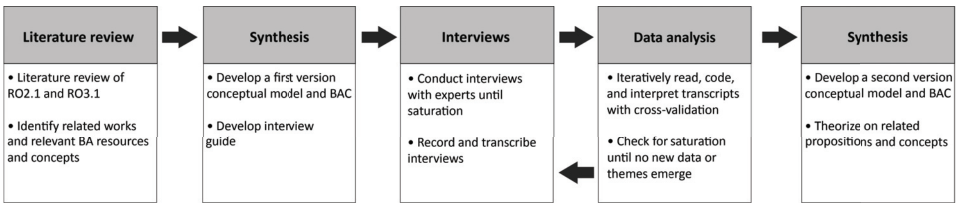


Figure 3.5: Research steps involved for the qualitative study (see paper 4 in part II for details)

The underlying logic of the conceptual model developed (as seen in Figure 3.6) incorporates both resource-picking (from the RBV) and capability-building (from the ROV) theory. The model posits that firms with a strong BAC position themselves with the capacity to strengthen existing circular strategies, implement new ones, improve their IT ROC, and increase their overall firm performance. As such, the effect of BAC on firm performance is fully mediated by firms' IT ROC and degree of CE implementation. Based on this, five hypotheses were generated for quantitative evaluation:

H1. BAC will have a positive effect on CE implementation.

H2. BAC will have a positive effect on ROC.

H3. CE implementation will have a positive effect on firm performance.

H4. ROC will have a positive effect on firm performance.

H5. BAC will have a positive indirect effect on firm performance, which will be fully mediated by a positive effect on CE implementation and ROC.

For the purpose of the identified hypotheses, we adopted a questionnaire-based survey method to allow for generalizability and replication of the results and

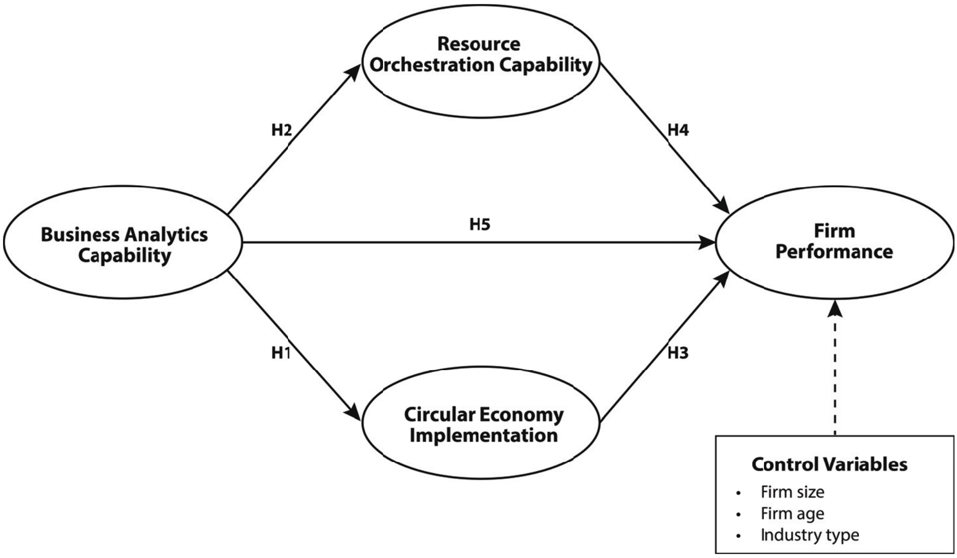


Figure 3.6: Conceptual model of the relationship between BAC, ROC, CE implementation and firm performance (see paper 5 in part II for a detailed explanation of the model, hypotheses, and definitions)

to facilitate simultaneous investigation of several factors (Kraemer et al., 1993). The methodology is well documented in exploratory settings and a robust way of identifying the general tendency and associations in a sample with predictive theory for generalization of results (Straub et al., 2004). We followed recommended guidelines for developing the questionnaire (Churchill Jr, 1979; Recker et al., 2010). In addition, we folled the recommendations and tactics (i.e., personalization, consent screening, and anonymity) by Cycyota and Harrison (2006) to improve response rates. Our trial questionnaire was shared with a panel of experts for careful assessment and refinement of indicators, questions, and wording. All items were measured on a 7-point Likert scale due to its suitability for quantifying constructs such as organizational resources and capabilities (N. Kumar et al., 1993). Following the panel review, a pretest was conducted in a small sample of 11 firms to test the statistical properties of the constructs and assess the face and content validity of items to ensure respondents interpreted the questions as intended. After completing the pretest, the respondents were contacted by email and asked about the quality of the questionnaire and to provide suggestions for improving the clarity of the questions. The aforementioned step satisfied the psychometric properties for suitability and validity of our questionnaire.

For the main sample, names and details of senior executives engaging in digital and CE activities were obtained from personal contacts, corporate directories, and professional forums. From this, 180 relevant executives and 11 industry networks with European companies were used to disseminate an electronic survey an electronic survey via Nettskjema (an online survey tool developed and operated by the University of Oslo, Norway). The respondents were invited by email and followed up by two reminders, each spaced two weeks apart. The data collection phase lasted for approximately two months (October 2020 – December 2020). The sample comprised 64 responses, 56 of which were complete and retained for further analysis. Due to the inadequate number of responses, a second data collection phase was performed using a panel service company to disseminate the questionnaire, lasting for approximately one month (January 2021). To ensure quality responses and consistency with the sample in phase one, the panel service was given strict criteria (guided by a list of control questions) on what would qualify a respondent for the survey. The second data collection phase resulted in 123 responses, 75 of which qualified for the survey with 69 complete responses. In total, the final sample consisted of 125 responses with an average completion time of 13 minutes.

To assess the validity and reliability of our conceptual model, we used PLS-SEM and the software package SmartPLS 3 to conduct the analysis (Ringle et al., 2015). Given that our proposed model is targeted towards exploratory theory building, as opposed to theory testing, PLS-SEM is seen as a better option than covariance-based SEM. Further, PLS-SEM allows the use of mixed model specification methods (i.e., simultaneous use of formative and reflective constructs in higher-order latent constructs), while covariance-based SEM methods do not (Akter et al., 2017). PLS-SEM is regarded as a robust and powerful statistical tool and has been applied across various disciplines (Joseph F Hair et al., 2012), including both BA and CE research (Akter et al., 2019; Khan et al., 2020; Mikalef et al., 2020). Moreover, PLS-SEM is recommended when the research is exploratory, focusing on predicting target constructs for complex structural models and allowing for simultaneous estimation of multiple relationships between one or more independent and dependent variables (Joe F Hair et al., 2011). Categorized as a variance-based soft modeling technique, PLS-SEM can be used to estimate both reflective and formative constructs and is a well-suited predictive tool for theory building of complex models using smaller samples (Nair et al., 2018). In terms of sample size requirements, the total of 125 respondents meant that our sample exceeded both requirements of: i) ten times the largest number of formative indicators used to measure one construct, and ii) ten times the largest number of structural paths directed at a particular latent construct in the model (Joe F Hair et al., 2011).

3.3.4 Case Study

In the fourth BA methodology stage of analytics implementation, we focused on understanding how firms employ the data science process for smart circular strategies. Detailed as RO2.2, we aimed to address shortcomings in the early phases of the data science process, specifically data understanding and preparation. For this objective, case study research was chosen as the methodology for empirical investigation (Yin, 1984). The case study research methodology is particularly suitable for empirical investigation (Jabbour et al., 2019a). It helps provide insights with a relatively good understanding of the complexity and nature of the phenomenon (Voss, 2010).

Moreover, even a single case study can provide scientific development through a deep understanding of the problem and the capturing of experiences (Flyvbjerg et al., 2011). A research protocol was used in order to ensure reliability and validity of the findings, including case study design, data collection, data analysis, and formalization of results (Yin, 1984). The company was selected based on a judgmental sampling technique (Henry, 1990). First, the company should be from the manufacturing industry and have experience with the CE. Second, the company should have IoT data available for analytics exploration. In this regard, a Nordic original equipment manufacturer developing and servicing industrial cranes was selected. The company was a large multinational corporation with extensive experience in multiple smart circular strategies, such as predictive maintenance. Following the research protocol, data collection was performed through five semi-structured interviews to gather general information about the company's context before IoT data were gathered and insights specific to analytics and predictive maintenance were collected. Following the data collection phase, an analytics investigation was performed to evaluate its CE potential and set implementation requirements. Then, the last phase of the protocol was conducted, looking for possible procedural improvements of the data science process to meet the requirements from analytics and CE. See paper 3 in part II for more details.

3.3.5 Summary

To summarize, the sequential mixed method research design of this thesis employed a multitude of methods and engaged a broad set of companies. Mixed method research fits the objective of this thesis well given its capacity to explain and provide understanding for complex organizational and social phenomena (Mingers, 2001). The approach allowed for investigating the research questions from multiple perspectives and alternating between an inductive and deductive frame of thought. This enabled a deep and rich understanding of the problem statement upon which to build new theory. See Table 3.1 for an outline of the methodologies applied for each respective research question.

Table 3.1: Mapping of research methodologies and research questions.

	RQ1	RQ2	RQ3
Design research methodology	•		
Literature review	•	•	•
Practice review	•		
Case study		•	
Expert interview		•	•
Questionnaire		•	•

4 Results

This chapter describes the main findings of the thesis. To structure our discussion, results are organized under each respective research question and corresponding research objectives.

4.1 Relationship Between Digital Technologies and Circular Economy - RQ1

For firms, it is necessary to have a systematic approach to breaking down high-level CE and digital business objectives to concrete operational strategies. For scholars, it is necessary to have frameworks rooted on well-established theoretical underpinnings to ground future research. Addressing this, we developed one CE framework (the *Circular Strategies Scanner*) and one digital CE framework (the *Smart CE framework*) with a corresponding knowledge base of examples. The Circular Strategies scanner provides a taxonomy of circular strategies and a systematic process and examples to support companies in the early stages of a COI process. Building on the principles from the Circular Strategies Scanner, the Smart CE framework and knowledge base integrates this with established ICT principles and underpinnings to further improve our understanding of the relationship between DTs and the CE through common technical mechanisms.

4.1.1 The Circular Strategies Scanner - RO1.1

Addressing the shortcomings in previous CE frameworks, the *Circular Strategies Scanner* (shown in Figure 4.1) presents a taxonomy of circular strategies based on business processes typically found in the manufacturing context. Drawing from both academic and practitioner perspectives, the Scanner framework provides circular strategies ranging from incremental to transformative, or from operational to strategic. Operational strategies include reducing, restoring, and avoiding impact in areas such as sourcing, manufacturing, product use, and logistics, as well as the recirculation of products, components, and materials into new or existing use cycles. Strategic applications include rethinking and reconfiguring value-generating architectures and reinventing the ‘paradigm’ for radical decoupling. In other words, the Scanner provides comprehensive support for manufacturing companies engaging in COI processes. For a detailed explanation of the framework, see paper 1 in part II.

A strength of using the Scanner in COI is that it provides a way of systematically exploring circular strategies. It thus provides guidance for identifying what business areas eco-innovation for CE is possible or necessary. For instance, when improved recycling is identified as an opportunity, the Scanner indicates that other circular strategies in the operational areas of raw materials and sourcing, manufacturing, product use and operation, and the recirculation of parts and products may be affected. Such impacts may be synergistic and result in increased overall circularity (e.g., the choice to change to a recyclable material to enable end-of-life recycling also enables recycling of waste within the manufacturing process), or they may take the form of trade-offs and require additional management or development for resolving them (e.g., changing to a recyclable material negatively affects the technical longevity of a product).

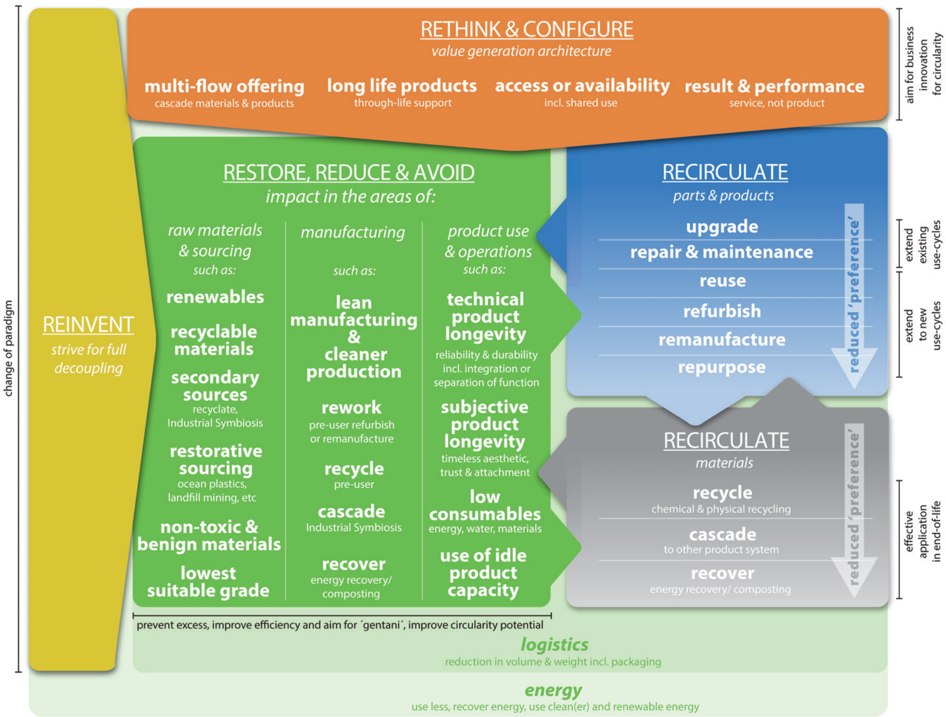


Figure 4.1: The Circular Strategies Scanner

Application of the Scanner furthermore strengthens the connection between eco-innovation and CE by linking it with transformative innovation (De Jesus et al., 2018). It does this in two ways in COI processes. First, due to possibilities uncovered in the operational area, it can trigger a re-evaluation of the value generation architecture. Second, when the value generation architecture is the starting point, the Scanner indicates that the role of the circular strategies on the operational level need to be revisited as their relevance may increase or diminish depending on the context. In both cases, the Scanner invites a reconsideration of the system the manufacturing company is attempting to transform and links circular strategies together in circular configurations: situations where two or more circular strategies work together (Blomsma, 2018).

4.1.2 The Smart Circular Economy framework - RO1.2

In order to better connect the emerging fields of DTs and the CE we developed the *Smart CE framework* (shown in Figure 4.2), which establishes a link between DTs and resource management[1] through an integrative model based on maturity thinking. The framework provides a detailed understanding of the relationship between DTs and the CE through technical mechanisms and BA requirements. It allows assessment of the current and future smart circular strategies with their associated and target level of maturity, and provides guidance on how to leverage DTs to maximize resource efficiency and productivity of strategies. This enables practitioners and academics to develop and implement roadmaps through BA gap analysis, find new opportunities for innovation through examples of best practices, and align people across the boundaries of disciplines.

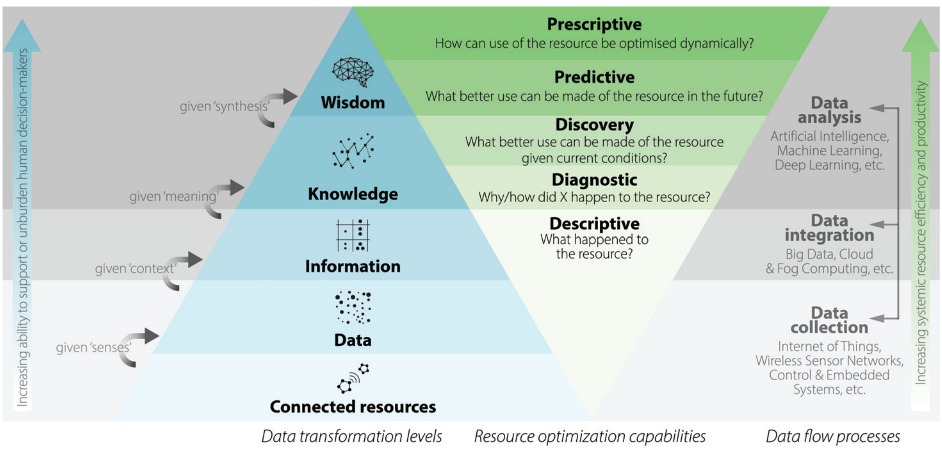


Figure 4.2: The Smart CE framework

The framework consists of three main elements: *data transformation levels* (blue triangle), *resource optimization capabilities* (green triangle), and a layer linking these elements together, *data flow processes* (grey background), as seen in Figure 4.2. The different elements were combined by using a hierarchy as the main organizing principle where each individual level relies on the previous ones. That is, for the data transformation levels, resources must be connected by an IoT sensor in order

[1] Here, we refer to physical resources such as materials, components, and products. Not organizational resources.

to generate data. This can then be turned into information by integrating it with other data sources and providing the context, and so on all the way up to wisdom. Likewise, for resource optimization capabilities, diagnostic analytics provide insights into why something happened and build upon descriptive insights of what actually transpired. Similarly, in the data flow processes, data is first collected and integrated to facilitate data analysis. The remainder of this section explains the three elements, illustrates their compatibility in a single framework, and details the various levels of adoption through maturity thinking. For a more detailed explanation of the framework, see paper 2 in part II.

4.1.3 Knowledge base of smart circular strategies - RO1.3

The literature review on smart circular strategies resulted in 65 included papers (27 from the database search). The practice review of case studies from the Circle Lab's knowledge hub was filtered using the label 'Incorporate digital technology, ' resulting in 207 results. Both the case descriptions in this database and the company website(s) illustrating the cases were consulted (in line with Adams et al. (2017)), resulting in 33 examples added for a total of 98 real-world and theoretical case examples.

The Circular Strategies Scanner and the Smart CE framework enabled mapping of strategies into a matrix (represented by three figures in paper 2 in part II with detailed case descriptions). The Scanner, representing the x-axis or the columns, covers a range of circular strategies relevant for manufacturing companies. The Smart CE framework, representing the y-axis or rows, covers DTs and different maturity levels of adoption (see also Figure 3.4 for a schematic illustration). Strategies were then placed in a cell corresponding to the category, DTs, and maturity of the application. See Table 4.1 for a summary of the examples mapped. The cases represent a mix of theorized applications and real-world examples.

The results show that both theorized and real-world examples embody all the circular strategy categories. Moreover, up to and including the prescriptive level, the matrix has good coverage for all the categories, except the recirculation of parts, products, and materials. To address this issue and outline avenues for future research, the authors propose examples of future strategies, where both literature and practice are incomplete. However, the overall satisfactory coverage of circular strategies supports the validity of the Smart CE framework. The final mapping outlined 100 theorized and real-world smart circular applications (including strategies from literature, practice, and the authors).

Table 4.1: Summary of results where { } are real world cases and [ ] are theoretical cases (see the appendix of paper 2 in part II for reference numbers)

	Strategic		Operational						
			Restore, reduce & avoid				Recirculate		
CE categories	Reinvent	Rethink	Raw materials & sourcing	Manufacturing	Product use and operation	Logistics and energy	Extend existing use cycles	Extend to new use cycles	Materials
Prescriptive		{48,91}, [7,31,40]	{56,67}, [10,31]	[85,89,92, 96]	{91,95}, [85]	{34,35,64, 77,86}, [6,10, 23,24,40]	[7]		
Predictive			{56,57,71}	[88,93]	{20,22}, [4,8,9,10, 14,19,21]	{36,50}	{20,22,76, 91,98}, [4,9,10, 14,21]	{22,53}, [10]	{48,86}
Discovery	{35,91,95}, [41,42,43, 84,85,96]	{26,51}, [5]	{26,51,56, 57}, [5,10]	[88,93]	{3,20,91}, [2,4,8, 9,12,13, 14,23]	{86}, [6]	{3,20,97}, [14]	{63,72}, [4,10]	{61,69}, [4,10]
Diagnostic		{26,45}, [5]	{26}, [5]	[92]	{37}	{45}	{3,20,76, 82}, [4,9, 14,21]	{49,52,54}	{45,74}
Descriptive		{22,46,58, 62,65,70, 80}, [4,19,33]	{27,56,57, 83}, [2,5,10]	{59,60}, [5]	{3,16,17, 20,22,44, 62,65,70, 80}, [2,4, 8,9,12, 13,14,21, 23,29,32]	{11,16,46, 66,69,75, 81}, [1,7,8, 10,15,21, 23,32]	{20,22,76}, [9,10,14, 32]	{22}	{23,48, 68,86,90}
Applicable to all levels	{87}, [2]	[2,25,28]	[38,39]	[18,31,94]	{16,17,20, 22,79}, [2,4,8,9, 12,13,14, 21,23,32]	{73}, [2,23, 30,33,47]	{55,69,78}, [2,10]		[2]

Data Transformation Levels / Resource Optimization Capabilities / Data Flow Processes

However, for brevity purposes we limit our discussion here to only a few illustrative examples. In Figure 4.3, we highlight the examples of industrial symbiosis, maintenance, and recycling. For each strategy, we expand the examples with digital and human requirements for each level to illustrate the increasing ability of DTs to support or unburden human decision makers (providing increased quality, productivity, and flexibility). One way to understand this is that the digital and human elements together represent all the decisions needed to coordinate the resource flow for a specific strategy. Hence, when the number of decisions made by DTs increases, the decisions made by humans decrease or shift, providing flexibility for pursuing strategic activities for increasing business value and resource productivity. Note that we are not detailing the 'ideal' digital and human requirements for implementation, but rather a proposed structure for explanatory purposes.

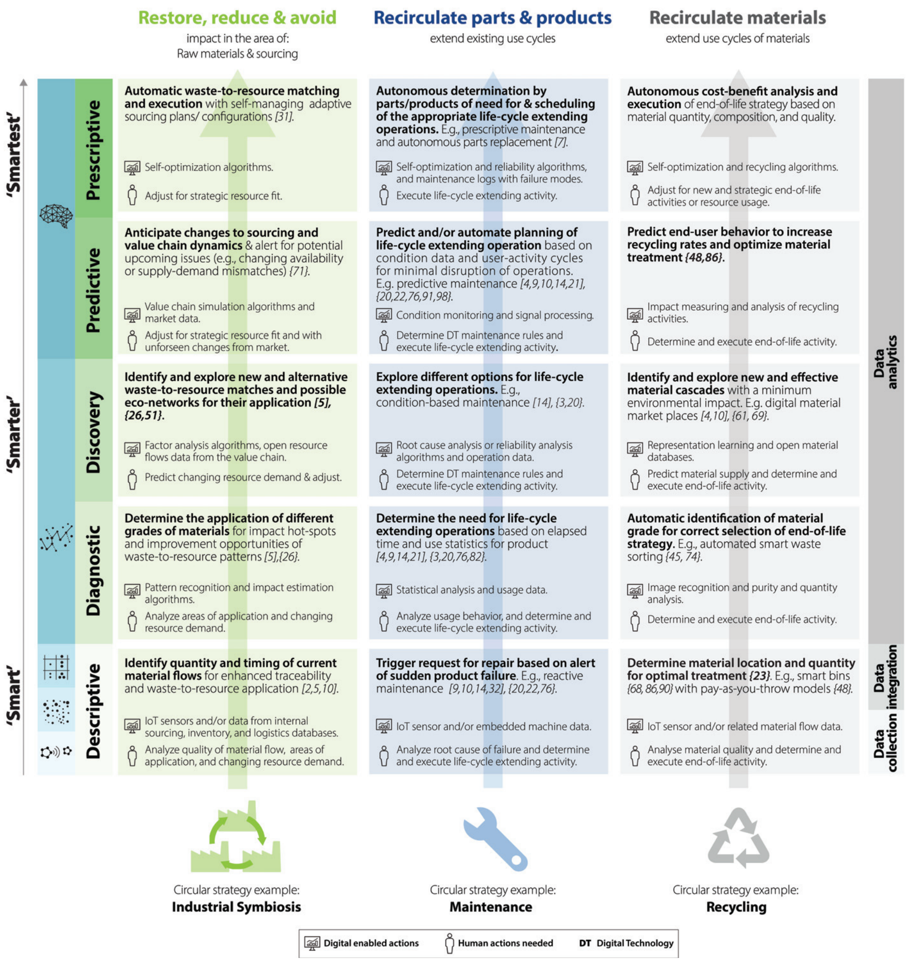


Figure 4.3: Illustrative examples with representative requirements (see paper 2 in part II for the full 100 examples with details)

4.2 Business Analytics Resources and Process - RQ2

The CE sets greater demand for firms to collect, integrate, analyze, and share data across organizational boundaries, both upstream and downstream in the value chain. Consequently, adopting circular strategies imposes different BA resources compared to previous BAC research. Building on the results of RQ1, we detailed the core artifacts of BA pertinent to CE and the associated data science process for implementing smart circular strategies.

4.2.1 Key Factors for Holistic Information Management - RO2.1

Overall, the expert interview results corroborate the findings of related qualitative studies, such as the importance of holistic information management for BA-enabled CE supply chains by Gupta et al. (2019). The role of BA was highlighted by all respondents as critical to the success of their organization's CE transition. The general consensus was that CE sets greater, and more holistic, demands for their firm's BAC. Specifically, several respondents called for a broader definition of BA reflecting the triple bottom line (economic, environmental, and social value) of the CE.

Based on the results of the interviews, the initial constructs of BA resources (identified in a separate literature review) were adjusted, refined, and further developed to reflect the theories and practices of CE, as can be seen in Table 4.2. Following this, we visualized the results in several tables to summarize the evidence for each theoretical construct, improve the testability of the theory, and strengthen the bridge between the qualitative evidence and the conceptual model (Eisenhardt et al., 2007). For brevity purposes, we only discuss the summary of these tables here (complementary tables can be seen in paper 4 in part II). Table 4.3 provides an overview of the BA resources the respondents had implemented for CE.

We observed a considerable discussion concerning the need of distinct BA resources for the CE. While several parallels were drawn to traditional BA resources, the respondents were unison in their response that effectively transitioning to the CE required new BA resources. In summary, eight key BA resources were identified. In Table 4.3 the importance of each resource is noted. Black circles (●) indicate that the resource was mentioned as an important aspect and/or implemented in the organization's strategy of using BA for CE, whereas half circles (◐) and blank circles (○) indicate that it was only somewhat or not implemented. The absence of a circle signals a lack of insight by the respondent or relevance to the company. For instance, the tangible resources of R4 and R10 were both left empty as they represent a one-person consultancy firm. Further empirical insights from the expert interviews into the key BA resources for circular strategies can be seen in paper 4 in part II.

Table 4.2: Definition of BA resources for CE

Resource	Adjustments made	Adapted from literature(s)
Tangible		
- Data: Organizations utilizing BA for CE need to capture both internal and external data from multiple sources, independently of structures and on a continuous basis. Further, aspects concerning data such as quality, sources, availability, and methods for curating needs handling.	Adjusted the content of the definition to comply with CE.	(Arunachalam et al., 2018; M. Gupta et al., 2016; Hedberg et al., 2019; Janssen et al., 2017; Kwon et al., 2014; Mikalef et al., 2017)
- Technology: Novel digital technologies are necessary for handling the large volume, diversity, and speed of data accumulated throughout circular value chains. The complexity of these value chains increases the need for firms to deploy advanced data generation, integration, analysis, and sharing infrastructures.	Adjusted the content of the definition to comply with CE.	(Arunachalam et al., 2018; M. Gupta et al., 2016; S. Gupta et al., 2019; Hedberg et al., 2019; Mikalef et al., 2017)
- Basic resources: Refers to an organization's investment of time and funds. This includes financial resources as direct investments in the support of these technologies and working hours allocated to experimentation with utilizing the potential of BA.	None.	(M. Gupta et al., 2016; Mikalef et al., 2017; Wamba et al., 2017)
Intangible		
- Data-driven culture: Describes the extent to which organizational members are committed to BA and make decisions based on insight derived from data.	None.	(Arunachalam et al., 2018; Dubey et al., 2016; M. Gupta et al., 2016; Mikalef et al., 2020)
- COI culture: Describes the extent to which CE goals, principles, and strategies are integrated into technical and market-based innovations to create value by enabling sustainable management of resources throughout the design of processes, products/services, and business models.	Identified the resource and developed the definition from relevant research.	(Brown et al., 2019; Institution, 2017; Munodawafa et al., 2019; Pauliuk, 2018; Prieto-Sandoval et al., 2019)
- Openness and co-creation: Describes the extent to which organizational members are mutually open about decisions and activities that affect the society/economy/environment and willing to communicate these in a clear, accurate, timely, honest, and complete manner to enhance formal and/or informal arrangements internally and externally to create mutual value.	Identified the resource and developed the definition from relevant research.	(S. Gupta et al., 2019; Hedberg et al., 2019; Institution, 2017; Pauliuk, 2018)
Human skills		
- Systems thinking skills: Refers to the competencies of employees to take a holistic approach for understanding larger contexts over longer periods of time, looking at connections and patterns of how individual decisions and activities impact environmental, economic, and social issues beyond the immediate first-tier scope.	Identified the resource and adjusted the definition from relevant research.	(N. Bocken et al., 2019; S. Gupta et al., 2019; Institution, 2017; Webster, 2013)
- Data science skills: Refers to the competencies of employees to formulate and implement machine learning problems, utilizing data analytics skills such as statistics, computing, and knowledge about correlation and causation.	Identified the resource and adjusted the definition from relevant research.	(Dhar, 2013; Dubey et al., 2019; M. Gupta et al., 2016; Power, 2016)

Table 4.3: Overview of outcomes on BA resources for CE of respondents 1 to 15 (R1-R15)

Resources	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15
Tangible															
- Data	●	●	●		●	●	●	●	◐		●	◐	●	●	●
- Technology	●	●	●		●	●	●	●	◐		●	◐			◐
- Basic resources	◐	●	◐		●	●	●	●	●		●	◐			●
Intangible															
- Data-driven culture	●	●	●	●	●	●	●	●	◐	●	●	●	○	●	●
- COI culture	○	●	◐	●	●	◐	●	○	●	●	◐	○	◐	◐	◐
- Openness and co-creation	◐	●	●	◐	●	◐	●	●	●	●	●	●	●	●	●
Human skills															
- Systems thinking skills	○	●	◐	◐	●	◐	●	●	●	●	◐	●	●	◐	◐
- Data science skills	●	●	●	●	○	●	◐	●		●	●		◐	●	○

4.2.2 The Data Science Process - RO2.2

Asset and process management research argue that data should be specifically structured for the intended use within a work flow (Haddar et al., 2013; Provost et al., 2013). Data science research concurs and notes that insights are more obtainable when the data has been preprocessed for a specific domain of analysis (James et al., 2013; Kun et al., 2019; Lin et al., 2007; Peng et al., 2010; Wood et al., 2014). Based on empirical findings from a case study and an in-depth analysis of shortcomings in existing data science process models, we propose extensions to the Cross Industry Standard Process for Data Mining (CRISP-DM) process model. The proposed process model adds an additional phase called *data validation*, and argues for the integration of *analytic profiles* for improved structure in the process. Figure 4.4 illustrates the enhanced CRISP-DM process model developed.

In CRISP-DM, there is no validation between the *data preparation* phase and the *modeling* phase against the specific business domain (Bahrepour, 2018; Newman et al., 2016). Specifically, once the data is prepared for modeling, only the criteria needed to ensure optimal analytics model performance are considered (Newman et al., 2016; Rüdiger Wirth et al., 2000). Thus, a complete understanding of whether the data is a valid representation of the original problem is not guaranteed. General data preparation methods alter the original data, and there is often loss in information specific to the domain that should be analyzed (Aremu et al., 2018; Newman et al., 2016). As such, this may result in sub-optimal solutions that miss the mark on the intended capturing of business and CE value (Ponsard et al., 2017; Viaene, 2013). Therefore, we argue that data validation should be done by the re-involvement of the business entity, and domain experts, to validate that a proper understanding of the data and business problem has been reached and best-practice data preparation methods from the analytic profile have been followed. The data validation phase may result in a re-iteration of the data understanding and/or the data preparation phase(s) (indicated by a single arrow back in the diagram).

Analytic profiles are defined as structures that standardize the collection, application, and re-use of analytics insights and models for key business entities (Schmarzo, 2015). As such, an analytic profile is an abstract collection of knowledge, mainly used in the business and data understanding phases, that lists the best practices for a particular analytics use case, or problem. Analytic profiles may have different levels of granularity depending on the use case and the organization's level of experience. However, information on the following elements should be included:

Use case description defining the business goal (e.g., predict the remaining useful life of a product),

Domain specific insights important for the use case (e.g., knowledge about typical product failures and causes),

Data sources relevant for the use case (e.g., time-series data of product operation and service data with failure modes),

Key Performance Indicators or metrics for assessing the analytics implementation performance (e.g., product failure rate, downtime and maintenance costs),

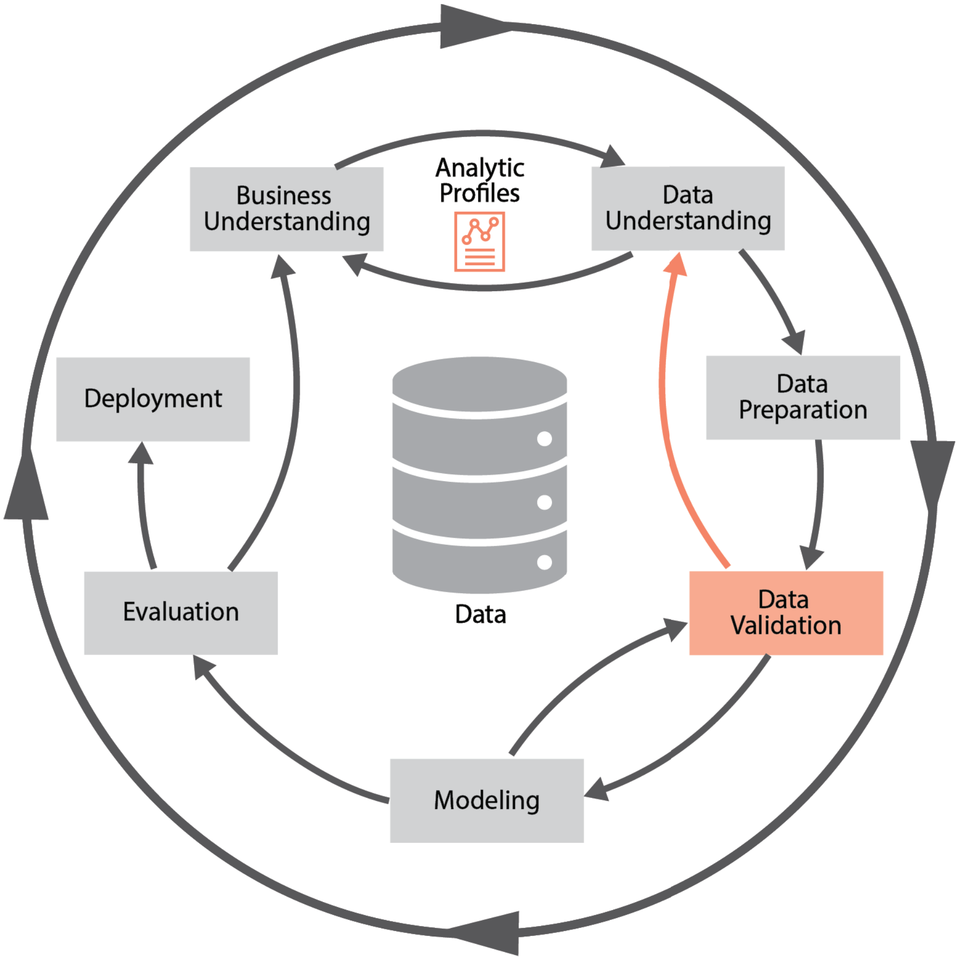


Figure 4.4: An enhanced CRISP-DM process model (changes highlighted in red)

Analytics models and tools with proven conformity for the given problem (e.g., long short-term memory networks and deep belief networks),

Short descriptions of previous implementations with lessons learned (e.g., deep belief networks for backlash error prediction in machining centers (Z. Li et al., 2017)).

As per the CRISP-DM process level breakdown (Chapman et al., 2000), analytic profiles can be regarded as a generic task particularly relevant between the business and data understanding phases (indicated by an analytic profile icon in the diagram). Through such a consolidation of the analytics knowledge base, organizations can more easily learn and reuse their own experience and the experience of others to accelerate the analytics development process. Furthermore, Kiron and Shockley (2011) state that organizations should appropriately structure their resources to align their analytics capability with their overall business strategies. Therefore, we argue that analytic profiles should be built for all business strategies, or use cases, relying on insights from analytics.

4.3 Towards a Business Analytics Capability - RQ3

As evidenced by the previous results, the significance of DTs for organizations adopting CE is the use of data; in other words, they become data-driven. However, becoming data-driven is more than a technical challenge and goes beyond the mere data science process. It requires a clear BA strategy, the right people and organizational culture, and managers to appropriately structure their departments to align BA resources and capabilities with circular strategies and corporate strategy. Once the core resources of BA pertinent to CE are identified (see Figure 4.5 for the classification), it is necessary to understand how they are structured, bundled, and leveraged towards a firm-wide BAC.

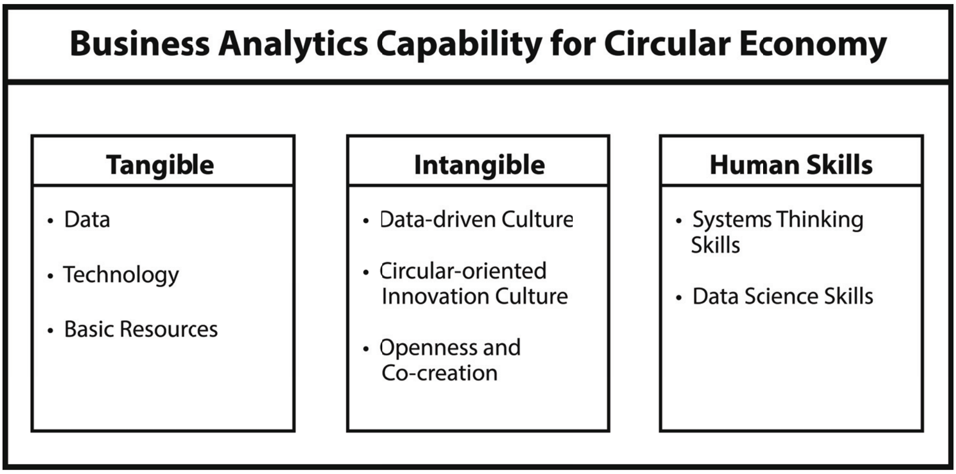


Figure 4.5: Classification of BAC for CE

4.3.1 Resource Orchestration - RO3.1

According to the RBV, resources that possess VRIN attributes (as the ones detailed above) tend to provide better opportunities for competitive performance (Eisenhardt et al., 2000; Mata et al., 1995). However, the findings from our expert interviews corroborate previous studies arguing that merely possessing such resources without leveraging them is counterproductive for the firm (Ahuja et al., 2017). To this end, ROV argues that resources have to be structured, bundled, and leveraged in order to create new capabilities and enable them to generate business value (Wright et al., 2012). Once these capabilities have been internalized, they are difficult for competitors to imitate.

Overall, we observed a great discourse among the respondents of our expert interviews on the importance of leveraging firms' BA resources and capabilities for implementation of circular strategies and competitive gains. In particular, managers were highlighted as crucial to the potential success, or failure, of developments under tangible resources and human skills, such as culture development and employee training. Given the variance in breadth and life cycle of the firms covered in the interviews (e.g., from waste management start-ups to large multinational IT service corporations), we observed a difference from the interview results in the approach and willingness of management to both adopt circular strategies and prioritize corresponding BA investments. This can be understood by drawing on the life cycle logic of the ROV, which states that the start-up stage requires a greater degree of resource-structuring behavior to support the firm's business model when compared to mature firms (Miller et al., 1984; Sirmon et al., 2011). Correspondingly, a mature firm's resources may exert a greater influence on its external environment (Smith et al., 1985). Despite variance in organizations' operating environment and development trajectory, their underlying capability development mechanism was conducive to the process of structuring, bundling, and leveraging, as detailed in the ROV.

Our results corroborate the findings of Wright et al. (2012) on the importance of selecting and structuring BA resources, a prerequisite for building a firm-wide BAC. Overall, we observed numerous activities related to the structuring process, from identifying resources of strategic importance and making investments related to them (e.g., sensor data and data science talent) to creating new organizational structures and business models (e.g., horizontal departments and product-service systems). For the process of bundling, we observed the effectiveness of firms' ability to bundle resources into capabilities frequently reflected in their governance practices and choice of IT archetypes. Traditional archetypes, such as functional silos where each unit handles its resource allocation, were seen as somewhat incompatible with the lateral nature of circular strategies, and several firms noted efforts to remove unnecessary silos and align around common KPIs. For the leveraging process, we noted a number of challenges among firms trying to deploy their newly developed capabilities. For instance, uncertainties were observed on how to mobilize such a capability to *i)* adopt an acceptable level of CE, *ii)* outperform rivals in the short term, and *iii)* maintain a competitive advantage in the long term. Many firms pointed to this being a result of lacking market demand, internal awareness, and the overall fast-moving pace of the field. In other words, this can be summarized as environmental uncertainty, characterized by a general condition of ambiguity and unpredictability of customer needs and technology developments (Pavlou et al., 2006). According to the ROV, this can be understood as an information deficit that affects the type of resources and capabilities needed to outperform rivals and the leveraging strategies required to realize a competitive advantage (Sirmon et al., 2007). The respondents credited CE with strategic relevance for reducing overall risks and for building the material sourcing flexibility needed for a turbulent business environment. For additional details, see paper 4 for insights from the interviews and paper 5 for the impact of firms' ROC.

4.3.2 Conceptual Model - RO3.2

To empirically validate the conceptual model, shown in Section 3.3.3, and BA resources previously identified, we operationalized the main constructs in the model using a hierarchical component model with respective sub-constructs (Sarstedt et al., 2019). We constructed *BAC* as a third-order formative construct consisting of tangible, intangible, and human skills resources as second-order formative constructs, each consisting of three first-order constructs, namely data, technology, basic resources, data-driven culture, COI culture, openness and co-creation, systems thinking skills, and data science skills. *CE implementation* was developed as a second-order formative construct consisting of three first-order formative constructs, namely reinvent and rethink, recirculate, and restore, reduce, and avoid. We constructed *ROC* as a second-order formative construct of three first-order formative constructs, namely structuring, bundling, and leveraging. *Firm performance* was constructed as a second-order formative construct of four first-order formative constructs, specifically environmental performance, financial performance, competitiveness, and corporate reputation. For *control variables*, we collected descriptive information on firm size and age, industry sector, country, ownership structure, experience levels with BA and CE, and the respondents' position within the firm. As our measurement model consisted of both formative and reflective constructs, we used several different assessment criteria to examine their validity and reliability. Further, we employed confirmatory composite analysis of the saturated model to assess its overall fit. Both reflective and formative constructs demonstrated satisfactory psychometric properties with empirical evidence supporting the latent variables constructed. See paper 5 in part II for associated tables and methods used for establishment of the measurement model.

The structural model from the PLS analysis is depicted in Figure 4.6 and presents the results of the structural model explained by the variance of endogenous variables (R^2) and the standardized path coefficient (β). The model was verified by assessing the coefficient of determination (R^2) values, path coefficients, and effect size of the predictor variable (f^2). To obtain significance levels of the estimates (t-statistics), we performed a bootstrap analysis using 5000 resamples. Since PLS-SEM does not require the data to meet any particular assumptions about sample distribution, parametric significance tests cannot be applied. Instead, PLS-SEM relies on the nonparametric bootstrap resampling approach where randomly drawn subsamples are used to derive standard errors, t-values, p-values, and confidence intervals (Joseph F Hair et al., 2016; Preacher et al., 2008). The structural model explained 59.3% of variance in CE implementation ($R^2 = 0.593$), 70.1% in ROC ($R^2 = 0.701$), and 52.2% of variance in firm performance ($R^2 = 0.522$). The expected magnitude of R^2 values is dependent on the phenomenon under investigation and should be judged relative to studies that investigate the same dependent variable (Benitez et al., 2020). In our case, all values exceeded the coefficient of determination in Khan et al.'s (2020) study on CE implementation and firm performance (reporting 0.180 and 0.409 respectively). Furthermore, as our R^2 values represent moderate to substantial predictive power (Henseler et al., 2009), all values are seen as satisfactory.

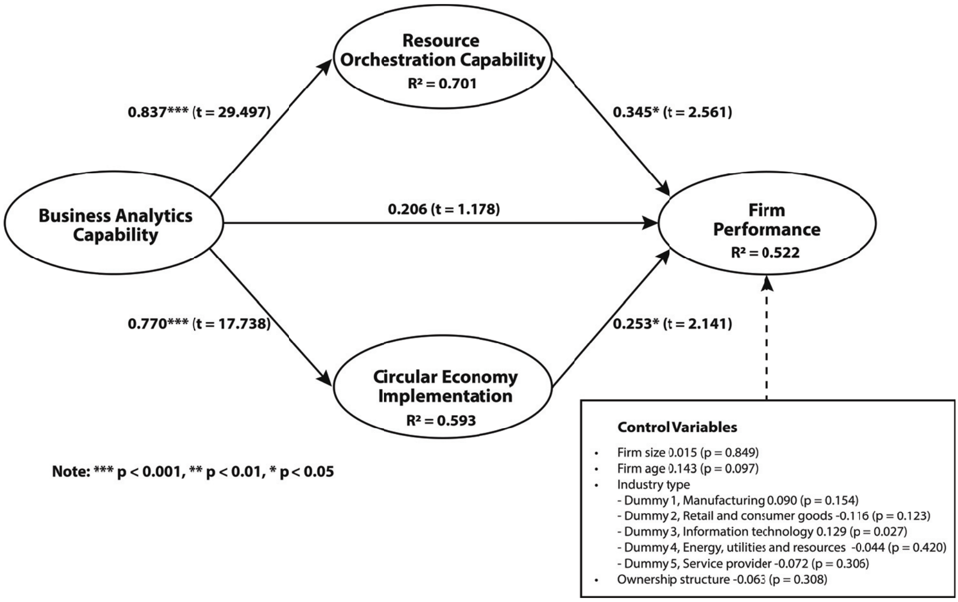


Figure 4.6: Results and estimated relationships of the structural model.

For the path coefficients, firms' BAC was found to have a significant direct impact on CE implementation (β= 0.770, T = 17.738, $p < 0.001$) and ROC (β= 0.837, T = 29.497, $p < 0.001$). The direct impact of BAC on firm performance was not significant (β= 0.206, T = 1.178, $p > 0.05$), as expected for mediation. Furthermore, the impacts of both CE implementation on firm performance (β= 0.253, T = 2.141, $p < 0.05$) and ROC on firm performance (β= 0.345, T = 2.561, $p < 0.05$) were significant. In our model, the f^2 values from BAC to CE implementation (1.454) and ROC (2.349) indicated a strong effect size, while the effect from CE implementation (0.051) and ROC (0.070) on firm performance indicated a weak effect size (Cohen, 2013). The effect size is useful to measure the practical relevance of relationships between constructs by indicating the extent to which the path coefficient exists in the population. The influence of control variables on the dependent variable, firm performance, was examined using dummy variables. All variables were found to have a nonsignificant relationship to firm performance, with the exception of information technology firms (β= 0.129, T = 2.204, $p < 0.05$). Despite having a significant path coefficient, the change in explained variance ($\Delta R^2 = 0.015$) was small and the effect size ($f^2 = 0.034$, T = 0.933, p = 0.351) was weak and nonsignificant. Furthermore, we believe this may not have any practical relevance for our model due to the time when the data was collected (during the Covid-19 pandemic). Information technology companies might have been less affected and this could be why they are more strongly correlated with firm performance. For complementary tables and details regarding tests for mediation and predictive validity, see paper 5 in part II.

5 Discussion

This chapter synthesizes the research findings from the previous chapter by discussing the contributions made in terms of research, practice, and policy implications. In addition, limitations are presented along with avenues for future work.

5.1 Research Implications

While real examples of information flows enabling circularity exist, and researchers' theoretical understanding of the relationship between DTs and CE has been improving (Nobre et al., 2020; Rosa et al., 2020), the mechanisms and conditions under which DTs can accelerate firms' CE implementation remain largely unexplored in empirical research. Addressing this gap, the concept of a Smart CE can be used as a point of reference for using DTs in supporting CE implementation and the enactment of circular strategies. While much of related IS literature is grounded on corresponding theoretical perspectives that explain the value-generating mechanisms of different strategies, the same cannot be stated in the context of circular strategies. At large, this work can be used as a basis upon which researchers can examine the impact that different DTs have on the enablement of circular strategies, sustainable development, and organizational performance.

In the case of DTs' contribution to CE, we developed the Smart CE framework and associated data science process to address DTs' lack of support for COI in manufacturing and significantly improve existing digital CE frameworks. The main difference between our work and related frameworks (Askoxylakis, 2018; Bianchini et al., 2018; de Sousa Jabbour et al., 2018; Ellen MacArthur Foundation, 2016; Ingemarsdotter et al., 2019; Jabbour et al., 2019a; Nobre et al., 2020; Okorie et al., 2018; Rosa et al., 2020; Ünal et al., 2018) is that existing frameworks summarize high-level strategies, possibilities, and/or capabilities, while our model extends this with a detailed structure to systematically support practitioners in searching, analyzing, and advancing smart circular strategies. In this context, we make six contributions:

- First, we give a detailed understanding of the relationship between the technical mechanisms and data science processes of DTs and the strategic and operational strategies of CE.

- Second, we enable strategies to be mapped with their associated and target level of maturity.
- Third, we provide the capacity to accommodate multiple circular strategies and find new opportunities for innovation through example best practices.
- Fourth, we provide the ability to derive digital requirements for implementing circular strategies.
- Fifth, we present guidance on how to leverage DTs to maximize resource efficiency and productivity for a given context.
- Sixth, we produce empirical support for how to effectively apply the data science process for correct utilization of analytics with circular strategies.

In addition, our framework allows both researchers and practitioners to communicate better across the boundaries of disciplines. It highlights key technical mechanisms needed for a more data-driven mode of CE business operations. By extension, our framework provides the basis for further exploration of the BA resources and capabilities central to the adoption of circular strategies. From a research standpoint, our framework highlights the role of novel DTs in shaping the information value chain within the context of CE. Thereby, it differentiates between strategic and operational circular strategies, decomposing them into specific attainable approaches and the corresponding digital requirements needed to foster them. Therefore, it introduces a structured approach in bridging the technical, operational, and strategic aspects of circular strategies.

Effectively leveraging the hype around these DTs through the concept of BA is pivotal for operationalizing the Smart CE. While practitioners seem to have been leading the way for such novel uses of data, academics have only recently begun to investigate the synergies of BA and CE (S. Gupta et al., 2019). Consequently, gaps remain in the literature on defining the building blocks of a BAC for CE and how firms can create one. From a theoretical perspective, our research contributes to the emerging literature on CE, strategic management literature on BAC, and managers' role in resource orchestration (Ahuja et al., 2017; Lahti et al., 2018; Mikalef et al., 2018; Rialti et al., 2019; Sirmon et al., 2011). In particular, the proposed BAC extends our proposed Smart CE framework by providing empirical insights into the key organizational resources and practices needed to leverage such smart circular strategies. By defining a BAC for CE, we make contributions to the existing literature in six main areas:

- First, we present a theoretically grounded framework and construct for examining firms' CE-specific BAC. This extends the literature on RBV and ROV by combining them with BA and CE literature and empirical insights.
- Second, we propose eight constructs that make up the key resources of this capability. These constructs provide valuable insights for future studies by offering a lens to analyze both qualitative and quantitative data.

- Third, we demonstrate that it is important to have this BAC and not just circular strategies in order to operationalize them, thus differentiating between strategy and its enactment.

- Fourth, we further extend the ROV by explaining how the processes of structuring, bundling, and leveraging influence the conversion of organizational resources into firm-wide capabilities along with role of managers for supporting these processes.

- Fifth, we highlight the effect of BAC on ROC, which is an assumption many studies carry but which has not been empirically validated.

- Sixth, we provide a deeper understanding of the mechanisms through which organizations leverage these capabilities for improved CE implementation and firm performance.

Furthermore, by analyzing both qualitative interview data and quantitative survey data, we make important contributions to both the IS and organizational sustainability research fields by exploring the inner mechanisms of how BA improves CE implementation along with their joint effect on firm performance. For research investigating how firms transition towards the CE, we demonstrate the importance of developing a strong BAC to enable the operationalization of circular strategies and to better leverage such strategies for increased value generation and firm performance. The thesis also contributes to strategic management theory by developing and empirically validating an instrument to measure the IT-based ROC of firms. This builds on previous literature showcasing the importance of BACs for developing dynamic capabilities and supporting decision-making across different stages of the industrial life cycle of assets (Mikalef et al., 2018; Wamba et al., 2017; G. Wang et al., 2016). The latter proposes interesting propositions on the roles of ROC and CE implementation in mediating BAC's effect on firm performance.

Our empirical findings are consistent with related BA and CE studies, such as the results by Gupta et al. (2019) on the importance of strategic investments in BA for CE, the effect of CE implementation for firm performance by Khan et al.'s (2020) and Mikalef et al.'s (2020) results on the contingent role of dynamic and operational capabilities in BACs' effect on firm performance. Our work raises several implications for DT-enabled CE research. Specifically, highlighting the role of digital transformation for sustainable development, explicated through the role of BA for accelerating firms' CE adoption and realization of business value. While the development of DTs is not a prerequisite for CE implementation, it can help organizations yield faster returns and greater impacts on their CE investments. Notwithstanding the direct effects of DTs on firm performance for general business operation (Akter et al., 2016), we highlight the importance of IS research to examine the impacts of IT beyond firm performance and strengthen the research in areas of CE and sustainability.

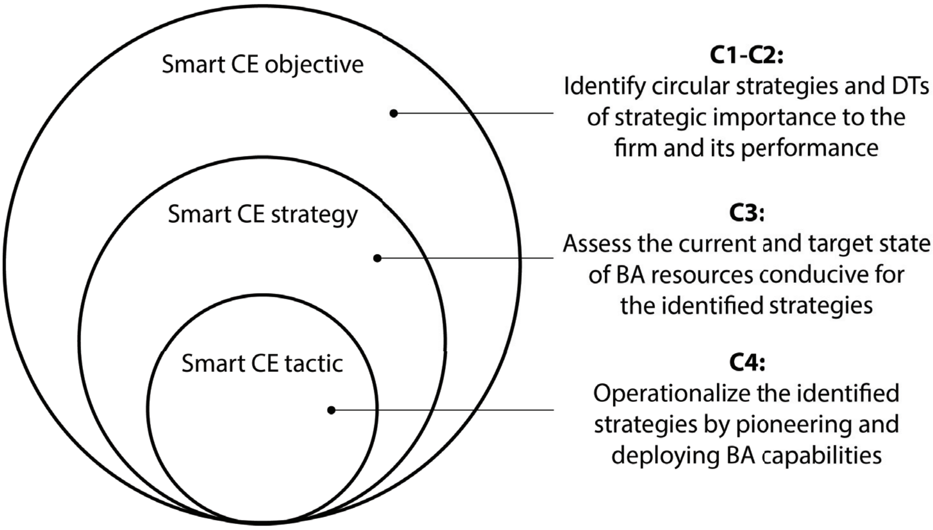


Figure 5.1: Smart CE research scope and contributions

5.2 Practical Implications

With the overall aim of investigating how companies can be supported in leveraging DTs for CE, the practical relevance of this work is indeed important. First and foremost, the Smart CE framework and accompanying knowledge base of examples represent the initial contact point and overarching 'process' for working with this research. The example strategies presented in the knowledge base, as explained in Section 4.1.3 and shown in Figure 4.3, when organized using the Smart CE framework, may be used by organizations for BA gap analysis and to create roadmaps towards CE implementation. A primary requirement for effectively leveraging smart circular strategies and tactics is the alignment of BA development with the business model. Hence, managers, in particular, may find both the framework and the knowledge base useful for effectively aligning DT implementation with COI and business model development in four areas. First, by identifying which smart circular strategies are primarily important to the company. Second, in mapping the current level of digital maturity and CE adoption. Third, establishing the required level of digital maturity necessary to implement a desired smart circular strategy, and fourth, deriving BA factors essential for its successful adoption.

To demonstrate such a mapping, we draw on a simplified version of the VMOST (vision, mission, objectives, strategy, tactics) framework (Sondhi, 1999). Frequently used by practitioners in different variations, the VMOST framework illustrates how high-level goals can be made increasingly more concrete by moving from vision to mission to objectives to strategy, and eventually, operational tactics. In Figure 5.1, we illustrate parts of such a scoping exercise from objectives to tactics, along with the contributions of this thesis. The Smart CE framework can also be used to gauge the target maturity level or smart circular strategy that is of strategic importance. This serves as a benchmark upon which managers can allocate necessary resources and deploy the corresponding technologies to attain the targeted level of maturity. Finally, by developing a roadmap for implementation using BA gap analysis, it is possible to compare the current and desired BA levels. This is particularly useful for practitioners, who typically have very few practical guidelines to proceed with digitally enabling circular strategies. The framework can, therefore, be used to not only identify the target objectives but also to provide support in realizing these strategies. It complements existing methods that are more focused on leveraging data artifacts and can be used in unison with the data science process proposed in this thesis.

Furthermore, in terms of practical relevance of the proposed CE-specific BAC, firms may find this useful in three main areas. First, to seek incentives for transitioning towards the Smart CE. In our empirical investigation, we found that combining BA with circular strategies strengthened firms' organizational performance in terms of competitiveness, corporate reputation, financial, and environmental performance. This is a valuable finding for firms as it presents a business rationale for implementing circular strategies and shows how to capitalize on BA investments. Furthermore, it provides strategic justifications for transitioning to a more sustainable mode of business operation. This may be particularly useful for forward-thinking managers and early CE adopters lacking arguments, or proofs, to support change in corporate strategy. Second, understanding which organizational resources and capabilities are important for leveraging BA for CE. As firms reposition their business to meet new customer needs and regulations for sustainability, investments will be crucial for the survival and sustained competitiveness of the firm. Therefore, correctly identifying which resources to invest in and which capabilities to develop will be critical. This thesis also shows that leveraging BA for CE requires investments across talent, culture, and technology. As evidenced by the eight distinct factors comprising the BAC for CE, companies should be wary of focusing only on tangible assets such as data and IT infrastructure, and should also target investment in their human capital—for instance, by improving managers' systems thinking skills and devotion to establishing a data-driven culture. By untangling the relationship between BA and CE, we advocate for more holistic information management, encouraging more focus on 'green digital transformation' within companies. These findings can support the development of more constructive guidelines for implementing circular strategies and help firms make more cost-effective BA investments. For instance, by developing the BAC into a benchmarking tool to map firms' maturity and guide their investments through customized roadmaps. Third, by establishing the ROC, we demonstrate the importance of managing BA resources in order to seize business value and performance returns of BACs. For instance, the ROC can be integrated in the BAC benchmarking tool and roadmap to aid firms in SWOT (strengths, weaknesses, opportunities, and threats) analyzes to understand where and how to target development activities. The ROC is confluent with previous strategic management theory (Wright et al., 2012), arguing that only procuring and holding valuable resources does not translate into business value or performance gains in itself. Instead, firms should focus on developing internal capabilities to better orchestrate such resources. Thus, firms may find this research useful to better manage their employees, at various levels, around the structuring, bundling, and leveraging processes of resource orchestration. By better understanding the relationship between BAC, firm performance, and the mechanisms in between, firms are better equipped to facilitate change.

5.3 Policy Implications

Despite the evident barriers of conflicting definitions and missing standardization of CE (ISO, 2020; Kirchherr et al., 2017), this also represents an array of opportunities for both developed and developing economies to form unique positions. As previously mentioned, studies have suggested a total annual benefit of €1.8 trillion for a full CE transition for Europe by 2030 (Ellen MacArthur Foundation, 2015). Additionally, as we are living in the 'age of data' with an unprecedented amount of data available (McAfee et al., 2012), data itself is becoming a key source of value generation for countries and may even become the biggest trading commodity of the future (Xiao et al., 2014). As an example, the Confederation of Norwegian Enterprise recently estimated Norway's value creation potential from data would surpass that of oil and gas by 2030 for a total of €30 billion each year (Skogli et al., 2019).

Despite great economic benefits to be found in a full transition to the nexus of these developments, the challenges by businesses and policymakers are diverse. This thesis focuses on the perspective of a single firm's transition and performance gains; hence it does not consider issues typical of policy development, such as how to deal with a multitude of stakeholders and their joint competitiveness for a fair value distribution in the CE. However, on the basis of the results identified in this research, we believe that maintaining an open and transparent digital ecosystem where data and services can be made available and shared in an environment of trust will be more important than ever before with the CE. With the core success criteria of the Smart CE being its ability to connect material flow with information flow, a framework and data governance model is needed for the free flow of nonpersonal data. For instance, data on the location, availability, and condition of assets alongside guidelines for tracking products, parts, and materials across value chains should be made available. In this respect, a set of criteria for the minimum amount of data to be shared for circular activities should be established. Providing a balance between data sharing and safeguarding of commercial and strategic information could support collaborative efforts and trust between companies – improving their ability to adopt circular strategies.

Policies and regulations should be investigated both within (e.g., how digitally enabled solutions can be used to improve the extended producer responsibility scheme of electronics or improve the data associated with waste streams) and across sectors (e.g., raising awareness and improving knowledge and competencies for government, industry, and consumers). To enable this, collaborative projects between authorities, industry, and academia should be established to improve knowledge and develop inspirational best-case scenarios. Pilot projects can be run in selected value chains with the aim of creating an overview of how to effectively connect information flow with material flow and establish a first version data governance model and framework for nonpersonal data sharing.

5.4 Limitations

Given the thesis followed a sequential mixed method research design, qualitative and quantitative data were analyzed using different measures of quality. The amalgamation of the quantitative paradigm with qualitative research through validity and reliability has changed the traditional meaning of these terms and what constitutes quality research from the qualitative researcher's perspective (Golafshani, 2003). Quantitative and qualitative studies are different in nature; while the former generally has the purpose of explaining, the latter has the purpose of understanding. This difference in purposes makes evaluating the quality of studies in quantitative and qualitative research dissimilar; Stenbacka (2001) even argues for the concept of reliability to be irrelevant and misleading in qualitative research. Similar arguments can be seen for the term of validity, but at the same time, qualitative researchers realize the need for some criteria of quality measures of their research (Creswell et al., 2000).

As a result, several concepts for assessing the quality of qualitative studies have been proposed, such as credibility, neutrality, consistency, transferability, rigor, and trustworthiness (Davies et al., 2002; Lincoln et al., 1990; Seale, 1999; Stenbacka, 2001). To discuss the validity and reliability of our qualitative findings, we utilized the eight 'big-tent' criteria for excellent qualitative research by Tracy (2010) (see Table 5.1). The eight criteria are: worthy topic, rich rigor, sincerity, credibility, resonance, significant contribution, ethics, and meaningful coherence. These markers provide a rigorous conceptualization of qualitative quality and a common language to discuss the excellence of qualitative research recognizable across differences in paradigms and a variety of audiences.

For the quantitative part of this research (paper 5 in part II), our questionnaire is constrained by certain limitations, as presented in Table 5.2. First, our survey relies on self-reported data. Despite being a common approach for collecting data in a number of disciplines, people are often biased when reporting on their own experience (meaning factual data may not coincide with respondents' perceptions) (Devaux et al., 2016). To remedy this, the respondents were informed about data protection and anonymity, and were encouraged to consult with colleagues when answering questions. Despite undertaking considerable efforts to reduce the potential of bias and ensure good data quality, the occurrence of bias cannot be excluded. Future studies could explore the topic for variance in levels of hierarchy and discrepancies between BA and CE expertise. For instance, by interviewing multiple levels and types of managers from the same firm and checking for interrater validity to improve internal validity. Second, as we did not include a different, and objective, data source (i.e., for firm performance), there is a risk of mono-method bias in our

Table 5.1: Quality criteria of the qualitative findings

Criteria for quality	Methods and tactics used
Worthy topic	Utilizing DTs for CE is an important topic of timely concern with significant relevance to research, industry, and policy.
Rich rigor	The research used rigorous theoretical frameworks (such as RBV and ROV) to ground the research.
Sincerity	The thesis is transparent about the methods used and tactics used to arrive at identified themes and concepts. The authors are reflective about their subjective values, biases and inclinations.
Credibility	The research is marked by concrete details and examples of how the data has been interpreted in the analysis. Triangulation of sources and cross-validation between the authors are employed.
Resonance	Based on thick descriptions of the themes identified with several graphical and tabular representations, transferability of findings is achieved.
Significant contribution	The research provides significant contributions of both academic, policy, and practical use. Propositions for future studies are provided, and the quantitative evaluation of the findings is possible.
Ethical	Appropriate ethical considerations were made throughout the research process to ensure respondents about their anonymity and data protection rights.
Meaningful coherence	The thesis employs appropriate methodologies to reach its stated goals and provides meaningful connections to extant literature, and calls for action.

quantitative study. Given the operational scope of this study, with companies from multiple countries and an alternative for full anonymity (meaning provision of company name and/or contact details was optional), we were unable to collect adequate data on objective firm performance. Establishing firm performance as a higher-order construct somewhat improves this issue as it provides multiple measures of performance. However, future studies should include objective measurement of both firm performance and CE implementation (e.g., using the circular transition indicators (WBCSD, 2021)).

Despite our efforts to develop an inclusive model and generic constructs, our conceptual model cannot be considered a universal model, fully applicable to all companies and applications. It is likely that some firms may need to develop different BA resources and/or resource orchestration processes to improve their performance and effectively leverage their circular strategies. In particular, we know from CE research that firms require a number of different circular strategies and business model configurations, highly contingent on their size, industry setting, and individual value chain (N. M. Bocken et al., 2014). Additionally, paradigm shifts, as introduced by the CE, require changes in systems and in people's mindsets, and they take decades to unfold (Koschmann, 1996). We are still in the very early stages, and adoption of the CE by industry is modest (Circle Economy, 2020). As our quantitative study is only a snapshot in time, longitudinal studies (e.g., a panel

Table 5.2: Limitations of quantitative findings

Limitation	Description
Self-reported data	Respondents are often bias when it comes to their own experiences. Reasons for this can, for instance, be the interpretation of questions, honesty, introspective ability, and knowledge.
Mono-method bias	With lacking triangulation of data sources and relying only on a single source of data poses a threat to construct validity.
Generalizability	Despite adopting generic constructs, the lateral and emerging nature of CE implies that firms will likely require different BA resources and capabilities as the CE concept matures and industry standards are developed.

survey) could help mitigate concerns of endogeneity and provide interesting findings on firms' development and stage-wise adoption of circular strategies. Nevertheless, this is an important and much needed first step towards a BA construct for CE. By crystallizing related IS theories, our research lays a solid foundation for future studies to extend the application of our conceptual model.

The contributions made on the basis of a theoretical development process (i.e., the Smart CE framework as part of paper 2 in part II) should be empirically validated with a set of companies to (i) determine the clarity of the framework elements and strategies presented, (ii) detail a process for self-assessment and BA gap analysis, and (iii) identify how it can be further improved to better support COI in manufacturing, related industries, and extended with a broader range of DTs (e.g., blockchain and 3D printing). It should also be noted that the framework was evaluated through a subjective interpretive process among the authors. However, the theoretical validation process, by mapping strategies, offers justification.

6 Conclusion

This PhD thesis examines the nexus between firms' sustainable and digital transformation through the concepts of CE and BA. Articulated as the *Smart CE*, this represents an emerging research stream offering pathways to explore new forms of innovative and forward-looking business models. The Smart CE address the main research question and can be thought of as a joint research stream, or framework, linking the fields of IS and CE. It provides a single point of reference for aligning people, activities, and strategies between the two disciplines. To the best of the author's knowledge, the thesis proposes novel contributions answering several calls for action within sustainable development, CE, and digital strategy (European Commission, 2020a; European Commission, 2020b; European Commission, 2021). The research was motivated by the challenge faced by firms in understanding how DTs can support circular strategies and which BA resources and capabilities they should develop to improve performance. The impact of this research goes beyond contributions to research and practice; for instance, the Smart CE framework has been used by the World Bank for policy development and makes up core parts in the business model reports of the Circular Economy Roadmap for Germany (Circular Economy Initiative Deutschland, 2021).

Based on an associated gap in research, a sequential mixed method research design was employed, starting from an exploratory approach to uncover key concepts and their relationships followed by a confirmatory study to examine effects. A broad set of methods was used (design research methodology, literature review, practice review of grey literature, case study, expert interview, and questionnaire) to analyze both qualitative and quantitative cross-sectional data. In total, the research engaged 144 firms (three for the design research method, one for the case study, 15 in the expert interviews, and 125 in the questionnaire) from a broad range of industries (i.e., manufacturing, service provider, consultancy, retail and consumer goods, information technology, and energy, utilities, and resources).

The research presented in this thesis has provided a critical view of how firms can leverage DTs for improved CE implementation and firm performance. This is done through four main contributions of:

C1 Improved understanding of the reciprocal relationship between DTs and the CE

C2 A new common framework for aligning activities across the boundaries of disciplines in the IS and CE fields

C3 New knowledge and tools for improving firms' ability to leverage DTs for circular strategies

C4 New knowledge and model of how BA improves firms' CE implementation and firm performance

While acknowledging the potential for effectively leveraging DTs for CE, this research has also highlighted the complexity of fully realizing this potential. Transitioning towards a Smart CE is complex, multifaceted, and requires several changes both within and across firms. It requires researchers, practitioners, and policymakers to develop a more holistic understanding of digital and circular developments. The main results of this PhD thesis, essentially the Smart CE framework and associated BA resources and capabilities, represent a concrete proposal to steer future research and innovation towards a more digital CE.

6.1 Avenues for Future Research

The results and smart circular applications mapped in this thesis clearly outline the pre-paradigmatic nature of this research field and the need to strengthen empirical research through both qualitative and quantitative studies investigating the cause-and-effect relationship between DTs and the CE. With regard to the contributions made by this thesis, several opportunities for future research were identified:

- Further detail the process of BA gap analysis and benchmark assessment of Smart CE maturity.
- Conduct longitudinal studies to explore firms' development trajectories in utilizing DTs for CE and examine the differences in firm performance between industry sectors, countries, and the effects of environmental dynamism.
- Investigate the triad relationship between research, practice, and policymaking in how developing countries can improve their sustainable and competitive performance in the future digital and circular marketplace.
- Further explore the mechanisms of how BA resources are orchestrated into capabilities and leveraged towards CE, sustainability, and performance.

Building on the rich underpinnings of the findings and the comprehensive theory covered in this thesis, the author anticipates that these issues may hold merit in contributing to future studies.

6.2 Final Remarks

Companies can leverage DTs for CE in several ways. First, as the *glue* between resource flows and information flows by improving data sharing and transparency along the value chain. This allows stakeholders to work together more closely, reducing friction and enabling resource flows to become more circular. Second, as a *catalyst* for advancing existing circular strategies by revealing inefficiencies and improvement opportunities in products, processes, and ecosystems. In other words, transitioning circular strategies to *smart* circular strategies – increasing both the efficiency and effectiveness of solutions and enabling more value to be captured. Third, as the *key* to understand and unlock new ideas, strategies, solution spaces, and ways of working in the CE. This means understanding core reasons of why and how resources are used and introducing new business models, services, and digital products that promote dematerialization of our economy.

Despite the potential of DTs to promote sustainable and circular offerings, environmental and social rebound effects of their implementation should be taken into account. The pitfalls are many, including increased dispersion of electronic materials, scarcity of rare earths minerals, energy use of data centers, and the mounting levels of e-waste. Therefore, to counter these effects, it is important that we do not build the digital economy next to the circular economy. We need to make sure that the *circular economy becomes digital* and the *digital economy becomes circular*. Only then can we truly deliver on the promises of the digital and sustainable transition.

References

Abbasi, A., Sarker, S. & Chiang, R. H. L. (2016). Big Data Research in Information Systems: Toward an Inclusive Research Agenda. *J. AIS*, *17*, 3.

Adams, R. J., Smart, P. & Huff, A. S. (2017). Shades of grey: Guidelines for working with the grey literature in systematic reviews for management and organizational studies. *International Journal of Management Reviews*, *19*(4), 432–454.

Agrifoglio, R., Cannavale, C., Laurenza, E. & Metallo, C. (2017). How emerging digital technologies affect operations management through co-creation. empirical evidence from the maritime industry. *Production Planning & Control*, *28*(16), 1298–1306.

Ahuja, S. & Chan, Y. E. (2017). Resource orchestration for IT-enabled innovation. *Kindai management review*, *5*(1), 78–96.

Akter, S., Fosso Wamba, S. & Dewan, S. (2017). Why pls-sem is suitable for complex modelling? an empirical illustration in big data analytics quality. *Production Planning & Control*, *28*(11-12), 1011–1021.

Akter, S., Wamba, S. F. & D'Ambra, J. (2019). Enabling a transformative service system by modeling quality dynamics. *International Journal of Production Economics*, *207*, 210–226.

Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R. & Childe, S. J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment? *International Journal of Production Economics*, *182*, 113–131.

Alcayaga, A., Wiener, M. & Hansen, E. G. (2019). Towards a framework of smart-circular systems: An integrative literature review. *Journal of Cleaner Production*, *221*, 622–634.

Alshenqeeti, H. (2014). Interviewing as a data collection method: A critical review. *English linguistics research*, *3*(1), 39–45.

Amit, R. & Schoemaker, P. J. H. (1993). Strategic assets and organizational rent. *Strategic management journal*, *14*(1), 33–46.

Antikainen, M., Uusitalo, T. & Kivikytö-Reponen, P. (2018). Digitalisation as an enabler of circular economy. *Procedia CIRP*, *73*, 45–49.

Aremu, O. O., Salvador Palau, A., Hyland-Wood, D., Parlikad, A. K. & McAree, P. R. (2018). Structuring data for intelligent predictive maintenance in asset management. In *16th ifac symposium on information control problems in manufacturing*.

Arunachalam, D., Kumar, N. & Kawalek, J. P. (2018). Understanding big data analytics capabilities in supply chain management: Unravelling the issues, challenges and implications for practice. *Transportation Research Part E: Logistics and Transportation Review*, *114*, 416–436.

Aruväli, T., Maass, W. & Otto, T. (2014). Digital object memory based monitoring solutions in manufacturing processes. *Procedia Engineering*, *69*, 449–458.

Askoxylakis, I. (2018). A framework for pairing circular economy and the internet of things. In *2018 ieee international conference on communications (icc)* (pp. 1–6). IEEE.

Atzori, L., Iera, A. & Morabito, G. (2010). The internet of things: A survey. *Computer networks*, *54*(15), 2787–2805.

Bahrepour, M. (2018). The forgotten step in CRISP-DM and ASUM-DM methodologies. https://sharing.luminis.eu/blog/the-forgotten-step-in-crisp-dm-and-asum-dm-methodologies/. Accessed: 2019-03-08.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of management*, *17*(1), 99–120.

Barney, J. B. (2001). Resource-based theories of competitive advantage: A ten-year retrospective on the resource-based view. *Journal of management*, *27*(6), 643–650.

Bassi, A. & Horn, G. (2008). Internet of things in 2020: A roadmap for the future. *European Commission: Information Society and Media*, *22*, 97–114.

Benitez, J., Henseler, J., Castillo, A. & Schuberth, F. (2020). How to perform and report an impactful analysis using partial least squares: Guidelines for confirmatory and explanatory is research. *Information & Management*, *57*(2), 103168.

Bharadwaj, A. S. (2000). A resource-based perspective on information technology capability and firm performance: an empirical investigation. *MIS quarterly*, 169–196.

Bianchini, A., Pellegrini, M., Rossi, J. & Saccani, C. (2018). A new productive model of circular economy enhanced by digital transformation in the fourth industrial revolution-an integrated framework and real case studies. *23rd Summer School 'Francesco Turco'-Industrial Systems Engineering*, 221–227.

Bin, S., Zhiquan, Y., Jonathan, L. S. C., Jiewei, D. K., Kurle, D., Cerdas, F. & Herrmann, C. (2015). A big data analytics approach to develop industrial symbioses in large cities. *Procedia CIRP*, *29*, 450–455.

Bititci, U. S., Martinez, V., Albores, P. & Parung, J. (2004). Creating and managing value in collaborative networks. *International Journal of Physical Distribution & Logistics Management*.

Blessing, L. T. & Chakrabarti, A. (2009). *Drm: A design reseach methodology*. Springer.

Blomsma, F. (2018). Collective 'action recipes' in a circular economy–on waste and resource management frameworks and their role in collective change. *Journal of Cleaner Production*, *199*, 969–982.

Blomsma, F. & Brennan, G. (2017). The emergence of circular economy: A new framing around prolonging resource productivity. *Journal of Industrial Ecology*, *21*(3), 603–614.

Blomsma, F. & Tennant, M. (2020). Circular economy: Preserving materials or products? Introducing the Resource States framework. *Resources, Conservation and Recycling*, *156*, 104698.

Bocken, N. M. & Antikainen, M. (2018). Circular business model experimentation: Concept and approaches. In *International conference on sustainable design and manufacturing* (pp. 239–250). Springer.

Bocken, N. M., Short, S. W., Rana, P. & Evans, S. (2014). A literature and practice review to develop sustainable business model archetypes. *Journal of cleaner production*, *65*, 42–56.

Bocken, N. M. & Short, S. (2016). Towards a sufficiency-driven business model: Experiences and opportunities. *Environmental Innovation and Societal Transitions*, *18*, 41–61.

Bocken, N., Strupeit, L., Whalen, K. & Nußholz, J. (2019). A review and evaluation of circular business model innovation tools. *Sustainability*, *11*(8), 2210.

Bogner, A., Littig, B. & Menz, W. (2009). *Interviewing experts*. Springer.

Boons, F. & Howard-Grenville, J. A. (2009). *The social embeddedness of industrial ecology*. Edward Elgar Publishing.

Braganza, A., Brooks, L., Nepelski, D., Ali, M. & Moro, R. (2017). Resource management in big data initiatives: Processes and dynamic capabilities. *Journal of Business Research*, *70*, 328–337.

Bressanelli, G., Adrodegari, F., Perona, M. & Saccani, N. (2018a). Exploring how usage-focused business models enable circular economy through digital technologies. *Sustainability*, *10*(3), 639.

Bressanelli, G., Adrodegari, F., Perona, M. & Saccani, N. (2018b). The role of digital technologies to overcome circular economy challenges in pss business models: An exploratory case study. *Procedia CIRP*, *73*, 216–221.

Brown, P., Bocken, N. & Balkenende, R. (2019). Why do companies pursue collaborative circular oriented innovation? *Sustainability*, *11*(3), 635.

Buer, S.-V., Strandhagen, J. O. & Chan, F. T. (2018). The link between industry 4.0 and lean manufacturing: Mapping current research and establishing a research agenda. *International Journal of Production Research*, *56*(8), 2924–2940.

Burin, A. R. G., Perez-Arostegui, M. N. & Llorens-Montes, J. (2020). Ambidexterity and it competence can improve supply chain flexibility? a resource orchestration approach. *Journal of Purchasing and Supply Management*, *26*(2), 100610.

Chadwick, C., Super, J. F. & Kwon, K. (2015). Resource orchestration in practice: Ceo emphasis on shrm, commitment-based hr systems, and firm performance. *Strategic Management Journal*, *36*(3), 360–376.

Chapman, P., Clinton, J., Kerber, R., Khabaza, T., Reinartz, T., Shearer, C., Wirth, R. [Rudiger] et al. (2000). Crisp-dm 1.0: Step-by-step data mining guide. *SPSS inc*, *9*, 13.

Chauhan, C., Sharma, A. & Singh, A. (2019). A sap-lap linkages framework for integrating industry 4.0 and circular economy. *Benchmarking: An International Journal.*

Chen, H., Chiang, R. H. L. & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. *MIS quarterly*, 1165–1188.

Choi, S. B., Lee, W. R. & Kang, S.-W. (2020). Entrepreneurial orientation, resource orchestration capability, environmental dynamics and firm performance: A test of three-way interaction. *Sustainability*, *12*(13), 5415.

Churchill Jr, G. A. (1979). A paradigm for developing better measures of marketing constructs. *Journal of marketing research*, *16*(1), 64–73.

Circle Economy. (2020). The Circularity Gap Report 2020. *Circle Economy: Amsterdam, The Netherlands.*

Circular Economy Initiative Deutschland. (2021). Circular business models: Overcoming barriers, unleashing potentials. https://static1.squarespace.com/static/5b52037e4611a0606973bc79/t/608a9b723926032d9f74aea2/1619696523596/GM_Gesamtbericht+EN. Accessed: 2021-05-5.

Cohen, J. (2013). *Statistical power analysis for the behavioral sciences.* Academic press.

Commission on Environment and Development. (1987). Report of the world commission on environment and development: Our common future. *Accessed Feb, 10.*

Conboy, K., Mikalef, P., Dennehy, D. & Krogstie, J. (2020). Using business analytics to enhance dynamic capabilities in operations research: A case analysis and research agenda. *European Journal of Operational Research*, *281*(3), 656–672.

Cooper, A. et al. (2012). What is analytics? definition and essential characteristics. *CETIS Analytics Series*, *1*(5), 1–10.

Creswell, J. W. & Clark, V. L. P. (2017). *Designing and conducting mixed methods research.* Sage publications.

Creswell, J. W. & Miller, D. L. (2000). Determining validity in qualitative inquiry. *Theory into practice*, *39*(3), 124–130.

Crook, T. R., Ketchen Jr, D. J., Combs, J. G. & Todd, S. Y. (2008). Strategic resources and performance: a meta-analysis. *Strategic management journal*, *29*(11), 1141–1154.

Cui, M. & Pan, S. L. (2015). Developing focal capabilities for e-commerce adoption: A resource orchestration perspective. *Information & Management*, *52*(2), 200–209.

Cycyota, C. S. & Harrison, D. A. (2006). What (not) to expect when surveying executives: A meta-analysis of top manager response rates and techniques over time. *Organizational Research Methods*, *9*(2), 133–160.

Davenport, T. (2014). *Big data at work: Dispelling the myths, uncovering the opportunities.* Harvard Business Review Press.

Davies, D. & Dodd, J. (2002). Qualitative research and the question of rigor. *Qualitative health research*, *12*(2), 279–289.

De Jesus, A., Antunes, P., Santos, R. & Mendonça, S. (2018). Eco-innovation in the transition to a circular economy: An analytical literature review. *Journal of cleaner Production*, *172*, 2999–3018.

de Sousa Jabbour, A. B. L., Jabbour, C. J. C., Godinho Filho, M. & Roubaud, D. (2018). Industry 4.0 and the circular economy: A proposed research agenda and original roadmap for sustainable operations. *Annals of Operations Research*, *270*(1-2), 273–286.

Del Giudice, M., Chierici, R., Mazzucchelli, A. & Fiano, F. (2020). Supply chain management in the era of circular economy: The moderating effect of big data. *The International Journal of Logistics Management*.

Deloitte. (2020). Study for a national strategy for circular economy. https://www.regjeringen.no/no/dokumenter/kunnskapsgrunnlag-for-nasjonal-strategi-for-sirkular-okonomi/id2714834/. Accessed: 2021-01-18.

Den Hollander, M. C., Bakker, C. A. & Hultink, E. J. (2017). Product design in a circular economy: Development of a typology of key concepts and terms. *Journal of Industrial Ecology*, *21*(3), 517–525.

Devaux, M. & Sassi, F. (2016). Social disparities in hazardous alcohol use: Self-report bias may lead to incorrect estimates. *The European Journal of Public Health*, *26*(1), 129–134.

Dhar, V. (2013). Data science and prediction. *Communications of the ACM*, *56*(12), 64–73.

Drnevich, P. L. & Kriauciunas, A. P. (2011). Clarifying the conditions and limits of the contributions of ordinary and dynamic capabilities to relative firm performance. *Strategic management journal*, *32*(3), 254–279.

Dubey, R., Gunasekaran, A., Childe, S. J., Papadopoulos, T., Luo, Z., Wamba, S. F. & Roubaud, D. (2019). Can big data and predictive analytics improve social and environmental sustainability? *Technological Forecasting and Social Change*, *144*, 534–545.

Dubey, R., Gunasekaran, A., Childe, S. J., Wamba, S. F. & Papadopoulos, T. (2016). The impact of big data on world-class sustainable manufacturing. *The International Journal of Advanced Manufacturing Technology*, *84*(1-4), 631–645.

EC. (2008). Directive 2008/98/ec of the european parliament and of the council of 19 november 2008 on waste and repealing certain directives. *Official Journal of the European Union L*, *312*(3).

Eckerson, W. W. (2007). Predictive analytics. *Extending the Value of Your Data Warehousing Investment. TDWI Best Practices Report*, *1*, 1–36.

Eisenhardt, K. M. & Graebner, M. E. (2007). Theory building from cases: Opportunities and challenges. *Academy of management journal*, *50*(1), 25–32.

Eisenhardt, K. M. & Martin, J. A. (2000). Dynamic capabilities: What are they? *Strategic management journal*, *21*(10-11), 1105–1121.

Ellen MacArthur Foundation. (2013). Towards the circular economy. *Journal of Industrial Ecology*, *2*, 23–44.

Ellen MacArthur Foundation. (2015). Growth within: A circular economy vision for a competitive europe. *Ellen MacArthur Foundation Cowes, UK*.

Ellen MacArthur Foundation. (2016). Intelligent assets. unlocking the circular economy potential. *Ellen MacArthur Foundation Cowes, UK*.

Ellen MacArthur Foundation. (2019). Artificial intelligence and the circular economy. *Ellen MacArthur Foundation Cowes, UK*.

European Commission. (2020a). A New Industrial Strategy for Europe.

European Commission. (2020b). Circular Economy Action Plan.

European Commission. (2021). A European strategy for data. Retrieved from https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52020DC0066

European Policy Centre. (2020). The circular economy: Going digital. https://wms.flexious.be/editor/plugins/imagemanager/content/2140/PDF/2020/DRCE_web.pdf. Accessed: 2020-04-7.

Flyvbjerg, B. & Budzier, A. (2011). Why your it project may be riskier than you think.

Frank, A. G., Dalenogare, L. S. & Ayala, N. F. (2019). Industry 4.0 technologies: Implementation patterns in manufacturing companies. *International Journal of Production Economics*, *210*, 15–26.

Al-Fuqaha, A., Guizani, M., Mohammadi, M., Aledhari, M. & Ayyash, M. (2015). Internet of things: A survey on enabling technologies, protocols, and applications. *IEEE communications surveys & tutorials*, *17*(4), 2347–2376.

Gartner. (2020a). Big data - gartner it glossary. (accessed on 6 April 2020). Retrieved from https://www.gartner.com/it-glossary/big-data/

Gartner. (2020b). Employ digital technology to enable a circular econoomy. https://www.gartner.com/en/newsroom/press-releases/2020-02-26-gartner-survey-shows-70--of-supply-chain-leaders-plan. Accessed: 2020-04-14.

Geissdoerfer, M., Savaget, P., Bocken, N. M. & Hultink, E. J. (2017). The circular economy–a new sustainability paradigm? *Journal of cleaner production*, *143*, 757–768.

Geng, Y. & Doberstein, B. (2008). Developing the circular economy in china: Challenges and opportunities for achieving'leapfrog development'. *The International Journal of Sustainable Development & World Ecology*, *15*(3), 231–239.

Geng, Y., Sarkis, J., Ulgiati, S. & Zhang, P. (2013). Measuring china's circular economy. *Science*, *339*(6127), 1526–1527.

Ghisellini, P., Cialani, C. & Ulgiati, S. (2016). A review on circular economy: The expected transition to a balanced interplay of environmental and economic systems. *Journal of Cleaner production*, *114*, 11–32.

Golafshani, N. (2003). Understanding reliability and validity in qualitative research. *The qualitative report*, *8*(4), 597–607.

Gong, Y., Jia, F., Brown, S. & Koh, L. (2018). Supply chain learning of sustainability in multi-tier supply chains. *International Journal of Operations & Production Management*.

Greene, J. C., Caracelli, V. J. & Graham, W. F. (1989). Toward a conceptual framework for mixed-method evaluation designs. *Educational evaluation and policy analysis*, *11*(3), 255–274.

Gubbi, J., Buyya, R., Marusic, S. & Palaniswami, M. (2013). Internet of things (iot): A vision, architectural elements, and future directions. *Future generation computer systems*, *29*(7), 1645–1660.

Gupta, A., Deokar, A., Iyer, L., Sharda, R. & Schrader, D. (2018). Big data & analytics for societal impact: Recent research and trends. *Information Systems Frontiers*, *20*(2), 185–194.

Gupta, M. & George, J. F. (2016). Toward the development of a big data analytics capability. *Information & Management*, *53*(8), 1049–1064.

Gupta, S., Chen, H., Hazen, B. T., Kaur, S., Santibañez Gonzalez, E. D. R. & Gonzalez, E. D. S. (2019). Circular economy and big data analytics: A stakeholder perspective. *Technological Forecasting and Social Change*, *144*, 466–474. doi:10.1016/j.techfore.2018.06.030

Guzzo, D., Trevisan, A. H., Echeveste, M. & Costa, J. M. H. (2019). Circular innovation framework: Verifying conceptual to practical decisions in sustainability-oriented product-service system cases. *Sustainability*, *11*(12), 3248.

Haas, W., Krausmann, F., Wiedenhofer, D. & Heinz, M. (2015). How circular is the global economy: An assessment of material flows, waste production, and recycling in the european union and the world in 2005. *Journal of Industrial Ecology*, *19*(5), 765–777.

Haddar, N., Tmar, M. & Gargouri, F. (2013). A framework for data-driven workflow management: Modeling, verification and execution. In *International conference on database and expert systems applications* (pp. 239–253). Springer.

Hair, J. F. [Joe F], Ringle, C. M. & Sarstedt, M. (2011). Pls-sem: Indeed a silver bullet. *Journal of Marketing theory and Practice*, *19*(2), 139–152.

Hair, J. F. [Joseph F], Hult, G. T. M., Ringle, C. & Sarstedt, M. (2016). *A primer on partial least squares structural equation modeling (pls-sem)*. Sage publications.

Hair, J. F. [Joseph F], Sarstedt, M., Pieper, T. M. & Ringle, C. M. (2012). The use of partial least squares structural equation modeling in strategic management research: A review of past practices and recommendations for future applications. *Long range planning*, *45*(5-6), 320–340.

Hashem, I. A. T., Chang, V., Anuar, N. B., Adewole, K., Yaqoob, I., Gani, A., ... Chiroma, H. (2016). The role of big data in smart city. *International Journal of Information Management*, *36*(5), 748–758.

Hazen, B. T., Skipper, J. B., Ezell, J. D. & Boone, C. A. (2016). Big data and predictive analytics for supply chain sustainability: A theory-driven research agenda. *Computers & Industrial Engineering*, *101*, 592–598.

Hedberg, A., Šipka, S. & Bjerkem, J. (2019). Creating a digital roadmap for a circular economy. *Sustainable Prosperity for Europe Programme*.

Helfat, C. E., Finkelstein, S., Mitchell, W., Peteraf, M., Singh, H., Teece, D. & Winter, S. G. (2009). *Dynamic capabilities: Understanding strategic change in organizations*. John Wiley & Sons.

Henry, G. T. (1990). *Practical sampling*. Sage.

Henseler, J., Ringle, C. M. & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. In *New challenges to international marketing*. Emerald Group Publishing Limited.

Hermann, M., Pentek, T. & Otto, B. (2016). Design principles for industrie 4.0 scenarios. In *2016 49th hawaii international conference on system sciences (hicss)* (pp. 3928–3937). IEEE.

Hindle, G. A. & Vidgen, R. (2018). Developing a business analytics methodology: A case study in the foodbank sector. *European Journal of Operational Research*, *268*(3), 836–851.

Hoffman, A. J. (2003). Linking social systems analysis to the industrial ecology framework. *Organization & Environment*, *16*(1), 66–86.

Hofmann, E. & Rüsch, M. (2017). Industry 4.0 and the current status as well as future prospects on logistics. *Computers in Industry*, *89*, 23–34.

Ingemarsdotter, E., Jamsin, E., Kortuem, G. & Balkenende, R. (2019). Circular strategies enabled by the internet of things—a framework and analysis of current practice. *Sustainability*, *11*(20), 5689.

Institution, B. S. (2017). *Framework for implementing the principles of the circular economy in organizations-guide*. BSI.

Irani, Z. & Sharif, A. M. (2018). Food security across the enterprise: A puzzle, problem or mess for a circular economy? *Journal of Enterprise Information Management*, *31*(1), 2–9.

ISO. (2020). Iso/tc 323 circular economyy. (accessed on 21 December 2020). Retrieved from https://www.iso.org/committee/7203984.html

Jabbour, C. J. C., de Sousa Jabbour, A. B. L., Sarkis, J. & Godinho Filho, M. (2019a). Unlocking the circular economy through new business models based on large-scale data: An integrative framework and research agenda. *Technological Forecasting and Social Change*, *144*, 546–552.

Jabbour, C. J. C., Fiorini, P. D. C., Ndubisi, N. O., Queiroz, M. M. & Piato, É. L. (2020). Digitally-enabled sustainable supply chains in the 21st century: A review and a research agenda. *Science of The Total Environment*, *725*, 138177.

Jabbour, C. J. C., Sarkis, J., de Sousa Jabbour, A. B. L., Renwick, D. W. S., Singh, S. K., Grebinevych, O., ... Godinho Filho, M. (2019b). Who is in charge? a review and a research agenda on the 'human side'of the circular economy. *Journal of cleaner production*, *222*, 793–801.

James, G., Witten, D., Hastie, T. & Tibshirani, R. (2013). *An introduction to statistical learning*. Springer.

Janssen, M., van der Voort, H. & Wahyudi, A. (2017). Factors influencing big data decision-making quality. *Journal of Business Research*, *70*, 338–345.

Jawahir, I. & Bradley, R. (2016). Technological elements of circular economy and the principles of 6r-based closed-loop material flow in sustainable manufacturing. *Procedia Cirp*, *40*, 103–108.

Johnson, R. B., Onwuegbuzie, A. J. & Turner, L. A. (2007). Toward a definition of mixed methods research. *Journal of mixed methods research*, *1*(2), 112–133.

Kagermann, H., Helbig, J., Hellinger, A. & Wahlster, W. (2013). *Recommendations for implementing the strategic initiative industrie 4.0: Securing the future of german manufacturing industry; final report of the industrie 4.0 working group*. Forschungsunion.

Khan, O., Daddi, T. & Iraldo, F. (2020). The role of dynamic capabilities in circular economy implementation and performance of companies. *Corporate Social Responsibility and Environmental Management*, *27*(6), 3018–3033.

Kirchherr, J., Reike, D. & Hekkert, M. (2017). Conceptualizing the circular economy: An analysis of 114 definitions. *Resources, Conservation and Recycling*, *127*, 221–232.

Kiron, D. & Shockley, R. (2011). Creating business value with analytics. *MIT Sloan Management Review*, *53*(1), 57.

Kitchenham, B. & Charters, S. (2007). Guidelines for performing systematic literature reviews in software engineering.

Kortuem, G., Kawsar, F., Sundramoorthy, V., Fitton, D. et al. (2009). Smart objects as building blocks for the internet of things. *IEEE Internet Computing*, *14*(1), 44–51.

Koschmann, T. (1996). Paradigm shifts and instructional technology: An introduction. *CSCL: Theory and practice of an emerging paradigm*, *116*, 1–23.

Kraaijenbrink, J., Spender, J.-C. & Groen, A. J. (2010). The resource-based view: A review and assessment of its critiques. *Journal of management*, *36*(1), 349–372.

Kraemer, K. & Pinsonneault, A. (1993). Survey research methodology in management information systems: An assessment. *Journal of Management Information Systems*, *10*(2), 75–106.

Kravchenko, M., Pigosso, D. C. & McAloone, T. C. (2019). Towards the ex-ante sustainability screening of circular economy initiatives in manufacturing companies: Consolidation of leading sustainability-related performance indicators. *Journal of Cleaner Production*, *241*, 118318.

Kumar, N., Stern, L. W. & Anderson, J. C. (1993). Conducting interorganizational research using key informants. *Academy of management journal*, *36*(6), 1633–1651.

Kumar, S. & Putnam, V. (2008). Cradle to cradle: Reverse logistics strategies and opportunities across three industry sectors. *International Journal of Production Economics*, *115*(2), 305–315.

Kun, W., Tong, L. & Xiaodan, X. (2019). Application of big data technology in scientific research data management of military enterprises. *Procedia Computer Science*, *147*, 556–561.

Kvale, S. & Brinkmann, S. (2009). *Interviews: Learning the craft of qualitative research interviewing*. sage.

Kwon, O., Lee, N. & Shin, B. (2014). Data quality management, data usage experience and acquisition intention of big data analytics. *International journal of information management*, *34*(3), 387–394.

Lacy, P., Long, J. & Spindler, W. (2020). *The circular economy handbook*. Springer.

Lahti, T., Wincent, J. & Parida, V. (2018). A definition and theoretical review of the circular economy, value creation, and sustainable business models: where are we now and where should research move in the future? *Sustainability*, *10*(8), 2799.

Laney, D. (2001). 3d data management: Controlling data volume, velocity and variety. *META group research note*, *6*(70), 1.

Lasi, H., Fettke, P., Kemper, H., Feld, T. & Hoffmann, M. (2014). Industry 4.0. business & information systems engineering, 6 (4), 239-242.

Li, S., Da Xu, L. & Zhao, S. (2015). The internet of things: A survey. *Information Systems Frontiers*, *17*(2), 243–259.

Li, Z., Wang, Y. & Wang, K. (2017). A data-driven method based on deep belief networks for backlash error prediction in machining centers. *Journal of Intelligent Manufacturing*, 1–13.

Liao, Y., Deschamps, F., Loures, E. d. F. R. & Ramos, L. F. P. (2017). Past, present and future of industry 4.0-a systematic literature review and research agenda proposal. *International journal of production research*, *55*(12), 3609–3629.

Lieder, M. & Rashid, A. (2016). Towards circular economy implementation: A comprehensive review in context of manufacturing industry. *Journal of Cleaner production*, *115*, 36–51.

Lin, J., Keogh, E., Wei, L. & Lonardi, S. (2007). Experiencing sax: A novel symbolic representation of time series. *Data Mining and knowledge discovery*, *15*(2), 107–144.

Lincoln, Y. S. & Guba, E. G. (1990). Judging the quality of case study reports. *Internation Journal of Qualitative Studies in Education*, *3*(1), 53–59.

Lindkvist, M. & Baumann, H. (2014). *A review of social science in five industrial ecology journals*. Chalmers University of Technology.

Low, J. S. C., Tjandra, T. B., Yunus, F., Chung, S. Y., Tan, D. Z. L., Raabe, B., ... Ramakrishna, S. et al. (2018). A collaboration platform for enabling industrial symbiosis: Application of the database engine for waste-to-resource matching. *Procedia CIRP*, *69*, 849–854.

Makadok, R. (2001). Toward a synthesis of the resource-based and dynamic-capability views of rent creation. *Strategic management journal*, *22*(5), 387–401.

Mata, F. J., Fuerst, W. L. & Barney, J. B. (1995). Information technology and sustained competitive advantage: A resource-based analysis. *MIS quarterly*, 487–505.

Mayer-Schönberger, V. & Cukier, K. (2013). *Big data: A revolution that will transform how we live, work, and think*. Houghton Mifflin Harcourt.

McAfee, A., Brynjolfsson, E., Davenport, T. H., Patil, D. & Barton, D. (2012). Big data: The management revolution. *Harvard business review*, *90*(10), 60–68.

McDonough, W. & Braungart, M. (2010). *Cradle to cradle: Remaking the way we make things*. North point press.

Meld. St. 13. (2021). Klimaplanen for 2021-2030. https://www.regjeringen.no/no/dokumenter/meld.-st.-13-20202021/id2827405/?ch=1. Accessed: 2021-04-7.

Mendoza, J. M. F., Sharmina, M., Gallego-Schmid, A., Heyes, G. & Azapagic, A. (2017). Integrating backcasting and eco-design for the circular economy: The bece framework. *Journal of Industrial Ecology*, *21*(3), 526–544.

Mikalef, P., Framnes, V. A., Danielsen, F., Krogstie, J. & Olsen, D. (2017). Big data analytics capability: Antecedents and business value. In *Pacific asia conference on information systems (pacis)*. Association For Information Systems.

Mikalef, P., Krogstie, J., Pappas, I. O. & Pavlou, P. (2020). Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. *Information & Management*, *57*(2), 103169.

Mikalef, P., Pappas, I. O., Krogstie, J. & Giannakos, M. (2018). Big data analytics capabilities: A systematic literature review and research agenda. *Information Systems and e-Business Management*, *16*(3), 547–578.

Miller, D. & Friesen, P. H. (1984). A longitudinal study of the corporate life cycle. *Management science*, *30*(10), 1161–1183.

Minerva, R., Biru, A. & Rotondi, D. (2015). Towards a definition of the internet of things (iot). *IEEE Internet Initiative*, *1*, 1–86.

Mingers, J. (2001). Combining is research methods: Towards a pluralist methodology. *Information systems research*, *12*(3), 240–259.

Miorandi, D., Sicari, S., De Pellegrini, F. & Chlamtac, I. (2012). Internet of things: Vision, applications and research challenges. *Ad hoc networks*, *10*(7), 1497–1516.

Moeuf, A., Pellerin, R., Lamouri, S., Tamayo-Giraldo, S. & Barbaray, R. (2018). The industrial management of smes in the era of industry 4.0. *International Journal of Production Research*, *56*(3), 1118–1136.

Moraga, G., Huysveld, S., Mathieux, F., Blengini, G. A., Alaerts, L., Van Acker, K., ... Dewulf, J. (2019). Circular economy indicators: What do they measure? *Resources, Conservation and Recycling*, *146*, 452–461.

Moreno, M., De los Rios, C., Rowe, Z. & Charnley, F. (2016). A conceptual framework for circular design. *Sustainability*, *8*(9), 937.

Munodawafa, R. T. & Johl, S. K. (2019). Big data analytics capabilities and eco-innovation: A study of energy companies. *Sustainability*, *11*(15), 4254.

Murray, A., Skene, K. & Haynes, K. (2017). The circular economy: An interdisciplinary exploration of the concept and application in a global context. *Journal of business ethics*, *140*(3), 369–380.

Myers, M. D. & Newman, M. (2007). The qualitative interview in is research: Examining the craft. *Information and organization*, *17*(1), 2–26.

Nair, S. R., Demirbag, M., Mellahi, K. & Pillai, K. G. (2018). Do parent units benefit from reverse knowledge transfer? *British Journal of Management*, *29*(3), 428–444.

Newman, R., Chang, V., Walters, R. J. & Wills, G. B. (2016). Model and experimental development for business data science. *International Journal of Information Management*, *36*(4), 607–617.

Niero, M. & Hauschild, M. Z. (2017). Closing the loop for packaging: Finding a framework to operationalize circular economy strategies. *Procedia Cirp*, *61*, 685–690.

Nobre, G. C. & Tavares, E. (2017). Scientific literature analysis on big data and internet of things applications on circular economy: A bibliometric study. *Scientometrics*, *111*(1), 463–492.

Nobre, G. C. & Tavares, E. (2020). Assessing the role of big data and the internet of things on the transition to circular economy: Part i-ii: An extension of the resolve framework proposal through a literature review. *Johnson Matthey Technology Review*, *64*(1), 32–41.

Norris, D., Baer, L. & Offerman, M. (2009). A national agenda for action analytics. In *National symposium on action analytics* (pp. 21–23).

Okorie, O., Salonitis, K., Charnley, F., Moreno, M., Turner, C. & Tiwari, A. (2018). Digitisation and the circular economy: A review of current research and future trends. *Energies*, *11*(11), 3009.

Pagoropoulos, A., Pigosso, D. C. & McAloone, T. C. (2017). The emergent role of digital technologies in the circular economy: A review. *Procedia CIRP*, *64*, 19–24.

Patton, M. Q. (1990). *Qualitative evaluation and research methods*. SAGE Publications, inc.

Patwa, N., Sivarajah, U., Seetharaman, A., Sarkar, S., Maiti, K. & Hingorani, K. (2020). Towards a circular economy: An emerging economies context. *Journal of Business Research*.

Pauliuk, S. (2018). Critical appraisal of the circular economy standard bs 8001: 2017 and a dashboard of quantitative system indicators for its implementation in organizations. *Resources, Conservation and Recycling*, *129*, 81–92.

Pavlou, P. A. & El Sawy, O. A. (2006). From it leveraging competence to competitive advantage in turbulent environments: The case of new product development. *Information systems research*, *17*(3), 198–227.

Pearce, C. L. & Ensley, M. D. (2004). A reciprocal and longitudinal investigation of the innovation process: The central role of shared vision in product and process innovation teams (ppits). *Journal of organizational Behavior*, *25*(2), 259–278.

Peng, Y., Dong, M. & Zuo, M. J. (2010). Current status of machine prognostics in condition-based maintenance: A review. *The International Journal of Advanced Manufacturing Technology*, *50*(1-4), 297–313.

Pham, T. T., Kuo, T.-C., Tseng, M.-L., Tan, R. R., Tan, K., Ika, D. S. & Lin, C. J. (2019). Industry 4.0 to accelerate the circular economy: A case study of electric scooter sharing. *Sustainability*, *11*(23), 6661.

Pieroni, M. P., McAloone, T. C. & Pigosso, D. C. (2019). Business model innovation for circular economy and sustainability: A review of approaches. *Journal of Cleaner Production*, *215*, 198–216.

Planing, P. (2015). Business model innovation in a circular economy reasons for non-acceptance of circular business models. *Open journal of business model innovation*, *1*(11).

Ponsard, C., Touzani, M. & Majchrowski, A. (2017). Combining process guidance and industrial feedback for successfully deploying big data projects. *Open Journal of Big Data (OJBD)*, *3*(1), 26–41.

Popovič, A., Hackney, R., Tassabehji, R. & Castelli, M. (2018). The impact of big data analytics on firms' high value business performance. *Information Systems Frontiers*, *20*(2), 209–222.

Porter, M. E. & Heppelmann, J. E. (2014). How smart, connected products are transforming competition. *Harvard business review*, *92*(11), 64–88.

Power, D. J. (2016). Data science: Supporting decision-making. *Journal of Decision systems*, *25*(4), 345–356.

Preacher, K. J. & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior research methods*, *40*(3), 879–891.

Prieto-Sandoval, V., Jaca, C., Santos, J., Baumgartner, R. J. & Ormazabal, M. (2019). Key strategies, resources, and capabilities for implementing circular economy in industrial small and medium enterprises. *Corporate Social Responsibility and Environmental Management*, *26*(6), 1473–1484.

Provost, F. & Fawcett, T. (2013). *Data science for business: What you need to know about data mining and data-analytic thinking*. " O'Reilly Media, Inc."

Rajput, S. & Singh, S. P. (2019). Industry 4.0- challenges to implement circular economy. *Benchmarking: An International Journal*.

Ramanathan, R., Philpott, E., Duan, Y. & Cao, G. (2017). Adoption of business analytics and impact on performance: A qualitative study in retail. *Production Planning & Control*, *28*(11-12), 985–998.

Raut, R. D., Mangla, S. K., Narwane, V. S., Gardas, B. B., Priyadarshinee, P. & Narkhede, B. E. (2019). Linking big data analytics and operational sustainability practices for sustainable business management. *Journal of cleaner production*, *224*, 10–24.

Ray, P. P. (2018). A survey on internet of things architectures. *Journal of King Saud University-Computer and Information Sciences*, *30*(3), 291–319.

Recker, J. C. & Rosemann, M. (2010). A measurement instrument for process modeling research: Development, test and procedural model. *Scandinavian Journal of Information Systems*, *22*(2), 3–30.

Reike, D., Vermeulen, W. J. & Witjes, S. (2018). The circular economy: New or refurbished as ce 3.0?—exploring controversies in the conceptualization of the circular economy through a focus on history and resource value retention options. *Resources, Conservation and Recycling*, *135*, 246–264.

Rialti, R., Marzi, G., Ciappei, C. & Busso, D. (2019). Big data and dynamic capabilities: a bibliometric analysis and systematic literature review. *Management Decision*.

Ringle, C., Wende, S. & Becker, J. (2015). Smartpls 3 [computer software]. *Retrived from http://www. smartpls. com*.

Rosa, P., Sassanelli, C. & Terzi, S. (2019). Towards circular business models: A systematic literature review on classification frameworks and archetypes. *Journal of Cleaner Production*, *236*, 117696.

Rosa, P., Sassanelli, C., Urbinati, A., Chiaroni, D. & Terzi, S. (2020). Assessing relations between circular economy and industry 4.0: A systematic literature review. *International Journal of Production Research*, *58*(6), 1662–1687.

Rüttimann, B. G. & Stöckli, M. T. (2016). Lean and industry 4.0—twins, partners, or contenders? a due clarification regarding the supposed clash of two production systems. *Journal of Service Science and Management*, *9*(6), 485–500.

Saidani, M., Yannou, B., Leroy, Y., Cluzel, F. & Kendall, A. (2019). A taxonomy of circular economy indicators. *Journal of Cleaner Production*, *207*, 542–559.

Sarker, S., Xiao, X. & Beaulieu, T. (2013). Guest editorial: Qualitative studies in information systems: A critical review and some guiding principles. *MIS quarterly*, *37*(4), iii–xviii.

Sarstedt, M., Hair Jr, J. F., Cheah, J.-H., Becker, J.-M. & Ringle, C. M. (2019). How to specify, estimate, and validate higher-order constructs in pls-sem. *Australasian Marketing Journal (AMJ)*, *27*(3), 197–211.

Savin-Baden, M. & Howell-Major, C. (2013). Qualititative research: The essential guide to theory and practice. *Qualitative Research: The Essential Guide to Theory and Practice. Routledge*.

Schmarzo, B. (2015). *Big data mba: Driving business strategies with data science*. John Wiley & Sons.

Schroeder, P., Anggraeni, K. & Weber, U. (2019). The relevance of circular economy practices to the sustainable development goals. *Journal of Industrial Ecology*, *23*(1), 77–95.

Seale, C. (1999). Quality in qualitative research. *Qualitative inquiry*, *5*(4), 465–478.

Seddon, J. J. J. M. & Currie, W. L. (2017). A model for unpacking big data analytics in high-frequency trading. *Journal of Business Research*, *70*, 300–307.

Seddon, P. B., Constantinidis, D., Tamm, T. & Dod, H. (2017). How does business analytics contribute to business value? *Information Systems Journal*. doi:10.1111/isj.12101

Shahbazi, S. & Jönbrink, A. K. (2020). Design guidelines to develop circular products: Action research on nordic industry. *Sustainability*, *12*(9), 3679.

Shrouf, F., Ordieres, J. & Miragliotta, G. (2014). Smart factories in Industry 4.0: A review of the concept and of energy management approached in production based on the Internet of Things paradigm. In *2014 ieee international conference on industrial engineering and engineering management* (pp. 697–701). doi:10.1109/IEEM.2014.7058728

Shuradze, G. & Wagner, H.-T. (2016). Towards a conceptualization of data analytics capabilities. In *2016 49th hawaii international conference on system sciences (hicss)* (pp. 5052–5064). IEEE.

Singh, S. K. & El-Kassar, A.-N. (2019). Role of big data analytics in developing sustainable capabilities. *Journal of cleaner production*, *213*, 1264–1273.

Siow, E., Tiropanis, T. & Hall, W. (2018). Analytics for the internet of things: A survey. *ACM Computing Surveys (CSUR)*, *51*(4), 74.

Sirmon, D. G., Hitt, M. A. & Ireland, R. D. (2007). Managing firm resources in dynamic environments to create value: Looking inside the black box. *Academy of management review*, *32*(1), 273–292.

Sirmon, D. G., Hitt, M. A., Ireland, R. D. & Gilbert, B. A. (2011). Resource orchestration to create competitive advantage: Breadth, depth, and life cycle effects. *Journal of management*, *37*(5), 1390–1412.

Skogli, A. E., Stokke, O. M., Hveem, E. B., Aamo, A. W., Scheffer, M. & Jakobsen, E. W. (2019). ER VERDISKAPING MED DATA NOE NORGE KAN LEVE AV? *Menon Economics*.

Smith, K. G., Mitchell, T. R. & Summer, C. E. (1985). Top level management priorities in different stages of the organizational life cycle. *Academy of management Journal*, *28*(4), 799–820.

Sondhi, R. (1999). *Total strategy*. Airworthy.

Song, M., Cen, L., Zheng, Z., Fisher, R., Liang, X., Wang, Y. & Huisingh, D. (2017). How would big data support societal development and environmental sustainability? insights and practices. *Journal of Cleaner Production*, *142*, 489–500.

Sousa-Zomer, T. T., Magalhães, L., Zancul, E. & Cauchick-Miguel, P. A. (2018). Exploring the challenges for circular business implementation in manufacturing companies: An empirical investigation of a pay-per-use service provider. *Resources, Conservation and Recycling*, *135*, 3–13.

Stahel, W. (2010). *The performance economy*. Springer.

Stenbacka, C. (2001). Qualitative research requires quality concepts of its own. *Management decision*.

Straub, D., Boudreau, M.-C. & Gefen, D. (2004). Validation guidelines for is positivist research. *Communications of the Association for Information systems*, *13*(1), 24.

Teece, D. J. (2014). A dynamic capabilities-based entrepreneurial theory of the multinational enterprise. *Journal of international business studies*, *45*(1), 8–37.

Tracy, S. J. (2010). Qualitative quality: Eight "big-tent" criteria for excellent qualitative research. *Qualitative inquiry*, *16*(10), 837–851.

Ünal, E., Urbinati, A. & Chiaroni, D. (2018). Circular industry 4.0: An integrative framework.

Van Barneveld, A., Arnold, K. E. & Campbell, J. P. (2012). Analytics in higher education: Establishing a common language. *EDUCAUSE learning initiative*, *1*(1), l–ll.

Van den Bossche, P. (2016). Sprint to digital manufacturing success. *Supply Chain Management Review*.

Venkatesh, V., Brown, S. A. & Bala, H. (2013). Bridging the qualitative-quantitative divide: Guidelines for conducting mixed methods research in information systems. *MIS quarterly*, 21–54.

Viaene, S. (2013). Data scientists aren't domain experts. *IT Professional*, *15*(6), 12–17.

Vidgen, R., Shaw, S. & Grant, D. B. (2017). Management challenges in creating value from business analytics. *European Journal of Operational Research*, *261*(2), 626–639.

Voss, C. (2010). Case research in operations management. In *Researching operations management* (pp. 176–209). Routledge.

Wade, M. & Hulland, J. (2004). The resource-based view and information systems research: Review, extension, and suggestions for future research. *MIS quarterly*, *28*(1), 107–142.

Wales, W. J., Patel, P. C., Parida, V. & Kreiser, P. M. (2013). Nonlinear effects of entrepreneurial orientation on small firm performance: The moderating role of resource orchestration capabilities. *Strategic Entrepreneurship Journal*, *7*(2), 93–121.

Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J.-f., Dubey, R. & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research*, *70*, 356–365.

Wang, G., Gunasekaran, A., Ngai, E. W. T. & Papadopoulos, T. (2016). Big data analytics in logistics and supply chain management: Certain investigations for research and applications. *International Journal of Production Economics*, *176*, 98–110.

Wang, J., Xue, Y. & Yang, J. (2020). Boundary-spanning search and firms' green innovation: The moderating role of resource orchestration capability. *Business Strategy and the Environment*, *29*(2), 361–374.

Ward, J. S. & Barker, A. (2013). Undefined by data: A survey of big data definitions. *arXiv preprint arXiv:1309.5821*.

WBCSD. (2021). *Circular Transition Indicators v2.0 – Metrics for business, by business*. Retrieved from https://www.wbcsd.org/Programs/Circular-Economy/Factor-10/Metrics-Measurement/Resources/Circular-Transition-Indicators-v2.0-Metrics-for-business-by-business

Webster, K. (2013). What might we say about a circular economy? some temptations to avoid if possible. *World Futures*, *69*(7-8), 542–554.

Weissbrod, I. & Bocken, N. M. (2017). Developing sustainable business experimentation capability–a case study. *Journal of Cleaner Production*, *142*, 2663–2676.

Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic management journal*, *5*(2), 171–180.

Wilts, C. H. & Berg, H. (2018). The digital circular economy: Can the digital transformation pave the way for resource-efficient materials cycles?

Wirth, R. [Rüdiger] & Hipp, J. (2000). Crisp-dm: Towards a standard process model for data mining. In *Proceedings of the 4th international conference on the practical applications of knowledge discovery and data mining* (pp. 29–39). Citeseer.

Wong, C. W., Wong, C. Y. & Boon-itt, S. (2018). How does sustainable development of supply chains make firms lean, green and profitable? a resource orchestration perspective. *Business Strategy and the Environment*, *27*(3), 375–388.

Wood, D., Zaidman, M., Ruth, L. & Hausenblas, M. (2014). *Linked data*. Manning Publications Co.

Wright, M., Clarysse, B. & Mosey, S. (2012). Strategic entrepreneurship, resource orchestration and growing spin-offs from universities. *Technology analysis & strategic management*, *24*(9), 911–927.

Wu, K.-J., Liao, C.-J., Tseng, M.-L., Lim, M. K., Hu, J. & Tan, K. (2017). Toward sustainability: using big data to explore the decisive attributes of supply chain risks and uncertainties. *Journal of Cleaner Production*, *142*, 663–676.

Wu, P.-J. & Huang, P.-C. (2018). Business analytics for systematically investigating sustainable food supply chains. *Journal of Cleaner Production*, *203*, 968–976. doi:10.1016/J.JCLEPRO.2018.08.178

Xiao, Y., Lu, L. Y., Liu, J. S. & Zhou, Z. (2014). Knowledge diffusion path analysis of data quality literature: A main path analysis. *Journal of Informetrics*, *8*(3), 594–605.

Yick, J., Mukherjee, B. & Ghosal, D. (2008). Wireless sensor network survey. *Computer networks*, *52*(12), 2292–2330.

Yin, R. K. (1984). Applied social research methods series case study research: Design and methods.

Zeiss, R., Ixmeier, A., Recker, J. & Kranz, J. (2020). Mobilising information systems scholarship for a circular economy: Review, synthesis, and directions for future research. *Information Systems Journal*, (July), 1–36. doi:10.1111/isj.12305

Zeng, H., Chen, X., Xiao, X. & Zhou, Z. (2017). Institutional pressures, sustainable supply chain management, and circular economy capability: Empirical evidence from chinese eco-industrial park firms. *Journal of cleaner production*, *155*, 54–65.

Zhang, D., Pan, S. L., Yu, J. & Liu, W. (2019). Orchestrating big data analytics capability for sustainability: A study of air pollution management in china. *Information & Management*, 103231.

Zhao, R., Liu, Y., Zhang, N. & Huang, T. (2017). An optimization model for green supply chain management by using a big data analytic approach. *Journal of Cleaner Production*, *142*, 1085–1097.

Part II

Research Papers

Research Papers

Main research papers added in full length:

P1 Blomsma, F., Pieroni, M., Kravchenko, M., Pigosso, D., Hildenbrand, J., Kristinsdottir, A. R., Kristoffersen, E. et al. (2019) **'Developing a circular strategies framework for manufacturing companies to support circular economy-oriented innovation.'** *Journal of Cleaner Production, p.118271.*

P2 Kristoffersen, E., Blomsma, F., Mikalef, P., Li, J. **'The Smart Circular Economy: A digital-enabled Circular Strategies Framework for Manufacturing Companies.'** *Journal of Business Research, 120, 241-261.*

P3 Kristoffersen, E., Aremu, O. O., Blomsma, F., Mikalef, P., Li, J. (2019) **'Exploring the Relationship Between Data Science and Circular Economy: An Enhanced CRISP-DM Process Model.'** In Conference on e-Business, e-Services and e-Society and Lecture Notes in Computer Science, 11701, 177-189.

P4 Kristoffersen, E., Mikalef, P., Blomsma, F. and Li, J. (2021) **'Towards a Business Analytics Capability for the Circular Economy.'** *Technological Forecasting and Social Change, 171, 120957.*

P5 Kristoffersen, E., Mikalef, P., Blomsma, F. and Li, J. (2021) **'The Effects of Business Analytics Capability on Circular Economy Implementation, Resource Orchestration Capability and Firm Performance.'** *International Journal of Production Economics, 239, 108205.*

Secondary research papers added with abstract.

SP1 Gupta, S., Justy, T., Shampy, K., Kumar, A., and Kristoffersen, E. (2021) **'Big Data and Firm Marketing Performance: Findings from Knowledge-Based View.'** *Technological Forecasting and Social Change, 171, 120986.*

SP2 Li, Z, Kristoffersen, E., and Li, J. **'A taxonomy and survey of deep learning driven approaches for predictive maintenance.'** *Manuscript complete.*

SP3 Li, Z, Kristoffersen, E., and Li, J. **'Using Deep Transfer Learning to Predict Failures with Insufficient Data.'** *Manuscript complete.*

SP4 Kristoffersen, E., Li, Z., Li, J., Jensen, T. H., Pigosso D. C. A., and McAloone, T. C., **'Smart Circular Economy: CIRCit Workbook 4.'** *Technical University of Denmark.*

SP5 Berg, H., Blévennec, K. L., Kristoffersen E., Strée, B., Witomski, A., Stein, N., Bastein, T., Ramesohl, S., and Vrancken, K. **'Digital circular economy as a cornerstone of a sustainable European industry transformation.'** *Global Sustainable Technology and Innovation Community Conference 2020.*

Paper 1

Developing a circular strategies framework for manufacturing companies to support circular economy-oriented innovation.

Fenna Blomsma, Marina Pieroni, Maria Kravchenk, Daniela C.A. Pigosso, Jutta Hildenbrand, Anna Rùna Kristinsdottir, Eivind Kristoffersen, Sasha Shahbazi, Kjartan Due Nielsen, Anna-Karin Jönbrink, Jingyue Li, Carina Wiik, Tim C. McAloone

In: Journal of Cleaner Production, 241, 118271.

Journal of Cleaner Production 241 (2019) 118271

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Developing a circular strategies framework for manufacturing companies to support circular economy-oriented innovation

Fenna Blomsma [a, *], Marina Pieroni [a], Mariia Kravchenko [a], Daniela C.A. Pigosso [a], Jutta Hildenbrand [b], Anna Rùna Kristinsdottir [b], Eivind Kristoffersen [c], Sasha Shahbazi [b], Kjartan Due Nielsen [d], Anna-Karin Jönbrink [b], Jingyue Li [c], Carina Wiik [e], Tim C. McAloone [a]

[a] Technical University of Denmark (DTU), Department of Mechanical Engineering, Nils Koppels Alle 404, DK- 2800 Kgs, Lyngby, Denmark
[b] RISE IVF, 43 122, Mölndal, Sweden
[c] NTNU: Norwegian University of Science and Technology, 7491, Trondheim, Norway
[d] Innovation Center Iceland, Árleynir 2-8, 112, Reykjavík, Iceland
[e] Technology Industries of Finland, Eteläranta 10, 00131, Helsinki, Finland

ARTICLE INFO

Article history:
Received 28 October 2018
Received in revised form
30 August 2019
Accepted 2 September 2019
Available online 4 September 2019

Handling editor: Charbel Jose Chiappetta Jabbour

Keywords:
Circular strategies framework
Closed loop
Resource productivity
Manufacturing companies
Innovation

ABSTRACT

This paper puts forward the Circular Strategies Scanner: a framework that introduces a taxonomy of circular strategies developed for use by manufacturing companies engaging in circular economy (CE) oriented innovation. Currently, a range of frameworks exists that propose a vision for how to operate in a CE, by identifying and organising relevant circular strategies. However, these frameworks have a limited applicability for specific business types, in particular manufacturing, and are unsuitable for use in CE oriented innovation, due to a lacking ability to support innovation processes through: 1) creating a comprehensive understanding of circular strategies, 2) mapping strategies currently applied and 3) finding opportunities for improved circularity across a range of business processes. This paper addresses these shortcomings by proposing a circular strategies framework for the manufacturing context, titled the Circular Strategies Scanner, which provides a comprehensive set of definitions of circular strategies and directly supports the early stages of CE oriented innovation. With this, the paper contributes to the body of work that develops CE transition methodology.

1. Introduction

The linear economy is frequently characterised by the presence of structural waste: instances where components, products or materials reach their end-of-use/life prematurely, or where their capacity for value creation is underutilised. To address this, the circular economy (CE) concept proposes a range of efficiency and productivity enhancing activities collectively known as circular strategies, such as reduce, reuse, repair, recycle, restore, cascading, etc (EMF, 2013). In this sense, CE is an umbrella concept: it groups a range of sub-concepts and imbues them with a new meaning by highlighting a shared feature of the sub-concepts (Blomsma and Brennan, 2017). This new meaning revolves around the notion that through the application of circular strategies both more value can be created (EMF, 2013) as well as value loss and destruction reduced (Murray et al., 2017).

Although CE has widely been recognised as an idea with potential merit, it has yet to be widely implemented and embedded within business and industry (Haas et al., 2015; Circle Economy, 2019). This is in line with the progression of umbrella concepts: when the transformative potential of an idea has been recognised, the attention then turns to operationalising it through frameworks, tools, methods and approaches. This, in turn, allows for further examination of the concept.

For CE this means that there is currently a focus on developing CE transition methodology. This is taking place in a number of aspects relevant for Circular Oriented Innovation (COI) (Brown et al., 2019), such as in business models (Bocken and Antikainen, 2019; Pieroni et al., 2019; Rosa et al., 2019), metrics and assessment (Kravchenko et al., 2019; Moraga et al., 2019; Saidani et al., 2019), product design (Moreno et al., 2016; den Hollander et al., 2017) and the creation of organisational capabilities such as experimentation,

* Corresponding author.
E-mail address: fblo@mek.dtu.dk (F. Blomsma).

https://doi.org/10.1016/j.jclepro.2019.118271

value chain innovation and other human factors (Weissbrod and Bocken, 2017; Chiappetta Jabbour et al., 2019; Nilsson-Lindén et al., 2019).

Previous academic work focuses on answering 'what' or 'how' to promote COI (Guzzo et al., 2019; Mendoza et al., 2017). However, supporting the early stages of COI through the establishment of a CE vision, i.e. answering why to perform COI, has so far achieved relatively little scholarly attention. Finding the 'why' for a CE transition, requires understanding the type of structural waste in the system, which can be accomplished with a systemic analysis across life cycle stages and various business processes and knowledge areas. This requires various actors within and across business to define and explore problem and solution spaces together (Brown et al., 2019). Specifically, in COI a high-level conceptual understanding of CE needs to be translated into a vision that is useful and meaningful on the level of decision making (Hoffman, 2003; Boons and Howard-Grenville, 2009; Lindkvist and Baumann, 2014). The importance of a shared vision in innovation projects has long since been acknowledged (Pearce and Ensley, 2004; Bititci et al., 2004), and it has been posited to be relevant for both inter and intra organisational COI efforts (Brown et al., 2019).

Currently, there exists a range of frameworks that could potentially be drawn from to support CE visioning. These take the form of circular strategies frameworks, such as the ReSOLVE framework (EMF, 2015), the Performance Economy (Stahel,2006), Cradle-to-Cradle™ (Braungart and McDonough, 2002), and the Waste Hierarchy (EC, 2008), but also the Ricoh Comet Circle™ (Ricoh, 2018), and the Seven Fronts of Mount Sustainability (Interface, 2018). Importantly, these frameworks can be seen as the visual representations of a vision for how to operate in a CE, since they select, name and organise circular strategies seen as relevant, such that their relationship becomes apparent.

However, Mendoza et al. (2017), Reike et al. (2018) and Blomsma (2018) observed that such circular strategies frameworks can identify or emphasise different (groups of) circular strategies, which can be linked to addressing different types of structural waste. As such, there is a risk that they do not include circular strategies with transformative potential for a particular context. Moreover, Blomsma (2018) points out that little work has been done with regard to ensuring that frameworks are seen as relevant and useful by their intended audiences. For these reasons, there is scope to further develop these frameworks to support visioning in COI. Mendoza et al. (2017), Niero and Hauschild (2017) and Blomsma (2018) therefore call for the development of such frameworks within academia.

This paper answers this call and addresses the question of how to develop circular strategies frameworks such that they are relevant for their intended audiences, in a manner that points to the transformative potential of CE and that assists with unpacking the complexity associated with COI. With this, this paper contributes to the body of work that develops CE transition methodology, focussing on the early stages of COI and engaging the affected audiences in a transdisciplinary approach (Sakao and Brambila-Macias, 2018).

As an illustrative case, we develop a circular strategies framework for manufacturing companies.[1] Manufacturing companies were chosen as the focus as they are important users of materials and energy, produce significant amounts of byproducts traditionally regarded as waste, and form an important employment sector[2] and contributor to GDP (Rashid et al., 2013). In addition, manufacturing companies play an important role in the creation of value to their customers and therefore have great potential to decouple this value provision from linear resource consumption.

After clarifying the research gap in the background section and exploring the shortfalls of current circular strategies frameworks to support COI within manufacturing, we continue with setting out the methodology applied in this paper. In the following sections we present the development of the criteria used for designing the new framework and explain the relevant details and outcomes of each subsequent development phase. Furthermore, in section 6, we provide an example of application of the framework in COI. We close with a discussion of the contributions of this paper and directions for further work.

2. Background and research clarification

Describing the complete landscape of circular strategies frameworks is beyond the scope of this paper. However, here we provide an overview of the current landscape of circular strategies framework, through offering a typology of five classes of frameworks. The first four classes describe a continuum where the scope becomes increasingly smaller: (1) the macro level of industrial systems or economies; (2) the meso level of sectors, materials and business types; (3) the micro level of companies; and (4) the nano level covering product (groups) (Saidani et al., 2017). The fifth level adds the layer of (5) networked and regional approaches, through which the other four levels are connected. See Fig. 1.

2.1. Overview of the landscape of circular strategies frameworks

Considering the landscape of current circular strategies frameworks, a number of observations can be made that explain why current circular strategies frameworks fall short in their capacity to support visioning for manufacturing. First, a circular strategies framework needs to create a comprehensive understanding of circular strategies, as relevant for the purpose (Brown et al., 2019) and context (Blomsma, 2018). Think, for instance, of the difference in the main functions of insurance and finance firms, retail and wholesale businesses, service providers, and manufacturing companies. Different circular strategies will be relevant in these contexts (Rashid et al., 2013; Johannsdottir, 2014; Upadhyay et al., 2019).

Currently a multitude of frameworks exist on all levels of the landscape. See for frameworks on the macro level, for example: Allwood et al. (2011), Reike et al. (2018), Bocken et al. (2016), or Braungart and McDonough (2002). Likewise, for meso level frameworks for materials, see for water (WssTP, 2015) and biomass (ECN, 2018); or fashion and textile frameworks by EMF (2017), Inditex (2016) and Mistra Future Fashion (2018). On the micro level, consider: Gispen's (2018) framework for circular furniture, *The 10 R's of Circularity* by (Mitsubishi Electra, 2018), the Ricoh Comet Circle™ (Ricoh, 2018) (first used in 1994), or the framework used by Konecranes (2018). Likewise, on the nano level: Circular Jeans by Levi Strauss & Co. (2015), and Re-Entry for carpet tiles (Interface, 2017). Lastly, on the networked level, consider: Ehrenfeld and Gertler (1997); Aguinaga et al. (2018); and Pauli (2010).

A notable exception of circular strategies frameworks exists on the meso level that apply to specific business types, in particular to manufacturing. One exception is the ResCom framework by Rashid et al. (2013), which targets manufacturing companies. However, this framework is also not well suited to supporting innovation processes, as it includes few circular strategies and contains a limited consideration of business processes.

In addition to creating a comprehensive understanding of

[1] We use the expression *manufacturing companies* to refer to secondary manufacturing, as opposed to primary production. Moreover, these companies are not contract manufacturers, but have a degree of control over their supply chain.

[2] Sector, as used here, refers to an area of economic activity such as food, medicine, construction, etc. See: https://unstats.un.org/unsd/classifications/.

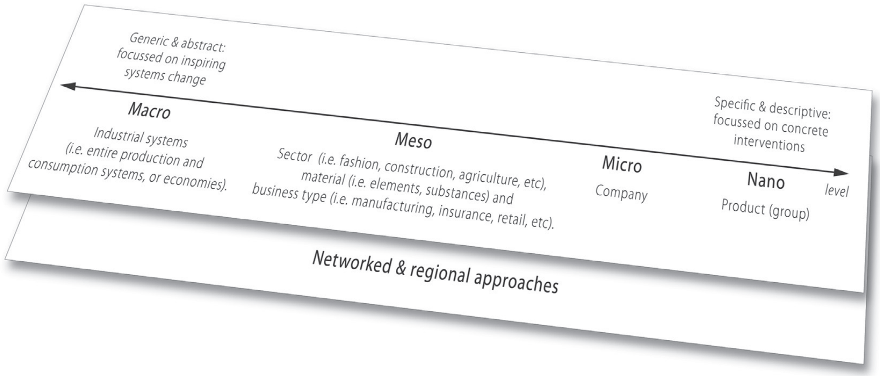


Fig. 1. Schematic illustrating the coverage of frameworks on the macro-meso-micro-nano scale, and their relationship with frameworks covering networked and regional approaches.

circular strategies, a circular strategies framework that supports visioning needs to both map strategies currently applied as well as find opportunities for improved circularity for a range of business processes from a systemic point of view. In this aspect, current frameworks are also lacking as they are often derived or compiled to serve as a summary or overview of a piece of (mostly theoretical) work, as opposed to being purposefully developed for use in COI in and with businesses (Niero and Hauschild, 2017; Kalmykova et al., 2018; Blomsma, 2018; Sakao and Brambila-Macias, 2018). However, to establish a vision it is important to both understand the current situation - e.g. what is already being done towards CE, or what capabilities provide a basis for this, as well as to identify what opportunities are present and desirable. Current circular strategies frameworks are not designed to capture an overview of both the current situation and ideas for future innovation.

Another shortcoming of current circular strategy frameworks is that they exhibit ambiguity with regards to the meaning of and relationships between the included circular strategies, allowing the same term to adopt multiple meanings - sometimes with radically different outcomes from a resource perspective (e.g. whether recycling keeps material quality on a consistently high level, or whether it represents downcycling) - or to be rendered inapplicable to some contexts (Reike et al., 2018; Blomsma, 2018).

This paper addresses these shortcomings, by a) providing an example of a process of how a circular strategies framework can be developed for a specific business type with the ability to support COI processes, b) proposing a circular strategies framework for the manufacturing context, resulting in the Circular Strategies Scanner, with c) an accompanying set of definitions of circular strategies (including commonly used synonyms). In addition to this, we provide d) an example of how such a framework can be used to structure and guide the early phases of COI, in order to show the relevance of visioning approaches within CE transition methodology.

3. Methodology

Design Research Methodology (DRM) was applied for the development of the new circular strategies framework for manufacturing, as this method is particularly suited to the deliberate iteration of methods and tools (Blessing and Chakrabarti, 2009). Next, a high-level overview of the aim and activities in each phase is provided. See Fig. 2 for an overview: more details are provided in the sections dedicated to each respective phase. The development of the proposed framework took place from November 2017 to July 2019.

Research clarification - This phase, already discussed in the previous section, served to refine the research gap and identify the need for a framework specifically for manufacturing companies.

Descriptive study I - This phase served three goals. First, a list of circular strategies to be included in the framework was compiled. Second, criteria that could be used to guide the development process of the new framework were articulated, which, third, were used to choose an existing framework as the basis for the development of the new framework. A series of workshops and meetings were held for this purpose. Iterations of the strategies list, their definitions and the framework requirements were performed throughout the project, but are presented as a single phase for clarity and brevity.

Prescriptive study I - A series of workshops and follow-up meetings were held to conceptualize and develop a first version of the circular strategies framework, as well as the corresponding clarifications and elaborations on strategies, and the relationship between them.

Descriptive Study II - In this phase the applicability and usefulness of the framework in the context of the manufacturing sector was evaluated and improvement opportunities sought. Workshops were performed with three manufacturing companies from the heavy machinery, electronics and furniture sector.

Prescriptive study II - A series of meetings was held to discuss the implementation of the improvement opportunities, based on insights from *Descriptive Study II* and the iterations of the *Research Clarification* and *Descriptive Study I* phases. A second version of the framework and a final list of strategies and their definitions were developed during this phase.

Moreover, the approach applied was deliberately transdisciplinary. That is, it aimed for establishing "a common system of axioms for a set of disciplines," which was achieved in two ways (Sakao and Brambila-Macias, 2018:1400), see also Fig. 2:

(1) *Adopting a systemic view* - In the context of (more) circular manufacturing this means the alignment of the different business processes, which together contribute to the creation of circular systems. The perspectives of these processes therefore need to be included.
(2) *Inclusion of non-academic stakeholders* - Creating (more) circular manufacturing systems entails affecting changes in manufacturing companies. As such, it is important to

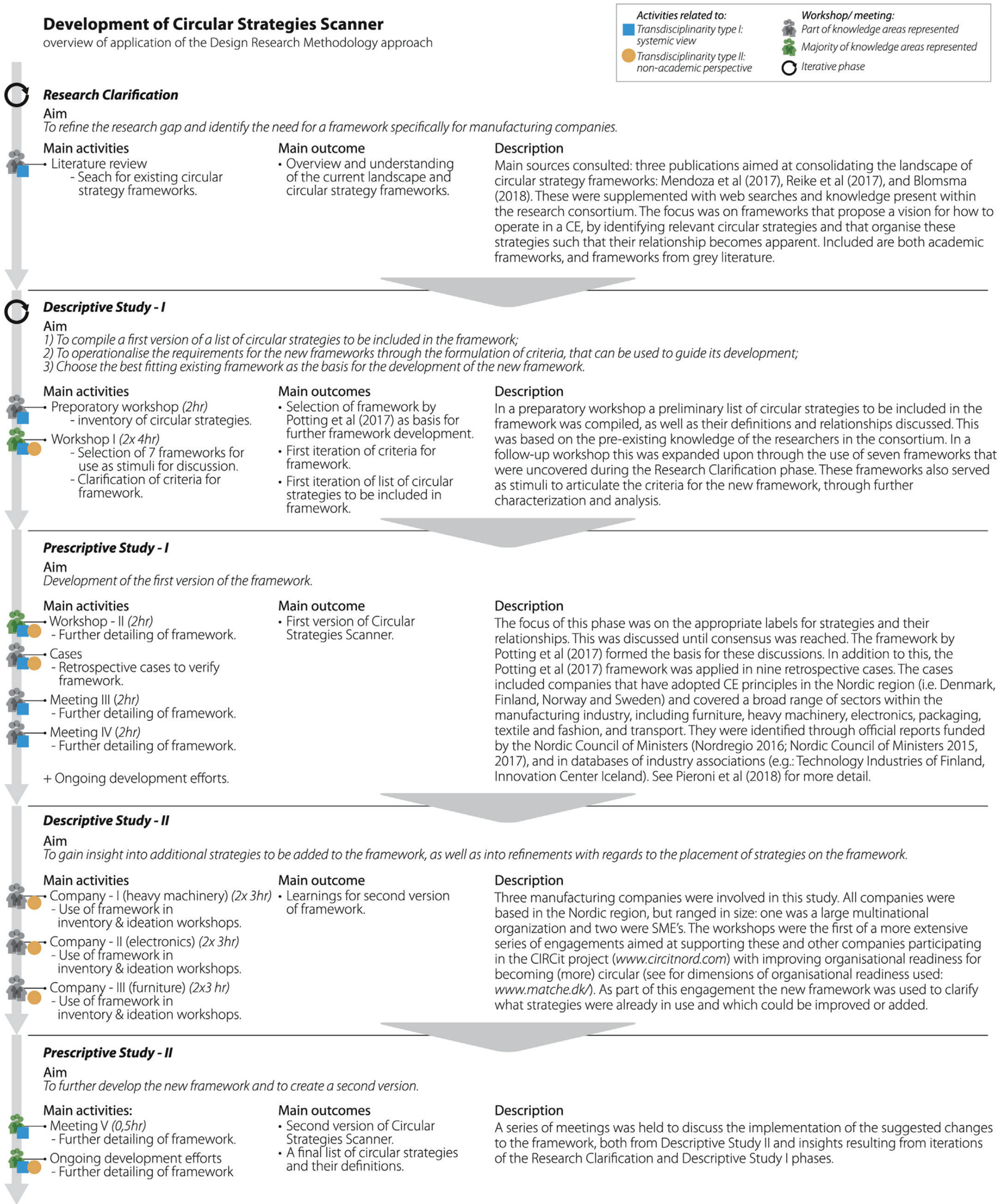


Fig. 2. Schematic illustration of the approach followed for the development of the Circular Strategies Scanner.

acknowledge the perspective of manufacturing companies in the development of the new framework.

The first type of transdisciplinarity was implemented through the creation of the CIRCit research consortium[3] to represent the knowledge related to business model strategy, product design, and a range of operational processes such as sourcing, manufacturing, logistics, through-life support, digital technologies and end-of-life operations, but also sustainability aspects and value chain management.

The second type of transdisciplinarity was implemented through application of the framework on retrospective company cases, as well as applying the framework in ongoing research that is actively supporting companies in implementing circular practices. Furthermore, the consortium contained representatives of the interests of manufacturing companies, such as industry associations. Through this, the perspective of 'real-world' considerations was added. Next, the outcomes of each phase is presented.

4. Descriptive Study I - criteria for a circular strategies framework for manufacturing companies

This phase served to establish a foundation for the development of the new framework. This was done in the following manner, see also Fig. 2.

4.1. Rationale behind Descriptive Study I

Due to the lack of suitable meso level frameworks with a business type orientation, macro frameworks were used as a starting point with the aim to adapt their generic applicability and generative capacity for manufacturing companies. From the macro frameworks 1) relevant circular strategies were extracted, and 2) criteria that could be used to guide the development process of the new framework were articulated, which 3) were used to choose the best fitting existing framework as the basis for the development of the new framework. In particular, seven macro level frameworks uncovered during the Research Clarification phase were used: Thierry et al. (1995), Parkinson and Thompson (2003), Allwood et al. (2011), Bocken et al. (2016), Nussholz (2017), Potting et al. (2017), and Blomsma (2018). These were included based on 1) their range of relevant strategies for the manufacturing context, 2) their inclusion of definitions and/or examples of these strategies and 3) representing a broad range of approaches to classify or organise the strategies in relation to each other. This served to have contrasting definitions and approaches that could be discussed and analysed.

4.2. Outcomes Descriptive Study I

The final version of the list of included strategies, their definitions and examples, which continued to be iterated throughout the development of the framework, can be found in Table 2 (see section 7. *Prescriptive study II*). Here, the focus is on the five criteria for the new framework that were developed to detail the main functions of a circular strategies framework (create understanding of CE, map current CE initiatives, generate ideas for increased circularity). The criteria were iterated until they represented five clear requirements for the development of the new framework. This section concludes with the selection of the best fitting existing framework.

4.2.1. Criterion #01: A tool for inspiring, motivating and aligning people

In innovation processes it is important to invoke relevant frames, acknowledge cognitive principles (which involve cognitive limits, but also principles of attention, inspiration and motivation) and, in collaborative settings, to consider the alignment of understanding, mindsets and interests between different stakeholders. Language, both visual and written, plays an important role in this: it helps directing attention, summarising and synthesising information from internal and external knowledge sources and it supports orientation towards relevant aspects of the context (Biloslavo et al., 2018; Breuer et al., 2018) and in the creation of a shared vision, also in the context of CE (Blomsma, 2018). Therefore, in line with the frameworks discussed above, the proposed framework should 01) represent a complex phenomenon in an easily accessible manner in order to inspire, motivate and align people.

4.2.2. Criterion #02: A tool for describing current situations and identifying opportunities, both incremental & transformative

A framework suitable for use by a wide variety of manufacturing businesses, cannot be broad in the sense of the frameworks on the macro level, as it will lose relevance. At the same time, it can also not be specific in the sense of the company and product frameworks, as this would mean it is limited in its reach and impact. However, the new framework should be suitable for describing both current initiatives and have the capacity to systematically explore relevant strategies and identify new opportunities. As such, the new framework should balance the strengths of the macro and meso level frameworks - which are generative and allow for the exploration of alternatives, with that of the micro and nano level frameworks - which offer greater specificity in relation to the context in which strategies are applied. Thus, the new framework should: 02a) balance the generation of new ideas, with that of describing existing situations. This indicates that it is preferable to include a diverse set of circular strategies, as opposed to high-level aggregated groups of strategies.

Furthermore, opportunity finding needs to point to the potential for improving existing strategies, as well as to radically different ways of achieving goals and creating, delivering and capturing value. This can involve the design, production and/or transport of physical products, but it can also require a change in the business logic and operations that changes how products are commercialized and consumed. Think of the implementation of access-over-ownership models, or radical dematerialisation through a change in paradigm. As such, the framework should 02b) provide an overview of the spectrum of available strategies ranging from incremental to transformative. This indicates that the set of included strategies should cover strategic as well as operational business processes.

4.2.3. Criterion #03: A tool for facilitating alignment of changes in business processes and capabilities

Circular strategies frameworks aimed at specific business types need to provide insight into which business processes relevant for that business type need to be aligned. This means, following Allwood et al. (2011), Potting et al. (2017) and Reike et al. (2018), that the new framework should indicate which circular strategies may apply to which flows. In the manufacturing context, this implies 03) indicating which strategies affect which business processes and related capabilities.

4.2.4. Criterion #04: A tool for bringing together efficiency and effectiveness strategies, and strategy configurations

Following e.g. Pauli (2010), Stahel (2006), Potting et al. (2017), Reike et al. (2018) and EMF (2015), we adopt the view that both

[3] See for more information about the consortium: www.circitnord.com.

resource-efficiency and resource-effectiveness are important in the manufacturing context. The new framework therefore should: 04a) explicitly include the reduction and avoidance of resource use and impacts, as well as resource productivity strategies aimed at continued use and value delivery.

Moreover, many manufacturing companies operate in complex scenarios, that can be thought of as circular configurations: situations where two or more circular strategies are present (Blomsma and Brennan, 2017; Blomsma, 2018). Think of product/service systems where direct reuse, but also repair, refurbishment and remanufacturing are taking place, in addition to the recycling of materials. As such, the proposed framework should: 04b) allow for generating insight into circular configurations.

4.2.5. Criterion #05: A tool for alignment with drivers: value creation & capture orientation

Businesses need to create and capture value to continue their activities. It is widely acknowledged that circular strategies have the capacity to contribute to this. However, not many current frameworks support the identification of the type of value that can be captured through which strategies. The new framework therefore needs to be aligned with the perspective of systemic value creation and capture. Support in identifying this can enable assessing and measuring outcomes and tracking potential deviations from the planned future state, which is fundamental to transition management (Breuer et al., 2018). As such, the proposed framework: 05) has to point to the value drivers that circular strategies can contribute to. That is: the framework has to help users identify relevant contributions to value creation and capture, such as improved efficiencies, supporting optimal use during the use phase, and value recovery opportunities, resulting in either financial or non-financial gains within or outside the company (Circle Economy, 2016). As these may be relevant for business shareholders, but also suppliers and customers, the environment and society they need to be formulated such that relevance for these stakeholders can be easily appreciated.

Next, the seven frameworks were compared and rated on these criteria, see Table 1. Although none have a perfect score, the framework by Potting et al. (2017) scores the highest: it represents a complex phenomenon in an easily accessible manner (criterion 01), contains a comprehensive set of circular strategies (criterion 02b), includes efficiency as well as effectiveness strategies (criterion 04a) and points to value drivers that circular strategies can contribute to (criterion 05). This framework was therefore chosen as a basis for further development of the new framework, with its relevance for different business processes and capabilities (criterion 03) identified as in need of further improvement.

5. Prescriptive Study I

During this phase the first version of the new framework was developed, through adding detail to Potting et al. (2017) as relevant for the manufacturing business type, guided by the criteria established in the above and the exploratory case studies (see Pieroni et al., 2018). The focus was on the appropriate labels for strategies, and how to convey the relationship between the included strategies.

5.1. Outcomes Prescriptive Study I

The outcomes of this phase is discussed in terms of the adaptations of the Potting et al. (2017) framework that were made. Only the major adaptations are elaborated upon: see for the first version of the framework Fig. 3 and the complete set of changes Appendix A. See for definitions and examples of individual strategies Table 2 (section *7. Prescriptive study II*).

5.1.1. Major adaptations #01 and #02: Organisation of circular strategies according to business processes, and greater specificity for 'Reduce'

The preliminary list of circular strategies from the previous phase was organised according to the business processes as typically found in the manufacturing context, to meet criterion #03. For this, the process of transformation of raw materials into finished or intermediate goods was divided as follows. First, two areas that are related to the corporate strategy were identified: the first is changing the paradigm of practices and was named 'Replace,' and the second is a reconsideration of how value is delivered, entitled 'Rethink.' The former strategy enables radical dematerialisation through different ways of performing functions (e.g. functional replacement or new practices), which can be enabled by new technologies. This strategy was renamed from Potting and colleagues' 'Refuse' (see Medium adaptation 1 in Appendix A). The latter strategy involves new business models that are more resource efficient, such as access-over-ownership offerings, enabled by commercial models based on leasing, renting or pay-as-you-go. As such, 'Replace' concerns the delivery of functionality through radically different means, whilst 'Rethink' delivers similar functionality through different customer relationships and which may involve a redefinition of the functional unit.

The remainder of the framework concerns operational processes. Potting et al.'s (2017) 'Reduce' was further divided to make its application to the following operational processes explicit: 'Raw materials and sourcing,' 'Manufacturing and logistics' and 'Product use/operation.' This indicates that in these phases, the focus is on efficient use of resources and the reduction of harmful impacts.

Table 1
Comparison of the seven frameworks that were used in Descriptive Study I using the development criteria.

Criteria The new framework should:	Bocken et al. (2016)	Allwood et al. (2011)	Parkinson and Thompson (2003)	Thierry et al. (1995)	Potting et al. (2017)	Nussholz (2017)	Blomsma (2018)
01) A tool for inspiring, motivating and aligning people.	+	++	0	++	++	+	+
02a) Balance the generation of new ideas, with that of describing existing situation.	0	+	0	+	++	+	0
02b) Provide an overview of the spectrum of available strategies ranging from incremental to transformative.	+	+	0	+	++	++	0
03) Indicate which strategies affect which business processes.	0	+	0	+	+	0	0
04a) Explicitly include the reduction and avoidance of resource use and impacts, as well as resource productivity strategies aimed at continued use and value delivery.	+	+	0	0	++	++	0
04b) Allow for generating insight into circular configurations.	+	++	0	++	++	+	+
05) Has to point to the value drivers that circular strategies can contribute to.	++	0	0	+	++	+	++

+++ = framework satisfies criterion very strongly, ++ = framework satisfies criterion strongly, + = framework satisfies criterion moderately, 0 = framework doesn't meet criterion or only marginally.

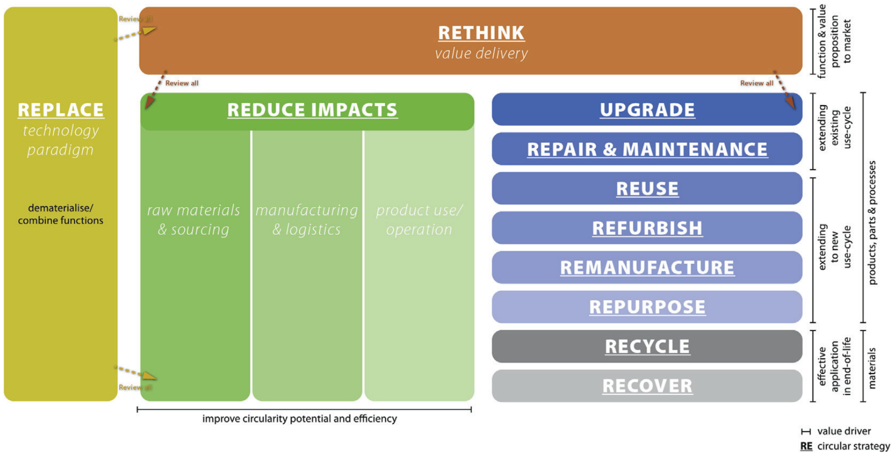


Fig. 3. The first version of the Circular Strategies Scanner.

The next two operational process areas respectively contain various end-of-use and end-of-life strategies. The first contains the strategies 'Upgrade' (see Minor adaptation 2), 'Repair & Maintenance' (see Minor adaptation 4), 'Reuse,' 'Refurbish,' 'Remanufacture,' and 'Repurpose'; and the second which contains the strategies 'Recycle' and 'Recover' (see Minor adaptation 1).

5.1.2. Major adaptation #03: Addition of the relationship between business processes

To capture the different relationships between the strategies (criterion 04b), a visual structure consisting of three levels has been created: the first occupied by 'Replace,' the second by 'Rethink' and the third by the remaining strategies. This is indicated by the relative placement of the boxes containing the strategies and the addition of arrows. This signals that, within the manufacturing context, some relationships between circular strategies are of a hierarchical nature, and some exist in the form of trade-offs and synergies. An example of a hierarchical relationship: 'Replace' may preclude the use of certain other circular strategies, when, for instance, a physical product is replaced by a virtual service. On the other hand, the application of 'Rethink' can require the support of repair and maintenance strategies to be viable, such as in certain product/service system offerings. As such, the application of either 'Replace' or 'Rethink' requires that the relevance of all strategies on the levels 'below' should be evaluated, as their relevance may change when these strategies are applied.

Examples of other relationships include trade-offs: the choice, for instance, for certain durable materials such as composites may impede recycling. In this case, a strategy that facilitates product longevity, conflicts with recycling the material at the end-of-life. On the other hand, certain interventions may cause cumulative or reinforcing effects, such as choosing a renewable material that at the end-of-life can be safely composted, allowing this single intervention to cover two circular strategies synergistically; the sourcing of materials that can be renewed and the 'recovery' of nutrients at the end-of-life. For this reason, the strategies that reduce impacts and that affect end-of-use/life are placed on the same level. When considering these strategies, therefore, it should be examined if trade-offs and/or synergies with other strategies on this level exist.

With this structure the new framework departs from the hierarchy that Potting and colleagues use. However, the value drivers have been preserved and further refined, in line with the different business processes (see Medium adaptations 2 and 3).

6. Descriptive Study II

In this phase the framework was tested in workshops within three manufacturing businesses from the heavy machinery, electronics and furniture sectors. The aim was to gain insight into additional strategies to be added, as well as into refinements with regards to the placement of strategies. Moreover, this section provides an example with regards to how a circular strategies framework can be used in the early stage of COI.

6.1. Use of the new framework in workshops in Descriptive Study II

With each business a two-part workshop was carried out. The first part mapped the circular strategies currently applied within a product or service (category). Participants were asked to prepare by classifying their offering (products, services or PSS), and to identify and describe the strategies currently applied. In the workshop, all strategies were mapped onto the Scanner and discussed: the current implementation level of the strategies, as well as their respective affinities to the business and their resource efficiency impact (e.g.: percentage of total sales or revenues, percentage of sold products recovered for end-of-use/life treatment). The second part of the workshop focused on scanning for new opportunities to enhance or append additional strategies, through the evaluation of the current state and the identification of gaps and improvement hot spots. Case examples of other companies employing strategies across the full range of strategies covered by the Scanner were used to stimulate the discussion with participants.

In total, each workshop lasted approximately 6 h and involved participants with diverse skills and expertise, such as marketing and sales, services and product development, after sales and customer services, operations, corporate social responsibility, IT, business strategy and finance. Moreover, representatives from the business leadership or top management participated in all workshops. The number of participants varied from three to ten, according to the business size.

6.2. Outcomes Descriptive Study II

An example of the mappings created in both phases of the workshop can be found in Fig. 4. The top part represents individual initiatives currently applied by one of the companies (one initiative per number). This represents current CE initiatives or current capabilities that can contribute towards increased circularity. The bottom represents improvement areas: circular strategies that could be improved or scaled up, or strategies that could feasibly be added. Comparing the current state with new opportunities, it can be seen that ideas were generated that increased the coverage of circular strategies, some even developing into more advanced concepts when synergies between circular strategies were identified.

During the workshops with the companies, the framework functioned as a boundary object (Star and Griesemer, 1989) for different participants to align their perceptions. That is: clarifying the current state together allowed participants to build a common picture of their organisations' ongoing CE initiatives and current capabilities, and to align their understanding of their nature and maturity. Moreover, the shared exploration of new opportunities helped the participants to share their perceptions of these opportunities, and set priorities for their innovation pipeline. In all cases the visioning exercise helped to identify why and where to focus,

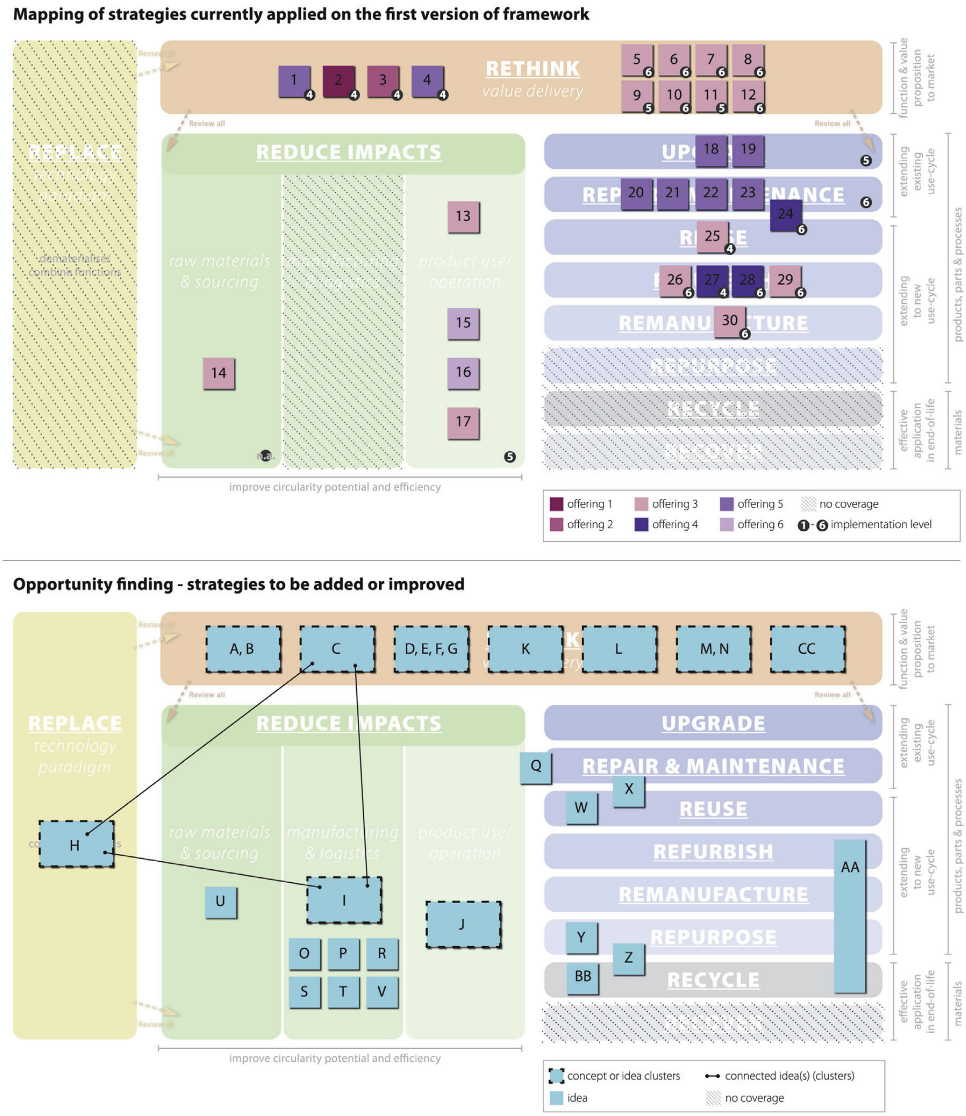


Fig. 4. Example of how the first version of the Circular Strategies Scanner was used in a two-part workshop with one of the companies participating in the CIRCit project. One or double letters are used per strategy: connected or grouped ideas represent closely related ideas that together constitute a new concept. Results are anonymised for reasons of confidentiality.

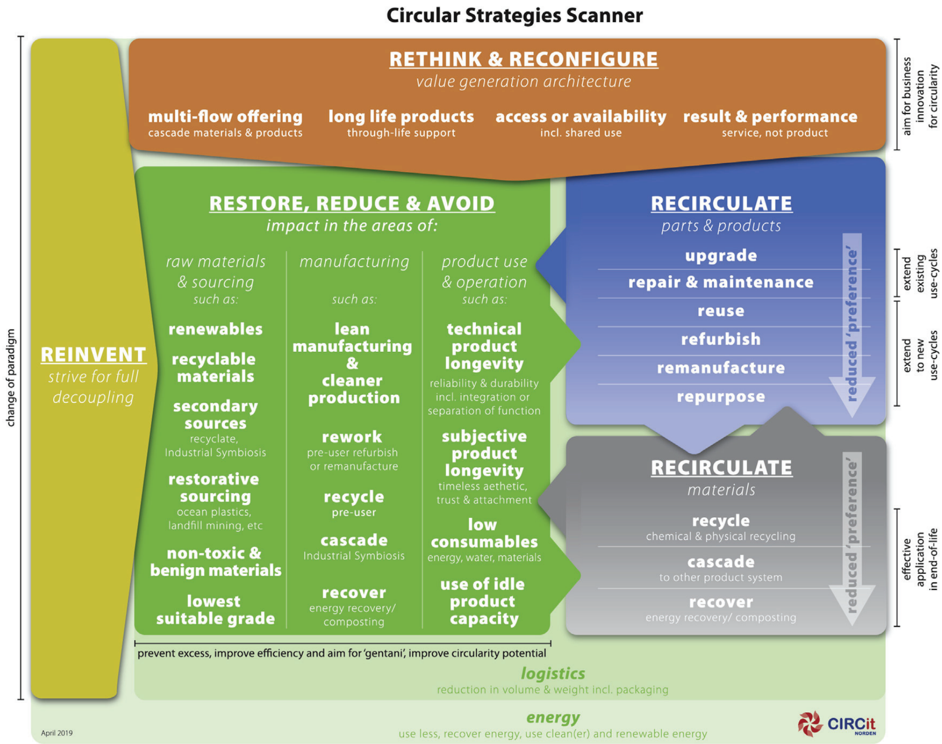


Fig. 5. The second version of the Circular Strategies Scanner.

whether in relation to the development of circular business models, applying circular product design principles, the application of smart technologies, the assessment of potential initiatives in relation to their sustainability impact and/or areas where collaboration with other stakeholders needed to be sought.[4] As such, this visioning exercise facilitated with the Scanner served to guide and direct the COI process to relevant initiatives and appropriately set the scope for these efforts early on. Direct feedback provided by individual participants supports this. Representative responses were "quite helpful", "great tools" and "visualization with the boards helped the conversation a lot."

However, observations were made that were used to improve the framework further. First, it was noted that efficient logistics is relevant throughout a product's life, and not just before, during and after manufacturing. That is: for operations extending existing life cycles or those that extend the product life to new use-cycles and in recovering materials for end-of-life treatment, logistics must be cost- and carbon efficient. It should be placed in such a way to indicate this broader relevance.

Moreover, it was observed that it is also possible to use the sourcing stage as an opportunity to recapture waste that has already entered the environment. The various projects around recovering plastic from the oceans are examples of this (The Ocean Cleanup, 2018; Plastic Oceans, 2018), and the framework should also highlight the possibility of sourcing such materials. These observations led to the Medium adaptations 1 and 2 discussed in the next section, see also Appendix C.

7. Prescriptive study II

The aim of this phase was to develop a second version of the framework on the basis of the identified improvement opportunities. The main activities were ongoing development efforts, supplemented by a series of meetings held to discuss the implementation of the suggested changes stemming from *Descriptive Study II* and the continued iteration of the *Research Clarification* and *Descriptive Study I.*

7.1. Outcomes Prescriptive Study II

No major adaptations were made, therefore the focus here is on medium adaptations: see for the second version of the framework Fig. 5 and the complete set of changes Appendix B. See for definitions of individual strategies Table 2.

'Logistics' was assigned a separate layer such that it encompasses all the operational process areas. In addition to this and in a response to additional sources considered, 'Energy' was added as a layer encompassing all circular strategies (Cullen, 2017; Mestre and Cooper, 2017). That is: circular strategies should be considered with the intent to reduce overall energy consumption, and the use of clean(er) and renewable sources wherever possible.

Moreover, the heading 'Reduce impacts' was changed to 'Restore, reduce & avoid' to more fully reflect the range of strategies relevant for raw materials and sourcing, manufacturing, and product use and operation. Also, more detail was added to the

[4] For more on this, see the CIRCit website (circitnord.com).

Table 2
Overview of the definitions of the circular strategies as used in the Circular Strategies Scanner.

Strategies included in the Circular Strategies Scanner (further developed from Potting et al., 2017)		
Driver	Strategy Synonyms	Area of application or sub category Recirculation strategy & synonyms *Definition (specifics)* • Example practice(s)/specifics
Enable smarter business concepts through striving for full decoupling.	**Reinvent** Refuse	**The paradigm** *Make physical products redundant by offering the same function or combined functions, usually enabled by radically different product, technology or both (Potting et al., 2017).* • The 'bring-your-own' movement facilitates replacing such single use items such as coffee cups. • Music and video streaming services negate the need for data carriers such as CDs and DVDs. • Multi-functional devices such as smart phones combine the functionality of multiple devices (camera, GPS, phone, calculator, alarm clock, sound system, computer) in a single device.
Enable smarter business concepts through business model innovation for circularity. Products tend to not radically change, although the technology can evolve.	**Rethink & reconfigure** Revolution Replace	**Business models** Multi-flow offering – cascade materials, parts & products *Extend the life of materials or products in a manner that exploits their residual value and becomes a significant part of the offering of the business. May involve providing new forms of value (Bocken et al., 2016).* • Leesmap (magazine subscription where the price decreases with the age of the magazines). • British Sugar (from the core-business of sugar, to also selling many different co-products). Long life products – through- life support *Extend the life of products through offering support during their lifetime (Tukker, 2004).* • Provision of maintenance, offering of repair services, or sales of spare parts. Access or availability – incl. shared use *Satisfying user needs without transferring ownership of physical products. Instead, user or consumer pays for access to the product for a certain period of time (Tukker, 2004).* • Bike or car sharing services (e.g. Bycyklen in Copenhagen, Santander Cycles in London, and many other cities around the world; Drive Now, Green Mobility, Zipcar, Blablacar). • Clothing rental and subscriptions (e.g. Rent the Runway, Vigga, Mud Jeans). Result & performance – service, not product *The provider of the service delivers an outcome for the customer (Tukker, 2004).* • Performance contracts (Rolls Royce - Power by the Hour).
Prevent excess, improve efficiency and aim for 'gentani', improve circularity potential.	**Restore, reduce & avoid**	**Raw materials & sourcing** *Improve circularity potential and efficiency in the sourcing process (Mestre and Cooper, 2017).* • Sourcing of renewables. • Sourcing of recyclable materials. • Secondary sources (recycled materials, Industrial Symbiosis, other cascades). • Restorative sourcing (Use former 'wastes' as input: Landfill re-mining or using ocean plastics). • Use of non-toxic or benign materials (to facilitate re-absorption in natural cycles). • Use the lowest suitable grade of materials suitable (Reserve the highest-quality resources for the most demanding task, and use used resources further down the chain). **Manufacturing** *Improve circularity potential and process efficiency in product manufacture through consuming fewer natural resources or energy, aim for 'gentani' (the absolute minimum input required to run a process) (Potting et al., 2017).* • Lean manufacturing & cleaner production (use less energy and materials, treat wastes, etc). • Rework (pre-user refurbishment or remanufacture). • Recycle (pre-user recycling). • Cascade (find uses for manufacturing waste: internally/at other facilities (Industrial Symbiosis)). • Recover (energy recovery, or recovery of biological nutrients). **Product use & operation** *Improve circularity potential and efficiency in product use and operation through wiser use and operation of products (usually enabled by digital technologies), and aim for 'gentani' (the absolute minimum input required to run a process) (Potting et al., 2017; Reike et al., 2018).* • Enable product longevity through high product integrity and robustness. • Use idle product capacity (historical usage data can be used for improvements such as better scheduling (of downtime), and (give insight into the possibilities for) pooled or shared use). • Low consumables of energy, water and materials during product use and operation. ***Logistics*** *Improve process efficiency in logistics operations, aim for 'gentani' (minimum input into a process (GreenBiz, 2014)* • Combine forward & return logistics. • Incentivize eco-friendly driving and transport. • Minimise, reuse or recycle (transit) packaging.

Table 2 (*continued*)

Strategies included in the Circular Strategies Scanner (further developed from Potting et al., 2017)		
		Energy *Improve energy efficiency and use clean(er) sources of energy (Cullen, 2017; Mestre and Cooper, 2017).* • Use less energy • Renewable energy
Driver	Strategy	Area of application or sub category Recirculation strategy & synonyms *Definition (specifics)* • Example practice(s)/specifics
Extend existing use cycles with the purpose of capturing (residual) value or to reduce value loss from continued use of parts and products	**Recirculate**	**Parts & products** Upgrade – Update, modernize, renew, retrofit, rebuild, overhaul, revive. *Extend existing use cycle by adding value or enhancing the function of a product in respect to previous versions (Parkinson and Thompson, 2003; Potting et al., 2017).* • Aesthetic upgrades (i.e. changing the coat or sleeve of a product due to a new preference). • Functional upgrades (i.e. software upgrades, hardware upgrades). Repair & maintenance – Corrective, condition based, predictive and prescriptive maintenance *Extend existing use cycle by countering wear and tear, and correcting faulty components of a defective product/part to return it to its original functionality. ((Partial) disassembly envisioned, limited warranty may be issued). (Thierry et al., 1995; Stahel, 2006).* • Providing a product with a service, which may involve the lubrication of critical parts, checking fasteners, the tension of chains and cables, the replacement of worn-out parts, etc. • Repair may involve the restoration or replacement of faulty parts and components.
Extend to new use cycles with the purpose of capturing (residual) value or to reduce value loss from continued use of parts and products.		Reuse – As-is reuse, redistribution, product cascading, minimise. *Extend to new use cycle by reusing a part/product (discarded/not in use) that is still in good condition and can fulfil its original function in a different use context (new customer/user). (May involve a minimum amount of condition monitoring such as cleaning or repackaging. No warranties are provided and no disassembly is involved.) (Saavedra et al., 2013)* • Selling used goods on platforms such as E-bay, • Return and resale of second hand goods through stores, such as Patagonia and Bergans. • The xStorage Home system (by Nissan and Eaton) gives old lithium-ion batteries from Nissan Leaf a second life inside of homes and businesses as backup and solar storage batteries. Refurbish – Recondition, retrofit, refresh, remodel. *Extend to new use cycles by returning a part/product (discarded/not in use) to a satisfactory working condition that may be inferior to the original specification. (This may involve: cleaning, repairing, resurfacing, repainting, re-sleeving. Partial disassembly envisioned*. In the case of traditional product sales, a warranty for all major parts may be issued (less than the newly manufactured equivalent)). (Ijomah, 2002, 2009; Saavedra et al., 2013).* • For example: taking in relatively modern, but disused white goods and performing repairs and/or replacing lost parts and finding new users for the refurbished products (e.g. Norsk Omburk). Remanufacture – Rebuild, overhaul, remake. *Extend to new use cycles by returning a product (discarded/not in use) to at least Original Equipment Manufacturer (OEM) performance specification and quality. (Usually more rigorous and costly than refurbishment and involves total disassembly and reassembly. In the case of traditional product sales, a warranty that is at least equal to that of a newly manufactured equivalent may be issued). (Ijomah, 2002, 2009; Saavedra et al., 2013).* • Renault engine blocks Repurpose – Alternate use. *Extend to new use cycles by using a product (discarded/not in use) or its parts for different functions (Potting et al., 2017; Reike et al., 2018).* • Mærsk providing containers to fit housing purposes in Copenhagen Village. • Using product packaging as storage or glassware (Nutella, Douwe Egberts).
Effective application in end-of-life of materials with the purpose of capturing (residual) value or to reduce value loss from continued use of materials.	**Recirculate**	**Materials** Recycle *Extend material lifespan by processing them in order to obtain the same or comparable quality (Allwood et al., 2011).* • Can-to-can recycling in beverage cans. • Chemical recycling of nylon. Cascade – Downcycling, upcycling. *A subsequent use that significantly transforms the chemical or physical nature of the material (Sirkin and Ten Houten, 1994).* • Repurposing of used clothing as an insulation material. • Used coffee grounds from coffee shops processed into biofuel, as medium for cultivation of edible mushrooms, for use in beauty products, etc. Recover *Recover energy or nutrients from composting or processing materials. (Reike et al., 2018).* • Incineration, pyrolysis or anaerobic digestion (recovery of energy). • Composting (recovery of biological nutrients).

Table 3
Overview of the improvements that the new framework makes in relation to the framework by Potting et al. (2017) that was used as a basis for its development.

Criteria The new framework should:	Potting et al. (2017)	Circular Strategies Scanner - v2.0	Summary of improvements that were realised
01) A tool for inspiring, motivating and aligning people.	++	+++	*Improved capacity to serve as a boundary object where stakeholders can clearly identify their (influence on) activities, and see the applicability and relevance of circular strategies (see also the criteria below).*
02a) Balance the generation of new ideas, with that of describing existing situation.	++	+++	*The Scanner can directly and without transformations be used as a tool for mapping the circular strategies that are present in a situation, as well as for exploring what strategies can be improved or added (see* section 6*).*
02b) Provide an overview of the spectrum of available strategies ranging from incremental to transformative.	++	+++	*The Scanner groups circular strategies according to their potential for change in circularity levels. Strategies that can be thought of as having potential for incremental change are grouped under* Restore, reduce & avoid*; strategies that aim for higher levels of circularity through business model innovation are grouped in* Rethink & reconfigure*; and strategies that radically transform both business and user practices and achieve radical decoupling are placed in* Reinvent*.*
03) Indicate which strategies affect which business processes and related capabilities.	+	++	*The circular strategies in the Scanner are organised according to the business processes they apply to.* Reinvent *and* Rethink & reconfigure *represent groups that affect business strategy, and the remaining groups respectively affect operational processes, ranging from raw materials and sourcing, manufacturing, product use and operation, to the recirculation of parts and products, and materials.*
04a) Explicitly include the reduction and avoidance of resource use and impacts, as well as resource productivity strategies aimed at continued use and value delivery.	++	+++	*The Scanner covers a wider range of circular strategies, giving a more comprehensive overview of circular strategies that aim for the reduction and avoidance of resource use and impacts, as well as those that improve resource productivity strategies.*
04b) Allow for generating insight into circular configurations.	++	+++	*The Scanner implements a means of systematically exploring connections between circular strategies, through organising them in three 'levels' that indicate their relationship. This relationship can be bi-directional: e.g. a change in circular strategies in* Restore, reduce & avoid *may impact the circular strategies in* Recirculate and vice-versa*; or it may may be a unidirectional relationship where a change in* Reinvent *requires the reexamination of the relevance of circular strategies in* Rethink & reconfigure*, or where a change in* Rethink & reconfigure *requires a reconsideration of the strategies applied in* Restore, reduce & avoid*.*
05) Has to point to the value drivers that circular strategies can contribute to.	++	+++	*Each group of circular strategies in the Scanner is clearly linked to a value driver that aids its users in identifying relevant contributions to value creation and capture, such as improved efficiencies, supporting optimal use during the use phase, and value recovery opportunities, pointing to opportunities for either financial or non-financial gains within or outside the company.*

+++ = framework satisfies criterion very strongly, ++ = framework satisfies criterion strongly, + = framework satisfies criterion moderately, 0 = framework doesn't meet criterion or only marginally.

visual representation of the framework, which entailed the addition of suggested strategies in this area (see Minor adaptation 2). These strategies are meant to be inspirational, rather than exhaustive. In some cases this resulted in allocating strategies to multiple places in the framework, which is in line with Potting et al. (2017) and Reike et al. (2018). Recycling, for instance, can be found in both the category Restore, Reduce and Avoid, as well as in the category Recirculate - Materials. This reflects the fact that pre- and post consumer recycling can take place. Similarly, cascading, or industrial symbiosis can take a variety of different forms: as a sourcing strategy, as a way of valorise manufacturing waste, but also as an end-of-life strategy for materials. These multiple occurrences are also due to departing from the hierarchical structure used by Potting et al. (2017) (see also section *5. Prescriptive Study I*). For clarity descriptors have been added to signal the specific application of a strategy (see Minor adaptation 3).

Similarly, detail was added to the Rethink & Reconfigure category to clarify the framework's relationship with business models aspects. Two sources were consulted for this: Bocken et al. (2016) and Tukker (2004), chosen because of their seminal importance in the CE field (Pieroni et al., 2019) These respective typologies were synthesised into four main categories that cover circular business model strategies available to manufacturers and that represent a fundamental change to the logic of how such a business operates: 'Multi-flow offering,' 'Long-life products,' 'Access or availability,' and 'Result and performance.' This, as opposed to including strategies that are more appropriately thought of as supporting operational strategies such as efficiency and encouraging sufficiency.

8. Discussion

The Circular Strategies Scanner illustrates how to support visioning in COI processes, through supporting the explication of CE, mapping current CE initiatives, and generating ideas for increased circularity. With this, the framework of Potting et al. (2017) was significantly improved upon for the manufacturing context, see Table 3.

A strength of using the Scanner in COI is that it provides a way of systematically exploring circular strategies. It thus provides guidance in identifying what business areas eco-innovation for CE is possible or necessary. For instance, when improved recycling is identified as an opportunity, the Scanner indicates that other circular strategies in the operational areas of raw materials and sourcing, manufacturing, product use and operation, and the recirculation of parts and products may be affected. Such impacts may be synergistic and result in increased overall circularity (e.g. the choice to change to a recyclable material to enable end-of-life recycling also enables recycling of waste within the manufacturing process), or they may take the form of trade-offs and require additional management or development for resolving them (e.g. changing to a recyclable material negatively affects the technical longevity of a product). Further work could focus on providing additional guidance with regards to how to systematically identify synergies and trade-offs.

Application of the Scanner furthermore strengthens the connection between eco-innovation and CE, by linking it with transformative innovation (de Jesus et al., 2018). It does this in two ways in COI processes. First, due to possibilities uncovered in the operational area, it can trigger a re-evaluation of the value generation architecture. Second, when the value generation architecture is the starting point, the Scanner indicates that the role of the circular strategies on the operational level need to be revisited as their relevance may increase or diminish depending on the context. In both cases, the Scanner invites a reconsideration of the system the manufacturing company is attempting to transform and links circular strategies together in circular configurations: situations where two or more circular strategies work together (Blomsma et al., 2018).

The range of sectors used for the validation efforts - heavy machinery, electronics and furniture - points to the broad applicability of the Scanner for manufacturing companies from different sectors. However, the framework could be further strengthened by validation with a wider set of manufacturing companies, including those that (also) operate within the biocycle, or that provide dissipative products (e.g. paints, lubricants, cleaning agents and other chemicals).

Further work should address how the Scanner can be linked to the assessment of (combinations of) circular strategies and different implementation scenarios, such that in the early stages of innovation processes the impact on economic, environmental and social systems can be evaluated and actions implemented to minimise negative impact and maximise positive impact. It could furthermore be explored whether the framework has potential to address the lack of a common understanding between value chain actors, which is perceived as an obstacle for the implementation of CE (Machacek et al., 2017; Lapko et al., 2018). In addition to using the Scanner by itself, there is also a need for understanding how different classes of circular strategies frameworks (e.g. macro, meso, micro, nano, networked) can best be used together.

9. Summary and conclusion

With this paper, we have contributed to the development of support tools for CE oriented innovation, or COI and to enable the translation of the CE concept in practice by creating support for visioning for CE. The contribution of this paper is four-fold: a) it provides an example of a process of how a circular strategies framework can be developed for a specific business type with the ability to support COI processes, b) it proposes a circular strategies framework for the manufacturing context, with c) an accompanying set of definitions of circular strategies, and d) it provides an example of how such a framework can be used in the early stages of a COI process. Next, it will be discussed how each goal was achieved and what the implications are for academia and industry.

In support of the first goal - to provide an example of the development of a circular strategies framework - this paper used the lens of Design Research Methodology (Blessing and Chakrabarti, 2009). This answered the call for the more deliberate and systematic development of circular strategies frameworks that are fit for purpose, voiced in Niero and Hauschild (2017) and Blomsma (2018). With manufacturing companies as the focus, it provided an example of how academia and industry can work together following a transdisciplinary approach (Sakao and Brambila-Macias, 2018) in developing resonant frameworks for specific audiences. The systematic development approach followed in this paper can be adapted and further expanded upon for other business types or other innovation contexts.

The second goal was achieved through the provision of the Circular Strategies Scanner. This framework can be used as a tool in COI and provides practitioners in manufacturing with a way of contextualising the CE concept, mapping current CE initiatives, and generating ideas for increased circularity. The third contribution, the set of circular strategies definitions included in the framework, served to support the consolidation of CE terminology and bringing academic and practitioner terminology closer together (Reike et al., 2018; Meste and Cooper, 2017; Kalmykova et al., 2018). This was achieved through drawing on both academic and practitioner perspectives with regards to these definitions in the development process. Together, these two points mean that an important iteration on the framework provided by Potting and colleagues was made, which brings more precision to the framework and which customises it for the manufacturing context. With this, the framework has been transformed from analytical framework into an innovation tool.

The fourth goal was achieved through illustrating how the Circular Strategies Scanner can be used in the early stages of a COI process to create a shared vision. The examples provided are of its application within businesses (see section 6). As well as with these companies, the Scanner was used with the other manufacturing companies participating in the CIRCit project. Specifically, it was used in the early stages of the action research, which allowed for a clear vision to be developed and establishing a clear direction for the work that followed, as it clarified with what aim different business activities relevant for COI needed to be deployed, whether this involved sustainability assessment, business model innovation, product design, digital technology strategies, the creation of take-back systems or value chain design.

Equally the Scanner could be applied across businesses, but also between business and academia, and beyond. In these contexts, the Scanner can serve as a boundary object where the stakeholders can clearly identify their activities or influence on different business processes across the life cycle, also enabling the comparison of CE initiatives and sharing of best practices.

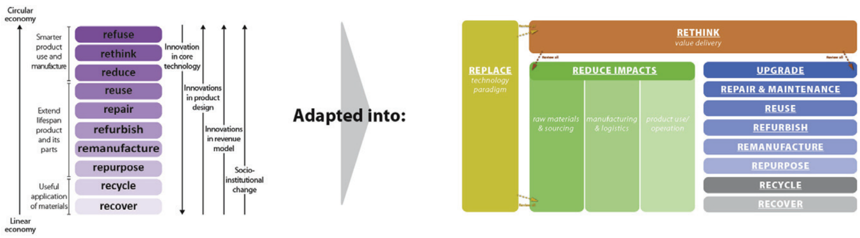
Acknowledgements

This article is one of the outcomes of the research project CIRCit (Circular Economy Integration in the Nordic Industry for Enhanced Sustainability and Competitiveness), which is part of the Nordic Green Growth Research and Innovation Programme (grant numbers: 83144) and funded by NordForsk, Nordic Energy Research, and Nordic Innovation. We would also like to thank the companies participating in the CIRCit project and the anonymous reviewers whose thoughtful feedback aided the development of this work.

Appendix A

This overview explains which changes were made to the Potting et al. (2017) framework in order to adapt it to the manufacturing context. It gives a complete overview of the major, medium and minor adaptations.

Overview of changes to adapt the Potting et al. (2017) framework for the manufacturing context

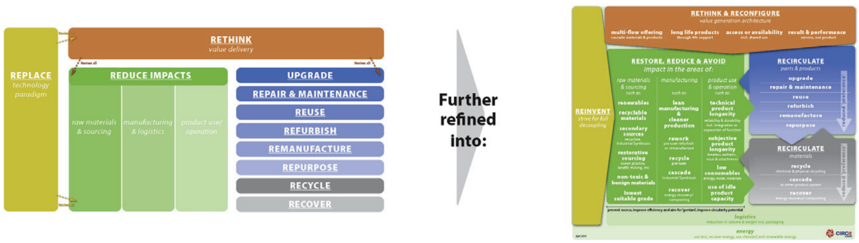


#	In Potting et al. (2017):	First version of Circular Strategies Scanner:
Major adaptations - changes in the structure of the framework		
1	Circular strategies organised hierarchically: ranging from those that are considered more linear to those that are increasingly more circular.	Circular strategies are organised according to the business functions they apply to, in five main areas: *Replace*, *Rethink*, *Reduce Impacts* and two other operational process areas respectively containing end-of-use and end-of-life strategies
2	'Reduce' presented a single high-level strategy.	Specified into 'Reduce impacts' and the sub-categories of 'raw materials & sourcing,' 'manufacturing & logistics,' and 'product use/operation.'
3	–	A visual structure consisting of three levels has been created to indicate the relationship of circular strategies, through the relative placement of the boxes containing the strategies, and the addition of arrows.
Medium adaptations - changes to the sub-groups or categories of the framework		
1	Inclusion of *Refuse* at the top of the hierarchy.	In the Circular Strategies Scanner, this strategy is understood as consisting of two sub-strategies and it was therefore split in two: *Refuse* (to abandon a practice altogether) and *Replace* (see Table 2). *Refuse* was subsequently not included in the framework, due to this framework targeting companies (see also Discussion section).
2	Contains the value driver: "Smarter product use and manufacture" for *Refuse*, *Rethink* and *Reduce*.	To refine this further, this value driver was split into "dematerialise/combine functions" for *Replace*, "function & value proposition to market" for *Rethink*, and "improve circularity potential and efficiency" for *Reduce Impacts*.
3	Contains the value driver: "Extend lifespan of products and parts" for *Reuse*, *Repair*, *Refurbish*, *Remanufacture* and *Repurpose*.	To refine this further, this value driver was split in two to align with the end-of-use and end-of-life groupings as in line with Potting. As a result, *Upgrade*, *Repair & Maintenance* and *Reuse* are assigned the driver "Extending existing use-cycle," and *Refurbish*, *Remanufacture* and *Repurpose* are assigned the driver "Extending to new use-cycle."
Minor adaptations – refinements in labels, definitions and the order of circular strategies		
1	Inclusion of *Recover*, as a strategy that refers to energy recovery through incineration, anaerobic digestion, pyrolysis.	The definition of *Recover* has been expanded to also include the recovery of biological nutrients and as such also covers such strategies as composting.
2	–	*Upgrade* was added to the framework to make explicit evolving quality and performance requirements of products.
3	*Reuse* comes before *Repair* in strategy order.	The order of *Reuse* and *Repair* was reversed, as Reuse that involves mere redistribution of products will – theoretically – maintain value to a higher degree with less added investment of resources, than redistribution that is also combined with repair activities.
4	Includes *Repair* as a circular strategy.	Repair was extended to also include maintenance, which is a common terminology in companies, and as such is indicated as *Repair & Maintenance* in the framework.

Appendix B

This overview explains which changes were made to the first version of the framework in order to develop the second and final version. It gives a complete overview of the medium and minor adaptations. No major adaptations were made at this stage.

Overview of changes to refine the 1st version of Circular Strategies Scanner and develop the 2nd version



Medium adaptations - changes to the sub-groups or categories of the framework

#	First version of framework	Second version of Circular Strategies Scanner:
1	The process of *Logistics* featured alongside *Manufacturing*.	*Logistics* is assigned a separate area in the framework, to better reflect that it covers all the operational process areas.
2	–	*Energy* was added as a relevant layer. That is: circular strategies should be considered with the intent to reduce overall energy consumption, and use clean(er) and renewable sources wherever possible.
3	Featured the strategy *Reduce Impacts*.	Label of strategy was changed to *Restore, Reduce and Avoid* to more fully reflect the range of strategies relevant for raw materials and sourcing, manufacturing and product use and operation.
4		Explicit addition of relevant strategies in *Restore, Reduce & Avoid*. Such as restorative sourcing (i.e. re-mining from landfill or using ocean plastics), lean and cleaner production practices and using idle product capacity. *Cascade* was also included: it can occur as Industrial Symbiosis and either as a secondary source sourcing strategy, or as a way of managing the co- and byproducts from manufacturing.
5	No detail provided regarding Rethink & Reconfigure.	To clarify the framework's relationship business models aspects, detail was added to the Rethink & Reconfigure category. This was done by drawing on Bocken et al. (2016) and Tukker's (2004) and adding the four main categories of Multi-flow offering, Long-life products, Access or availability, and Result and performance.
6	No explicit place for product and process design.	Product and process design are explicitly acknowledged by including them as box between Rethink & Reconfigure and the operational process of Restore, Reduce & Avoid and the Recirculate parts, products & materials.

Minor adaptations - refinements in labels, definitions and the order of circular strategies

#	First version of framework	Second version of Circular Strategies Scanner
1	Value drivers largely based on Potting et al. (2017).	Value drivers were further refined: for *Reinvent* it was changed to "strive for radical decoupling," and for *Rethink* to "aim for business innovation for circularity," and for *Restore, Reduce and Avoid,* to "prevent excess, improve efficiency and aim for 'gentani' and improve circularity potential."
2	Visual structure consisting of three levels has been created to indicate the relationship of circular strategies, through the relative placement of the boxes, and the addition of arrows.	Visual layering emphasised through depicting it using the visual metaphor of physical layers, which takes the form of drop shadows and arrows to indicate the relationship between the process areas. Hierarchical relationships indicated by a single arrow, trade-offs and synergies by bi-directional arrows.
3	No indication of hierarchy of end-of-use and end-of-life strategies	Arrows were added to indicate the (theoretically) preferred application order of these strategies.
4	Headings only applied for *Replace, Rethink* and *Reduce Impacts.*	For consistency, all five process areas are given headings. End-of-use processes are titled *Recirculate – parts & products* and end-of-life processes are titled *Recirculate – materials*.
5	–	*Cascade* was added to *Recirculate – materials*. This adds the distinction between recycling – i.e. those processes that keep material circulating at or near virgin levels of performance, and cascades – i.e. those processes that extend the life of materials through allowing for reduction or redefinition of performance characteristics.
6		Addition of descriptors to strategies to aid in clarifying the type of application. For example: recycling can take place at the manufacturing stage, where it involves re-entering waste from the manufacturing process back into the process: pre-user recycling. It can also take place post-user at the *Recirculate – materials* stage, in the form of chemical or physical (mechanical) recycling.
7	Featured the strategy label *Replace*.	*Replace* was changed to *Reinvent - strive for full decoupling*, to prevent confusion in relation the replacing harmful chemicals with less harmful or benign ones. Moreover, this term better conveys the transformative nature of this strategy.
8	Featured the strategy label *Rethink value delivery.*	Changed to *Rethink & Reconfigure value generation architecture.*

References

Aguiñaga, E., Henriques, I., Scheel, C., Scheel, A., 2018. Building resilience: a self-sustainable community approach to the triple bottom line. J. Clean. Prod. 173, 186–196. https://doi.org/10.1016/j.jclepro.2017.01.094.

Allwood, J.M., Ashby, M.F., Gutowski, T.G., Worrell, E., 2011. Material efficiency: a white paper. Resour. Conserv. Recycl. 55, 362–381. https://doi.org/10.1016/j.resconrec.2010.11.002.

Biloslavo, R., Bagnoli, C., Edgar, D., 2018. An eco-critical perspective on business models: the value triangle as an approach to closing the sustainability gap. J. Clean. Prod. 174, 746–762. https://doi.org/10.1016/j.jclepro.2017.10.281.

Bititci, U.S., Martinez, V., Albores, P., Parung, J., 2004. Creating and managing value in collaborative networks. Int. J. Phys. Distrib. Logist. Manag. 34, 251–268. https://doi.org/10.1108/09600030410533574.

Blessing, L.T.M., Chakrabarti, A., 2009. DRM, a Design Research Methodology. Springer-Verlag, London.

Blomsma, F., 2018. Collective 'action recipes' in a circular economy – on waste and resource management frameworks and their role in collective change. J. Clean. Prod. 199, 969–982. https://doi.org/10.1016/j.jclepro.2018.07.145.

Blomsma, F., Brennan, G., 2017. The emergence of circular economy: a new framing around prolonging resource productivity. J. Ind. Ecol. 21. https://doi.org/10.1111/jiec.12603.

Blomsma, F., Kjaer, L., Pigosso, D., McAloone, T., Lloyd, S., 2018. Exploring circular strategy combinations - towards understanding the role of PSS. In: Procedia CIRP. In: https://doi.org/10.1016/j.procir.2017.11.129.

Bocken, N.M.P., Antikainen, M., 2019. Circular business model experimentation: concept and approaches. In: Dao, D., Howlett, R.J., Setchi, R., Vlacic, L. (Eds.), Sustainable Design and Manufacturing 2018. Springer International Publishing, Cham, pp. 239–250.

Bocken, N.M.P., de Pauw, I., Bakker, C., van der Grinten, B., 2016. Product design and business model strategies for a circular economy. J. Ind. Prod. Eng. 33, 308–320. https://doi.org/10.1080/21681015.2016.1172124.

Boons, F., Howard-Grenville, J., 2009. The Social Embeddedness of Industrial Ecology. Edward Elgar Publishing Ltd, Cheltenham, UK.

Braungart, M., McDonough, W., 2002. Cradle to Cradle: Remaking the Way We Make Things, first ed. North Point Press, New York.

Breuer, H., Fichter, K., Freund, F.L., Tiemann, I., 2018. Sustainability-oriented business model development: principles, criteria and tools. Int. J. Entrepreneurial Ventur. 10, 256. https://doi.org/10.1504/IJEV.2018.092715.

Brown, P., Bocken, N., Balkenende, R., 2019. Why do companies pursue collaborative circular oriented innovation? Sustainability 11, 635. https://doi.org/10.3390/su11030635.

Chiappetta Jabbour, C.J., Sarkis, J., Lopes de Sousa Jabbour, A.B., Scott Renwick, D.W., Singh, S.K., Grebinevych, O., Kruglianskas, I., Filho, M.G., 2019. Who is in charge? A review and a research agenda on the 'human side' of the circular economy. J. Clean. Prod. 222, 793–801. https://doi.org/10.1016/j.jclepro.2019.03.038.

Cullen, J.M., 2017. Circular economy: theoretical benchmark or perpetual motion machine? J. Ind. Ecol. 21, 483–486. https://doi.org/10.1111/jiec.12599.

de Jesus, A., Antunes, P., Santos, R., Mendonça, S., 2018. Eco-innovation in the transition to a circular economy: an analytical literature review. J. Clean. Prod. 172, 2999–3018. https://doi.org/10.1016/j.jclepro.2017.11.111.

den Hollander, M.C., Bakker, C.A., Hultink, E.J., 2017. Product design in a circular economy: development of a typology of key concepts and terms. J. Ind. Ecol. 21, 517–525. https://doi.org/10.1111/jiec.12610.

EC (European Parliament and Council), 2008. Directive 2008/98/EC of the European Parliament and of the Council of 19 November 2008 on Waste and Repealing Certain Directives (Waste Framework).

ECN (European Compost Network), 2018. European Compost Network ECN e.V [WWW Document]. Organ. website. https://www.compostnetwork.info/about-ecn/. accessed 10.25.18.

Circle Economy, 2016. Master Circular Business with the Value Hill – Circle Economy.

Circle Economy, 2019. The Circularity Gap Report 2019.

Ehrenfeld, J., Gertler, N., 1997. Industrial ecology in practice: the evolution of interdependence at kalundborg. J. Ind. Ecol. 1, 67–79. https://doi.org/10.1162/jiec.1997.1.1.67.

EMF (Ellen MacArthur Foundation), 2013. Towards the Circular Economy: Economic and Business Rational for an Accelerated Transition.

EMF (Ellen MacArthur Foundation), 2015. Growth within: a circular economy vision for a competitive europe (https://doi.org/Article).

EMF (Ellen MacArthur Foundation), 2017. A New Textiles Economy: Redesigning Fashion's Future. Isle of Wight.

Gispen, 2018. Circular furniture [WWW Document]. Co. website. https://www.gispen.com/en/circular-economy/circular-furniture-circular-economy. accessed 10.25.18.

GreenBiz, 2014. How Toyota uses gentani to optimize performance and cut waste [WWW Document]. Organ. website. https://www.greenbiz.com/article/how-toyota-uses-gentani-optimize-performance-and-cut-waste. accessed 10.25.18.

Guzzo, D., Trevisan, A.H., Echeveste, M., Costa, J.M.H., 2019. Circular innovation framework: verifying conceptual to practical decisions in sustainability-oriented product-service system cases. Sustainability 11, 3248. https://doi.org/10.3390/su11123248.

Haas, W., Krausmann, F., Wiedenhofer, D., Heinz, M., 2015. How circular is the global economy?: an assessment of material flows, waste production, and recycling in the European Union and the world in 2005. J. Ind. Ecol. 19, 765–777. https://doi.org/10.1111/jiec.12244.

Hoffman, A.J., 2003. Linking social systems analysis to the industrial ecology framework. Organ. Environ. 16, 66–86. https://doi.org/10.1177/1086026602250219.

Ijomah, W.L., 2002. A Model-Based Definition of the Generic Remanufacturing Business Process, vol. 420 https://doi.org/10026.1/601.

Ijomah, W., 2009. Addressing decision making for remanufacturing operations and design-for-remanufacture. Int. J. Sustain. Eng. 2, 91–202. https://doi.org/10.1080/19397030902953080.

Inditex, 2016. Towards a circular economy [WWW Document]. Co. website. http://static.inditex.com/annual_report_2016/en/our-priorities/commitment-to-the-excellence-of-our-products/towards-a-circular-economy.php. accessed 10.2.18.

Interface, 2017. The ReEntryTM Carpet Recycling Program [WWW Document]. http://www.interface.com/APAC/en-AU/about/mission/ReEntry-en_AU. (Accessed 8 November 2017).

Interface, 2018. A look back: interface's sustainability journey [WWW Document]. Co. website. http://www.interface.com/US/en-US/campaign/climate-take-back/Sustainability-A-Look-Back-en_US. accessed 9.25.18.

Johannsdottir, L., 2014. Transforming the linear insurance business model to a closed-loop insurance model: a case study of Nordic non-life insurers. J. Clean. Prod. 83, 341–355. https://doi.org/10.1016/j.jclepro.2014.07.010.

Kalmykova, Y., Sadagopan, M., Rosado, L., 2018. Circular economy – from review of theories and practices to development of implementation tools. Resour. Conserv. Recycl. 135, 190–201. https://doi.org/10.1016/j.resconrec.2017.10.034.

Konecranes, 2018. Circular economy [WWW Document]. Co. website. https://www.konecranes.com/about-konecranes/corporate-responsibility/circular-economy. accessed 10.25.18.

Kravchenko, M., McAloone, T.C., Pigosso, D.C.A., 2019. Implications of developing a tool for sustainability screening of circular economy initiatives. Procedia CIRP 80, 625–630. In: https://doi.org/10.1016/j.procir.2019.01.044.

Lapko, Y., Trianni, A., Nuur, C., Masi, D., 2018. In pursuit of closed-loop supply chains for critical materials: an exploratory study in the green energy sector. J. Ind. Ecol. 23 (1). https://doi.org/10.1111/jiec.12741.

Levi Strauss & Co., 2015. TO infinity and beyond: HOW WE'RE embracing the circular economy [WWW Document]. Co. website. https://levistrauss.com/unzipped-blog/2015/07/21/embracing-the-circular-economy/. accessed 10.2.18.

Lindkvist, M., Baumann, H., 2014. A Review of Social Science in Five Industrial Ecology Journals (Gothenburg, Sweden).

Machacek, E., Richter, J., Lane, R., 2017. Governance and risk–value constructions in closing loops of rare earth elements in global value chains. Resources 6, 59. https://doi.org/10.3390/resources6040059.

Mendoza, J.M.F., Sharmina, M., Gallego-Schmid, A., Heyes, G., Azapagic, A., 2017. Integrating backcasting and eco-design for the circular economy: the BECE framework. J. Ind. Ecol. 21, 526–544. https://doi.org/10.1111/jiec.12590.

Mestre, A., Cooper, T., 2017. Circular product design. A multiple loops life cycle design approach for the circular economy. Des. J. 20, S1620–S1635. https://doi.org/10.1080/14606925.2017.1352686.

Mistra Future Fashion, 2018. Sustainable Fashion ([WWW Document]. Organ. website).

Mitsubishi Electric - Mitsubishi Elevator Europe, 2018. M-use - van bezit naar gebruik (from ownership to use) [WWW Document]. https://www.mitsubishi-liften.nl/m-use/.

Moraga, G., Huysveld, S., Mathieux, F., Blengini, G.A., Alaerts, L., Van Acker, K., de Meester, S., Dewulf, J., 2019. Circular economy indicators: what do they measure? Resour. Conserv. Recycl. 146, 452–461. https://doi.org/10.1016/j.resconrec.2019.03.045.

Moreno, M., De los Rios, C., Rowe, Z., Charnley, F., 2016. A conceptual framework for circular design. Sustainability 8, 937. https://doi.org/10.3390/su8090937.

Murray, A., Skene, K., Haynes, K., 2017. The circular economy: an interdisciplinary exploration of the concept and application in a global context. J. Bus. Ethics 140, 369–380. https://doi.org/10.1007/s10551-015-2693-2.

Niero, M., Hauschild, M.Z., 2017. Closing the loop for packaging: finding a framework to operationalize circular economy strategies. Procedia CIRP 61, 685–690. In: https://doi.org/10.1016/j.procir.2016.11.209.

Nilsson-Lindén, H., Baumann, H., Rex, E., 2019. LCM development: focusing on the LC promoters and their organizational problem-solving. Int. J. Life Cycle Assess. 24, 297–309. https://doi.org/10.1007/s11367-018-1523-z.

Nußholz, J., 2017. Circular business models: defining a concept and framing an emerging research field. Sustainability 9, 1810. https://doi.org/10.3390/su9101810.

Parkinson, H.J., Thompson, G., 2003. Analysis and taxonomy of remanufacturing industry practice. J. Process Mech. Eng. 217, 243–256. https://doi.org/10.1243/095440803322328890.

Pauli, G., 2010. The Blue Economy: 10 Years, 100 Innovations, 100 Million Jobs. Paradigm Publications.

Pearce, C.L., Ensley, M.D., 2004. A reciprocal and longitudinal investigation of the innovation process: the central role of shared vision in product and process innovation teams(PPITs). J. Organ. Behav. 25, 259–278. https://doi.org/10.1002/job.235.

Pieroni, M.P.P., Blomsma, F., McAloone, T.C., Pigosso, D.C.A., 2018. Enabling circular strategies with different types of product/service-systems. Procedia CIRP 73, 179–184. In: https://doi.org/10.1016/j.procir.2018.03.327.

Pieroni, M.P.P., McAloone, T.C., Pigosso, D.C.A., 2019. Business model innovation for circular economy and sustainability: a review of approaches. J. Clean. Prod. 215,

198–216. https://doi.org/10.1016/j.jclepro.2019.01.036.
Plastic Ocean, 2018. #RethinkPlastic [WWW Document]. Organ. website. https://plasticoceans.org/. accessed 10.25.18.
Potting, J., Hekkert, M.P., Worrell, E., Hanemaaijer, A., 2017. Circular Economy: Measuring Innovation in the Product Chain (The Hague, The Netherlands).
Rashid, A., Asif, F.M.A., Krajnik, P., Nicolescu, C.M., 2013. Resource conservative manufacturing: an essential change in business and technology paradigm for sustainable manufacturing. J. Clean. Prod. 57, 166–177. https://doi.org/10.1016/j.jclepro.2013.06.012.
Reike, D., Vermeulen, W.J.V., Witjes, S., 2018. The circular economy: new or refurbished as CE 3.0? — exploring controversies in the conceptualization of the circular economy through a focus on history and resource value retention options. Resour. Conserv. Recycl. 135, 246–264. https://doi.org/10.1016/j.resconrec.2017.08.027.
Ricoh, 2018. "Vision—the Comet CircleTM" [WWW Document]. Co. website. https://www.ricoh.com/environment/management/concept.html. accessed 9.25.18.
Rosa, P., Sassanelli, C., Terzi, S., 2019. Towards Circular Business Models: a systematic literature review on classification frameworks and archetypes. J. Clean. Prod. 236, 117696. https://doi.org/10.1016/j.jclepro.2019.117696.
Saavedra, Y.M.B., Barquet, A.P.B., Rozenfeld, H., Forcellini, F.A., Ometto, A.R., 2013. Remanufacturing in Brazil: case studies on the automotive sector. J. Clean. Prod. 53, 267–276. https://doi.org/10.1016/j.jclepro.2013.03.038.
Saidani, M., Yannou, B., Leroy, Y., Cluzel, F., 2017. How to assess product performance in the circular economy? Proposed requirements for the design of a circularity measurement framework. Recycling 2, 6. https://doi.org/10.3390/recycling2010006.
Saidani, M., Yannou, B., Leroy, Y., Cluzel, F., Kendall, A., 2019. A taxonomy of circular economy indicators. J. Clean. Prod. 207, 542–559. https://doi.org/10.1016/j.jclepro.2018.10.014.
Sakao, T., Brambila-Macias, S.A., 2018. Do we share an understanding of transdisciplinarity in environmental sustainability research? J. Clean. Prod. 170, 1399–1403. https://doi.org/10.1016/j.jclepro.2017.09.226.
Sirkin, T., Houten, M. ten, 1994. The cascade chain. A theory and tool for achieving resource sustainability with applications for product design. Resour. Conserv. Recycl. 10, 213–276. https://doi.org/10.1016/0921-3449(94)90016-7.
Stahel, W., 2006. The Performance Economy, second ed. Palgrave MacMillan.
Star, S.L., Griesemer, J.R., 1989. Institutional ecology, 'Translations' and boundary objects: amateurs and professionals in berkeley's museum of vertebrate zoology, 1907-39. Soc. Stud. Sci. 19, 387–420. https://doi.org/10.1177/030631289019003001.
The Ocean Cleanup, 2018. The largest cleanup in history [WWW Document]. Organ. website. https://www.theoceancleanup.com/ (accessed 10.25.18).
Thierry, M., Salomon, M., Van Nunen, J., Van Wassenhove, L., 1995. Strategic issues in product recovery management. Calif. Manag. Rev. 37, 114–136. https://doi.org/10.2307/41165792.
Tukker, A., 2004. Eight types of product–service system: eight ways to sustainability? Experiences from SusProNet. Bus. Strateg. Environ. 13, 246–260. https://doi.org/10.1002/bse.414.
Upadhyay, A., Akter, S., Adams, L., Kumar, V., Varma, N., 2019. Investigating "circular business models" in the manufacturing and service sectors. J. Manuf. Technol. Manag. 30, 590–606. https://doi.org/10.1108/JMTM-02-2018-0063.
Weissbrod, I., Bocken, N.M.P., 2017. Developing sustainable business experimentation capability – a case study. J. Clean. Prod. 142, 2663–2676. https://doi.org/10.1016/j.jclepro.2016.11.009.
WssTP, 2015. The role of water in the circular economy [WWW Document]. in: Vlakwa. https://www.vlakwa.be/en/publications/news/nieuwsbericht-en/news/new-ec-circular-economy-package-and-water/. accessed 10.2.18.

Paper 2

The Smart Circular Economy: A digital-enabled Circular Strategies Framework for Manufacturing Companies.

Eivind Kristoffersen, Fenna Blomsma, Patrick Mikalef, and Jingyue Li.

In: Journal of Business Research, 120, 241-261.

Journal of Business Research 120 (2020) 241–261

Contents lists available at ScienceDirect

Journal of Business Research

journal homepage: www.elsevier.com/locate/jbusres

The smart circular economy: A digital-enabled circular strategies framework for manufacturing companies

Eivind Kristoffersen[a,*], Fenna Blomsma[b], Patrick Mikalef[a], Jingyue Li[a]

[a] Norwegian University of Science and Technology, NO-7491 Trondheim, Norway
[b] University of Hamburg, 20146 Hamburg, Germany

ARTICLE INFO

Keywords:
Digital circular economy
Digitalization
Circular economy
Sustainability
Industry 4.0
Big data analytics

ABSTRACT

Digital technologies (DTs), such as the Internet of Things (IoT), big data, and data analytics, are considered essential enablers of the circular economy (CE). However, as both CE and DTs are emerging fields, there exists little systematic guidance on how DTs can be applied to capture the full potential of circular strategies for improving resource efficiency and productivity. Furthermore, there is little insight into the supporting business analytics (BA) capabilities required to accomplish this. To address this gap, this paper conducts a theory- and practice-based review, resulting in the Smart CE framework that supports translating the circular strategies central to the goals of manufacturing companies in contributing the United Nation's (UN) 12th Sustainable Development Goal, that is, "sustainable consumption and production," into the BA requirements of DTs. Both scholars and practitioners may find the framework useful to (1) create a common language for aligning activities across the boundaries of disciplines such as information systems and the CE body of knowledge, and (2) identify the gap between the current and entailed BA requirements and identify the strategic initiatives needed to close it. Additionally, the framework is used to organize a database of case examples to identify some best practices related to specific smart circular strategies.

1. Introduction

The concept of circular economy (CE) has gained momentum among businesses, policymakers, and researchers by virtue of its potential to contribute to sustainable development (Geissdoerfer, Savaget, Bocken, & Hultink, 2017; Ghisellini, Cialani, & Ulgiati, 2016) through a range of efficiency- and productivity-enhancing activities collectively known as circular strategies (EMF, 2013). For instance, consider circular strategies such as reduce, reuse, repair, recycle, restore, and industrial symbiosis.

For two reasons, the CE holds potential to contribute to multiple UN Sustainable Development Goals (SDGs) (Schroeder, Anggraeni, & Weber, 2019). First, the CE proposes that negating or reducing structural waste decreases the demand for virgin finite material. That is, through the application of circular strategies, the otherwise underused capacity of resources[1] can be applied to deliver value (EMF, 2015, 2015). Second, the CE promotes moving away from using the natural environment as a "sink" to dump used resources (Irani & Sharif, 2018). The CE is attributed with the ability to avoid, reduce, and negate value loss and destruction through, for instance, lower emissions, reduced pollution levels, and loss of biodiversity and habitats associated with resource extraction (EMF, 2013; Kumar & Putnam, 2008).

For these reasons, CE practices are strongly linked to SDG 12 (responsible consumption and production) and can have an additional beneficial impact on related goals, such as SDG 6 (clean water and sanitation), SDG 7 (affordable and clean energy), and SDG 15 (life on land) (Schroeder et al., 2019). Given the strong link with SDG 12 and the importance of manufacturing companies for this SDG, our study focuses on the manufacturing industry and the reduction of structural waste through improved resource management. At present, the adoption of circular strategies in industry is somewhat modest (Circle Economy, 2020; Haas, Krausmann, Wiedenhofer, & Heinz, 2015; Planing, 2015; Sousa-Zomer, Magalhães, Zancul, & Cauchick-Miguel, 2018). Moreover, this also holds true for manufacturing firms; although they play a vital role in the creation of value, there are few improvements to decouple from the linear consumption of finite resources (Sousa-Zomer et al., 2018). There are multiple reasons for this. First, the CE is an emergent concept, implying lack of tools for conducting CE-oriented innovation, or circular-oriented innovation (COI) (Blomsma & Brennan, 2017; Brown, Bocken, & Balkenende, 2019). Second, the link between CE and possible enabling digital technologies (DTs) is not yet well established (Alcayaga, Wiener, & Hansen, 2019; Jabbour, de Sousa

* Corresponding author.
E-mail addresses: eivind.kristoffersen@ntnu.no (E. Kristoffersen), fenna.blomsma@uni-hamburg.de (F. Blomsma), patrick.mikalef@ntnu.no (P. Mikalef), jingyue.li@ntnu.no (J. Li).

[1] Here, we refer to physical resources such as materials, components, and products.

https://doi.org/10.1016/j.jbusres.2020.07.044
Received 30 August 2019; Received in revised form 24 July 2020; Accepted 25 July 2020
Available online 25 August 2020
0148-2963/

Jabbour, Sarkis, & Godinho Filho, 2019; Jawahir & Bradley, 2016; Nobre & Tavares, 2017; Okorie et al., 2018).

Digital technologies could be critical enablers of CE by tracking the flow of products, components, and materials and making the resultant data available for improved resource management and decision making across different stages of the industry life cycle (Antikainen, Uusitalo, & Kivikytö-Reponen, 2018; Bressanelli, Adrodegari, Perona, & Saccani, 2018b; EMF, 2019, 2016; European Commission, 2020a, 2020b; Lacy, Long, & Spindler, 2020; Nobre & Tavares, 2017; Pagoropoulos, Pigosso, & McAloone, 2017). As such, DTs can play an important role in positioning information flows that enable resource flows to become more circular. For instance, the Internet of Things (IoT) can enable automated location tracking and monitoring of natural capital (EMF, 2016). Big data facilitates several aspects of circular strategies, such as improving waste-to-resource matching in industrial symbiosis systems via real-time gathering and processing of input-output flows (Bin et al., 2015; Low et al., 2018). Moreover, data analytics (simply known as *analytics*) can serve as a tool to predict product health and wear, reduce production downtime, schedule maintenance, order spare parts, and optimize energy consumption (Conboy, Mikalef, Dennehy, & Krogstie, 2020; Lacy et al., 2020; Porter & Heppelmann, 2014; Shrouf, Ordieres, & Miragliotta, 2014). These examples illustrate that DTs' contribution to the CE include a range of circular strategies and business processes: from recycling to reuse, and designing new offerings to managing maintenance.

Although there are real and theorized examples of information flows enabling circularity, there remains a gap between the expected, and largely unrealized, potential to use DTs to leverage circular strategies (Nobre & Tavares, 2019; Pagoropoulos et al., 2017; Rosa, Sassanelli, Urbinati, Chiaroni, & Terzi, 2020). So far, the answers to questions such as *in what areas* and *in which ways*, DTs support for implementing circular strategies for manufacturing companies have been insufficiently systematized. However, there is lack of support for improving the existing and new ways in which DTs can support the CE through *smart circular strategies* (Kristoffersen, Aremu, Blomsma, Mikalef, & Li, 2019; Kristoffersen et al., 2020). A Gartner survey of 1374 supply chain leaders supports this premise. The results show that 70% of the respondents are planning to invest in the CE; however, only 12% have so far linked their digital and circular strategies (Gartner, 2020b). In other words, there is lack of guidance on how to leverage DTs to maximize resource efficiency and productivity for a specific circular strategy.

This paper addresses this gap by linking the two emerging fields of DTs and the CE and developing the *Smart CE framework*, which establishes a link between DTs and resource management through an integrative model based on maturity thinking. The framework provides detailed understanding of the relationship between DTs and the CE through technical mechanisms and business analytics (BA) capabilities. It allows assessment of the current and future smart circular strategies with their associated and target level of maturity, and provides guidance on how to leverage DTs to maximize resource efficiency and productivity for a specific circular strategy. This will enable practitioners and academics to develop and implement roadmaps through BA gap analysis, find new opportunities for innovation through examples of best practices, and align people across the boundaries of disciplines. Existing digital CE frameworks present techniques to understand these two fields, mainly by summarizing high-level integrative strategies, enablers, and barriers. However, none provide the necessary support to systematically search, analyze, and advance such strategies, as presented within the Smart CE framework.

The rest of the paper is organized as follows. Section 2 details the gaps identified in applying DTs in the CE. Section 3 explains the study design, that is, the conduct of literature and practice reviews central to this research. Section 4 presents the proposed Smart CE framework and real-world examples collected from the practice review. Next, Section 5 discusses the practical implications and limitations of the research. Section 6 summarizes and presents the conclusive remarks.

2. Background

This section presents the definitions of the key constituents of DTs; next, we highlight the difficulties in leveraging them for manufacturing, focusing on their role in CE. Lastly, we articulate the scope of this paper and the associated research objectives.

2.1. Digital technologies in manufacturing

The term *digital technologies* encompasses several related technological trends such as IoT, big data, and data analytics. Furthermore, DTs, also known as *Industry 4.0* (Kagermann, Helbig, Hellinger, & Wahlster, 2013; Lasi, Fettke, Kemper, Feld, & Hoffmann, 2014; Liao, Deschamps, Loures, & Ramos, 2017), are transforming operations management in fields such as automation and industrial manufacturing, supply chain management, agile and lean production, and total quality management (Agrifoglio, Cannavale, Laurenza, & Metallo, 2017). For instance, DTs have the ability to give production systems the capacity to use historical data to improve quality by detecting abnormal behavior and adjusting performance thresholds accordingly (Aruväli, Maass, & Otto, 2014). Furthermore, the improved sharing of information throughout the value chain helps to control and make real-time adjustments of operations according to varying demand (Moeuf, Pellerin, Lamouri, Tamayo-Giraldo, & Barbaray, 2018). This increases operational efficiency and provides insights into the potential for new products, services, and business models (Kagermann et al., 2013). For the remainder of the paper, however, we focus leveraging circular strategies, as opposed to finding new offerings and business models.

Digital technologies are still an emerging field (Van den Bossche, 2016), lacking support for effective implementation for manufacturing at scale (Brettel, Friederichsen, Keller, & Rosenberg, 2014, 2018, 2019, 2016, 2017, 2016). A possible explanation for this is that ambiguous definitions without clear descriptions of the key constituent elements (i.e., IoT, big data, and data analytics) (Moeuf et al., 2018) are hampering the field. In Table 1, we illustrate the breadth of DT definitions in the extant literature and clarify our use of these terms in this paper.

In addition, a study of 161 manufacturing firms has identified three key barriers to using DTs to facilitate circular strategies: lack of interface design (e.g., challenges with compatibility, interfacing, and networking), difficulties in upgrading technology (e.g., bringing data analytics and IoT implementation to (near) state-of-the-art), and outdated automated synergy models (e.g., collaborative models, process digitalization, and automation) (Rajput & Singh, 2019). In this study, we limit our scope of DTs to focus on the upgrade of existing technologies and adoption of new tools, that is, IoT, big data, and data analytics, for exploring BA requirements central to circular strategies.

2.2. Difficulties in leveraging digital technologies for the circular economy

When confronted with the need to support the leveraging of a circular strategy—such as tracking stocks of natural capital, supporting industrial symbiosis matchmaking, and monitoring and managing product health—BA capabilities required to satisfy the need must be established.

For any data-driven business, and within the CE, this entails leveraging the full strategic potential of information flows by assembling, integrating, and deploying analytics-related resources (Shuradze & Wagner, 2016). This includes both tangible and intangible organizational resources such as data governance, existence of a data-driven culture, presence of suitable managerial and technical skills, and processes for data-driven organizational learning (Mikalef, Pappas, Krogstie, & Giannakos, 2018).

To date, efforts supporting information systems research primarily focused on explaining the mechanisms through which BA leads to competitive performance, for example, through the mediating role of dynamic and operational capabilities (Mikalef, Krogstie, Pappas, & Pavlou, 2019). As such, unpacking how the application of analytics unfolds within an organization to generate new or improved sources of value remains an underexplored area of research (George, Haas, & Pentland, 2014). Specifically, how DTs—through strategies of BA—lead to enhanced resource management, consistent with the CE, remain to be detailed.

Acknowledging the potential of DTs for the CE, various sources have

Table 1
Overview of definitions in extant literature and those adapted for this study. (See below-mentioned references for further information.)

Internet of Things		
Example 1	"The worldwide network of interconnected objects uniquely addressable based on standard communication protocols"	(Gubbi et al., 2013)
Example 2	"Things having identities and virtual personalities operating in smart spaces using intelligent interfaces to connect and communicate within social, environmental, and user contexts"	(Bassi and Horn, 2008)
Example 3	"[...] Smart and dynamic objects with emergent behavior, embedded intelligence and knowledge functions as tools and become an (external) extension to the human body and mind. [...]"	(Minerva et al., 2015)
Used within this research	The Internet of Things is a dynamic global network infrastructure with self-configuring capabilities based on standards and interoperable communication protocols. It merges the physical and virtual worlds through uniquely identifiable objects, or "things," with sensing and actuating capabilities, enabling data and the state of the thing to be collected and changed from anywhere, anytime, and by anything.	Adapted from: (Al-Fuqaha et al., 2015; Atzori et al., 2010; Kortuem et al., 2009; Li et al., 2015; Miorandi et al., 2012; Ray, 2018; Yick et al., 2008)
Big Data		
Example 1	"The broad range of new and massive data types that have appeared over the last decade or so."	(Davenport, 2014)
Example 2	"A term describing the storage and analysis of large and or complex datasets using a series of techniques including, but not limited to: NoSQL, MapReduce, and machine learning"	(Ward and Barker, 2013)
Example 1	"The ability of society to harness information in novel ways to produce useful insights or goods and services of significant value and [...] things one can do at a large scale that cannot be done at a smaller one, to extract new insights or create new forms of value."	(Mayer-Schönberger and Cukier, 2013)
Used within this research	Big data is high-volume, high-velocity and high-variety datasets that require advanced techniques for processing, storage, distribution, and management in order to turn data into information.	Adapted from: (Gartner, 2020a; Laney, 2001)
Data Analytics		
Example 1	"An overarching concept that is defined as data-driven decision making."	(Van Barneveld et al., 2012)
Example 2	"The processes of data assessment and analysis that enable us to measure, improve, and compare the performance of individuals, programs, departments, institutions or enterprises, groups of organizations, and/or entire industries."	(Norris et al., 2009)
Example 1	"A set of Business Intelligence technologies that uncovers relationships and patterns within large volumes of data that can be used to predict behavior and events."	(Eckerson, 2007)
Used within this research	Data analytics is the process of deriving knowledge and actionable insights from data and information, predominantly involving a series of methods and techniques including, but not limited to Data Mining, Artificial Intelligence, Knowledge Discovery in Databases, Big Data Analytics, Machine Learning, and Deep Learning.	Adapted from: (Cooper et al., 2012; Siow et al., 2018)

reported the need for work that links DTs and the CE. For instance (Chauhan, Sharma, & Singh, 2019; EMF, 2019, 2016; European Commission, 2020b; European Policy Centre, 2020; Okorie et al., 2018; Rosa et al., 2020), aim to raise awareness on DTs' potential for the CE and support further development through research and innovation. Other authors have investigated how DTs relate to servitized business models and CE value drivers (Alcayaga et al., 2019; Bressanelli, Adrodegari, Perona, & Saccani, 2018a; Pham et al., 2019) and the type of DTs needed within the various categories of well-known CE frameworks, such as the ReSOLVE (regenerate, share, optimize, loop, virtualize, exchange) framework (de Sousa Jabbour, Jabbour, Godinho Filho, & Roubaud, 2018b; Jabbour et al., 2019; Nobre & Tavares, 2019). Policy initiatives are also underway, such as the Circular Economy Action Plan, which includes a call for the creation of an architectural and governance infrastructure in the form of a dataspace for smart circular applications (European Commission, 2020a).

However, there is a gap between theory and practice (Rosa et al., 2020): research is presently in a pre-paradigmatic stage, as frameworks that support linking DTs and the CE have started to appear only recently, and no dominant framework has emerged as yet (Askoxylakis, 2018; Bianchini, Pellegrini, Rossi, & Saccani, 2018; Ingemarsdotter, Jamsin, Kortuem, & Balkenende, 2019; Rosa et al., 2020; Ünal, Urbinati, & Chiaroni, 2018). Although such frameworks may include a range of circular strategies, none systematically cover circular strategies that are relevant for manufacturing companies, and none detail the BA requirements needed to implement and improve them. That is, such frameworks do not allow for unpacking technical architectures, integrations, or implementations in terms of the principles of information and communications technology (ICT) or according to their different potential to contribute toward improving resource productivity and efficiency. As such, existing frameworks do not support bridging the gap between an organization's CE objectives and the operational alignment required to achieve them. This alignment is an essential step in COI (Brown et al., 2019) and the continuous improvement processes within manufacturing companies.

This research gap can be understood by drawing on a simplified version of the VMOST (vision, mission, objectives, strategy, tactics) framework (Sondhi, 1999); see Fig. 1. This framework illustrates how high-level goals can be made increasingly more concrete by moving from Vision to Mission to Objectives to Strategy, and eventually, operational Tactics. Here, we are concerned with the three last components of translating CE objectives into digital tactics.

As part of this COI and continuous improvement, it is necessary to have the ability to systematically search, analyze, and advance smart circular strategies to the highest possible levels of resource productivity and efficiency (EMF, 2016, 2019; Nobre & Tavares, 2017). For this reason, this

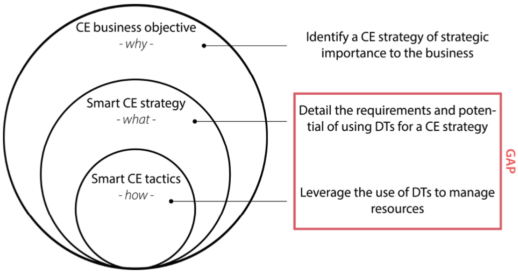


Fig. 1. Research scope.

paper focuses on the development of such a systematic approach to breaking down high-level circular business objectives into subsequent requirements for operational digital tactics.

3. Research methodology

3.1. Research scope and objectives

As already mentioned, we focus only (supporting) on leveraging circular strategies in the context of technological upgrades (e.g., data analytics and IoT development challenges) (Rajput & Singh, 2019). Thus, we do not answer *why* a CE strategy may be of importance to the business. Based on this scope, we outline two research objectives (ROs):

RO1 Develop a framework that supports the systematic identification of BA requirements needed to advance different smart circular strategies.

RO2 Consolidate and further advance the framework through the development of a knowledge base that can be used for BA gap analysis and the creation of roadmaps for the application of smart circular strategies within organizations.

3.2. Research design

Given the emerging and burgeoning characteristic of the domain, our study investigated not only academic sources but also practice case study examples and "grey literature" (i.e., published material that has not been subject to a peer review process; Adams, Smart, & Huff (2017)). We followed the methodology used by Bocken, Short, Rana, and Evans (2014), who detail three iterative phases for a practice and literature review: (1) identification of themes and categorizations by literature review, (2) synthesis by developing an integrative framework, and (3) identification and mapping of examples from practice to validate and further develop the framework. In addition, we adhered to the guidelines for reviewing academic literature by Kitchenham and Charters (2007) and those for grey literature by Adams et al. (2017).

3.2.1. Phase 1 - Literature review

In phase 1, we built on previous evaluation and review of existing CE frameworks, conducted in (Blomsma et al., 2019). This work created the Circular Strategies Scanner, which organizes circular strategies relevant to manufacturing companies.

In addition, we performed two systematic literature reviews following the guidelines of Kitchenham and Charters (2007). The literature review comprised two parts: (a) existing digital CE frameworks, and (b) digital frameworks to address RO1. For part (a), we sought frameworks that detail the connection between DTs and the CE. For part (b), we sought organizing principles that provide complementary insights into how different DTs relate to one another.

Two databases, Scopus and Web of Science, were selected for the reviews based on their broad coverage of journals relevant for both DTs and CE. See Fig. 2 for the search strings generated for RO1 and the steps involved. Additionally, see Appendix C for the full search string and synonyms used. Papers were limited to English peer-reviewed articles in conferences and journals. Articles were extracted from the databases on March 27, 2020. The database search included articles published over the past ten years, due to the burgeoning characteristic of the field. See Section 4.1 for an overview of the results of phase 1 of the review.

For part (a), we established inclusion criteria comprising only papers that illustrate a structured relationship between one or more DTs and circular strategies relevant to manufacturing. As such, articles that were too narrow in scope and focused on a specific circular strategy (e.g., supply chain management) or business model proposal (e.g., product-service system) were excluded, as they did not provide a range of circular strategies (e.g., only providing value drivers or enablers/barriers), were not scoped for manufacturing (e.g., targeting cities, economies, and countries at large), and did not give a clear description of a framework, organizing principles, or mechanisms. Furthermore, manual additions were prepared to complement the searches. This resulted in ten included papers, with six were from the database search. Following the criterion development process by Blomsma et al. (2019), existing frameworks were used to develop framework criteria to guide development in the synthesis phase. The criteria were iterated until they represented four precise requirements that the new digital CE framework should address.

For part (b), to extend the frameworks identified in part (a), inclusion criteria were set to include only papers that provided insights into how DTs relate to one another through common ICT architectures and taxonomies. As such, we excluded articles as they were too narrow in scope, did not define or give a detailed explanation of the DTs, or did not provide a clear description of a framework, organizing principles, or mechanisms. To complement these searches, manual additions were based on the researchers' general reading. This resulted in 32 included papers, with 22 from database search. Relevant information on approaches and principles underpinning the relationship between different DTs was extracted from the papers and aggregated in a spreadsheet.

3.2.2. Phase 2 - Synthesis: developing a smart CE framework

In phase 2, the resulting organizing principles, frameworks, and development criteria of phase 1 were used to synthesize and develop a detailed understanding of how DTs relate to the CE. First, development criteria were used to rate existing digital CE frameworks, highlight gaps, and guide the synthesis via the choice of organizing principles. Second, existing digital frameworks and principles were presented in tabular form using spreadsheets and analyzed for commonalities and theoretical underpinnings that allowed for connecting DTs to CE resource management. Next, approaches and principles that converged or correlated were combined, creating a more robust foundation to the underlying logic and organizing principles used. At this point, it became evident that operational maturity could be linked to both an increase in the level of resource productivity and unburdening of human decision makers. See Section 4.2 for a description of the results of the synthesis.

3.2.3. Phase 3 - State-of-the-practice review

In phase 3, to address RO2, we performed a broader systematic search of "DTs & CE strategies" in the literature, supplemented by a practice review aimed at uncovering examples (real or theorized) where DTs support or enable specific circular strategies related to manufacturing. Although the same methodology was followed for systematic literature reviews (Kitchenham & Charters, 2007), broader search terms and inclusion criteria were used to generate a larger set of sources likely to contain relevant examples. See Appendix C for the full search string and synonyms used.

To combine the Smart CE framework and the Circular Strategies Scanner (Blomsma et al., 2019) (detailed in Section 4.1), a matrix or grid was created, with the hierarchical dimensions from the Smart CE framework on the y-axis, and the CE strategy categories from the Scanner on the x-axis (see Fig. 3 for illustration). Examples that provide insights into how DTs can support circular strategies at different levels of operational maturity were sought. The examples collected in phase 3 were mapped onto this matrix and served as a validation of the Smart CE framework. If these

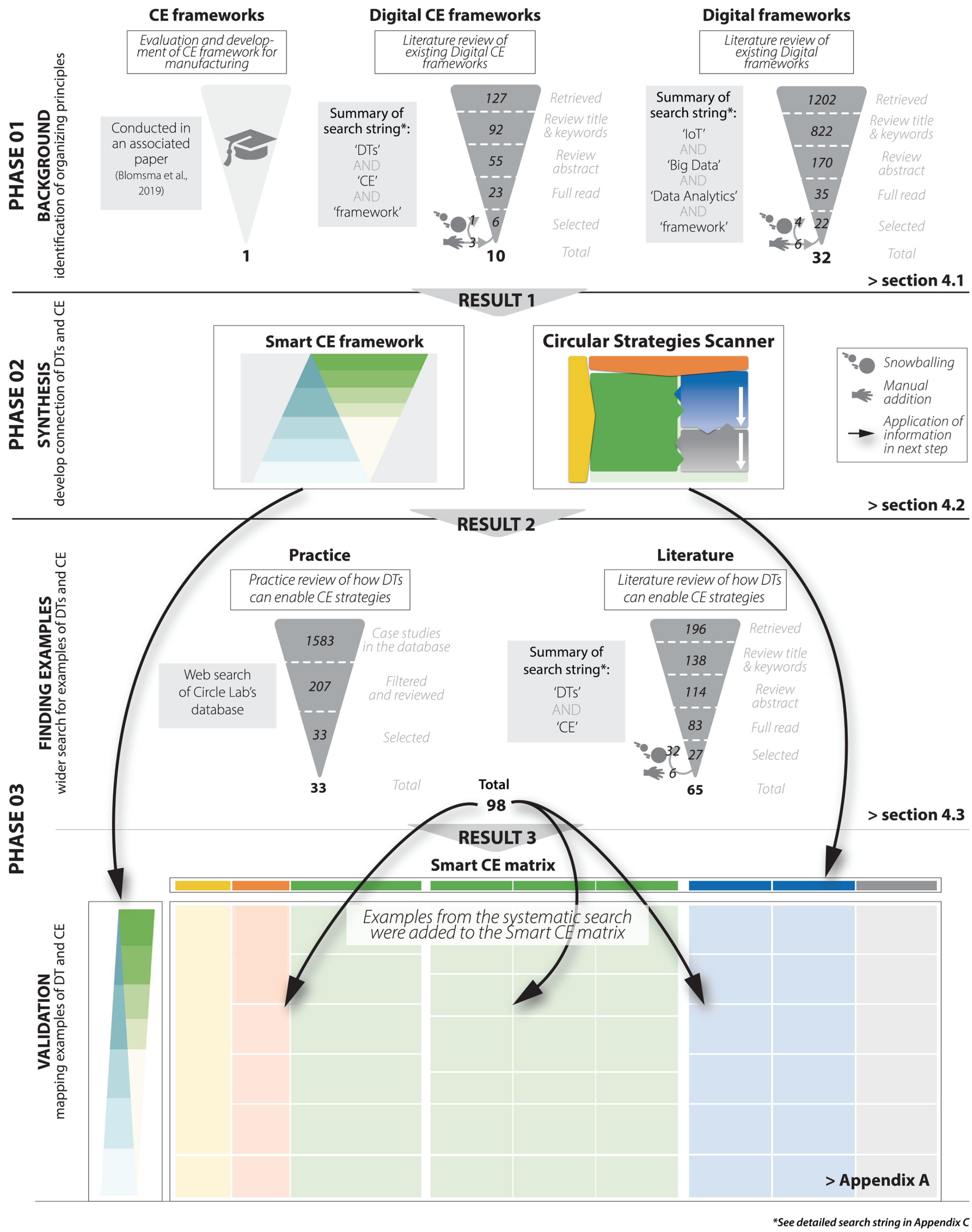


Fig. 2. Schematic illustration of the research approach that was followed to develop the Smart CE framework and matrix.

examples were not assigned a place, it would indicate an inadequate relationship between DTs and the CE.

Relatively few cells could be populated through this review, therefore, we decided to extend this part of the assessment with a practice review and include grey literature, consistent with (Bocken et al., 2014). The Circle Lab's knowledge hub, which (at that time) contained 1583 case studies, was the main source, thus making it the largest global open access innovation platform for CE case studies and examples (CircleLab, 2020). The result is a matrix that contains relatively few examples drawn from the academic literature, and more from the practice review. This may reflect that practice can be ahead of academia as both DTs and the CE represent emerging fields.

This resulted in 98 included papers and case studies for RO2 (with 65 added from the literature and 33 from practice). See Section 4.3 for an overview of the included examples. After complementing with cases from grey literature, 94% of the cells (46 out of 49) are detailed.

4. Research results

4.1. Results of Phase 1 - Literature review

4.1.1. CE frameworks

Building on previous evaluation and review of CE frameworks, the Circular Strategies Scanner was selected (Blomsma et al., 2019). The Scanner (shown in Fig. 3) presents a taxonomy of circular strategies based on business processes typically found in the manufacturing context. Drawing from both academic and practitioner perspectives, the framework provides circular strategies ranging from incremental to transformative, or from operational to strategic. Operational strategies include reducing, restoring, and avoiding impact in areas such as sourcing, manufacturing, product use, and logistics, as well as the recirculation of products, components, and materials into new or existing use cycles. Strategic applications include rethinking and reconfiguring value-generating architectures and reinventing the "paradigm" for radical decoupling. In other words, the Scanner provides comprehensive support for manufacturing companies engaging in COI processes. Compared to other CE frameworks (Bocken, De Pauw, Bakker, & van der Grinten, 2016; Nußholz, 2017; Potting, Hekkert, Worrell, & Hanemaaijer, 2017), the framework has an improved capacity to (i) create a comprehensive understanding of circular strategies, (ii) map current strategies applied, and (iii) identify opportunities for improved circularity for different business processes (Blomsma et al., 2019).

4.1.2. Digital CE frameworks

Based on the stated research gap and frameworks identified from the review, insights and theoretical underpinnings were used to develop four framework criteria to guide the development and synthesis of the framework.

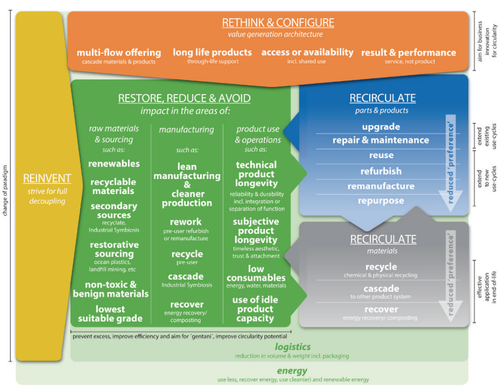


Fig. 3. The Circular Strategies Scanner.

114

Criterion (1) draws on the needs in the COI process, where it is important to align understanding, mindsets, and disciplines and represent a complex phenomenon in an easily comprehensible manner to inspire and motivate people (Blomsma et al., 2019; Brown et al., 2019). Criterion (2) addresses the suitability of the framework in a CE manufacturing setting. As there are different types of businesses, the framework should include a comprehensive set of circular strategies and facilitate the alignment of associated business processes (Blomsma et al., 2019; Potting et al., 2017). In a survey of Industry 4.0 implementation patterns in manufacturing companies, advanced adopters were leading all underlying DTs and not any specific technology (Frank, Dalenogare, & Ayala, 2019). A Gartner survey corroborates this and claims that a synthesis of DTs will enable companies to transition toward the CE (Gartner, 2020b). Building on this, criterion (3) establishes the need for the framework to represent multiple DTs and to be logically sound in terms of its relation to common ICT architectures and taxonomies. The former survey also indicates variance in the adoption of DTs related to varying organizational maturity (Frank et al., 2019). Hence, criterion (4) addresses the applicability of frameworks in an industrial setting to support adoption at various levels of maturity, BA gap analysis, and optimization of circular outcomes detailed here as resource efficiency and productivity.

The ten frameworks identified (Askoxylakis, 2018; Bianchini et al., 2018; de Sousa Jabbour et al., 2018b; EMF, 2016; Jabbour et al., 2019; Ingemarsdotter et al., 2019; Nobre & Tavares, 2019; Okorie et al., 2018; Rosa et al., 2020; Ünal et al., 2018) were compared and rated based on the above criteria (as in Table 2). Overall, the frameworks provide novel insights into the value of leveraging DTs for CE and different perspectives on understanding the digital CE through distinct theoretical assessments. Moreover, contributions varied from adaptation of the technical life cycle (Okorie et al., 2018) and product life cycle (Askoxylakis, 2018; Bianchini et al., 2018) to extensions of the ReSOLVE framework (de Sousa Jabbour et al., 2018b; Jabbour et al., 2019; Nobre & Tavares, 2019) and mappings of value-generating mechanisms (EMF, 2016; Ünal et al., 2018). Two frameworks presented new innovative models (Ingemarsdotter et al., 2019; Rosa et al., 2020).

Although a few frameworks addressed some of the criteria effectively, such as Rosa et al. (2020, 2019, 2019, 2018b), they were unable to satisfactorily address the majority of the criteria, in particular, criteria (3) and (4). Overall, the inability of existing frameworks to facilitate BA gap analysis, support companies at various stages of implementation or maturity, and effectively optimize resource efficiency and productivity of strategies support the emergent state of the field and justify the framework development.

4.1.3. Digital frameworks

Given the fact that digital CE frameworks do not support criteria (3) and (4), additional ICT principles and technical mechanisms were sought in a review of digital frameworks.

Of the 32 papers included, five papers used the Open Systems Interconnection (OSI) model as the underlying logic (Akhbar, Chang, Yao, & Muñoz, 2016; Da Xu, He, & Li, 2014; Jin, Gubbi, Marusic, & Palaniswami, 2014; Marjani et al., 2017; Tsai, Lai, & Vasilakos, 2014). Four papers presented a pyramid as a central element in the framework (Ardolino et al., 2018; Li, Yu, et al., 2017; Mishra, Lin, & Chang, 2015; Siow, Tiropanis, & Hall, 2018), and two of these used the Data-Information-Knowledge-Wisdom (DIKW) pyramid (Ardolino et al., 2018; Siow et al., 2018).

Fourteen papers encompassed all three DTs: IoT, big data, and analytics (Addo-Tenkorang & Helo, 2016, 2018, Queiroz, Wamba, Machado, & Telles, 2020, 2019, 2018, 2020, 2019, 2015, 2017, 2017, 2015, 2018, 2019, 2018).

Fifteen papers mentioned one or more workflows synonymous with data collection, data integration, data storage, data processing, and data analysis (Addo-Tenkorang & Helo, 2016; Babar & Arif, 2017; Da Xu et al., 2014; Dai, Wang, Xu, Wan, & Imran, 2019; Darwish & Bakar, 2018; Fatorachian & Kazemi, 2020; Jin et al., 2014; Li, Yu, et al., 2017; Marjani et al., 2017; Merezeanu & Florea, 2017; Mishra et al., 2015;

Table 2
Comparison of frameworks identified from the review based on development criteria.

Criteria of the new framework:	Rosa et al. (2020)	Nobre and Tavares (2019)	Ingemarsdottir et al. (2019)	Okorie et al. (2018)	de Sousa Jabbour et al. (2018b)	Jabbour et al. (2019)	Askoxylakis (2018)	EMF (2016)	Ünal et al. (2018)	Bianchini et al. (2018)
(1) A tool for inspiring, motivating and aligning people across disciplines	+	+	+ +	0	+	+	+	+	0	+
(2a) Include a broad range of circular strategies (from strategic to operational)	+	+ +	+	+	+	+	0	+	0	+
(2b) Support the translation of circular strategies to business processes relevant for manufacturing	+ +	0	+ +	+	0	0	+	+ +	0	+
(3a) Include a broad range of DTs	+ +	+ +	0	+	+ +	0	+	0	+	+
(3b) Provide an overview of the underlying technical mechanisms of how the DTs relate	0	0	+ +	+	0	+	+ +	+	0	0
(4a) Facilitate (self) assessment and BA gap analysis	+	+	0	0	+ +	0	0	0	0	0
(4b) Include digital maturity levels of adoption	0	0	0	0	+	0	0	0	0	0
(4c) Include resource optimization levels for maximizing resource efficiency and productivity	0	0	0	0	0	0	+	0	0	0

+ + + = framework satisfies criterion very strongly, + + = framework satisfies criterion strongly, + = framework satisfies criterion moderately, 0 = framework does not meet criterion or only marginally.

Siow et al., 2018; Tsai et al., 2014; ur Rehman et al., 2018; Wu et al., 2014). However, only one paper included different levels of data analytics and contrasted these with the DIKW pyramid (Siow et al., 2018).

In summary, most papers built on well-known ICT principles enabled the development of three separate organizing principles, or technical mechanisms. First, Software-Oriented Architecture, the DIKW pyramid, and OSI models were integrated under different *data transformation levels*. Second, workflows, such as data collection, integration, and analysis, were connected under *data flow processes*, along with the corresponding DTs. Finally, data analytics levels, such as descriptive and predictive analytics, were arranged under *analytics capabilities* (Siow et al., 2018).

4.2. Results of Phase 2 - Developing a smart CE framework

Guided by the above criteria, the proposed Smart CE framework addresses the shortcomings of existing digital CE frameworks. A detailed overview of the improvements for each criterion is presented in Table 4 in Section 5.1.

The framework consists of three main elements: *data transformation levels* (blue triangle), *resource optimization capabilities* (green triangle), and a layer linking these elements together, *data flow processes* (grey background), as seen in Fig. 4. The different elements were combined by using a hierarchy as the main organizing principle where each individual level relies on the previous ones. That is, for the data transformation levels, resources must be connected by an IoT sensor in order to generate data. This can then be turned into information by integrating it with other data sources and providing the context, and so on all the way up to wisdom.

Likewise, for resource optimization capabilities, diagnostic analytics provide insights into why something happened and build upon descriptive insights of what actually transpired. Similarly, in the data flow processes, data is first collected and integrated to facilitate data analysis. The remainder of this section explains the three elements, illustrates their compatibility in a single framework, and details the various levels of adoption through maturity thinking.

4.2.1. Data transformation levels

The data transformation levels draw on the DIKW pyramid, a widely recognized model in the information and knowledge literature introduced by Ackoff (1989). The DIKW hierarchy presents the terms *data*, *information*, *knowledge*, and *wisdom* to illustrate the computer processes involved in transforming raw data into insights (Rowley, 2007). Inspired by the physical layer in the OSI model, we modified the traditional DIKW model to include a fifth layer at the bottom named "connected resources." Each of the five layers are detailed below:

- **Connected resources** are products, components, and materials connected through, for instance, an IoT device. This enables to collect data across different stages of the resources' industrial life cycle.
- **Data** are merely raw, elementary symbols based on the observation of objects, events, and/or their environment (Ackoff, 1989; Rowley, 2007). On their own, data lack interpretation and need contextualization to offer direct value or usability.
- **Information** is inferred or transformed from data through techniques such as aggregation, interpretation, selection, and sorting. As such, information is contained within descriptions and provides answers to questions raised by words such as *who*, *what*, *where*, and *when* (Ackoff, 1989; Rowley, 2007).
- **Knowledge** represents the transformation of information into actionable instructions, knowhow, and valuable insights, and answers questions such as *how* and *why* (Ackoff, 1989; Rowley, 2007). As such, knowledge can be considered as the refinement of information with inference rules and increased understanding (Jankowski & Skowron, 2007).
- **Wisdom** connects actionable instructions of knowledge to autonomous decisions and actions. Wisdom combines knowledge with *interactive processes* and *adaptive judgment*. Interactive processes are the sequence of actions and reactions, while adaptive judgment is the actual decision made based on the evaluation of interactive processes and their current status (Jankowski & Skowron, 2007).

For instance, consider an IoT device for measuring temperature in a machine with the objective of extending its life cycle. Then, the raw

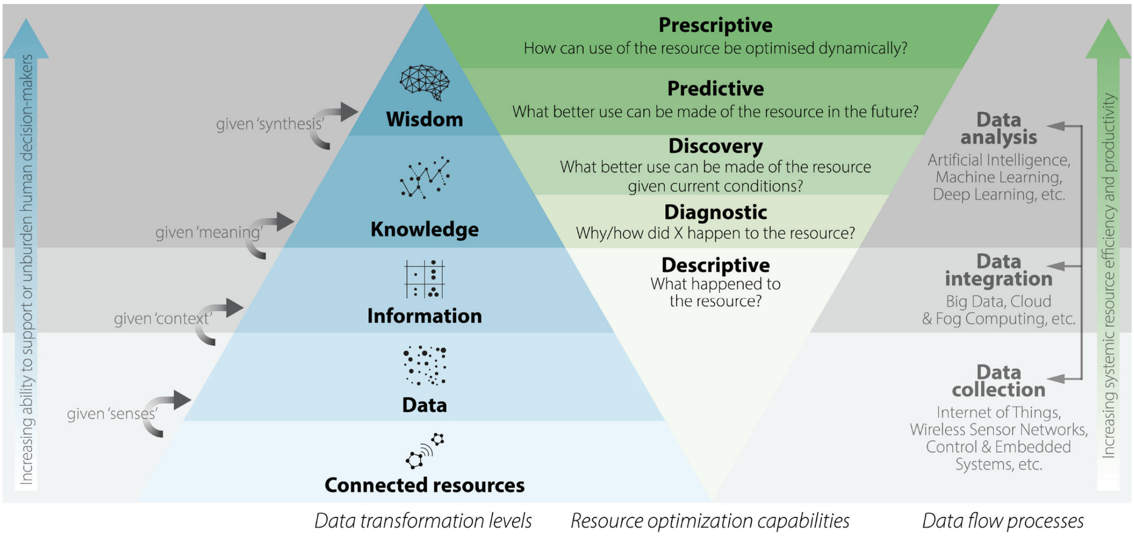


Fig. 4. The Smart CE framework.

temperature readings form the data. Thus, information is interpretation of this temperature represented by an average over the operating hours, or a description of the machine overheating. This could be an indication of an impending failure of the machine, for which a reactive maintenance scheme is created. Perhaps, knowledge can identify the possible reasons for the machine's abnormal temperature readings. Known as condition-based maintenance, this could give insights into the machine's actual condition and schedule maintenance. Finally, wisdom could then identify a specific trend in the temperature readings and project this across future operational planning and provide an optimal service window to correct the problem based on these predictions, known as predictive maintenance.

4.2.2. Resource optimization capabilities

Building on the analytics capabilities and generic interpretations by Siow et al. (2018), we provide the analytic capabilities, resource-specific interpretations, and supplementary questions to conform to COI and CE resource management. The resulting resource optimization capabilities present five levels of *descriptive*, *diagnostic*, *discovery*, *predictive*, and *prescriptive* analytics:

- **Descriptive** is the preliminary step that answers the question "what happened" or "what is happening." As such, it can be considered as the process of describing, aggregating, and adding context to raw data from an IoT device, thus transforming it into information.
- **Diagnostic** builds on the information obtained from the descriptive level to understand "why something happened." It tries to unravel the cause and effect of events and behaviors and augments knowledge to the information. As a bridge to business models and intelligence, both descriptive and diagnostic levels provide *hindsight value* of what happened and why.
- **Discovery** addresses the acute problem of high volumes in the IoT and big data. It employs inference, reasoning, and detection of non-trivial knowledge from information and data. It attempts to build a deeper understanding of why something happened by discovering additional trends and clusters, or something novel. As such, discovery provides *oversight value*.
- **Predictive** provides *foresight value* by identifying future probabilities and trends to determine "what is likely to happen." Predictive methods convert past knowledge to forecast events and behaviors, thereby obtaining wisdom.

116

- **Prescriptive** draws actions and judgments from the forecasts provided by the predictive level, allowing for investigation of future opportunities or issues, and provides the best course of action. As such, the prescriptive level considers the inherent uncertainty of predicting the future and combines this with advanced optimization to answer the question "what if."

These capabilities can, for example, be observed in organizations adopting three levels of analytics: aspirational, experienced, and transformed. Aspirational organizations use analytics in hindsight as a justification of actions. Experienced organizations apply analytics to gain insights to guide decisions, while transformed organizations can achieve foresight and prescribe actions in advance of decision making (Siow et al., 2018). Likewise, for the CE, these capabilities represent organizational potential to increase resource efficiency and productivity.

4.2.3. Data flow processes

Similarly, data flow processes represent a hierarchical structure. Nonetheless, this is not necessarily always the case in practice. For instance, all three processes of data collection, integration, and analytics may be employed to perform a descriptive analysis of what has happened. However, the rationale underlying this structure is emphasizing where the different DTs typically interconnect.

- **Data collection** is the process of generating and gathering data from various heterogeneous sources such as the IoT, wireless sensor networks, and embedded systems.
- **Data integration** is the process of contextualizing and curating these disparate data sources for analysis by preprocessing and aggregation. It relies on interoperability and context-awareness, which are typically included by big data, cloud computing, and fog computing.
- **Data analysis** is the process of understanding the data for underpinning or deriving actionable decisions. It includes deployment and application of data with associated insights and foresight, facilitated by techniques such as artificial intelligence, machine learning, and deep learning.

Furthermore, storage and computing are abstract processes involved in each of the above steps. Overall, data can be piped from one step to another, and thus do not necessarily require physical storage in

Table 3
Summary of results where **{}** are real world cases and **[]** are theoretical cases.

Data Transformation Levels / Resource Optimization Capabilities	Strategic		Operational						
			Restore, reduce & avoid				Recirculate		
CE categories	Reinvent	Rethink	Raw materials & sourcing	Manufac.	Product use and operation	Logistics and energy	Extend existing use cycles	Extend to new use cycles	Materials
Prescriptive	{35,91,95}, [41,42,43, 84,85,96]	{48,91}, [7,31,40]	{56,67}, [10,31]	[85,89,92, 96]	{91,95}, [85]	{34,35,64, 77,86}, [6,10, 23,24,40]	[7]		
Predictive			{56,57,71}	[88,93]	{20,22}, [4,8,9,10, 14,19,21]	{36,50}	{20,22,76, 91,98}, [4,9,10, 14,21]	{22,53}, [10]	{48,86}
Discovery		{26,51}, [5]	{26,51,56, 57}, [5,10]	[88,93]	{3,20,91}, [2,4,8, 9,12,13, 14,23]	{86}, [6]	{3,20,97}, [14]	{63,72}, [4,10]	{61,69}, [4,10]
Diagnostic		{26,45}, [5]	{26}, [5]	[92]	{37}	{45}	{3,20,76, 82}, [4,9, 14,21]	{49,52,54}	{45,74}
Descriptive		{22,46,58, 62,65,70, 80}, [4,19,33]	{27,56,57, 83}, [2,5,10]	{59,60}, [5]	{3,16,17, 20,22,44, 62,65,70, 80}, [2,4, 8,9,12, 13,14,21, 23,29,32]	{11,16,46, 66,69,75, 81}, [1,7,8, 10,15,21, 23,32]	{20,22,76}, [9,10,14, 32]	{22}	{23,48, 68,86,90}
Applicable to all levels	{87}, [2]	[2,25,28]	[38,39]	[18,31,94]	{16,17,20, 22,79}, [2,4,8,9, 12,13,14, 21,23,32]	{73}, [2,23, 30,33,47]	{55,69,78}, [2,10]		[2]

Data Flow Processes

separate locations. Similarly, computation can be done on a physical device or in transit (e.g., fog computing), and a separate computing component is not required (Siow et al., 2018).

4.2.4. Maturity levels

The hierarchical structure presented in the framework serves both as an organizing and adoption principle. Building on maturity thinking, the upper levels represent a greater potential of strategies to support or unburden human decision makers (blue arrow) and increase the efficiency and productivity (green arrow) of the systemic resource. In other words, the structure illustrates different levels of operational maturity in implementing DTs for decoupling value creation from the consumption of finite resources, building on extant research that considers the adoption of Industry 4.0 (Dalenogare, Benitez, Ayala, & Frank, 2018; de Sousa Jabbour et al., 2018b; Frank et al., 2019; Qu, Ming, Liu, Zhang, & Hou, 2019).

Moreover, the hierarchical structure of increasing maturity also indicates the aggregation of DTs as “Lego” blocks (Frank et al., 2019) for the application of autonomous functions (Qu et al., 2019). Hence, when a company matures and implements more advanced DTs (IoT, cloud computing, big data, and analytics, respectively), it can leverage self-sensing, self-adaptive, self-organizing, and self-deciding functions.

Based on this, we theorize a correlation between increasing industrial automation and expanding systemic resource efficiency and productivity in a CE. Support for this can be seen in the automatic production processes of smart manufacturing, enabling improved quality, productivity, and flexibility of large-scale production for sustainable resource consumption (Dalenogare et al., 2018; de Sousa Jabbour, Jabbour, Foropon, & Godinho Filho, 2018a).

4.3. Results of Phase 3 - State-of-the-practice review

The literature review on smart circular strategies resulted in 65 included papers (27 from the database search). The practice review of case studies from the Circle Lab’s knowledge hub was filtered using the label “Incorporate digital technology,” resulting in 207 results. Both the case descriptions in this database and company website(s) illustrating the cases were consulted (in line with Adams et al. (2017)), resulting in 33 examples added for a total of 98 real-world and theoretical case examples.

The Circular Strategies Scanner and the Smart CE framework enabled mapping of strategies into a matrix (represented by Figs. A.1–A.3 in Appendix A). The Scanner, representing the x-axis or the columns, covers a range of circular strategies relevant for manufacturing companies. The Smart CE framework, representing the y-axis or rows, covers DTs and different maturity levels of adoption. Strategies were then placed in a cell corresponding to the category, DTs, and maturity of the application. See Table 3 for a summary of the examples mapped or Appendix A for the detailed matrix and complementary case descriptions. The cases represent a mix of theorized applications and real-world examples (see Appendix B for reference number and theoretical/real-world labeling).

The results show that both theorized and real-world examples embody all the circular strategy categories. Moreover, up to and including the prescriptive level, the matrix has good coverage for all the categories, except the recirculation of parts, products, and materials. To address this issue and outline avenues for future research, the authors propose examples of future strategies, where both literature and practice are incomplete. However, the overall satisfactory coverage of circular strategies supports the validity of the Smart CE framework. The final mapping outlined 100 theorized and real-world smart circular applications (including strategies from literature, practice, and the authors).

In the following subsections, we explain how DTs can leverage various circular strategies, from operational processes to corporate strategies, along with excerpts from the example cases. However, for the purpose of this study, the focus is on operational strategies.

4.3.1. Digital technologies supporting circular strategies in operational processes

The first category of circular strategies discussed is *Restore*, *Reduce*, and *Avoid*. These strategies apply to raw materials and sourcing (e.g., use of recyclable materials and sourcing of waste), manufacturing (e.g., reworking and cascading by industrial symbiosis), logistics and energy (e.g., optimized routing and renewable energy), and product use and operations (e.g., product longevity and use of idle product capacity). In addition, end-of-use and end-of-life processes can be found in the strategies of *Recirculation*, both for parts and products (e.g., reuse and remanufacturing) and for materials (e.g., recycling and composting).

To facilitate our discussion, we use an illustrative example (see Fig. 5) from each of these categories. The strategies are taken from Figs. A.1–A.3 in Appendix A and highlight examples of industrial symbiosis, maintenance, and recycling. In Fig. 5, we expand the examples with digital and human requirements for each level to illustrate the increasing ability of DTs to support or unburden human decision makers (providing increased quality, productivity, and flexibility). One way to understand this is that the digital and human elements together represent all the decisions needed to coordinate resource flow for a specific strategy. Hence, when the number of decisions made by DTs increases, the decisions made by humans decrease or shift, providing flexibility for pursuing increased resource productivity. Note that we are not detailing the ideal digital and human requirements for implementation, but rather a proposed structure for explanatory purposes.

Restore, Reduce, and Avoid

In this category, the strategies target the prevention of excessive resource use and improve the inherent efficiency and circularity potential in the manufacturing process. For instance, industrial symbiosis, where the outgoing flow from one manufacturing facility is used by another, reduces and, in some cases, replaces a company's reliance on virgin raw materials. The descriptive level of DTs can support this strategy by describing and monitoring the type, quantity, and timing of input for current material flows (Bin et al., 2015; EMF, 2016; Pagoropoulos et al., 2017). This requires, for instance, IoT sensors for accurate collection and measurement of flow and/or aggregated information from internal sourcing, inventory, and logistics databases. When integrated with analytics, this may allow the discovery of new and alternative waste-to-resource matches and potential eco-networks for their application (if linked with information from other manufacturing facilities) (Bin et al., 2015; Low et al., 2018; Song, Yeo, Kohls, & Herrmann, 2017). Ultimately, on a prescriptive level, self-optimizing algorithms may be capable of automatically prescribing and arranging the exchange of flows through self-adapting sourcing plans (Srai et al., 2016).

Similar solutions, with analytics capabilities ranging from descriptive to prescriptive, can be envisioned for other strategies, including agriculture (EMF, 2016; Smart Bin, 2020) and natural resource conservation (Aquabyte, 2020; CreateView, 2020), manufacturing (Airfaas, 2020; Fisher, Watson, Escrig, & Gomes, 2019; KemConnect, 2020), product use and operations (Bressanelli et al., 2018b; Pham et al., 2019; Rymaszewska, Helo, & Gunasekaran, 2017), logistics (12Return, Liebig, Piatkowski, Bockermann, & Morik, 2020; Liebig et al., 2014), and energy (Shrouf et al., 2014; Tomra, 2020). For instance, examples include optimized vehicle and fleet usage (Sensoneo, 2020), reverse logistics planning (Cirmar, 2020), and operational scheduling based on the availability of renewable energy (Qayyum et al., 2015) (see Figs. A.1 and A.2 in Appendix A for further examples and details).

Recirculation of Parts and Products

In this category, strategies recirculate parts and products by extending existing use cycles and introducing new ones. Strategies extending the existing use cycle typically fall under the subcategories of upgrade, repair, and maintenance. Strategies extending the new use cycle fall under the reuse, refurbish, remanufacture, and repurpose subcategories. An example of DTs leveraging such processes can be seen in various levels of data-driven maintenance. First, on the descriptive level, DTs can trigger a request for repair based on sudden product failure, for instance, through a reactive maintenance scheme (Bressanelli et al., 2018a; Caterpillar, 2020; Rymaszewska et al., 2017). Furthermore, the information obtained from the descriptive strategy can be used to explore and discover new patterns or potential for alternative life cycle-extending operations, for instance, through a condition-based maintenance scheme (Baines & Lightfoot, 2014; Bressanelli et al., 2018b; Rymaszewska et al., 2017). Ultimately, a prescriptive maintenance scheme may be employed to autonomously determine the need for, and scheduling of, maintenance and replacement of parts (Rajala, Hakanen, Mattila, Seppälä, & Westerlund, 2018). This requires more advanced algorithms, for instance, deep learning methods such as artificial neural networks and operational data paired with maintenance logs and failure data for improved fault diagnosis and decision support (Li, Wang, & Wang, 2017) (see Fig. A.3 in Appendix A for further examples and details).

Recirculation of Materials

In this category, strategies recirculate materials via the effective application of end-of-life strategies, with the purpose of capturing (residual) value or reducing value loss through the continued use of materials. Moreover, these strategies can be further categorized into recycling, cascading, and recovery.

An example of DTs supporting such strategies can be observed with smart bins (Bin-e, 2020; GreenSpin, 2018; Sensoneo, 2020), which increase the traceability of materials location and quantity to correctly select an end-of-life strategy (Nasiri, Tura, & Ojanen, 2017), or in the incentivization of increased recycling based on pay-as-you-throw models (WasteIQ, 2020). If paired with material grades, this information can, in turn, be used to discover new and more effective material cascades, for instance, through digital material marketplaces (Cirmar, 2020; Excess Materials Exchange, 2020) utilizing data mining methods on open access material databases. Finally, data on materials quantity, composition, and quality can be used by self-optimizing algorithms (e.g., swarm intelligence or long short-term memory networks) to perform automatic cost-benefit analysis and optimal selection of end-of-life strategies (see Fig. A.3 in Appendix A for further examples and details).

4.3.2. Digital technologies supporting circular strategies related to corporate strategy

Reinvent the Paradigm

Reinvent, or refuse, strategies strive to fully decouple value creation from the consumption of finite resources. This may be achieved by making physical products redundant through offering the same function, or combined functions, in other products/services. The prominent technical mechanism in this category is virtualization. The virtual contrasts with the real or physical, and implies having the essence, or effect, without a real-life appearance or form. As such, virtualization has an inherent use for reinvention and refusal.

Virtualization removes fundamental constraints concerning location, time, and human observation (Verdouw, Beulens, & Van Der Vorst, 2013). This is a fundamental element, or building block, of DTs' contribution to the CE as it allows to gather information across different stages of the industrial life cycle. Furthermore, virtualization enables the design of more modular, repairable products that can be easily (digitally) updated (Antikainen et al., 2018), and the simulation of new and alternative CE approaches (Lieder, Asif, & Rashid, 2020).

Industrial examples are digital twins (Kuehn, 2018; Pham et al., 2019), virtual supply chains (Liebig et al., 2014), and digital manufacturing (Jeschke, Brecher, Meisen, Özdemir, & Eschert, 2017; Qu

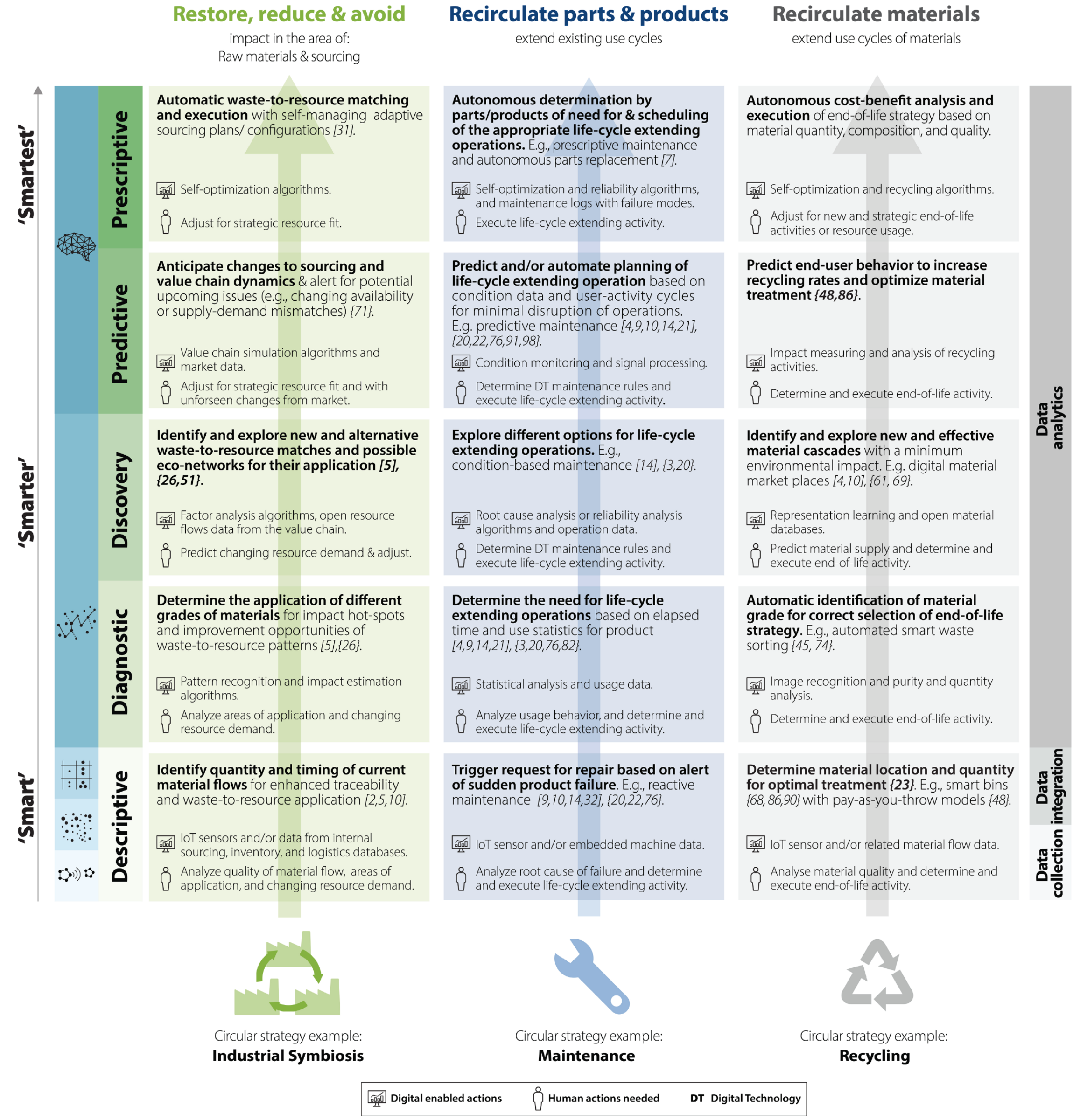


Fig. 5. Illustrative examples with representative requirements (see Figs. A.1–A.3 in Appendix A for further examples and details).

et al., 2019). An example of digital twins, virtual representation of products is combined with analytics for better decision making in complex manufacturing scenarios. For instance, by simulating future production plans or operational modes, digital twins can be used to test-drive various circular strategies in a virtual environment before a decision is applied to the real-world system (Kuehn, 2018). This enables organizations to reinvent and explore strategies before their application (see Fig. A.1 in Appendix A for further examples and details).

Rethink & Reconfigure Value Chain Creation Architecture

Rethink, or reconfigure, strategies focus on new ways of delivering a function and/or value proposition through circular business model innovations, such as usage and performance-based models (Bundles, 2020; Klickrent, 2020; WasteIQ, 2020). Broadly, the design of most physical products does not change radically with time. However, with the recent digitalization efforts, many products are now embedded with software and analytics (or digital materiality) that do change. This opens for new smart product-service systems and business model configurations (Alcayaga et al., 2019).

Integrating DTs to rethink and reconfigure value creation mechanisms requires companies to strengthen their BA capabilities and become data-driven. A data-driven organization entails that decision makers base their actions on data and insights generated from analytics rather than instinct. Studies evidence that companies that embrace a data-driven approach experienced noticeable gains in business development,

119

productivity, and profitability (McAfee, Brynjolfsson, Davenport, Patil, & Barton, 2012; Waller & Fawcett, 2013), suggesting that similar gains in sustainable development and the CE could be found. For instance, Romero and Noran (2017) introduce the concept of "green sensing virtual enterprises," whose predictive and agile capabilities enable better self-environmental awareness and intelligence for the CE (see Fig. A.1 in Appendix A for further examples and details).

5. Discussion

5.1. Research implications

This work presents a digital-enabled circular strategies framework and extends the existing body of knowledge on how to leverage DTs for CE adoption. To the best of the authors' knowledge, the paper contributes by proposing a novel framework and database to align several calls for action within sustainable development and the CE, such as that by the European Commission (2020a). As such, it provides a concrete framework that can be used as a point of reference for using DTs in supporting and enabling CE adoption and the enactment of circular strategies. While much of the business-related literature is grounded on corresponding theoretical perspectives that explain the value-generating mechanisms of different strategies, the same cannot be stated in the context of circular strategies. As such, the proposed framework can be used as a basis upon which researchers can examine the impact that different technologies, applied in different contexts, have on the enablement of circular strategies and corresponding SDGs.

Our framework is scoped to address DTs' lack of support for COI in manufacturing and significantly improve on the existing digital CE frameworks; see Table 4. The main difference between related frameworks and our framework is that existing frameworks summarize high-level strategies, possibilities, and/or capabilities, while our model extends this with a detailed structure to systematically support practitioners in searching, analyzing, and advancing smart circular strategies. Our framework makes the following contributions: (1) a detailed understanding of the relationship between the technical mechanisms of DTs and the strategic and operational strategies of the CE, (2) the ability to map strategies with their associated and target level of maturity, (3) the ability to accommodate multiple circular strategies and find new opportunities for innovation through example best practices, (4) the ability to derive digital requirements and BA capabilities for implementing circular strategies, and (5) guidance on how to leverage DTs to maximize resource efficiency and productivity for a given context.

In addition, our framework complements previous contributions by allowing both researchers and practitioners to communicate better across the boundaries of disciplines. It highlights key technical mechanisms needed for a more data-driven mode of CE business operations. By extension, our framework provides the basis for further exploration of the BA resources and capabilities central to the adoption of circular strategies. From a research standpoint, our framework highlights the role of novel DTs in shaping the information value chain within the context of the CE. Thereby, it differentiates between strategic and operational circular strategies, decomposing them into specific attainable approaches and the corresponding DT resources required to foster them. Therefore, it introduces a structured approach in bridging the technical, operational, and strategic aspects of circular strategies.

5.2. Practical implications

The example strategies presented in the matrix form a knowledge base that, when organized using the Smart CE framework, may be used by organizations for BA gap analysis and to create roadmaps toward CE

Table 4
Overview of the improvements the new framework makes in relation to the development criteria.

Criteria of the new framework:	Smart CE framework	Summary of improvements
(1) A tool for inspiring, motivating and aligning people across disciplines	+ + +	The Smart CE has an improved capacity to serve as a hub, or gateway, where stakeholders can easily connect through a combined set of intuitive framework elements and inspiring examples.
(2a) Include a broad range of circular strategies	+ + +	Drawing from the Circular Strategies Scanner, the Smart CE encompasses a broad range of strategies, from incremental (e.g., restore, reduce, and avoid) to transformative (e.g., rethink and reconfigure).
(2b) Support the translation of circular strategies to business processes relevant for manufacturing	+ +	Building on the categories from the Circular Strategies Scanner, the Smart CE organizes circular strategies into business processes they are applicable. For instance, rethink and reconfigure applies to strategic initiatives and business model innovation while the rest apply to operational processes such as material sourcing and product use and operations.
(3a) Include a broad range of DTs	+ +	The Smart CE combines three system-level DTs of IoT, Big Data, and Data Analytics—each integrating several base-level DTs (e.g., embedded systems and machine learning). The respective DTs have been comprehensively evaluated and defined for the purpose of the framework.
(3b) Provide an overview of the underlying technical mechanisms of how the DTs relate	+ + +	The three elements of data transformation levels, resource optimization capabilities, and data flow processes provide a comprehensive structure (based on well-known ICT architectures and theoretical underpinnings) to understand, detail, and integrate DTs.
(4a) Facilitate (self) assessment and BA gap analysis	+ + +	The Smart CE can be directly used as a tool for mapping strategies that are currently applied, explore new ones, and how they can be improved through digital and/or human interventions.
(4b) Include digital maturity levels of adoption	+ + +	The hierarchical structure of the Smart CE builds on maturity thinking and Industry 4.0 adoption by representing a structure gradually increasing in complexity through the aggregation of DTs and autonomous functions.
(4c) Include resource optimization levels for maximizing resource efficiency and productivity	+ +	The Smart CE unites levels of digital maturity with resource optimization and provides guidance on how to leverage DTs to maximize resource efficiency and productivity for a specific circular strategy.

+ + + = framework satisfies criterion very strongly, + + = framework satisfies criterion strongly, + = framework satisfies criterion moderately, 0 = framework does not meet criterion or only marginally.

adoption. A primary requirement for effectively leveraging smart circular strategies and tactics is the alignment of BA development with the business model. Hence, managers, in particular, may find both the framework and the knowledge base useful for effectively aligning DT implementation with COI and business model development by (1) identifying which smart circular strategies are primarily important to the company, (2) mapping the current level of digital maturity and CE adoption, (3) establishing the required level of digital maturity necessary to implement a desired smart circular strategy, and (4) deriving BA factors essential for its successful adoption.

To demonstrate this, Fig. 1 illustrates how parts of such a mapping could be done by first identifying which current circular strategies and DTs have been implemented. Second, the framework can be used to gauge the target maturity level or smart circular strategy that is of strategic importance. This serves as a benchmark upon which managers can allocate necessary resources and deploy the corresponding technologies to attain the targeted level of maturity. Finally, by developing a roadmap for implementation using BA gap analysis, it is possible to compare the current and desired BA capabilities. This is a particularly useful tool for practitioners, who typically have very few practical guidelines to proceed with digitally enabling circular strategies. The framework can, therefore, be used to not only identify the target objectives but also to provide support in realizing these strategies. It also complements existing methods that are more focused on leveraging data artefacts, or that consider such strategies from a broader industry perspective (van de Wetering, Mikalef, & Helms, 2017). Some empirical studies have worked in this direction, such as that of Kristoffersen et al. (2019), who provide a custom data science process and analytic support for the CE.

5.3. Limitations and avenues for future research

This paper is a first step in detailing the mechanisms and strategies of a Smart CE. The work seeks to balance both comprehensiveness and relevance. However, the work possesses certain limitations and further investigation and alignment between researchers and practitioners can help to build the research stream and ensure merit.

First, as the paper presents theoretical groundings, it advocates further empirical research on the Smart CE research stream, for instance, in the form of expert interviews and surveys to investigate the organizational aspects that are decisive when adopting DTs for the CE. Specifically, researchers could study the key BA factors (i.e., organizational resources and capabilities) needed to effectively leverage circular strategies, for example, through the lens of the resource-based view. Furthermore, this should be extended with practical implications and lessons for managers, explicitly addressing their role in effectively organizing firm resources for Smart CE adoption.

Second, given its theoretical development process, the proposed framework should be empirically validated with a set of companies to (1) determine the clarity of the framework elements and strategies presented, (2) detail a process for self-assessment and BA gap analysis, and (3) identify how it can be further improved to better support COI in manufacturing, related industries, and extended with a broader range of DTs (e.g., blockchain and 3D printing). It is also noted that the definitions, organizing principles, and frameworks were evaluated through a subjective interpretive process. However, the theoretical validation process, by mapping strategies, offers justification.

Third, alignment with data science and BA process methodologies should be explored in greater depth, as done by Kristoffersen et al. (2019). This could take the form of in-depth case studies of specific smart circular strategies, such as predictive maintenance, to provide an in-depth understanding of the implementation practices and process methodologies.

Building on the rich underpinnings of the strategies described and the comprehensive theory covered in this study, the authors anticipate that these issues may hold merit in contributing to future studies. The theoretical and real-world applications mapped clearly outline the pre-paradigmatic nature of this subject and the need to strengthen empirical research through in-depth case studies, action research, and quantitative surveys to investigate the cause-and-effect relationship between DTs and the CE.

6. Conclusion

Motivated by the role of DTs and the CE in achieving SDG 12 of “sustainable consumption and production,” by reducing the need for extraction of finite and virgin resources, this paper proposes a theoretically grounded framework and database of examples of the Smart CE. It supports the identification of new and alternative manufacturing strategies that can provide additional value propositions to customers, while negating or reducing structural waste. Through a review of extant research and frameworks, organizing principles and synthesis were given by the Smart CE framework on how to understand the relationship between DTs and the CE through common technical mechanisms.

To validate and elaborate the framework, several examples of different circular strategies relevant to manufacturing companies were collected from both academic literature and real-world case databases. The examples were aggregated in a matrix by combining the Smart CE framework and the Circular Strategies Scanner. The placement of these cases within the framework confirms that DTs and associated BA capabilities indeed hold different potential with regards to optimizing resource efficiency and productivity. These examples illustrate how different DTs and their associated BA capabilities support capturing different levels of resource efficiency and productivity. Using the framework and matrix as a guide, (self) assessments can be conducted to evaluate the DTs and BA capabilities companies presently have and those needed to capitalize on the desired value creation and capture capacities of circular strategies. As such, the Smart CE framework and associated knowledge base of theorized and real-world cases serves as a novel contribution in this emerging research field.

This work has contributed to the body of knowledge for the successful implementation of the CE by appropriately leveraging data from intelligent resources. Both practitioners and researchers may find this work useful to (1) create roadmaps, prioritize strategic initiatives, set targets, and facilitate gap analysis between BA requirements and capabilities to achieve new or improved smart circular strategies, and (2) create a common language for aligning activities across the boundaries of disciplines (e.g., information systems and CE fields). Accordingly, this paper establishes a much needed, and underexplored, link between two emerging fields. The Smart CE shows how DTs can support in becoming more resource-efficient. Specifically, for businesses, this work shows the BA capabilities required for accomplishing this.

The smart use of resources in the CE can be supported by the creation, extraction, processing, and sharing of data from DTs. Effectively using this digital transformation will be pivotal for organizations in transitioning to, and leveraging, the CE at scale.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

The authors would like to thank the reviewers of this paper. The authors acknowledge that this work was conducted as part of the research project CIRCit (Circular Economy Integration in the Nordic Industry for Enhanced Sustainability and Competitiveness), which is part of the Nordic Green Growth Research and Innovation Programme (Grant No.: 83144), and funded by NordForsk, Nordic Energy Research, and Nordic Innovation.

Appendix A. The smart CE matrix

Figs. A.1–A.3.

		REINVENT - *the paradigm*	**RETHINK & RECONFIGURE** - *business models*	**RESTORE, REDUCE & AVOID** - *impact in the areas of: raw materials & sourcing*
Wisdom	**Prescriptive** How can use of the resource be optimised dynamically?	• **Virtualization** removes fundamental constraints concerning location, time, and human observation through liquification, resource density, and digital materiality. > **Liquification**, also referred to as digitization, is the separation of data from the physical resources enabling data to be easily re-located and re-manifested for different uses *[43]*.	• **Provide foresight value** by predictive and prescriptive analytics, aiding in the concretization of circular business models through preemptive decision-making and navigation of strategic goals. Predictive and prescriptive analytics provides the ability to create an overview of something beyond the bounds of the present and foresee what might happen or will be needed in the future. > *e.g., performance-based business models* **[7, 31,40], {48,91}**	• **Automatic gathering and processing of real-time and aggregated data** such as changing market prices of materials, 'impact status' of materials, inventory status of suppliers and customers, and manufacturing schedules allow for increased efficiencies and reduced impact through the facilitation of secondary source sourcing (buying byproducts), or sourcing of materials with low environmental impact in self-managing and adaptive sourcing plans or configurations. > *e.g., automated industrial symbiosis matching and execution* **[31]** • **Increase yield of biomass** through automated, and optimized distribution of biological nutrients based on soil condition in farming [10] or avoid and reduce farming losses through automatic identification of influential factors (weather, connected farms, governmental alerts, regulations, etc.). > *e.g., smart farming* **[10], {67}** *and feed optimization* **{56}**
	Predictive What better use can be made of the resource in the future?	> **Resource density** is the mobilization of physical and virtual resources (independent of location) for a particular situation in order to create the optimal value and cost result *[42,43]*. E.g., in order to reduce unnecessary transport		• **Anticipate changes to sourcing and value chain dynamics** and alert for potential upcoming issues, so that alternatives can be sought as in changing availability of (different grades) of raw materials and supply-demand mismatches or vulnerabilities. > *e.g., industrial symbiosis simulation and reduce waste and storage capacity need by predicting customer purchase amounts* **{71}** • **Biomass health, appetite, and growth prediction.** Ensure sustainable biomass growth and reduce waste by making preemptive decisions based on accurate biomass predictions and estimations. > *e.g., fish health and welfare prediction* **{56,57}**
Knowledge	**Discovery** What better use can be made of the resource given current conditions?	> **Digital materiality** refers to what the analytics software embedded within, or connected to; the physical resource can do by manipulating the virtual representation of the physical resource *[41]*. For instance, production equipment self-sensing, adapting, organizing, and deciding its operational performance to minimize wear and optimize utilization *[85]* .	• **Provide oversight value** through discovery analytics. The data is investigated for something new, novel, or different (e.g., trends, exceptions, or clusters) **[5], {26,51}**.	• **Identify and explore new and alternative waste-to-resource matches and possible eco-networks for their application.** > *e.g., industrial symbiosis matching* **[5],{26,51}** • **Identify new scenarios for the application of (different grades) of raw materials** that optimize sustainability impact (environment, social, economic) and reduce (the impact of) quantity, quality, and timing fluctuations. • **Land and biomass condition monitoring**. *Immediate identification of signs degradation by automated condition assessment (e.g., air quality, fish shoal health, forest productivity, or coral reef health)* **[10], {56,57}**
	Diagnostic Why/ how did X happen to the resource?	> *e.g., Digital twins* **[84], {91}**, *virtual supply chains* **{35}**, *and digital manufacturing* **[85,96].** • ***Simulatie new and alternative approaches in a circular economy market acceptance context {95}.***	• **Provide insight value** through diagnostic analytics by acquiring an understanding of why something happened **[5], {26, 45}**.	• **Identify waste-to-resource patterns** (timing, quality, quantity) to identify improvement opportunities. > *e.g., find industrial symbiosis patterns* **[5],{26}** • **Determine the application of (different grades) of raw materials** to identify impact hotspots and improvement opportunities for sustainability impact (environment, social, economic).
Information **Data** **Connected resources**	**Descriptive** What happened to the resource?		• **Provide hindsight value** through with descriptive analytics by describing what has happened or developed. > *e.g., usage-focused business models* **[4,19,33], {22, 46,58,62,65,70,80}**	• **Identify quantity and timing of current input flows*** supported by automated input registration through sensors. > *e.g., Big Data input-output (I/O) database with all waste-to-resource information* **[5]** *and track material input flows* **[2,10]** • **Automated location tracking and monitoring of natural capital** *[10], {56,57}* • **Monitoring av greenhouse gasses, emissions and air quality** *{27,83}* ** See output flows in next column/ manufacturing*
General benefits applicable to majority of levels		• **Reduce costs, save resources, provide accurate and trustable data** and help to design modular, repairable products that can be remotely updated **[2], {87}**	• **General decision-making support** from analytics for asset evaluation, business strategy, and management support for business co-evolution **[2,25,28]**	• Reduction of the 'bullwhip effect' *[38,39]*

References are categorized as follows: ***[x]*** = conceptual/theoretical examples, ***{x}*** = real-life/case examples. Find detailed references in ***Appendix B.***

Fig. A.1. The Smart CE matrix I/III.

RESTORE, REDUCE & AVOID - *impact in the areas of:*

		manufacturing	product use & operation	logistics & energy
Wisdom	**Prescriptive** How can use of the resource be optimised dynamically?	• **Preventing excess through self-managing make-to-order and assemble-to-order manufacturing systems** based on dynamic demand forecasts and proactive operation modes simulation ***[89]***. • **Improve efficiency and reduction of rejects and rework** through the dynamic and automatic identification of bottlenecks, determination of appropriate intervention type, and time to reduce interruption. > e.g., data-driven forecasting for waste valorization and process resilience across manufacturing environments ***[92]*** and process simulation ***[85,96]***. • **Automated facilitation of secondary source sourcing** through the selling of co- and byproducts from the manufacturing process.	• **Enhance product longevity and utilization** through product self-evaluation and subsequent digital upgrade of product performance (product-pull update). > *e.g., through with prescriptive maintenance* ***{91}*** • **Product self-adapts** (configures rpm of motors, voltage, ampere, work angles etc.) operational performance to minimize wear and optimize utilization based on real-time performance demand ***[85]***. • **Product self-decides the need for redistribution** based on operating capacity (see also next column). • ***Simulatie product use and circular economy market acceptance.*** > e.g., by data-driven models that "learn" choice behavior of a small customer group and then replicate that choice behavior on a larger population ***{95}***.	• **Optimize vehicle and fleet usage** to reduce fuel consumption, vehicle wear, emission, driving time, and improve utilization rate ***[10,23]***. > *e.g., smart route planning* ***{34,77,86}*** *and smart fuel consumption* ***{64}*** • **Automatic triggering and scheduling of (reverse) logistics requests** based on product condition • **Reduce lost or damaged perishable/sensitive goods** (food and medicines) through optimized cold chain distribution and on-shelf time ***[6,24]*** • **Reduce the need for operational entities** through virtual supply chains ***{35}*** • **Product autonomously schedules operation based on the availability of renewable energy.** > *e.g., dynamic home appliance scheduling such as washing machines* ***[40]***
	Predictive What better use can be made of the resource in the future?	• **Improve efficiency and reduction of rejects and rework** ***[93]*** by increased process quality. E.g., through predicting resource needs, potential bottlenecks, and impact of interventions • **Simulate outcome of new lean and clean manufacturing models** ***[88]*** in order to gain insight into the 'critical path,' uncover potential bottlenecks, and improve capacity planning.	• **Reduce and prevent unscheduled downtime** by knowing when to intervene in the use-cycle as to cause minimal disruption to this > *e.g. enhance product use and operation with predictive maintenance* ***[4,9,10,14,21], {20,22}*** • **Recommend different product use pattern** based on predicting wear, utilization and energy consumption ***[4,8,10,14,19,21], {20}***	• **Predict fuel consumption, vehicle wear, emission, and driving time of route plans.** > *e.g., intelligent traffic systems and vehicular data clouds* ***{36}*** • **Predict the distribution time of products** to reduce lost or damaged perishable/sensitive goods based on market and customer trends. • **Reduce downtime and equipment destruction by predicting disturbances in the power system** ***{50}***
Knowledge	**Discovery** What better use can be made of the resource given current conditions?	• **Identify new lean and clean manufacturing models** ***[88]*** through simulation of manufacturing models in order to gain insight into the 'critical path' uncover potential bottlenecks, and improve capacity planning (taking into consideration technology/ process required, running hours available, etc.). • **Explore different process parameters for improved productivity** • **Reduce reworks through automated quality inspection based on estimated product quality** ***[93]***	• **Reduce and prevent unscheduled downtime** by monitoring product condition. > *e.g. enhance product use and operation with condition-based maintenance* ***[14], {3,20}*** • **Identify new product use patterns** that minimize wear and energy consumption and thus increase utilization • **Enhance product longevity through discouraging careless behaviour** by condition monitoring ***[2,4,8,9,12,13,14,23], {20,91}***	• **Identify new route plans that reduce fuel consumption, vehicle wear, emission and driving time** ***{86}*** • **Identify new and more sustainable distribution strategies** • **Identify alternative operation timeslots based on the availability of renewable energy** • **Reduce lost or damaged perishable/sensitive goods** (food and medicines) during transportation through simulating cold chain conditions ***[6]***
	Diagnostic Why/ how did X happen to the resource?	• **Determine status of current lean and clean manufacturing models** through analyzing the impact of existing bottlenecks and fluctuations in yield ***[92]***	• **Automatic anomaly detection and product diagnosis** > *e.g., smart building semantic diagnosis from heterogenous data sources* ***{37}***	• **Improve energy efficiency** by integrating energy data into operational planning ***{45}*** • **Determine the sustainability level of current distribution partners, route plans, and strategies.** > *e.g., through Big Data analytics of publically available data*
Information **Data** **Connected resources**	**Descriptive** What happened to the resource?	• **Enhance existing lean and clean manufacturing models** based on immediate feedback data from manufacturing (i.e., feedback-driven R&D) • **Monitor process productivity** > *e.g., Kemira smart process management* ***{60}*** • **Identify quality, quantity, and timing of current output flows** > *e.g. Big Data input-output (I/O) database with all waste-to-resource information* ***[5]*** • **Share unused manufacturing capacity** > *e.g., Airfaas "Airbnb of factories"* ***{59}***	• **Reduced unscheduled downtime by reacting to swift alerts of sudden product failure** ***[2,4,8,9,12,13,14,21,23], {16,17,20}*** > e.g. through with reactive maintenance • **Increase product utilization by sharing idle capacity** > *e.g., digital marketplace for product rental* ***{62,65,80}*** *and pay-per-use washing machines* ***{70}*** • **Enhance product longevity and utilization through digital upgrade of product performance** (company push update) ***[29,32],{3,20,22}*** > *e.g., Tesla's over-the-air update* ***{44}***	• **Track product location for swift and accurate transportation** ***[7,8,10,21,23,32], {75}*** • **Track product location and current owner for reverse logistics planning** ***[1,10,15,23],{11,16, 69,81}*** • **Reduce the amount of lost and damaged perishable/sensitive goods** (food and medicines) through value chain monitoring. > *e.g. monitoring the conditions inside the truck with IoT sensors [6] and smart food chain* ***{66}*** • **Pay per energy use** intelligent lighting and energy systems g. > *e.g., "Pay-per-lux" model* ***{46}***
General benefits applicable to majority of levels		• **Distributed manufacturing -** producing close to markets to minimize product miles, support with capacity planning. Enabled by IT infrastructure of IoT, big data and AI ***[31,94]*** • **Analyze and control industrial metallurgical systems and processes in manufacturing** ***[18]***	• **Monitor and track product activity** ***[2,4,8,9,12,13,14,21,23], {16,17,20,22,79}*** • **Profiling and behaviour tracking** ***[32],{79}***	• **Fleet efficiency optimization** ***[23], {73}*** • **Improved value chain configuration** ***[2,30,33]*** • **Reduce energy waste** by leveraging energy use data ***[47]***

References are categorized as follows: ***[x]*** = conceptual/theoretical examples, ***{x}*** = real-life/case examples. Find detailed references in ***Appendix B.***

Fig. A.2. The Smart CE matrix II/III.

		RECIRCULATE - *parts & products* *Extend existing use cycles*	*Extend to new use cycles*	**RECIRCULATE -** *materials*
Wisdom	**Prescriptive** How can use of the resource be optimised dynamically?	• **Autonomous determination by parts/ products of the need for and scheduling of the appropriate life cycle extending operations** (upgrade/ repair/ maintenance). Product or part self-assessment in combination with a prescriptive maintenance regime and usage patterns (when utilization is low and thus disruption of operations minimal). This allows for product/part to autonomously schedule repair and maintenance, such as in 'self-owning' cars. *> e.g., autonomous 'flat-for-full' car battery swaps* ***[7]***	• **Autonomous cost-benefit analysis by parts/ products for type of and degree of desired upgrading, refurbishment, or remanufacturing** based on part/ product health. • **Autonomous market exchanges based on the matching of product/ part health to reuse and repurpose markets** (may involve the cannibalization of parts from products).	• **Autonomous cost-benefit analysis and execution** of end-of-life strategy based on material quantity, composition and quality, expected environmental impact of treatment, distance to treatment location, and market demand and prices (can involve recycling, composting, material cascading, or waste-to-energy).
	Predictive What better use can be made of the resource in the future?	• **Prediction and automated planning of product/ part life-cycle extending operations** (upgrade/ repair/ maintenance) based on condition data (i.e., product health) and aggregated (failure) data for the product (group) and taking into account user-activity cycles for minimal disruption of operations. *> e.g., extend existing use cycle by predicting impending failures through with predictive maintenance* ***[4,9,10,14,21], {20,22,76,91,98}***	• **Predict the impact of different life-cycle scenarios** (e.g., reuse, refurbish, remanufacture, repurpose) on the product health and suggest courses of action or use this as input to compare and decide between them and support human decision making on this front. *> e.g. predictive and effective remanufacturing* ***[10], {22, 53}*** • **Model and predict customer acceptance/ adoption of secondary products** based on comparing different user-activity-cycles (i.e., the utilization rate of first vs. secondary products)	• **Predict the impact of recycling and cascading on material composition and quality** and direct materials to appropriate treatment systems. • **Model and predict the environmental impact of end-of-life scenarios** (recycling, composting, material cascading, or waste-to-energy). • **Predict end-user behavior to optimize collection** *> e.g., as seen with Sensoneo* ***{86}*** *and WasteIQ* ***{48}***
Knowledge	**Discovery** What better use can be made of the resource given current conditions?	• **Explore different options for product/ part life cycle extending operations** (upgrade/ repair/ maintenance) based on condition data (i.e., product health) and predetermined rules using aggregated (failure) data for th product (group). *> e.g., extend existing use cycle through condition-based maintenance* ***[14], {3,20}*** • **Data-driven simulation for shop-floor decision-making support in remanufacturing processes** ***{97}***	• **Accurate product evaluation through comparison with other products** (e.g., resale price based on product health) *>* ***[10]*** • **Identify new markets and users and explore relevant factors for product adoption by secondary users** and for redistribution, product cascades and alternate use *> e.g., understanding search and resale patterns on digital product marketplaces* ***[4,10], {63}*** *and digital marketplace for surplus food* ***{72}***	• **Identify and explore new and effective material cascades** with a minimum environmental impact *> e.g., digital material marketplaces* ***[4,10]*** • **Understand relevant factors in adoption of end-of-life materials in markets.** • **Identify new markets and users of secondary materials** *> e.g., secondary material marketplaces* ***{61, 69}***
	Diagnostic Why/ how did X happen to the resource?	• **Determine the need for life-cycle extending operations** (upgrade/ repair/ maintenance) based on elapsed time and use statistics for product (group) ***[4,9,14,21], {3,20,76,82}***	• **Determine product health to establish fit for a new purpose in product cascading** *> e.g., integrating construction supply chains with building information modeling (BIM) systems* ***{52}*** • **Determine end-of-life and reusability performance** *> e.g., disassembly and deconstruction analytics system* ***{49}*** and reusability analytics ***{54}*** for buildings	• **Automatic identification of material grade for correct selection of end-of-life strategy** by analyzing purity, constitutions, and quality. *> e.g., automated waste sorting using sensors and AI as seen in Tomra* ***{45}*** *and smart textile sorting* ***{74}***
Information **Data** **Connected resources**	**Descriptive** What happened to the resource?	• **Trigger request for repair based on alert of sudden product failure** (augmented/ smart run-to-failure/ reactive maintenance) *> e.g., extend existing use cycle through with reactive maintenance* • **Technical support and guided replacement service** such as remote maintenance and support for remote sites (e.g., oil rigs) ***[9,10,14,32], {20,22,76}***	• **Tracking and tracing of part/ product location** for collection and treatment (e.g., reuse, refurbish, remanufacture, repurpose) ***{22}***.	• **Determine the material location and quantity** for optimal collection and treatment (recycling, composting, material cascading, or waste-to-energy) ***{23}***. *> e.g., smart bins* ***{68, 86,90}*** • **Incentivize increased recycling based on pay-as-you-throw models** *> e.g., the smart waste management platform to WasteIQ* ***{48}***
General benefits applicable to majority of levels		• **IoT product passport** *[2,10], {55, 69,78}*		• **Track material flows** *[2]*

References are categorized as follows: ***[x]*** = conceptual/theoretical examples, ***{x}*** = real-life/case examples. Find detailed references in ***Appendix B.***

Fig. A.3. The Smart CE matrix III/III.

Appendix B. Reference coding of the smart circular strategies

T: theoretical case (40 cases in total), **R**: real world case (58 cases in total)

1. (Govindan, Soleimani, & Kannan, 2015) - T
2. (Pagoropoulos et al., 2017) - T
3. (Bressanelli et al., 2018b) - R
4. (Antikainen et al., 2018) - T
5. (Bin et al., 2015) - T
6. (Nechifor, Petrescu, Damian, Puiu, & Târnaucă, 2014) - T
7. (Rajala et al., 2018) - T
8. (Romero & Noran, 2017) - T
9. (Spring & Araujo, 2017) - T
10. (EMF, 2016) - T
11. (Zhou, Cai, Xiao, Chen, & Zeng, 2018) - R
12. (Nobre & Tavares, 2017) - T
13. (Jabbour et al., 2019) - T
14. (Baines & Lightfoot, 2014) - T
15. (Jayaraman, Ross, & Agarwal, 2008) - R
16. (Lenka, Parida, & Wincent, 2017) - R
17. (Parida, Sjödin, Wincent, & Kohtamäki, 2014) - R
18. (Reuter, 2016) - T
19. (Reim, Parida, & Örtqvist, 2015) - T
20. (Rymaszewska et al., 2017) - R

21. (Porter & Heppelmann, 2014) - T
22. (Bressanelli et al., 2018a) - R
23. (Nasiri et al., 2017) - T
24. (Vargheese & Dahir, 2014) - T
25. (Gupta, Chen, Hazen, Kaur, & Gonzalez, 2019) - T
26. (Low et al., 2018) - R
27. (Molka-Danielsen, Engelseth, & Wang, 2018) - R
28. (Salminen, Ruohomaa, & Kantola, 2017) - T
29. (Ge & Jackson, 2014) - T
30. (Lieder & Rashid, 2016) - T
31. (Srai et al., 2016) - T
32. (Allmendinger & Lombreglia, 2005) - T
33. (EMF, 2013) - T
34. (Liebig et al., 2014) - R
35. (Verdouw et al., 2013) - R
36. (He, Yan, & Da Xu, 2014) - T
37. (Ploennigs, Schumann, & Lécué, 2014) - R
38. (Hofmann, 2017) - T
39. (Odero, Ochara, & Quenum, 2017) - T
40. (Qayyum et al., 2015) - T
41. (Yoo, Boland, Lyytinen, & Majchrzak, 2009) - T
42. (Normann, 2001) - T
43. (Michel, Vargo, & Lusch, 2008) - T
44. (Marshall, 2018) - R
45. (Tomra, 2020) - R
46. (Phillips, 2020) - R
47. (Shrouf et al., 2014) - T
48. (WasteIQ, 2020) - T
49. (Akanbi, Oyedele, Omoteso, et al., 2019) - R
50. (Torsæter, 2019) - R
51. (Song et al., 2017) - R
52. (Akinade & Oyedele, 2019) - R
53. (Yang, Aravind Raghavendra, Kaminski, & Pepin, 2018) - R
54. (Akanbi, Oyedele, Davila Delgado, et al., 2019) - R
55. (Gligoric et al., 2019) - R
56. (Aquabyte, 2020) - R
57. (CreateView, 2020) - R
58. (Smith, 2013) - R
59. (Airfaas, 2020) - R
60. (KemConnect, 2020) - R
61. (Excess Materials Exchange, 2020) - R
62. (DOZR, 2020) - R
63. (The Internet of Clothes, 2020) - R
64. (The Economist, 2017a) - R
65. (Style Lend, 2020) - R
66. (Los Angeles Times, 2013) - R
67. (Smart Bin, 2020) - R
68. (GreenSpin, 2018) - R
69. (Cirmar, 2020) - R
70. (Bundles, 2020) - R
71. (The Economist, 2017b) - R
72. (Too Good To Go, 2020) - R
73. (MIND Mobility, 2020) - R
74. (FIBERSORT, 2020) - R
75. (TimAnn-Box, 2020) - R
76. (Caterpillar, 2020) - R
77. (Peters, 2016) - R
78. (Madaster, 2020) - R
79. (Aurora, 2019) - R
80. (Klickrent, 2020) - R
81. (12Return, 2020) - R
82. (Aiir Innovations, 2020) - R
83. (Clancy, 2017) - R
84. (Kuehn, 2018) - R
85. (Qu et al., 2019) - T
86. (Sensoneo, 2020) - R

87. (Jabbour et al., 2020) - R
88. (Dev, Shankar, & Qaiser, 2020) - T
89. (Monostori et al., 2016) - T
90. (Bin-e, 2020) - R
91. (Pham et al., 2019) - R
92. (Fisher et al., 2019) - T
93. (Lin, Yu, & Chen, 2019) - T
94. (Turner et al., 2019) - T
95. (Lieder et al., 2020) - R
96. (Jeschke et al., 2017) - T
97. (Charnley et al., 2019) - R
98. (Li, Wang, et al., 2017) - R

Appendix C. Literature review search strings

Table C.1

Table C.1
Literature review search strings.

Keyword	Keyword set
Internet of Things	IoT, internet of things, pervasive computing, ubiquitous computing, intelligent assets, industrial internet, web of things
Big Data	big data, cloud computing, and fog computing
Data Analytics	machine learning, artificial intelligence, deep learning, analytics
DTs	IoT, internet of things, pervasive computing, ubiquitous computing, ubicom, ambient intelligence, intelligent asset*, internet of everything, smart device*, connected device*, connected object*, smart product*, connected product*, industrial internet, industry 4.0, machine to machine, m2m, device to device, d2d, web of things, domotics, second internet, digiti*ation, disruptive technologies, technical asset*, smart sensor*, smart city, smart home, cyber-physical system*, cyber physical system*, machine learning, artificial intelligence, deep learning, big data, cloud computing, fog computing and analytics
CE	circular econom*, circl* econom*, cycl* econom*, closed loop econo*, closed loop * chain*, clos* material loop*, and circulation economics
Framework	framework, model, architecture, and conceptuali*ation

References

12Return (2020). Reverse supply chain platform. URL https://www.12return.com/. Accessed on 6 April 2020.

Ackoff, R. L. (1989). From data to wisdom. *Journal of Applied Systems Analysis, 16*, 3–9.

Adams, R. J., Smart, P., & Huff, A. S. (2017). Shades of grey: guidelines for working with the grey literature in systematic reviews for management and organizational studies. *International Journal of Management Reviews, 19*, 432–454.

Addo-Tenkorang, R., & Helo, P. T. (2016). Big data applications in operations/supply-chain management: A literature review. *Computers & Industrial Engineering, 101*, 528–543.

Agrifoglio, R., Cannavale, C., Laurenza, E., & Metallo, C. (2017). How emerging digital technologies affect operations management through co-creation. Empirical evidence from the maritime industry. *Production Planning & Control, 28*, 1298–1306.

Aiir Innovations (2020). Aiir innovations - bringing artificial intelligence to the maintenance industry. URL https://www.aiir.nl/. Accessed on 6 April 2020.

Airfaas (2020). Airfaas. URL https://airfaas.com/. Accessed on 6 April 2020.

Akanbi, L., Oyedele, L., Davila Delgado, J. M., Bilal, M., Akinade, O., Ajayi, A., & Mohammed-Yakub, N. (2019). Reusability analytics tool for end-of-life assessment of building materials in a circular economy. *World Journal of Science, Technology and Sustainable Development, 16*, 40–55.

Akanbi, L. A., Oyedele, L. O., Omoteso, K., Bilal, M., Akinade, O. O., Ajayi, A. O., ... Owolabi, H. A. (2019). Disassembly and deconstruction analytics system (d-das) for construction in a circular economy. *Journal of Cleaner Production, 223*, 386–396.

Akhbar, F., Chang, V., Yao, Y., & Muñoz, V. M. (2016). Outlook on moving of computing services towards the data sources. *International Journal of Information Management, 36*, 645–652.

Akinade, O. O., & Oyedele, L. O. (2019). Integrating construction supply chains within a circular economy: An anfis-based waste analytics system (a-was). *Journal of Cleaner Production, 229*, 863–873.

Al-Fuqaha, A., Guizani, M., Mohammadi, M., Aledhari, M., & Ayyash, M. (2015). Internet of things: A survey on enabling technologies, protocols, and applications. *IEEE Communications Surveys & Tutorials, 17*, 2347–2376.

Alcayaga, A., Wiener, M., & Hansen, E. G. (2019). Towards a framework of smart-circular systems: An integrative literature review. *Journal of Cleaner Production, 221*, 622–634.

Allmendinger, G., & Lombreglia, R. (2005). Four strategies for the age of smart services. *Harvard Business Review, 83*, 131.

Antikainen, M., Uusitalo, T., & Kivikytö-Reponen, P. (2018). Digitalisation as an enabler of circular economy. *Procedia CIRP, 73*, 45–49.

Aquabyte (2020). Aquaculture meets machine learning. URL https://www.aquabyte.no/. Accessed on 6 April 2020.

Ardolino, M., Rapaccini, M., Saccani, N., Gaiardelli, P., Crespi, G., & Ruggeri, C. (2018). The role of digital technologies for the service transformation of industrial companies. *International Journal of Production Research, 56*, 2116–2132.

Aruväli, T., Maass, W., & Otto, T. (2014). Digital object memory based monitoring solutions in manufacturing processes. *Procedia Engineering, 69*, 449–458.

Askoxylakis, I. (2018). A framework for pairing circular economy and the internet of things. *2018 IEEE International Conference on Communications (ICC)* (pp. 1–6). IEEE.

Atzori, L., Iera, A., & Morabito, G. (2010). The internet of things: A survey. *Computer Networks, 54*, 2787–2805.

Aurora (2019). The power of data. URL http://www3.gehealthcare.com//media/services/resources/aurora-health-care-casestudy_final.pdf. Accessed on 6 june 2019.

Babar, M., & Arif, F. (2017). Smart urban planning using big data analytics to contend with the interoperability in internet of things. *Future Generation Computer Systems, 77*, 65–76.

Baines, T., & Lightfoot, H. W. (2014). Servitization of the manufacturing firm. *International Journal of Operations & Production Management*.

Bassi, A., & Horn, G. (2008). Internet of things in 2020: A roadmap for the future. *European Commission: Information Society and Media, 22*, 97–114.

Bianchini, A., Pellegrini, M., Rossi, J., & Saccani, C. (2018). *A new productive model of circular economy enhanced by digital transformation in the fourth industrial revolution-an integrated framework and real case studies.* XXIII Summer School "Francesco Turco"–Industrial Systems Engineering (pp. 1–7).

Bin, S., Zhiquan, Y., Jonathan, L. S. C., Jiewei, D. K., Kurle, D., Cerdas, F., & Herrmann, C. (2015). A big data analytics approach to develop industrial symbioses in large cities. *Procedia CIRP, 29*, 450–455.

Bin-e (2020). Bin-e - smart waste bin. URL http://bine.world/. Accessed on 6 April 2020.

Blomsma, F., & Brennan, G. (2017). The emergence of circular economy: A new framing around prolonging resource productivity. *Journal of Industrial Ecology, 21*, 603–614.

Blomsma, F., Pieroni, M., Kravchenko, M., Pigosso, D. C., Hildenbrand, J., Kristinsdottir, A. R., ... McAloone, T. C. (2019). Developing a circular strategies framework for manufacturing companies to support circular economy-oriented innovation. *Journal of Cleaner Production, 241*, 118271.

Bocken, N. M., De Pauw, I., Bakker, C., & van der Grinten, B. (2016). Product design and business model strategies for a circular economy. *Journal of Industrial and Production Engineering, 33*, 308–320.

Bocken, N. M., Short, S. W., Rana, P., & Evans, S. (2014). A literature and practice review to develop sustainable business model archetypes. *Journal of Cleaner Production, 65*, 42–56.

Van den Bossche, P. (2016). Sprint to digital manufacturing success. *Supply Chain Management Review*.

Bressanelli, G., Adrodegari, F., Perona, M., & Saccani, N. (2018a). Exploring how usage-focused business models enable circular economy through digital technologies. *Sustainability, 10*, 639.

Bressanelli, G., Adrodegari, F., Perona, M., & Saccani, N. (2018b). The role of digital technologies to overcome circular economy challenges in pss business models: an

exploratory case study. *Procedia CIRP, 73*, 216–221.
Brettel, M., Friederichsen, N., Keller, M., & Rosenberg, M. (2014). How virtualization, decentralization and network building change the manufacturing landscape: An industry 4.0 perspective. *International Journal of Mechanical, Industrial Science and Engineering, 8*, 37–44.
Brown, P., Bocken, N., & Balkenende, R. (2019). Why do companies pursue collaborative circular oriented innovation? *Sustainability, 11*, 635.
Buer, S. V., Strandhagen, J. O., & Chan, F. T. (2018). The link between industry 4.0 and lean manufacturing: mapping current research and establishing a research agenda. *International Journal of Production Research, 56*, 2924–2940.
Bundles (2020). Miele washing machine, tumble dryer and dishwasher in a subscription. URL https://bundles.nl/en/. Accessed on 6 April 2020.
Caterpillar (2020). Cat connect technology & services. URL http://www.cat.com/en_US/support/operations/cat-connect-solutions.html. Accessed on 6 April 2020.
Charnley, F., Tiwari, D., Hutabarat, W., Moreno, M., Okorie, O., & Tiwari, A. (2019). Simulation to enable a data-driven circular economy. *Sustainability, 11*, 3379.
Chauhan, C., Sharma, A., & Singh, A. (2019). A sap-lap linkages framework for integrating industry 4.0 and circular economy. *Benchmarking: An International Journal*.
Circle Economy (2020). The circularity gap report 2020. Circle Economy: Amsterdam, The Netherlands.
CircleLab (2020). About us. URL https://circle-lab.com/about. Accessed on 6 April 2020.
Cirmar (2020). What is cirmar? URL https://cirmar.com/. Accessed on 6 April 2020.
Clancy, H. (2017). Microsoft's cloud serves up energy emissions data in near real time. URL https://www.greenbiz.com/article/microsofts-cloud-serves-energy-emissions-data-near-real-time.
Conboy, K., Mikalef, P., Dennehy, D., & Krogstie, J. (2020). Using business analytics to enhance dynamic capabilities in operations research: A case analysis and research agenda. *European Journal of Operational Research, 281*, 656–672.
CreateView (2020). Createview. URL https://www.createview.no/. Accessed on 6 April 2020.
Cooper, A. (2012). What is analytics? Definition and essential characteristics. *CETIS Analytics Series, 1*, 1–10.
Da Xu, L., He, W., & Li, S. (2014). Internet of things in industries: A survey. *IEEE Transactions on Industrial Informatics, 10*, 2233–2243.
Dai, H. N., Wang, H., Xu, G., Wan, J., & Imran, M. (2019). Big data analytics for manufacturing internet of things: opportunities, challenges and enabling technologies. *Enterprise Information Systems,* 1–25.
Dalenogare, L. S., Benitez, G. B., Ayala, N. F., & Frank, A. G. (2018). The expected contribution of industry 4.0 technologies for industrial performance. *International Journal of Production Economics, 204*, 383–394.
Darwish, T. S., & Bakar, K. A. (2018). Fog based intelligent transportation big data analytics in the internet of vehicles environment: Motivations, architecture, challenges, and critical issues. *IEEE Access, 6*, 15679–15701.
Davenport, T. (2014). *Big data at work: Dispelling the myths, uncovering the opportunities.* Harvard Business Review Press.
Dev, N. K., Shankar, R., & Qaiser, F. H. (2020). Industry 4.0 and circular economy: Operational excellence for sustainable reverse supply chain performance. *Resources, Conservation and Recycling, 153*, 104583.
DOZR (2020). Dozr. URL https://dozr.com/overview. Accessed on 6 April 2020.
Eckerson, W. W. (2007). Predictive analytics. Extending the Value of Your Data Warehousing Investment. *TDWI Best Practices Report, 1*, 1–36.
EMF (2013). *Towards the Circular Economy: Economic and business rationale for an accelerated transition.* Cowes, UK: Ellen MacArthur Foundation.
EMF (2015). *Delivering the circular economy: A toolkit for policymakers.* Cowes, UK: Ellen MacArthur Foundation.
EMF (2015). *Growth within: A circular economy vision for a competitive Europe.* Cowes, UK: Ellen MacArthur Foundation.
EMF (2016). *Intelligent Assets: Unlocking the Circular Economy Potential.* Cowes, UK: Ellen MacArthur Foundation.
EMF (2019). *Artificial intelligence and the circular economy.* Cowes, UK: Ellen MacArthur Foundation.
European Commission (2020a). Circular economy action plan. URL https://ec.europa.eu/environment/circular-economy/pdf/new_circular_economy_action_plan.pdf. Accessed on 7 April 2020.
European Commission (2020b). A new industrial strategy for Europe. URL https://ec.europa.eu/info/sites/info/files/communication-eu-industrial-strategy-march-2020_en.pdf. Accessed on 7 April 2020.
European Policy Centre (2020). The circular economy: Going digital https://wms.flexious.be/editor/plugins/imagemanager/content/2140/PDF/2020/DRCE_web.pdf. Accessed on 7 April 2020.
Excess Materials Exchange (2020). A dating site for secondary materials. URL http://excessmaterialsexchange.com/. Accessed on 6 April 2020.
Fatorachian, H., & Kazemi, H. (2020). Impact of industry 4.0 on supply chain performance. *Production Planning & Control,* 1–19.
FIBERSORT (2020). Fibersort. URL http://www.valvan.com/products/equipment-for-used-clothing-wipers/sorting-equipment/fibersort/. Accessed on 6 April 2020.
Fisher, O. J., Watson, N. J., Escrig, J. E., & Gomes, R. L. (2019). Intelligent resource use to deliver waste valorisation and process resilience in manufacturing environments. *Johnson Matthey Technology Review*.
Frank, A. G., Dalenogare, L. S., & Ayala, N. F. (2019). Industry 4.0 technologies: Implementation patterns in manufacturing companies. *International Journal of Production Economics, 210*, 15–26.
Gartner (2020a). Big data - gartner it glossary. URL https://www.gartner.com/it-glossary/big-data/. Accessed on 6 April 2020.
Gartner (2020b). Employ digital technology to enable a circular economy. URL https://www.gartner.com/en/newsroom/press-releases/2020-02-26-gartner-survey-shows-70-of-supply-chain-leaders-plan. Accessed on 14 April 2020.
Ge, X., & Jackson, J. (2014). The big data application strategy for cost reduction in automotive industry. *SAE International Journal of Commercial Vehicles, 7*, 588–598.
Geissdoerfer, M., Savaget, P., Bocken, N. M., & Hultink, E. J. (2017). The circular economy–A new sustainability paradigm? *Journal of Cleaner Production, 143*, 757–768.
George, G., Haas, M. R., & Pentland, A. (2014). Big data and management.
Ghisellini, P., Cialani, C., & Ulgiati, S. (2016). A review on circular economy: The expected transition to a balanced interplay of environmental and economic systems. *Journal of Cleaner Production, 114*, 11–32.
Gligoric, N., Krco, S., Hakola, L., Vehmas, K., De, S., Moessner, K., ... Van Kranenburg, R. (2019). Smarttags: Iot product passport for circular economy based on printed sensors and unique item-level identifiers. *Sensors, 19*, 586.
Govindan, K., Soleimani, H., & Kannan, D. (2015). Reverse logistics and closed-loop supply chain: A comprehensive review to explore the future. *European Journal of Operational Research, 240*, 603–626.
GreenSpin (2018). Greenspin. https://www.greenspin.de/.
Gubbi, J., Buyya, R., Marusic, S., & Palaniswami, M. (2013). Internet of things (iot): A vision, architectural elements, and future directions. *Future Generation Computer Systems, 29*, 1645–1660.
Gupta, S., Chen, H., Hazen, B. T., Kaur, S., & Gonzalez, E. D. S. (2019). Circular economy and big data analytics: A stakeholder perspective. *Technological Forecasting and Social Change, 144*, 466–474.
Haas, W., Krausmann, F., Wiedenhofer, D., & Heinz, M. (2015). How circular is the global economy?: An assessment of material flows, waste production, and recycling in the european union and the world in 2005. *Journal of Industrial Ecology, 19*, 765–777.
He, W., Yan, G., & Da Xu, L. (2014). Developing vehicular data cloud services in the iot environment. *IEEE Transactions on Industrial Informatics, 10*, 1587–1595.
Hermann, M., Pentek, T., & Otto, B. (2016). Design principles for industrie 4.0 scenarios. In *2016 49th Hawaii international conference on system sciences (HICSS)* (pp. 3928–3937). IEEE.
Hofmann, E. (2017). Big data and supply chain decisions: the impact of volume, variety and velocity properties on the bullwhip effect. *International Journal of Production Research, 55*, 5108–5126.
Hofmann, E., & Rüsch, M. (2017). Industry 4.0 and the current status as well as future prospects on logistics. *Computers in Industry, 89*, 23–34.
Ingemarsdotter, E., Jamsin, E., Kortuem, G., & Balkenende, R. (2019). Circular strategies enabled by the internet of things—A framework and analysis of current practice. *Sustainability, 11*, 5689.
Irani, Z., & Sharif, A. M. (2018). Food security across the enterprise: A puzzle, problem or mess for a circular economy? *Journal of Enterprise Information Management, 31*, 2–9.
Jabbour, C. J. C., Fiorini, P. D. C., Wong, C. W., Jugend, D., Jabbour, A. B. L. D. S., Seles, B. M. R. P., ... da Silva, H. M. R. (2020). First-mover firms in the transition towards the sharing economy in metallic natural resource-intensive industries: Implications for the circular economy and emerging industry 4.0 technologies. *Resources Policy, 66*, 101596.
Jabbour, C. J. C., de Sousa Jabbour, A. B. L., Sarkis, J., & Godinho Filho, M. (2019). Unlocking the circular economy through new business models based on large-scale data: An integrative framework and research agenda. *Technological Forecasting and Social Change, 144*, 546–552.
Jankowski, A., & Skowron, A. (2007). A wistech paradigm for intelligent systems. In *Transactions on rough sets VI* (pp. 94–132). Springer.
Jawahir, I., & Bradley, R. (2016). Technological elements of circular economy and the principles of 6r-based closed-loop material flow in sustainable manufacturing. *Procedia Cirp, 40*, 103–108.
Jayaraman, V., Ross, A. D., & Agarwal, A. (2008). Role of information technology and collaboration in reverse logistics supply chains. *International Journal of Logistics: Research and Applications, 11*, 409–425.
Jeschke, S., Brecher, C., Meisen, T., Özdemir, D., & Eschert, T. (2017). Industrial internet of things and cyber manufacturing systems. *Industrial Internet of Things* (pp. 3–19). Springer.
Jin, J., Gubbi, J., Marusic, S., & Palaniswami, M. (2014). An information framework for creating a smart city through internet of things. *IEEE Internet of Things Journal, 1*, 112–121.
Kagermann, H., Helbig, J., Hellinger, A., & Wahlster, W. (2013). Recommendations for implementing the strategic initiative INDUSTRIE 4.0: Securing the future of German manufacturing industry; final report of the Industrie 4.0 Working Group. *Forschungsunion*.
Kaivo-Oja, J., Virtanen, P., Jalonen, H., & Stenvall, J. (2015). The effects of the internet of things and big data to organizations and their knowledge management practices. In *International Conference on Knowledge Management in Organizations* (pp. 495–513). Springer.
KemConnect, K. (2020). Kemira kemconnect. https://www.kemira.com/kemconnect/. Accessed on 6 April 2020.
Kitchenham, B., & Charters, S. (2007). Guidelines for performing systematic literature reviews in software engineering.
Klickrent (2020). Das grosste vermieternetzwerk deutschlands. URL https://www.klickrent.de/. Accessed on 6 April 2020.
Kristoffersen, E., Aremu, O. O., Blomsma, F., Mikalef, P., & Li, J. (2019). Exploring the relationship between data science and circular economy: An enhanced crisp-dm process model. In *Conference on e-Business, e-Services and e-Society* (pp. 177–189). Springer.
Kristoffersen, E., Li, Z., Li, J., Jensen, T. H., Pigosso, D., & McAloone, T. (2020). Smart circular economy: Circit workbook 4.
Kortuem, G., Kawsar, F., Sundramoorthy, V., & Fitton, D. (2009). Smart objects as building blocks for the internet of things. *IEEE Internet Computing, 14*, 44–51.

Kuehn, W. (2018). Digital twins for decision making in complex production and logistic enterprises. *International Journal of Design & Nature and Ecodynamics, 13*, 260–271.

Kumar, S., & Putnam, V. (2008). Cradle to cradle: Reverse logistics strategies and opportunities across three industry sectors. *International Journal of Production Economics, 115*, 305–315.

Lacy, P., Long, J., & Spindler, W. (2020). *The Circular Economy Handbook: Realizing the Circular Advantage.* Springer Nature.

Laney, D. (2001). 3d data management: Controlling data volume, velocity and variety. *META Group Research Note, 6*, 1.

Lasi, H., Fettke, P., Kemper, H., Feld, T., & Hoffmann, M. (2014). *Industry 4.0. business & information systems engineering, 6*(4), 239–242.

Lenka, S., Parida, V., & Wincent, J. (2017). Digitalization capabilities as enablers of value co-creation in servitizing firms. *Psychology & Marketing, 34*, 92–100.

Li, J. Q., Yu, F. R., Deng, G., Luo, C., Ming, Z., & Yan, Q. (2017). Industrial internet: A survey on the enabling technologies, applications, and challenges. *IEEE Communications Surveys & Tutorials, 19*, 1504–1526.

Li, S., Da Xu, L., & Zhao, S. (2015). The internet of things: A survey. *Information Systems Frontiers, 17*, 243–259.

Li, Z., Wang, Y., & Wang, K. S. (2017). Intelligent predictive maintenance for fault diagnosis and prognosis in machine centers: Industry 4.0 scenario. *Advances in Manufacturing, 5*, 377–387.

Liao, Y., Deschamps, F., Loures, E. d. F. R., & Ramos, L. F. P. (2017). Past, present and future of industry 4.0-a systematic literature review and research agenda proposal. *International Journal of Production Research* 55, 3609–3629.

Liebig, T., Piatkowski, N., Bockermann, C., & Morik, K. (2014). Predictive trip planning-smart routing in smart cities. In *EDBT/ICDT Workshops* (pp. 331–338).

Lieder, M., Asif, F. M., & Rashid, A. (2020). A choice behavior experiment with circular business models using machine learning and simulation modeling. *Journal of Cleaner Production, 120894*.

Lieder, M., & Rashid, A. (2016). Towards circular economy implementation: A comprehensive review in context of manufacturing industry. *Journal of Cleaner Production, 115*, 36–51.

Lin, K. P., Yu, C. M., & Chen, K. S. (2019). Production data analysis system using novel process capability indices-based circular economy. *Industrial Management & Data Systems*.

Los Angeles Times (2013). Southland restaurants devise recipes for reducing food waste. URL http://www.latimes.com/business/la-fi-food-waste-20131129-story.html.

Low, J. S. C., Tjandra, T. B., Yunus, F., Chung, S. Y., Tan, D. Z. L., Raabe, B., ... Herrmann, C. (2018). A collaboration platform for enabling industrial symbiosis: Application of the database engine for waste-to-resource matching. *Procedia CIRP, 69*, 849–854.

Madaster (2020). Madaster. URL https://www.madaster.com/en. Accessed on 6 April 2020.

Marjani, M., Nasaruddin, F., Gani, A., Karim, A., Hashem, I. A. T., Siddiqa, A., & Yaqoob, I. (2017). Big iot data analytics: Architecture, opportunities, and open research challenges. *IEEE Access, 5*, 5247–5261.

Marshall, A. (2018). Tesla's Braking System Gets an Over-the-Air Update — WIRED. https://www.wired.com/story/tesla-model3-braking-software-update-consumer-reports/. Accessed on 6 April 2020.

Mayer-Schönberger, V., & Cukier, K. (2013). *Big data: A revolution that will transform how we live, work, and think.* Houghton Mifflin Harcourt.

McAfee, A., Brynjolfsson, E., Davenport, T. H., Patil, D., & Barton, D. (2012). Big data: The management revolution. *Harvard Business Review, 90*, 60–68.

Merezeanu, D. M., & Florea, A. I. (2017). Framework for developing lifecycle management based on iot and rfid. *Journal of Control Engineering and Applied Informatics, 19*, 111–120.

Michel, S., Vargo, S. L., & Lusch, R. F. (2008). Reconfiguration of the conceptual landscape: A tribute to the service logic of richard normann. *Journal of the Academy of Marketing Science, 36*, 152–155.

Mikalef, P., Krogstie, J., Pappas, I. O., & Pavlou, P. (2019). Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. *Information & Management*.

Mikalef, P., Pappas, I. O., Krogstie, J., & Giannakos, M. (2018). Big data analytics capabilities: A systematic literature review and research agenda. *Information Systems and e-Business Management, 16*, 547–578.

MIND Mobility (2020). Mind mobility. URL https://mindmobility.nl/. Accessed on 6 April 2020.

Minerva, R., Biru, A., & Rotondi, D. (2015). Towards a definition of the internet of things (iot). *IEEE Internet Initiative, 1*, 1–86.

Miorandi, D., Sicari, S., De Pellegrini, F., & Chlamtac, I. (2012). Internet of things: Vision, applications and research challenges. *Ad hoc Networks, 10*, 1497–1516.

Mishra, N., Lin, C. C., & Chang, H. T. (2015). A cognitive adopted framework for iot big-data management and knowledge discovery prospective. *International Journal of Distributed Sensor Networks, 11*, 718390.

Moeuf, A., Pellerin, R., Lamouri, S., Tamayo-Giraldo, S., & Barbaray, R. (2018). The industrial management of smes in the era of industry 4.0. *International Journal of Production Research, 56*, 1118–1136.

Molka-Danielsen, J., Engelseth, P., & Wang, H. (2018). Large scale integration of wireless sensor network technologies for air quality monitoring at a logistics shipping base. *Journal of Industrial Information Integration, 10*, 20–28.

Monostori, L., Kádár, B., Bauernhansl, T., Kondoh, S., Kumara, S., Reinhart, G., ... Ueda, K. (2016). Cyber-physical systems in manufacturing. *Cirp Annals, 65*, 621–641.

Nasiri, M., Tura, N., & Ojanen, V. (2017). Developing disruptive innovations for sustainability: A review on impact of internet of things (iot). *2017 Portland International Conference on Management of Engineering and Technology (PICMET)* (pp. 1–10). IEEE.

Nechifor, S., Petrescu, A., Damian, D., Puiu, D., & Târnaucă, B. (2014). Predictive analytics based on cep for logistic of sensitive goods. *2014 International Conference on Optimization of Electrical and Electronic Equipment (OPTIM)* (pp. 817–822). IEEE.

Nobre, G. C., & Tavares, E. (2017). Scientific literature analysis on big data and internet of things applications on circular economy: A bibliometric study. *Scientometrics, 111*, 463–492.

Nobre, G. C., & Tavares, E. (2019). Assessing the role of big data and the internet of things on the transition to circular economy: Part i–ii. *Johnson Matthey Technology Review*.

Normann, R. (2001). *Reframing business: When the map changes the landscape.* John Wiley & Sons.

Norris, D., Baer, L., & Offerman, M. (2009). A national agenda for action analytics. In *National Symposium on Action Analytics* (pp. 21–23).

Nußholz, J. (2017). Circular business models: Defining a concept and framing an emerging research field. *Sustainability, 9*, 1810.

Odero, K., Ochara, N. M., & Quenum, J. (2017). Towards big data-driven logistics value chains for effective decision making and performance measurement, in. *ECISM 2017 11th European Conference on Information Systems Management, Academic Conferences and publishing limited* (pp. 233). .

Okorie, O., Salonitis, K., Charnley, F., Moreno, M., Turner, C., & Tiwari, A. (2018). Digitisation and the circular economy: A review of current research and future trends. *Energies, 11*, 3009.

Pagoropoulos, A., Pigosso, D. C., & McAloone, T. C. (2017). The emergent role of digital technologies in the circular economy: A review. *Procedia CIRP, 64*, 19–24.

Parida, V., Sjödin, D. R., Wincent, J., & Kohtamäki, M. (2014). Mastering the transition to product-service provision: Insights into business models, learning activities, and capabilities. *Research-Technology Management, 57*, 44–52.

Peters, A. (2016). This bee-inspired algorithm helps delivery companies plan the most efficient route. URL https://www.fastcompany.com/3062836/this-bee-inspired-algorithm-helps-delivery-companies-plan-the-most-effi.

Pham, T. T., Kuo, T. C., Tseng, M. L., Tan, R. R., Tan, K., Ika, D. S., & Lin, C. J. (2019). Industry 4.0 to accelerate the circular economy: A case study of electric scooter sharing. *Sustainability, 11*, 6661.

Phillips (2020). Selling light as a service. https://www.ellenmacarthurfoundation.org/case-studies/selling-light-as-a-service.

Planing, P. (2015). Business model innovation in a circular economy reasons for non-acceptance of circular business models. *Open Journal of Business Model Innovation* 1.

Ploennigs, J., Schumann, A., & Lécué, F. (2014). Adapting semantic sensor networks for smart building diagnosis. In *International Semantic Web Conference* (pp. 308–323). Springer.

Porter, M. E., & Heppelmann, J. E. (2014). How smart, connected products are transforming competition. *Harvard Business Review, 92*, 64–88.

Potting, J., Hekkert, M., Worrell, E., & Hanemaaijer, A. (2017). *Circular economy: Measuring innovation in the product chain.* 2544. PBL Publishers.

Qayyum, F., Naeem, M., Khwaja, A. S., Anpalagan, A., Guan, L., & Venkatesh, B. (2015). Appliance scheduling optimization in smart home networks. *IEEE Access, 3*, 2176–2190.

Qu, Y., Ming, X., Liu, Z., Zhang, X., & Hou, Z. (2019). Smart manufacturing systems: state of the art and future trends. *The International Journal of Advanced Manufacturing Technology, 103*, 3751–3768.

Queiroz, M. M., Wamba, S. F., Machado, M. C., & Telles, R. (2020). Smart production systems drivers for business process management improvement. *Business Process Management Journal*.

Rajala, R., Hakanen, E., Mattila, J., Seppälä, T., & Westerlund, M. (2018). How do intelligent goods shape closed-loop systems? *California Management Review, 60*, 20–44.

Rajput, S., & Singh, S. P. (2019). Connecting circular economy and industry 4.0. *International Journal of Information Management, 49*, 98–113.

Ray, P. P. (2018). A survey on internet of things architectures. *Journal of King Saud University-Computer and Information Sciences, 30*, 291–319.

ur Rehman, M. H., Ahmed, E., Yaqoob, I., Hashem, I. A. T., Imran, M., & Ahmad, S. (2018). Big data analytics in industrial iot using a concentric computing model. *IEEE Communications Magazine* 56, 37–43.

Reim, W., Parida, V., & Örtqvist, D. (2015). Product–service systems (pss) business models and tactics–A systematic literature review. *Journal of Cleaner Production, 97*, 61–75.

Reuter, M. A. (2016). Digitalizing the circular economy. *Metallurgical and Materials Transactions B, 47*, 3194–3220.

Romero, D., & Noran, O. (2017). Towards green sensing virtual enterprises: Interconnected sensing enterprises, intelligent assets and smart products in the cyber-physical circular economy. *IFAC-PapersOnLine, 50*, 11719–11724.

Rosa, P., Sassanelli, C., Urbinati, A., Chiaroni, D., & Terzi, S. (2020). Assessing relations between circular economy and industry 4.0: A systematic literature review. *International Journal of Production Research, 58*, 1662–1687.

Rowley, J. (2007). The wisdom hierarchy: representations of the dikw hierarchy. *Journal of Information Science, 33*, 163–180.

Rüttimann, B. G., & Stöckli, M. T. (2016). Lean and industry 4.0—twins, partners, or contenders? a due clarification regarding the supposed clash of two production systems. *Journal of Service Science and Management, 9*, 485–500.

Rymaszewska, A., Helo, P., & Gunasekaran, A. (2017). Iot powered servitization of manufacturing–An exploratory case study. *International Journal of Production Economics, 192*, 92–105.

Salminen, V., Ruohomaa, H., & Kantola, J. (2017). Digitalization and big data supporting responsible business co-evolution. *Advances in Human Factors, Business Management, Training and Education* (pp. 1055–1067). Springer.

Schroeder, P., Anggraeni, K., & Weber, U. (2019). The relevance of circular economy practices to the sustainable development goals. *Journal of Industrial Ecology, 23*, 77–95.

Sensoneo (2020). Sensoneo - manage waste smarter. URL https://sensoneo.com/waste-management-solution/. Accessed on 6 April 2020.

Shrouf, F., Ordieres, J., & Miragliotta, G. (2014). Smart factories in Industry 4.0: A review of the concept and of energy management approached in production based on the Internet of Things paradigm. *2014 IEEE International Conference on Industrial Engineering and Engineering Management* (pp. 697–701). IEEE. https://doi.org/10.1109/IEEM.2014.7058728.

Shuradze, G., & Wagner, H. T. (2016). Towards a conceptualization of data analytics capabilities. In *2016 49th Hawaii International Conference on System Sciences (HICSS)* (pp. 5052–5064). IEEE.

Siow, E., Tiropanis, T., & Hall, W. (2018). Analytics for the internet of things: A survey. *ACM Computing Surveys (CSUR), 51*, 74.

Smart Bin (2020). Smartbin: Smart monitoring and iot waste management: Smart city solutions. URL https://www.smartbin.com/. Accessed on 6 April 2020.

Smith, D. J. (2013). Power-by-the-hour: the role of technology in reshaping business strategy at rolls-royce. *Technology Analysis & Strategic Management, 25*, 987–1007.

Sondhi, R. (1999). *Total strategy.* Airworthy.

Song, B., Yeo, Z., Kohls, P., & Herrmann, C. (2017). Industrial symbiosis: Exploring big-data approach for waste stream discovery. *Procedia CIRP, 61*, 353–358.

de Sousa Jabbour, A. B. L., Jabbour, C. J. C., Foropon, C., & Godinho Filho, M. (2018a). When titans meet–can industry 4.0 revolutionise the environmentally-sustainable manufacturing wave? the role of critical success factors. *Technological Forecasting and Social Change, 132*, 18–25.

de Sousa Jabbour, A. B. L., Jabbour, C. J. C., Godinho Filho, M., & Roubaud, D. (2018b). Industry 4.0 and the circular economy: A proposed research agenda and original roadmap for sustainable operations. *Annals of Operations Research, 270*, 273–286.

Sousa-Zomer, T. T., Magalhães, L., Zancul, E., & Cauchick-Miguel, P. A. (2018). Exploring the challenges for circular business implementation in manufacturing companies: An empirical investigation of a pay-per-use service provider. *Resources, Conservation and Recycling, 135*, 3–13.

Spring, M., & Araujo, L. (2017). Product biographies in servitization and the circular economy. *Industrial Marketing Management, 60*, 126–137.

Srai, J. S., Kumar, M., Graham, G., Phillips, W., Tooze, J., Ford, S., ... Tiwari, A. (2016). Distributed manufacturing: Scope, challenges and opportunities. *International Journal of Production Research, 54*, 6917–6935.

Style Lend (2020). Style lend. URL https://www.stylelend.com/. Accessed on 6 April 2020.

The Economist (2017a). A computer program that learns how to save fuel. URL https://www.economist.com/science-and-technology/2017/01/26/a-computer-program-that-learns-how-to-save-fuel?fsrc=rss.

The Economist (2017b). How Germany's otto uses artificial intelligence. URL https://www.economist.com/business/2017/04/12/how-germanys-otto-uses-artificial-intelligence.

The Internet of Clothes (2020). The internet of clothes. URL https://netofclothes.com/. Accessed on 6 April 2020.

TimAnn-Box (2020). Box - innovating air-freight logistics. URL http://timann-box.com/. Accessed on 6 April 2020.

Tomra (2020). Tomra ai recognition. URL https://www.tomra.com. Accessed on 6 April 2020.

Too Good To Go (2020). Too good to go. URL https://toogoodtogo.com/en-us. Accessed on 6 April 2020.

Torsæter, B. N. (2019). Preliminary results show that machine learning can predict faults and disturbances in the power system - #SINTEFblog. URL https://blog.sintef.com/sintefenergy/machine-learning-can-predict-faults-and-disturbances-in-the-power-system/.

Tsai, C. W., Lai, C. F., & Vasilakos, A. V. (2014). Future internet of things: Open issues and challenges. *Wireless Networks, 20*, 2201–2217.

Turner, C., Moreno, M., Mondini, L., Salonitis, K., Charnley, F., Tiwari, A., & Hutabarat, W. (2019). Sustainable production in a circular economy: A business model for re-distributed manufacturing. *Sustainability, 11*, 4291.

Ünal, E., Urbinati, A., & Chiaroni, D. (2018). Circular industry 4.0: an integrative framework.

Van Barneveld, A., Arnold, K. E., & Campbell, J. P. (2012). Analytics in higher education: Establishing a common language. *EDUCAUSE Learning Initiative, 1* l–ll.

Vargheese, R., & Dahir, H. (2014). An iot/ioe enabled architecture framework for precision on shelf availability: Enhancing proactive shopper experience. *2014 IEEE International Conference on Big Data (Big Data)* (pp. 21–26). IEEE.

Verdouw, C. N., Beulens, A., & Van Der Vorst, J. (2013). Virtualisation of floricultural supply chains: A review from an internet of things perspective. *Computers and Electronics in Agriculture, 99*, 160–175.

Waller, M. A., & Fawcett, S. E. (2013). Data science, predictive analytics, and big data: A revolution that will transform supply chain design and management. *Journal of Business Logistics, 34*, 77–84.

Ward, J. S., & Barker, A. (2013). Undefined by data: a survey of big data definitions. arXiv preprint arXiv:1309.5821.

WasteIQ (2020). Wasteiq - the open waste management platform. URL https://www.wasteiq.no/. Accessed on 6 April 2020.

van de Wetering, R., Mikalef, P., & Helms, R. (2017). Driving organizational sustainability-oriented innovation capabilities: A complex adaptive systems perspective. *Current Opinion in Environmental Sustainability, 28*, 71–79.

Wu, Q., Ding, G., Xu, Y., Feng, S., Du, Z., Wang, J., & Long, K. (2014). Cognitive internet of things: A new paradigm beyond connection. *IEEE Internet of Things Journal, 1*, 129–143.

Yang, S., Aravind Raghavendra, M. R., Kaminski, J., & Pepin, H. (2018). Opportunities for industry 4.0 to support remanufacturing. *Applied Sciences* 8, 1177.

Yick, J., Mukherjee, B., & Ghosal, D. (2008). Wireless sensor network survey. *Computer Networks, 52*, 2292–2330.

Yoo, Y., Boland, R. J., Lyytinen, K., & Majchrzak, A. (2009). Organizing for innovation in the digitized world. *Organization Science, 20*, 278–279.

Zheng, P., Sang, Z., Zhong, R. Y., Liu, Y., Liu, C., Mubarok, K., ... Xu, X. (2018). Smart manufacturing systems for industry 4.0: Conceptual framework, scenarios, and future perspectives. *Frontiers of Mechanical Engineering, 13*, 137–150.

Zhou, Z., Cai, Y., Xiao, Y., Chen, X., & Zeng, H. (2018). The optimization of reverse logistics cost based on value flow analysis–A case study on automobile recycling company in china. *Journal of Intelligent & Fuzzy Systems, 34*, 807–818.

Eivind Kristoffersen is a PhD candidate at the Department of Computer Science of the Norwegian University of Science and Technology and a Research Scientist in SINTEF Digital. His research focus on bridging the digital and sustainable through the strategic use of information systems and IT-business value for circular economy, known as the smart circular economy. In the past, Eivind has worked in industry as an IT solutions architect and received his M.Sc. in Engineering and ICT from the Norwegian University of Science and Technology.

Fenna Blomsma is a Junior Professor at Hamburg University, holding the chair in Circular Economy and Systems Innovation, as part of the School of Business, Economics and Social Science of the University of Hamburg. Her work focuses on unpacking the complexity involved in circular oriented innovation, how to design and implement sustainable circular business models, and on the design and development of circular value chains. Previously, Fenna worked in the Department of Mechanical Engineering at the Technical University of Denmark (DTU). Before, she did a doctoral research at the Centre for Environmental Policy (Imperial College London), and she also holds degrees from Cranfield University and Delft University of Technology.

Patrick Mikalef is an Associate Professor in Data Science and Information Systems at the Department of Computer Science and a research scientist in SINTEF Digital. In the past, he has been a Marie Skłodowska-Curie post-doctoral research fellow working on the research project "Competitive Advantage for the Data-driven Enterprise" (CADENT). He received his B.Sc. in Informatics from the Ionian University, his M.Sc. in Business Informatics for Utrecht University, and his Ph.D. in IT Strategy from the Ionian University. His research interests focus on the strategic use of information systems and IT-business value in turbulent environments. He has published over 100 papers in international conferences and peer-reviewed journals including the Journal of Business Research, European Journal of Information Systems, British Journal of Management and Information and Management.

Jingyue Li is an associate professor at the Department of Computer Science at the Norwegian University of Science and Technology in the area of Software Engineering and Artificial Intelligence.

Paper 3

Exploring the Relationship Between Data Science and Circular Economy: An Enhanced CRISP-DM Process Model.

Eivind Kristoffersen, Oluseun Omotola Aremu, Fenna Blomsma, Patrick Mikalef, and Jingyue Li.

In: Conference on e-Business, e-Services and e-Society and Lecture Notes in Computer Science, 177.

Exploring the Relationship Between Data Science and Circular Economy: An Enhanced CRISP-DM Process Model

Eivind Kristoffersen[1]( ), Oluseun Omotola Aremu[2], Fenna Blomsma[3], Patrick Mikalef[1], and Jingyue Li[1]

[1] Norwegian University of Science and Technology, 7491 Trondheim, Norway
eivind.kristoffersen@ntnu.no
[2] The University of Queensland, Brisbane, QLD 4072, Australia
[3] Technical University of Denmark, 2800 Kgs Lyngby, Denmark

Abstract. To date, data science and analytics have received much attention from organizations seeking to explore how to use their massive volumes of data to create value and accelerate the adoption of Circular Economy (CE) concepts. The correct utilization of analytics with circular strategies may enable a step change that goes beyond incremental efficiency gains towards a more sustainable and circular economy. However, the adoption of such smart circular strategies by the industry is lagging, and few studies have detailed how to operationalize this potential at scale. Motivated by this, this study seeks to address how organizations can better structure their data understanding and preparation to align with overall business and CE goals. Therefore, based on the literature and a case study the relationship between data science and the CE is explored, and a generic process model is proposed. The proposed process model extends the Cross Industry Standard Process for Data Mining (CRISP-DM) with an additional phase of *data validation* and integrates the concept of *analytic profiles*. We demonstrate its application for the case study of a manufacturing company seeking to implement the smart circular strategy - predictive maintenance.

Keywords: Data science · Circular Economy · Predictive maintenance · Business analytics · CRISP-DM

1 Introduction

In recent years, the concept of Circular Economy (CE) has received significant attention from businesses, policymakers, and researchers as a way to promote sustainable development [25]. With the aim of decoupling value-creation from the consumption of finite resources, CE leverages a range of restorative, efficiency, and productivity oriented strategies to keep products, components, and materials in use for longer [16,17]. Nevertheless, the adoption of CE by the industry so far is modest [26,54,61]. This also holds for manufacturing companies. Although

I. O. Pappas et al. (Eds.): I3E 2019, LNCS 11701, pp. 177–189, 2019.
https://doi.org/10.1007/978-3-030-29374-1_15

they play a vital role in the creation of value, little improvements are seen in their decoupling from linear consumption of resources.

In parallel, the emergence of new technologies as the Internet of Things, Big Data, and Artificial Intelligence - collectively known as Digital Technologies (DTs) - have encouraged a paradigm shift for industrial production, the 'Fourth Industrial Revolution'. These DTs are seen as one of the key enablers for a wider adoption and accelerated transition to CE [19,20]. Moreover, they form the operational building blocks of a more efficient and effective CE, the Smart CE.

The significance of DTs to transition to a CE however is argued to be more than a technical challenge [64]. First, it requires a clear data and business analytics strategy, the right people to effect a data-driven cultural change, and it demands the organization to appropriately structure their departments to align the analytics capability with their overall business strategy. Kiron and Shockley [36], concur and note that organizations have to develop data-oriented management systems both to make sense of the increasing volumes of data and, more importantly, for transforming the insights into business value and a competitive advantage. Supporting this transformation, by the use of analytics methods, is the data science process[1] [57]. However, there seems to be a gap between the output of these insights and the generation of business value [14,44,66]. As highlighted by extensive research, this is often due to the ineffective integration of data science methods within the organization [2,14,21,38,66].

Extant data science methodologies have not yet been scoped or demonstrated for the context of CE. For instance, the study [20] only presents the need for a process covering data collection, data engineering, algorithm development, and algorithm refinement within the CE without detailing how to operationalize it. Contributions are more commonly seen on topics such as service design [45], or the technical details of analyzing data, e.g., [11]. In this work, we recognize the importance of aligning an organizations analytics development with overall business and CE initiatives. The process discussed in this paper differs from previous contributions in three ways: First, it extends the Cross-Industry Standard Process for Data Mining (CRISP-DM) with an additional phase of *data validation*. Second, it consolidates an organization's analytics knowledge base by integrating the concept of *analytic profiles*. Third, the process is demonstrated for the context of CE by the case study of predictive maintenance (PdM) for an original equipment manufacturer (OEM). We use PdM as an example here as it is a prominent smart circular strategy (facilitating for extending the use-cycle, increasing the utilization and looping/cascading assets), allowing for generalization to other strategies.

The remainder of the work is detailed in following sections. Section 2 gives background on the data science and the concept of CE, thereafter Sect. 3 presents the research approach followed for this work. Section 4 presents the proposed CRISP-DM process model modifications, whilst Sect. 4.1 details the case study of PdM for CE. Finally, the paper is concluded and further work presented in Sect. 5.

[1] In this paper, we use the expressions process, method, and methodology interchangeable as a set of activities that interact to produce a result.

2 Background

2.1 Data Science

Data science is a multidisciplinary field encompassing tools, methods, and systems from statistics and data analytics (hereby referred to as analytics) applied to large volumes of data with the purpose of deriving insights for decision-making support [21,38,48,57,66]. As such, data science may include the collection and use of data to: *(i)* better understand the business operation and provide current state evaluation of performance, *(ii)* transform the organization from being reactive to proactive in business decision-making through use of predictive analytics, *(iii)* improve customer service through use of data to build a more coherent knowledge base and understanding of customer needs, and *(iv)* increase the efficiency, enhance the effectiveness and facilitate the implementation of CE concepts at scale (e.g., by optimizing circular infrastructures, business models, and products-service systems) [13,20,44,47,48].

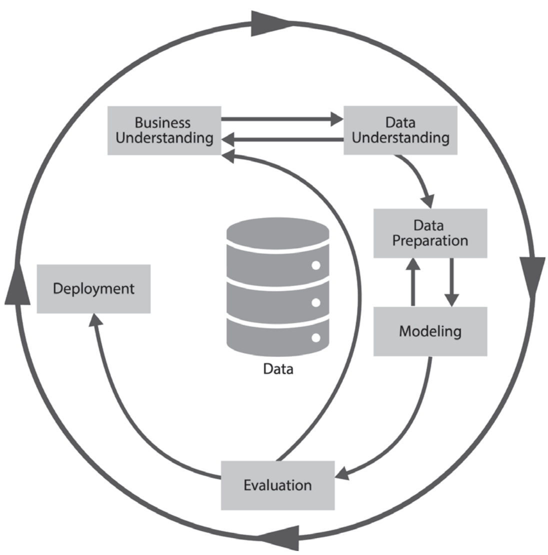


Fig. 1. Phases of the CRISP-DM process model [10]

Research shows that companies embracing data science have experienced noticeable gains in business development (i.e., productivity and profitability) [44,66]. However, the impact of data science is not limited to commercial endeavours alone. For instance, studies show improved sustainability for building energy management [46], predictive capabilities in supply chain management [66], health care services in the medical industry [50] and environmental impact of the manufacturing and process industry [29,34]. However, the effects for the CE is still largely unexplored.

To support the effective integration of data science within organizations, various methodologies have been proposed in the literature (e.g., KDD and SEMMA [22,59]). The most commonly used is the CRISP-DM process model created by IBM, reporting a use level of 43% followed by 28% of companies using their own methodology [53]. CRISP-DM is described in terms of a hierarchical and cyclic process model composed of six phases (see Fig. 1), each consisting of several generic tasks (e.g., clean data), specialized tasks (e.g., cleaning of numerical and categorical values) and process instances (i.e., how these tasks are operationalized through different actions, decisions and results). The methodology is designed to be generic, complete and stable, meaning that it should cover the whole analytics development process for all possible applications, and should be valid for yet unforeseen developments (e.g., new analytics modeling techniques) [10]. Despite the high reported level of use, the methodology appears to not be in active development. We recognize that IBM have later proposed an extension to CRISP-DM called the Analytics Solutions Unified Method (ASUM-DM) [30]. However, ASUM-DM differs only in the operational/deployment aspects of the process and describes the same phases for development. Therefore, given CRISP-DM's continued widespread adoption from practitioners and inherent generic, complete and stable design, we have chosen it as our reference model. As a stand-alone data science process, CRISP-DM has been successful within its bounds [67]. However, suggestions for the following shortcomings have been made [6,55] (the issues are addressed in Sect. 4):

(i) the lack of a good management view to track and communicate knowledge/insights,
(ii) the lack of assessment of analytics implementation feasibility (e.g. by leveraging a maturity assessment or gap analysis),
(iii) despite its widespread adoption, the process is not always understood by the wider business community, hence it is difficult to manage actual business value of the analyses,
(iv) the iterations do not loop back to the business level (prior to analytics modeling) for domain specific knowledge after the first two phases,
(v) and lack of control of added value.

2.2 Circular Economy

CE emerged as an umbrella concept in the 2010s as an approach to achieve sustainability [7], and encompass a range of strategies for narrowing, slowing and closing material and energy flows [8,18] as a means for addressing structural waste. Although the CE concept continues to grow and gain attention, it remains in an early stage of development. Therefore, a detailed definition of CE is still missing in the literature [24,31,35,41]. However, one of the most prominent definitions has been provided by the Ellen MacArthur Foundation [15,17], where CE is defined as a system *"that provides multiple value creation mechanisms, which are decoupled from the consumption of finite resources."*

CE strategies span from operational processes (i.e., restore, reduce, recirculate, and avoid) to more strategic, and business models related, strategies (i.e., reinvent, rethink, and reconfigure). DTs is highlighted by literature as an important enabler of CE strategies [4,9,19,49,51]. However, the adoption by industry is meager, and the research is still in a pre-paradigmatic stage [51]. Using DTs for the CE, Smart CE, promotes a sustainable ecosystem where assets (products, components, materials, and so on) are given virtual, or digital counterparts that allows for the sensing, communication, interaction, and exchange of data. By embedding software and analytics intelligence within or connected to these assets allows for easier manipulation and automation of the assets and of the environment, or system, in which they operate - enabling an increase of the systemic resource efficiency and productivity of the CE. This can for instance be seen with the data-driven maintenance strategy, or smart circular strategy, PdM [1,43,62]. PdM is a pertinent strategy for OEMs seeking to transition to the CE. OEMs offer one of the highest potential for environmental and economic impact of any sector [19]. In the European Union, material savings alone have been estimated to USD 650 billion for a full CE transition [15]. A gross part of this potential can be linked back to PdM by its three CE value drivers [19]:

Extending the life cycle: correct condition-assessment for need of and scheduling of appropriate life cycle extending operations,
Increasing utilization: reduce unplanned downtime and increased equipment effectiveness,
Looping the asset: improve insight and transparency into asset's condition and usage history.

Achieving a Smart CE requires companies to reconfigure and blend their existing value creation mechanisms with new innovative digital strategies. Blending digital strategies with value offerings require companies to become data-driven (i.e., decision-makers base their actions on data and insights generated from analytics, rather than instinct). Supporting this, Janssen et al. [33] argue that the quality of these evidence-based decisions depends largely on the quality of the inputs and the process that transforms these inputs into outputs - essentially the data science process.

3 Research Approach

The proposed process was developed based on an analysis of the *data understanding* and *data preparation* phases of the current CRISP-DM 1.0 step-by-step data mining guide [10] together with insights from company engagement under the CIRCit research project [12]. Given the exploratory nature of the research and the pre-paradigmatic stage of the field [51], case study research was chosen as the methodology for empirical investigation [69]. The case study research methodology is particularly suitable for the initial stage of investigation [31] as it help provide insights with relatively good understanding of the complexity and nature of the phenomenon [65]. Moreover, even a single case study can provide scientific development through a deep understanding of the problem and the capturing of experiences [23].

A research protocol was used in order to ensure reliability and validity of the findings, including case study design, data collection, data analysis, and formalization of results [69]. The company was selected based on a judgmental sampling technique [28]. First, the company should be from the manufacturing industry and have interest in, or experience with, the CE. Second, the company need to have sensory/operation data available for analytics and Smart CE investigation for this paper. To this regard, a Nordic OEM company manufacturing and servicing industrial cranes, who is particular interested in PdM, was contacted and accepted to participate in the project and case study. However, the company identity has been concealed here to protect their business interests.

Following the research protocol, data collection was performed through several semi-structured interviews to first gather general information about the context of the company before the operation data were exchanged and insights specific to analytics and PdM were collected. Following the collection of organizational and operation data, analytics investigation was performed to evaluate the potential PdM and set implementation requirements. Then, the last face of the protocol was conducted, looking for possible procedural improvements of the CRISP-DM model to meet the requirements from analytics.

4 An Enhanced CRISP-DM Process Model

Asset and process management research argue that data should be specifically structured for the intended use within the work flow [27,57]. Analytics research concur and note that insight is more obtainable when the data has been preprocessed for a specific domain of analysis [32,37,42,52,68]. To this effect, and to address the previous highlighted shortcomings, we propose an extended CRISP-DM process model. The proposed process model adds an additional phase called *data validation* (addressing issues (iv) and (v)), and argues for the integration of *analytic profiles* (addressing issues (i) and (iii)) as a core element of the process. Figure 2 illustrates the enhanced CRISP-DM process model developed.

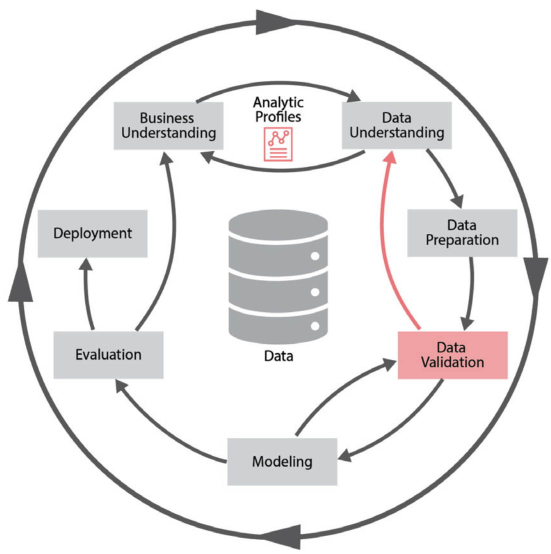


Fig. 2. An enhanced CRISP-DM process model

In CRISP-DM, there is no validation between the *data preparation* phase and the *modeling* phase against the specific business domain [6,48]. Specifically, once the data is prepared for modeling, only the criterion needed to ensure optimal analytics model performance are considered [48,67]. Thus, a complete understanding of whether the data which is prepared is a valid representation of the original problem is not guaranteed. General data preparation methods alter the original data, and there is often loss in information specific to the domain that should be monitored [5,48]. As such, this may result in sub-optimal solutions that miss the mark on the intended capturing of business value [55,63]. Therefore, we argue that data validation should be done by the re-involvement of the business entity, or domain experts, to validate that a proper understanding of the data and business problem have been reached, and include data preparation methods tailored for the given analytic profile. The data validation phase may result in a re-iteration of the data understanding and/or the data preparation phase(s) (indicated by a single arrow back in the diagram).

Analytic profiles are defined as structures that standardize the collection, application and re-use of analytics insights and models for key business entities [60]. As such, an analytic profile is an abstract collection of knowledge, mainly used in the business and data understanding phases, that lists the best practices for a particular analytics use case, or problem. Analytic profiles may have different levels of granularity depending in the use case and the organization's level of experience. However, information on the following elements should be included:

- **Use case description** defining the business goal (e.g., predict the remaining useful life of a crane),
- **Domain specific insights** important for the use case (e.g., knowledge about typical crane failures and causes),
- **Data sources** relevant for the use case (e.g., time-series data of crane operation and service data with failure modes),
- **Key Performance Indicators (KPIs)** or metrics for assessing the analytics implementation performance (e.g., crane failure rate, downtime and maintenance costs),
- **Analytics models and tools** with proven conformity for the given problem (e.g., long short-term memory networks and deep belief networks),
- **Short descriptions of previous implementations** with lessons learned (e.g., deep belief networks for backlash error prediction in machining centers [40]).

As per the CRISP-DM process level breakdown [10], analytic profiles can be regarded as a generic task particularly relevant between the business and data understanding phases (indicated by an analytic profile icon in the diagram). Through such a consolidation of the analytics knowledge base, organizations can more easily learn and reuse their own experience and the experience of others to catalyze the analytics development process. Furthermore, Kiron and Shockley [36] state that organizations should appropriately structure their resources to align their analytics capability with their overall business strategies. Therefore, we argue that analytic profiles should be build for all business strategies, or use cases, relying on insights from analytics.

4.1 Case Study: Predictive Maintenance for an Original Equipment Manufacturer

In this section we give detail to the strategy of PdM for the context of CE together with insights from the case study to validate the adaptations made to CRISP-DM. However, we only detail the structuring of data from the data understanding phase to the data validation phase. As such, we do not cover the whole analytics development process or the full contents of the analytic profile of PdM.

According to EN 13306:2010, predictive maintenance is defined as condition-based maintenance carried out following a forecast from analytics or known characteristics of the features of the degradation of an asset. It contrasts traditional, or non-predictive, maintenance actions that are only based on information of the current condition. Therefore, as PdM integrates multiple DTs (e.g. Internet of Things and Artificial Intelligence) it enables real-time access to detailed information about the assets' location, condition, and availability. This allows for augmenting human decision-making by predicting product health, wear, usage, and energy consumption [56]. This *"sense and respond"* capability is crucial for the CE as it allow for greater transparency of assets' actual condition throughout their life cycle, and enable triggering of appropriate life cycle extending operations for the OEM or service provider [58].

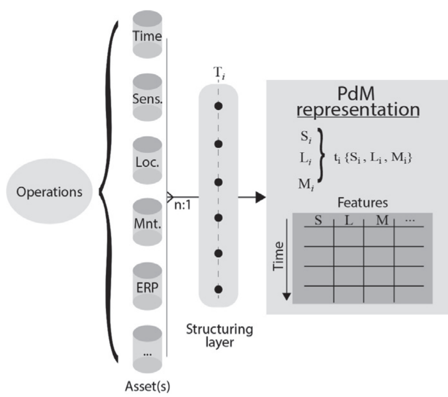


Fig. 3. Example structuring of data for a PdM analytic profile

The main goal of the analytics exploration was to evaluate the current status of analytics development towards the implementation of PdM within the company. For the case of a PdM analytic profile, the occurrence of faults or degradation and their influence during assets' life cycle are considered domain specific knowledge [3,5]. Therefore, the data must contain life cycle observations in which information or knowledge pertaining to the occurrence of faults, degradation, or process change can be inferred [39,52,62]. In general, this can be decomposed to sensor measurements S, location L, and maintenance logs M which describe the condition at various time steps. Figure 3 illustrates such a structuring of an asset's data in which its attributes are collected from multiple data sources, such as time, sensory/monitoring data, location, maintenance logs, and Enterprise Resource Planning (ERP) system data. The observation at an arbitrary time t_i describes the condition of the asset per set of attributes $t_i(S_i, L_i, M_i)$. This structuring ensures the data is useful for the intended analysis, and when combined with involvement from the business entity by domain experts makes up the *data validation* phase. However, the analytics exploration performed by the researchers showed that the current collected features were not sensitive enough to the failure categories required by PdM. This means that the provided data lacked in quality and did not contain the necessary level of detail of failure modes needed in order to predict impending failures. Consequently, the business goal and targeted analyses had to be changed to less advanced analyses. In this case, the goal was transferred to abnormality identification and the development of a method to evaluate the severity degree of the cranes. High severity degree means that the behaviour of the sample crane is different from the majority, thus is more likely to have impending failures. Also, it is not uncommon that important information, or observations, within the data might get 'lost', or disregarded, in the data preparation phase (due to misunderstanding of the business goal). Therefore, we argue that it is crucial for the success of data science initiatives to include a phase of data validation prior to modeling. In summary, the data validation phase ensures that modeling happens on the right data for the right reasons.

Following the data preparation and data validation phases, the standard CRISP-DM phases of *modeling*, *evaluation*, and *deployment* should be followed. In these phases, analytics methods are applied to, e.g., provide predictions or current state inferences of the manufacturing operation. This may include the accurate identification and prediction of impending failures, degradations, or abnormal behaviour, which can then be used for decision-making support or directive actions for operations management. Finally, when the process of PdM has been structured in such a way that it allows for standardized collection, application and re-use of its analytics insights.

Interviews with the case company revealed that such a structuring of the data and standardized use of analytic profiles had not been systematically integrated within the organization. In the intervention after the analytics exploration the researchers presented the results of their analyses with suggestions for how to appropriately structure their data science process model (e.g., how to link the abnormality identification with typical uses cases and KPIs). Feedback from the company showed the new data science process, especially with the active use of KPIs, could provide a better management view for easier communication of knowledge, tracking of business value and CE impact.

5 Conclusion and Future Work

This paper proposed an enhanced CRISP-DM process model and a case study discussing how to structure the data of the analytic profile of PdM for the context of CE. We addressed the issues (iv) and (v) (lack of iterations looping back to the business level and no control of added value) by introducing an additional phase of data validation. As such, we highlighted the importance of the re-involvement of the business entity, or domain experts, to include domain specific knowledge for structuring and validating the data prior to modeling. Furthermore, we partly addressed the issues (i) and (iii) (lack of good management view and difficulty in managing actual business value of analyses) by introducing analytic profiles as an integrative part of the process model. Motivated by the benefits of the Smart CE, we discussed how data science is fundamental for using DTs to increase the efficiency, enhance the effectiveness and facilitate the implementation of CE strategies. For future work, we aim to extend on the business analytics and CE connection to the data science process. Essentially, detailing the business understanding and data understanding phases with CE related business model scoping and analytics leverage assessment. Lastly, greater detail and empirical evaluation of the suggested CRISP-DM modification should be added.

Acknowledgment. The authors would like to thank the reviewers of this paper. Also, the authors would like to acknowledge that this work was conducted as part of the research project CIRCit (Circular Economy Integration in the Nordic Industry for Enhanced Sustainability and Competitiveness), which is part of the Nordic Green Growth Research and Innovation Programme (grant number: 83144), and funded by NordForsk, Nordic Energy Research, and Nordic Innovation.

References

1. Alaswad, S., Xiang, Y.: A review on condition-based maintenance optimization models for stochastically deteriorating system. Reliab. Eng. Syst. Saf. **157**, 54–63 (2017)
2. Amankwah-Amoah, J., Adomako, S.: Big data analytics and business failures in data-rich environments: an organizing framework. Comput. Ind. **105**, 204–212 (2019)
3. An, D., Choi, J.H., Kim, N.H.: Prognostics 101: a tutorial for particle filter-based prognostics algorithm using Matlab. Reliab. Eng. Syst. Saf. **115**, 161–169 (2013)
4. Antikainen, M., Uusitalo, T., Kivikytö-Reponen, P.: Digitalisation as an enabler of circular economy. Proc. CIRP **73**, 45–49 (2018)
5. Aremu, O.O., Salvador Palau, A., Hyland-Wood, D., Parlikad, A.K., McAree, P.R.: Structuring data for intelligent predictive maintenance in asset management. In: 16th IFAC Symposium on Information Control Problems in Manufacturing (2018)
6. Bahrepour, M.: The forgotten step in CRISP-DM and ASUM-DM methodologies. https://sharing.luminis.eu/blog/the-forgotten-step-in-crisp-dm-and-asum-dm-methodologies/. Accessed 08 Mar 2019
7. Blomsma, F., Brennan, G.: The emergence of circular economy: a new framing around prolonging resource productivity. J. Ind. Ecol. **21**(3), 603–614 (2017)

8. Bocken, N.M., Short, S.: Towards a sufficiency-driven business model: experiences and opportunities. Environ. Innov. Soc. Transitions **18**, 41–61 (2016)
9. Bressanelli, G., Adrodegari, F., Perona, M., Saccani, N.: The role of digital technologies to overcome circular economy challenges in PSS business models: an exploratory case study. Proc. CIRP **73**, 216–221 (2018)
10. Chapman, P., Clinton, J., Kerber, R., Khabaza, H., Reinartz, T., Shearer, C., Wirth, R.: CRISP-DM 1.0 Step-by-step data mining guide. Technical report (2000)
11. Cielen, D., Meysman, A., Ali, M.: Introducing data science: big data, machine learning, and more, using Python tools. Manning Publications Co. (2016)
12. CIRCit: Circit project page (2019). http://circitnord.com/
13. Dhar, V.: Data science and prediction. NYU Working Paper No. 2451/31635 (2012)
14. Domino Data Lab: Key factors on the journey to become model-driven - a survey report (2018)
15. MacArthur, E.: Towards a Circular Economy and Business Rationale for an Accelerated Transition. Ellen MacArthur Foundation, Cowes, UK (2013)
16. Ellen MacArthur Foundation: Delivering the circular economy: a toolkit for policymakers (2015)
17. MacArthur, E.: Growth within: a circular economy vision for a competitive Europe. Ellen MacArthur Foundation, Cowes, UK (2015)
18. Ellen MacArthur Foundation: Towards a circular economy: business rationale for an accelerated transition (2015). Accessed 25 Oct 2016
19. MacArthur, E.: Intelligent assets. unlocking the circular economy potential. Ellen MacArthur Foundation, Cowes, UK (2016)
20. MacArthur E.: Artificial intelligence and the circular economy. Ellen MacArthur Foundation, Cowes, UK (2019)
21. Elshawi, R., Sakr, S., Talia, D., Trunfio, P.: Big data systems meet machine learning challenges: towards big data science as a service. Big data research (2018)
22. Fayyad, U., Piatetsky-Shapiro, G., Smyth, P.: From data mining to knowledge discovery in databases. Al Mag. **17**(3), 37 (1996)
23. Flyvbjerg, B., Budzier, A.: Why your it project may be riskier than you think (2011)
24. Geng, Y., Doberstein, B.: Developing the circular economy in China: challenges and opportunities for achieving 'leapfrog development'. Int. J. Sustain. Develop. World Ecol. **15**(3), 231–239 (2008)
25. Ghisellini, P., Cialani, C., Ulgiati, S.: A review on circular economy: the expected transition to a balanced interplay of environmental and economic systems. J. Clean. Prod. **114**, 11–32 (2016)
26. Haas, W., Krausmann, F., Wiedenhofer, D., Heinz, M.: How circular is the global economy: an assessment of material flows, waste production, and recycling in the European Union and the world in 2005. J. Ind. Ecol. **19**(5), 765–777 (2015)
27. Haddar, N., Tmar, M., Gargouri, F.: A framework for data-driven workflow management: modeling, verification and execution. In: Decker, H., Lhotská, L., Link, S., Basl, J., Tjoa, A.M. (eds.) DEXA 2013. LNCS, vol. 8055, pp. 239–253. Springer, Heidelberg (2013). https://doi.org/10.1007/978-3-642-40285-2_21
28. Henry, G.T.: Practical Sampling, vol. 21. Sage (1990)
29. Ho, T.C., Mat, S.C.K.M.Z., San, L.H., et al.: A prediction model for CO2 emission from manufacturing industry and construction in Malaysia. In: 2015 International Conference on Space Science and Communication (IconSpace). pp. 469–472. IEEE (2015)
30. IBM: Analytics solutions unified method - implementations with agile principles (2016). ftp://ftp.software.ibm.com/software/data/sw-library/services/ASUM.pdf

31. Jabbour, C.J.C., de Sousa Jabbour, A.B.L., Sarkis, J., Godinho Filho, M.: Unlocking the circular economy through new business models based on large-scale data: an integrative framework and research agenda. Technol. Forecast. Soc. Change **144** 546–552 (2017)
32. James, G., Witten, D., Hastie, T., Tibshirani, R.: An Introduction to Statistical Learning, vol. 112. Springer, New York (2013). https://doi.org/10.1007/978-1-4614-7138-7
33. Janssen, M., van der Voort, H., Wahyudi, A.: Factors influencing big data decision-making quality. J. Bus. Res. **70**, 338–345 (2017)
34. Kameswari, U.S., Babu, I.R.: Sensor data analysis and anomaly detection using predictive analytics for process industries. In: 2015 IEEE Workshop on Computational Intelligence: Theories, Applications and Future Directions (WCI), pp. 1–8. IEEE (2015)
35. Kirchherr, J., Reike, D., Hekkert, M.: Conceptualizing the circular economy: an analysis of 114 definitions. Resour. Conserv. Recycl. **127**, 221–232 (2017)
36. Kiron, D., Shockley, R.: Creating business value with analytics. MIT Sloan Manage. Rev. **53**(1), 57 (2011)
37. Kun, W., Tong, L., Xiaodan, X.: Application of big data technology in scientific research data management of military enterprises. Proc. Comput. Sci. **147**, 556–561 (2019)
38. Larson, D., Chang, V.: A review and future direction of agile, business intelligence, analytics and data science. Int. J. Inf. Manag. **36**(5), 700–710 (2016)
39. Lei, Y., Li, N., Guo, L., Li, N., Yan, T., Lin, J.: Machinery health prognostics: a systematic review from data acquisition to RUL prediction. Mech. Syst. Signal Process. **104**, 799–834 (2018)
40. Li, Z., Wang, Y., Wang, K.: A data-driven method based on deep belief networks for backlash error prediction in machining centers. J. Intell. Manuf. 1–13 (2017). https://doi.org/10.1007/s10845-017-1380-9
41. Lieder, M., Rashid, A.: Towards circular economy implementation: a comprehensive review in context of manufacturing industry. J. Clean. Prod. **115**, 36–51 (2016)
42. Lin, J., Keogh, E., Wei, L., Lonardi, S.: Experiencing sax: a novel symbolic representation of time series. Data Min. Knowl. Disc. **15**(2), 107–144 (2007)
43. Liu, B., Liang, Z., Parlikad, A.K., Xie, M., Kuo, W.: Condition-based maintenance for systems with aging and cumulative damage based on proportional hazards model. Reliab. Eng. Syst. Saf. **168**, 200–209 (2017)
44. McAfee, A., Brynjolfsson, E., Davenport, T.H., Patil, D., Barton, D.: Big data: the management revolution. Harvard Bus. Rev. **90**(10), 60–68 (2012)
45. Meierhofer, J., Meier, K.: From data science to value creation. In: Za, S., Drăgoicea, M., Cavallari, M. (eds.) IESS 2017. LNBIP, vol. 279, pp. 173–181. Springer, Cham (2017). https://doi.org/10.1007/978-3-319-56925-3_14
46. Molina-Solana, M., Ros, M., Ruiz, M.D., Gómez-Romero, J., Martín-Bautista, M.J.: Data science for building energy management: a review. Renew. Sustain. Energy Rev. **70**, 598–609 (2017)
47. Nath, P., Nachiappan, S., Ramanathan, R.: The impact of marketing capability, operations capability and diversification strategy on performance: a resource-based view. Ind. Mark. Manag. **39**(2), 317–329 (2010)
48. Newman, R., Chang, V., Walters, R.J., Wills, G.B.: Model and experimental development for business data science. Int. J. Inf. Manag. **36**(4), 607–617 (2016)
49. Nobre, G.C., Tavares, E.: Scientific literature analysis on big data and internet of things applications on circular economy: a bibliometric study. Scientometrics **111**(1), 463–492 (2017)

50. Ottenbacher, K.J., Graham, J.E., Fisher, S.R.: Data science in physical medicine and rehabilitation: opportunities and challenges. Phys. Med. Rehabil. Clin. N. Am. **30**(2), 459–471 (2019)
51. Pagoropoulos, A., Pigosso, D.C., McAloone, T.C.: The emergent role of digital technologies in the circular economy: a review. Proc. CIRP **64**, 19–24 (2017)
52. Peng, Y., Dong, M., Zuo, M.J.: Current status of machine prognostics in condition-based maintenance: a review. Int. J. Adv. Manuf. Technol. **50**(1–4), 297–313 (2010)
53. Piatetsky, G.: CRISP-DM, still the top methodology for analytics, data mining, or data science projects. In: KDD News (2014)
54. Planing, P.: Business model in novation in a circular economy reasons for non-acceptance of circular business models. Open J. Bus. Model Innov. **1**, 11 (2015)
55. Ponsard, C., Touzani, M., Majchrowski, A.: Combining process guidance and industrial feedback for successfully deploying big data projects. Open J. Big Data (OJBD) **3**(1), 26–41 (2017)
56. Porter, M.E., Heppelmann, J.E.: How smart, connected products are transforming competition. Harvard Bus. Rev. **92**(11), 64–88 (2014)
57. Provost, F., Fawcett, T.: Data Science for Business: What You Need to Know about Data Mining and Data-Analytic Thinking. O'Reilly Media Inc, Newton (2013)
58. Romero, D., Noran, O.: Towards green sensing virtual enterprises: interconnected sensing enterprises, intelligent assets and smart products in the cyber-physical circular economy. IFAC-PapersOnLine **50**(1), 11719–11724 (2017)
59. SAS: Semma. https://www.sas.com/en_gb/software/analytics-overview.html. Accessed 10 Apr 2019
60. Schmarzo, B.: Big Data MBA: Driving Business Strategies with Data Science. Wiley, Hoboken (2015)
61. Sousa-Zomer, T.T., Magalhães, L., Zancul, E., Cauchick-Miguel, P.A.: Exploring the challenges for circular business implementation in manufacturing companies: an empirical investigation of a pay-per-use service provider. Resour. Conserv. Recycl. **135**, 3–13 (2018)
62. Susto, G.A., Schirru, A., Pampuri, S., McLoone, S., Beghi, A.: Machine learning for predictive maintenance: a multiple classifier approach. IEEE Trans. Ind. Inf. **11**(3), 812–820 (2015)
63. Viaene, S.: Data scientists aren't domain experts. IT Prof. **15**(6), 12–17 (2013)
64. Vidgen, R., Shaw, S., Grant, D.B.: Management challenges in creating value from business analytics. Eur. J. Oper. Res. **261**(2), 626–639 (2017)
65. Voss, C.: Case research in operations management. In: Researching operations management, pp. 176–209. Routledge (2010)
66. Waller, M.A., Fawcett, S.E.: Data science, predictive analytics, and big data: a revolution that will transform supply chain design and management. J. Bus. Logistics **34**(2), 77–84 (2013)
67. Wirth, R., Hipp, J.: CRISP-DM: towards a standard process model for data mining. In: Proceedings of the 4th International Conference on the Practical Applications of Knowledge Discovery and Data Mining, pp. 29–39. Citeseer (2000)
68. Wood, D., Zaidman, M., Ruth, L., Hausenblas, M.: Linked Data. Manning Publications Co. (2014)
69. Yin, R.K.: Applied social research methods series case study research: design and methods (1984)

Paper 4

Towards a Business Analytics Capability for the Circular Economy.

Eivind Kristoffersen, Patrick Mikalef, Fenna Blomsma, and Jingyue Li.

In: Technological Forecasting and Social Change, 171, 120957.

Technological Forecasting & Social Change 171 (2021) 120957

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

Towards a business analytics capability for the circular economy

Eivind Kristoffersen [a,b,*], Patrick Mikalef [a,b], Fenna Blomsma [c], Jingyue Li [a]

[a] Department of Computer Science, Norwegian University of Science and Technology, Sem Sælandsvei 9, 7491, Trondheim, Norway
[b] SINTEF Digital, S. P. Andersens Veg 5, 7031 Trondheim, Norway
[c] University of Hamburg, 20146 Hamburg, Germany

ARTICLE INFO

Keywords:
Digital circular economy
Sustainability
Big data analytics
Competitive advantage
Resource-based view
Expert interviews

ABSTRACT

Digital technologies are growing in importance for accelerating firms' circular economy transition. However, so far, the focus has primarily been on the technical aspects of implementing these technologies with limited research on the organizational resources and capabilities required for successfully leveraging digital technologies for circular economy. To address this gap, this paper explores the business analytics resources firms should develop and how these should be orchestrated towards a firm-wide capability. The paper proposes a conceptual model highlighting eight business analytics resources that, in combination, build a business analytics capability for the circular economy and how this relates to firms' circular economy implementation, resource orchestration capability, and competitive performance. The model is based on the results of a thematic analysis of 15 semi-structured expert interviews with key positions in industry. Our approach is informed by and further develops, the theory of the resource-based view and the resource orchestration view. Based on the results, we develop a deeper understanding of the importance of taking a holistic approach to business analytics when leveraging data and analytics towards a more efficient and effective digital-enabled circular economy, the smart circular economy.

Introduction

Sustainability has been an issue subject to extensive research and discussion ever since the Brundtland report in 1987 (Commission on Environment and Development, 1987). Following this, the concept of circular economy (CE) has gained attention by policymakers, researchers, and organizations alike as a way to promote sustainable development (Geissdoerfer et al., 2017; Ghisellini et al., 2016). The CE envisions a global economy in which value-creation is decoupled from the consumption of finite resources by leveraging a range of productivity and efficiency-enhancing as well as restorative strategies to keeping products, components, and materials in use for longer (Blomsma and Tennant, 2020; EMF, 2015a, 2015b). In other words, the CE promotes two ideas at the heart of sustainable development: economic development combined with reducing the environmental burden of economic activity. As a result, the CE is rapidly gathering momentum as a way of boosting economies, while addressing mounting resource-related challenges, creating jobs, spurring innovation, and generating substantial environmental benefits (European Commission, 2020a, 2020b; Stahel, 2010). However, so far, the adoption of CE principles in the industry has been modest (Circle Economy, 2020; Haas et al., 2015; Planing, 2015; Sousa-Zomer et al., 2018).

Simultaneously, the rapid innovations of digital technologies have raised data and analytics to the top of corporate agendas along with claims that '*data is the new oil*' that is to be refined to extract unprecedented value (Brown et al., 2011; McAfee et al., 2012). Hence, the capacity to gather, process, structure, and use data in decision-making, known as business analytics (BA), is increasingly seen as a source of competitive advantage (Mortenson et al., 2015; Provost and Fawcett, 2013). Correspondingly, we see a growing interest from organizations in leveraging BA for an accelerated transition towards the CE (Antikainen et al., 2018b; Bressanelli et al., 2018a; EMF, 2016, 2019; Kristoffersen et al., 2020; Nobre and Tavares, 2017; Pagoropoulos et al., 2017). BA can support firms' CE transition in various ways. For one, BA can be used to optimize circular strategies such as reverse logistics, energy consumption, and maintenance (Bressanelli et al., 2018b; Lenka et al., 2017; Rymaszewska et al., 2017). Second, BA may serve to identify and address structural waste, such as underused product capacity or waste-to-resource matching in industrial symbiosis systems (Bin et al., 2015; Low et al., 2018). Third, BA may support the innovation process of

* Corresponding author.
E-mail addresses: eivindk@outlook.com (E. Kristoffersen), patrick.mikalef@ntnu.no (P. Mikalef), fenna.blomsma@uni-hamburg.de (F. Blomsma), jingyue.li@ntnu.no (J. Li).

https://doi.org/10.1016/j.techfore.2021.120957
Received 14 July 2020; Received in revised form 28 May 2021; Accepted 10 June 2021
Available online 18 June 2021

future circular strategies through simulating impacts of life cycle scenarios or identifying possible life cycle extending activities (Lieder et al., 2020). In this capacity, BA can be used to identify novel business opportunities and alternative sources of competitive advantage.

Currently, however, most studies connecting the fields of BA and CE are in a nascent stage and offer mostly anecdotal evidence (Kristoffersen et al., 2020). Unsurprisingly, there is limited empirical work grounded on established management, information systems (IS), and CE theories (Lahti et al., 2018). A gap exists in understanding how to wield BA in a targeted way to support circular strategies operationally and find new CE opportunities. As a result, questions of whether, under what conditions, and how BA can improve firms' competitive performance through the enhanced leveraging of circular strategies, remains unanswered. However, to answer this, an instrument to empirically investigate BA's contribution towards CE must be developed. An important first step is to identify which distinctive BA resources[1] that, in combination, build a business analytics capability (BAC) for CE and the processes through which firms orchestrate and leverage them.

Notwithstanding the number of studies on BA capabilities for general business operation and supply chain management (Akter et al., 2016; Wang et al., 2016), these are all rooted in the linear economic model and way of thinking. Hence, they lack alignment with more holistic information management and sustainable principles core to the CE (Gupta et al., 2019). This applies both to strategic and operational activities such as reinventing and reconfiguring business models and value chains, reducing raw material sourcing and manufacturing impacts, and recirculating products and materials to additional use cycles. The CE sets greater demand for firms to collect, integrate, analyze, and share data across organizational boundaries, both upstream and downstream in the value chain. Consequently, adopting CE imposes different BA resources compared to previous BAC research. This lack of research and limited understanding severely hampers organizations' ability to transition to the CE, restructure organizational resources, and fully capitalize on their BA investments. Therefore, to obtain relevant theoretical and practical insights, for researchers and practitioners alike, it is essential to identify what the core artifacts of BA pertinent to CE are, and how they are structured, bundled, and leveraged within firms.

To address this gap, this study employs thematic analysis of a series of semi-structured interviews to identify the core organizational resources, or building blocks, of a BAC for CE (RQ1) and examines how firms orchestrate these resources into a firm-wide BAC for CE (RQ2). We build on a qualitative exploratory approach in order to isolate the key resources that comprise a BAC for CE, and to identify the mechanisms through which they are leveraged. The research questions addressed in this study are:

RQ1 What are the business analytics resources required for circular economy?

RQ2 How should firms structure, bundle, and leverage their business analytics resources into a business analytics capability for circular economy?

The rest of this work is detailed in the following sections. First, Section 2 provides background on the relation between CE, digital technologies, and BA together with theory on developing organizational capabilities. Section 3 explains the research methodology followed to analyze 15 semi-structured expert interviews. We then present the result of our analysis of emergent factors, conceptual model, and how firms manage their BA resources for CE Section 4. Our results uncover eight key organizational resources of a BAC, along with insights on how to deploy them. Finally, in Section 0 and 6, we provide a discussion of the findings along with limitations, avenues for future research, and conclusive remarks.

[1] Here, we refer to BA resources as a subset of organizational resources under the resource-based view theory.

Background

Smart circular economy

Despite the growing interest from industry and academia alike, CE is still in its infancy, and a unified definition is missing (Kirchherr et al., 2017). In their analysis of 114 definitions, Kirchherr et al. (2017) provide the following meta-definition: "*A CE describes an economic system that is based on business models which replace the 'end-of-life' concept with reducing, alternatively reusing, and recycling […] materials in production/distribution and consumption processes, […], with the aim to accomplish sustainable development, which implies creating environmental quality, economic prosperity and social equity, to the benefit of current and future generations*". As such, CE may be understood as an umbrella concept, in which various frames exist Blomsma and Brennan (2017), but that has as a common goal to replace current 'take--make-use-dispose' systems with systems addressing structural waste. Instrumental to this is the application of circular strategies, which provides new value creation opportunities and reduce value loss and destruction by narrowing, slowing, and closing material and energy flows Bocken and Short (2016). For instance, think of recycling materials instead of shipping them to landfill or incineration and reusing parts and products through repair, remanufacturing, sharing, or access-over-ownership models.

However, companies embracing a CE may be subject to several risks, such as a mismatch between fluctuating demand, supply, and value of used assets, causing uncertainties with cost and return on investment (de Sousa Jabbour et al., 2018). Consequently, to date, resources[2] are reused at marginal volumes. One of the fundamental causes to these issues is the missing information throughout the industrial life cycle Wilts and Berg (2018). From an IS point of view, the CE transition can be understood as a problem of information logistics. Digital technologies can support this by addressing key operational barriers in the loss of information that typically results in linear value chains, such as no insight into location, availability, or condition of assets (Su et al., 2013). Hence, effectively leveraging the abundant sources of data available throughout the industrial life cycle to fully connect material- and information flows may provide the step change needed for companies to go beyond incremental efficiency gains towards the CE. To this end, the emergence and increased uptake of digital technologies are highlighted as vital for CE implementation (Antikainen et al., 2018a; Bressanelli et al., 2018a; de Sousa Jabbour et al., 2018; EMF, 2019, 2016; Kristoffersen et al., 2019; Nobre and Tavares, 2017). In this context, the term *digital technologies* encompass various related concepts, such as the internet of things, big data, artificial intelligence, BA, cloud computing, cyber-physical systems, and blockchain. In this study, we limit our focus to BA due to its potential to leverage data for improved resource management and decision-making support across the different stages of the industrial life cycle.

In other words, an increased drive towards digitalizing the CE could pave the way for a more efficient and effective CE, known as the *Smart CE* (Kristoffersen et al., 2020). Acknowledging the potential of a Smart CE, various sources have voiced the need for research into how organizations can leverage digital business practices for CE implementation and value creation (Chauhan et al., 2019; EMF, 2019, 2016; European Commission, 2020b; Okorie et al., 2018; Rosa et al., 2020). To address this, several theoretical frameworks connecting CE with digital strategies have been presented (Askoxylakis, 2018; Bianchini et al., 2018; Ingemarsdotter et al., 2019; Kristoffersen et al., 2020; Rosa et al., 2020; Ünal et al., 2018). However, no dominant framework has yet emerged, and only one provides detail on the underlying technical mechanisms needed for identifying BA resources (Kristoffersen et al., 2020). Thus, for

[2] Here, we refer to physical resources such as materials, components, and products.

the purpose of this study, we draw on the *Smart CE framework* by Kristoffersen et al. (2020) for contextual alignment.

Resource-based view and resource orchestration

Building on the works by Wernerfelt (1984) and Amit and Schoemaker (1993), developing and sustaining a competitive advantage is fundamental to strategic management literature. To date, the resource-based view (RBV) is considered to be one of the most rigorous theories to explain firm performance through the resources they own and control Barney (2001). The theory has also been under considerable scholarly attention under the notion of IT capabilities Bharadwaj (2000). RBV proposes that a firm generates competitive advantage through the collection of tangible and intangible resources, specifically the ones that are valuable, rare, inimitable, and non-substitutable (known as VRIN) Barney (1991). Despite decades of empirical work and recent meta-analysis supporting the importance of these resources for competitive performance, scholars argue that the theory requires additional specification to explain differences amongst firms' outcomes (Crook et al., 2008; Kraaijenbrink et al., 2010; Sirmon et al., 2011). The core assumptions of VRIN also pose a challenge when applied to the context of BA, as the core resource, data, is often not rare, but an open and shared resource (Braganza et al., 2017).

Amit and Schoemaker (1993) define organizational resources as stocks of tradable and nonspecific assets in the firm, and capabilities as the firms specific and non-tradable ability to deploy such resources, through organizational processes, to affect a desired end. Hence, one can distinguish between the notion of resource-picking (identifying resources of strategic value) and capability-building (orchestrating these resources into useful assets) Makadok (2001). Much attention from IS research has been paid to the resource-picking aspects of firms' BAC, but less to capability-building (Mikalef et al., 2018). To this end, Sirmon et al. (2011) propose the resource orchestration view (ROV) to extend the understanding of RBV by explaining the role of managers for transforming resources into capabilities.

The research stream of ROV builds on RBV and dynamic capabilities through the complementary integration of the resource management framework by Sirmon et al. (2007) and the asset orchestration framework by Helfat et al. (2009). The integrated framework provides a more robust perspective of managers' specific role in the processes of structuring, bundling, and leveraging capabilities across differences in firm characteristics (i.e., scope, life cycle stage, and levels in the managerial hierarchy). Each process includes several sub-processes with varying relative importance depending on the firm's characteristics, suggesting variance in the type and importance of managerial actions in orchestrating the firm's resources (Sirmon et al., 2011) (see Table 2 for details). Despite limited studies on research orchestration and BAC, the framework has been applied to the role of IT resources, capabilities, and dynamic capabilities for innovation Ahuja and Chan (2017). Ahuja and Chan (2017) used the retrospective case study of Barclays 'digital eagles' program to examine the process of 'IT resource orchestration' to explain how the firm transformed its IT resources into IT capabilities and dynamic capabilities for increased innovation and firm performance. The motivation for choosing RBV and ROV as the theoretical groundings in this study is because the former presents a solid foundation whereupon all organizational resources can be identified, while the latter provides a lens to examine how these resources are managed and turned into capabilities to leverage circular strategies for increased competitive performance.

Business analytics capability

The term *intelligence* was first used by artificial intelligence researchers back in the 1950s, later spurring the concept of *business intelligence* in the 1990s closely followed by *business analytics* in the 2000s (Chen et al., 2012). While numerous definitions exist, BA is frequently referred to as the collection of technologies, methodologies, practices, and applications that enable the analysis of critical business data to make more sound and evidence-based business decisions (Chen et al., 2012; Seddon and Currie, 2017). Recently, the term big data analytics have emerged to describe the set of techniques and application in which the (big) data sets are too large and complex for traditional methods (Chen et al., 2012). For the purpose of this study, we treat BA and big data analytics as a unified term and draw on the systematic literature review by Mikalef et al. (2018). As highlighted in their review, many data characteristics exist; however, the attributes of *volume, velocity*, and *variety* are highlighted as key to underpinning the notion of BA (McAfee et al., 2012). Recent studies have extended this with characteristics such as veracity (Abbasi et al., 2016; Akter et al., 2016), *visualization* (Seddon and Currie, 2017), and *variability* (Seddon et al., 2017).

Nevertheless, effectively leveraging and transforming data into business value and actionable insights require companies to go beyond the technical aspects of data characteristics (Vidgen et al., 2017). Becoming a data-driven organization is a complex and multifaceted task requiring the transformation of multiple organizational resources with attention from several levels of managers. To address these challenges and provide guidelines for practitioners, scholars have introduced the concept of a *business analytics capability* to indicate an organizations' ability to leverage data for increased strategic and operational insight (Mikalef et al., 2018). Mikalef et al. (2018) define BAC as a firm's proficiency in capturing and analyzing data towards the generation of insights by effectively managing its data, technology, and talent.

Present BA research streams in IS have put considerable efforts into defining the building blocks, or resources, of a firm's BAC through the RBV. However, little is known about the orchestration process required to leverage these resources into a firm-wide capability (Mikalef et al., 2018). Specifically, a gap exists in explicitly addressing managers' roles and actions in effectively structuring, bundling, and leveraging firm resources through the ROV (Sirmon et al., 2011). Furthermore, efforts in BA research have primarily focused on the mechanisms through which it generates competitive performance while mostly disregarding the impact in areas of CE and sustainability. The review by Rialti et al. (2019) advocates for future research to explore the additional effects of BA capabilities apart from competitive performance. Despite interest in the role of BA for sustainable supply chain management, as seen in (Dubey et al., 2016; Hazen et al., 2016; Wang et al., 2016; Wu et al., 2017; Zhao et al., 2017) and circular supply chain management in (Gupta et al., 2019), there has been significantly less research on its role in leveraging a broader range of circular strategies. To date, most studies connecting the fields of BA and CE are in a nascent stage and offer only anecdotal evidence (Kristoffersen et al., 2020). Unsurprisingly, there are limited empirical work grounded on established management, IS, and CE theories (Lahti et al., 2018). Hence, it needs to be established, which factors of BA companies adopting CE should leverage, and how. For any data-driven business, this includes assembling, integrating, and deploying both tangible and intangible analytics-related organizational resources (Mikalef et al., 2018; Shuradze and Wagner, 2016).

Research methodology

Research design

Given the emergent state of the field, we employed an exploratory qualitative study to develop the first instance of an instrument to empirically investigate BA's contribution towards CE. Specifically, a construct for measuring firms' CE-specific BAC and a conceptual model with propositions for the mechanisms through which this capability improves competitive performance in terms of paths and mediating roles of CE implementation and resource orchestration capability. Utilizing the RBV and the ROV as the grounding theoretical frameworks, we employed a literature review in combination with semi-structured interviews (see Fig. 1 for the steps involved). Provided no previous

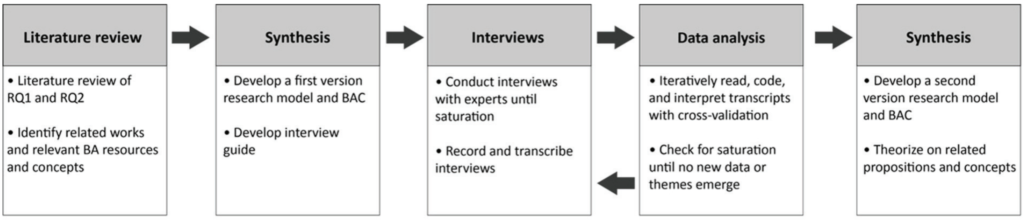


Fig. 1. Research steps.

measures of BAC for CE exist, it was necessary to conduct an exploratory qualitative study before any confirmatory quantitative studies can proceed. This was done in order to explore key concepts and their associations to ensure that no important concepts were omitted from further studies. It is also argued by several method studies that exploratory research should precede confirmatory quantitative studies, in order to explore the construct space and the intricacies of the concept being examined (Sarker et al., 2013).

We started by conducting a literature review with a focus on the critical aspects and organizational resources of a CE-specific BAC. The purpose of the review was to identify the main underlying concepts from related research streams in both BAC theory and CE theory. Based on this, we developed the first version of a theoretically guided conceptual model and BAC for CE (see Fig. 2 and Table 3 for the final versions). Following the literature review, a gap remained in identifying the dimensions of a BAC for CE and understanding how firms orchestrate these resources into capabilities. To address this, we employed a series of semi-structured interviews, following the guidelines of Bogner et al. (2009) and Patton (1990), with experts from key positions in industry. In this context, experts are defined as someone with privileged knowledge about the topic of interest (Bogner et al., 2009). The interviews were supported by an interview guide developed on the basis of the literature review and in accordance with the recommendations of Myers and Newman (2007). Semi-structured interviews represent an effective way to elicit rich data (Alshenqeeti, 2014; Kvale and Brinkmann, 2009), understand why some resources are more important than others, and under which conditions they are used for capability-building activities. The benefit of this approach, in contrast with structured interviews or quantitative approaches, is that it allows for thematic analysis and the discovery of new perspectives and relationships between topics that were previously not conceptualized Savin-Baden and Howell-Major (2013). This enabled, after the interviews, updating the initial constructs, definitions, and relationships in the conceptual model and through this the core organizational resources or building blocks of BACs. In particular, it allowed us to explore and refine the key concept of this study, the BAC for CE.

Data collection

Data were collected over a period of two months, from November 2019 to December 2019. Interviews lasted between 50–120 min and covered a total of 15 organizations (see Table 1 for details of respondents). The interviews followed a conversational style, opening with a general discussion about the company, CE, and BA before proceeding to more detailed questions on BA resources. Interviews were the primary source of data, in which the respondents' thoughts, opinions, and beliefs together with personal, firm, and industry experiences were captured. When necessary, clarifications and mining questions were used to encourage more detailed and accurate responses. All interviews were recorded and later transcribed according to the defined themes, as seen in Table 2 and Table 3.

Following the rationale of Sirmon et al. (2011) to develop a more robust theoretical perspective along with a wide representation of circular strategies, we employed purposeful sampling with snowballing to target experts from firms across variance in breadth (scope of the firm) and life cycle (stage of maturity), resulting in a total of 74 potential respondents. The extensive and diverse industry experience of the respondents allowed for several key strategies and decision areas of the CE to be represented.

Data analysis

The data analysis was performed through an iterative process of reading, coding, and interpreting the transcriptions Myers and Newman (2007). We employed cross-interview analysis along with the visual mapping strategy and the continuous comparison strategy (Eisenhardt, 1989; Patton, 2014). Firstly, following the open coding scheme by Yin (2017), concepts and factors were identified based on the theoretical

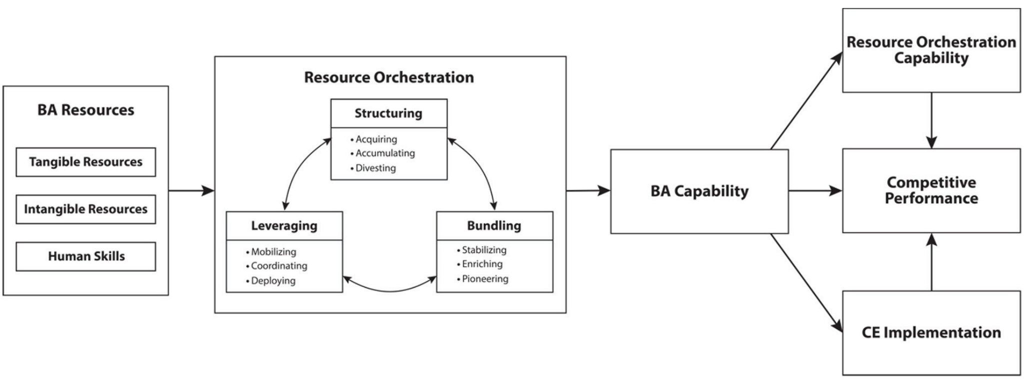


Fig. 2. Conceptual Model.

Table 1
Details of respondents.

Respondent	Role	Business area	Employees	Experience	Education
R1	Data scientist	Deep sea shipping (spot market)	3500	5 years	PhD
R2	CEO	IT services (product management)	12	13 years	MSc
R3	Director	IT services (blockchain protocol)	104	19 years	MSc
R4	CEO	Consultancy (IT and sustainability)	1	37 years	PhD
R5	Director	IT services (waste management)	4	24 years	BSc
R6	Director	IT services (advanced analytics)	40	15 years	MSc
R7	Manager	Renewables and environment	4000	14 years	BSc
R8	Director	IT services and infrastructure	150 000	23 years	PhD
R9	Executive	Consultancy (IT and CE)	30	23 years	MSc
R10	CEO	Consultancy (Sustainability and urban development)	1	22 years	MSc
R11	Manager	IT services (waste management)	23	15 years	BSc
R12	CEO	IT services (waste management)	6	23 years	BSc
R13	Service designer	IT services	150	12 years	MSc
R14	Executive	Civil engineering	21	31 years	MSc
R15	Executive	Retail	100 000	17 years	MSc

Table 2
Thematic support for the theoretical framework.

Concept	Source
Business analytics resources	
- *Business analytics resources* are stocks of tradable and nonspecific BA assets in the firm that can be divided into tangible (e.g., financial and physical resources), intangible (e.g., organizational culture and organizational learning), and human skills (e.g., employees' knowledge and skills) types.	(Mikalef et al., 2018)
Business analytics capability	
- *Business analytics capability* is the ability of a firm to mobilize and deploy BA resources effectively, utilize BA resources, and align BA planning with firm strategy to gain competitive advantage and improve firm performance.	(Garmaki et al., 2016)
Resource orchestration	
- *Structuring* is the process of acquiring, accumulating, and divesting resources to form the firm's resource portfolio.	(Sirmon et al., 2011)
- *Bundling* is the process of integrating these resources to form capabilities; it includes stabilizing, enriching, and pioneering activities.	(Sirmon et al., 2011)
- *Leveraging* is the process of exploiting the firm's capabilities and take advantage of specific market opportunities; it includes mobilizing, coordinating, and deploying these capabilities to create value. Resource orchestration capability	(Sirmon et al., 2011)
- *Resource orchestration capability* is the ability of a firm to effectively structure, bundle, and leverage the resource portfolio towards firm performance.	(Choi et al., 2020; Sirmon et al., 2011; Wang et al., 2020)
CE implementation	
- *CE implementation* is the degree to which a firm effectively leverage circular strategies for value creation and capture as relevant for the perspective of the firm.	(Bocken et al., 2016; Khan et al., 2020)
Competitive performance	
- *Competitive performance* is the degree to which a firm has superior performance relative to its competition in areas of operations excellence, customer relationship, and revenue growth.	(Rai et al., 2006)

underpinnings established from the literature review, as identified in Table 2. On this ground, we identified a large number of codes ranging from practices, tools, challenges, strategies, resources, enablers, and barriers. This allowed us to cluster the data according to themes using a tabular structure and grouping the data into high-level categories and analyze for internal homogeneity (coherence and consistency) and external heterogeneity (distinctive and representative with a clear connection to the research questions) (Miles et al., 1994). Through the application of visual maps and continuous comparison, the data were iteratively compared to the theoretical lens and existing literature to improve the conceptual model until saturation by no further data being added or new themes and concepts emerging Eisenhardt (1989). Satisfactory saturation was achieved after 15 interviews. To strengthen the credibility and validity of our findings, we cross-validated the analysis result between the authors and employed triangulation of sources, including secondary data such as firm websites and industry reports Tracy (2010).

Findings

Overall, our results corroborate the findings of related qualitative studies, such as the importance of holistic information processing and sharing for BA-enabled CE supply chains by Gupta et al. (2019). The role of BA is highlighted by all respondents as critical to the success of their organization's CE transition. The general consensus was that CE sets greater, and more holistic, demands for a firm's BAC. Consequently, several respondents argue that a broader definition of BA should be developed to reflect the triple bottom line (economic, environmental, and social value) of the CE, as was mentioned for instance by R10:

"There has to be a broader definition of analytics. Because right now, it is just based on financial analysis and profit return for shareholders and loose analysis without a lot of understanding of social and environmental impact. It is very important that BA is used more holistically. It cannot just be a single bottom line. BA has to include social and ecological value or impact."

Based on the results of the interviews, the initial constructs of BA resources from literature were adjusted, refined, and further developed to reflect the theories and practices of CE, as can be seen in Table 3. Following this, we visualized the results in five tables to summarize the evidence for each theoretical construct, improve the testability of the theory, and strengthen the bridge between the qualitative evidence and the conceptual model Eisenhardt and Graebner (2007). First, an overview is given in Table 4 of the BA resources respondents have implemented for CE. Following this, Table 5, Table 6, and Table 7 provide detail for each resource with subthemes, sample quotes, and key takeaways. Finally, Table 8 presents the results for resource orchestration, CE implementation, and competitive performance.

Business analytics capability

Considerable discussion concerned the issue of a separate BAC for the CE. While several parallels were drawn to preexisting BA resources, the respondents were unison in their response that effectively transitioning to the CE required new BA resources. In summary, eight BA resources were identified that, in combination, build a BAC for CE. In Table 4 the importance of each resource is noted, black circles (●) indicate that the resource was mentioned as an important aspect and/or implemented in the organization's strategy of using BA for CE, whereas half circles (◑)

Table 3
Definition of BA resources for CE.

Resource	Adjustments made	Adapted from literature (s)
Tangible		
- ***Data***: Organizations utilizing BA for CE need to capture both internal and external data from multiple sources, independently of structures and on a continuous basis. Further, aspects concerning data such as quality, sources, availability, and methods for curating needs handling.	Adjusted the content of the definition to comply with CE.	(Arunachalam et al., 2018; Gupta and George, 2016; Hedberg et al., 2019; Janssen et al., 2017; Kwon et al., 2014; Mikalef et al., 2017)
- ***Technology***: Novel digital technologies are necessary for handling the large volume, diversity, and speed of data accumulated throughout circular value chains. The complexity of these value chains increases the need for firms to deploy advanced data generation, integration, analysis, and sharing infrastructures.	Adjusted the content of the definition to comply with CE.	(Arunachalam et al., 2018; Gupta and George, 2016; Gupta et al., 2019; Hedberg et al., 2019; Mikalef et al., 2017)
- ***Basic resources***: Refers to an organization's investment of time and funds. This includes financial resources as direct investments in the support of these technologies and working hours allocated to experimentation with utilizing the potential of BA.	None.	(Gupta and George, 2016; Mikalef et al., 2017; Wamba et al., 2017)
Intangible		
- ***Data-driven culture***: Describes the extent to which organizational members are committed to BA and make decisions based on insight derived from data.	None.	(Arunachalam et al., 2018; Dubey et al., 2019; Gupta and George, 2016; Mikalef et al., 2019)
- ***Circular-oriented innovation culture***: Describes the extent to which CE goals, principles, and strategies are integrated into technical and market-based innovations to create value by enabling sustainable management of resources throughout the design of processes, products/services, and business models.	Identified the resource and developed the definition from relevant research.	(Brown et al., 2019; Gupta et al., 2019; Munodawafa and Johl, 2019; Pauliuk, 2018; Prieto-Sandoval et al., 2019; The British Standards Institution, 2017)
- ***Openness and co-creation***: Describes the extent to which organizational members are mutually open about decisions and activities that affect the society/economy/environment and willing to communicate these in a clear, accurate, timely, honest, and complete manner to enhance formal and/or informal arrangements internally and externally to create mutual value.	Identified the resource and developed the definition from relevant research.	(Gupta et al., 2019; Hedberg et al., 2019; Pauliuk, 2018; The British Standards Institution, 2017)
Human Skills		
- ***Systems thinking skills***: Refers to the competencies of employees to take a holistic approach for understanding larger contexts over longer periods of time, looking at connections and patterns of how individual decisions and activities impact environmental, economic, and social issues beyond the immediate first-tier scope.	Identified the resource and adjusted the definition from relevant research.	(Bocken et al., 2019; Gupta et al., 2019; Pauliuk, 2018; The British Standards Institution, 2017; Webster, 2013)
- ***Data science skills***: Refers to the competencies of employees to formulate and implement machine learning problems, utilizing data analytics skills such as statistics, computing, and knowledge about correlation and causation.	Identified the resource and adjusted the definition from relevant research.	(Dhar, 2013; Dubey et al., 2019; Gupta and George, 2016; Power, 2016)

and blank circles (○) indicates that it was only somewhat or not implemented. The absence of a circle signals a lack of insight by the respondent or relevance for the company. For instance, the tangible resources of R4 and R10 were both left empty as they represent a one-person consultancy firm.

Tangible resources

Generally, the type of tangible BA resources required for CE is similar to that of standard BA capabilities and the categories of data, technology, and basic resources presented by Gupta and George (2016). However, the respondents highlight that the increased lifespan of products, new business models, and the complexity of circular value chains sets different requirements for these tangible resources. For instance, R7 cites that increasing the lifespan of their products required additional life cycle data and more advanced analytics to estimate the products' remaining useful life. In addition, R3, R5, and R6 note that CE business models have a longer time period for their return of investment (ROI) and increased demand for upfront investment. Further, R3 explained that circular value chains are often more complex and involve multiple stakeholders, increasing the importance of having a holistic data collection and integration infrastructure in order to maintain a single-source-of-truth.

Data

Data itself was frequently cited as a key building block and its importance acknowledged by most all respondents (see Table 4 for details). From the analysis, we were able to identify three themes: single-source-of-truth, data quality and availability, and metadata preservation (see Table 5 for details). In general, the type of data needed to enable the CE was mentioned to be sector- and use case-specific. Nevertheless, having a standardized format for collecting location, availability, and condition data of products and materials throughout the supply chain, their life cycle, and across ownership transfers would be critical, as detailed by R2:

"The kind of data you need for the CE has information about the product

Table 4
Overview of outcomes on BA resources for CE.

Resources	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15
Tangible															
- Data	●	●	●		●	●	●	●	◑		●	◑	●	●	●
- Technology	●	●	●		●	●	●	●	◑		●	◑			◑
- Basic resources	◑	●	◑		●	●	●	●	●		●	◑			●
Intangible															
- Data-driven culture	●	●	●	●	●	●	●	●	◑	●	●	●	○	●	●
- Circular-oriented innovation culture	○	●	◑	●	●	◑	●	○	●	●	◑	○	◑	◑	◑
- Openness and co-creation	◑	●	●	◑	●	◑	●	●	●	●	●	●	●	●	●
Human Skills															
- Systems thinking skills	○	●	◑	◑	●	◑	●	●	●	●	◑	●	●	◑	◑
- Data science skills	●	●	●	●	○	●	◑	●		●	●		◑	●	○

Note: ○, Not implemented; ◑, Partly implemented; ●, Implemented

(what are the components, where are you buying and sourcing from, what are the materials, and so on).”

However, R2 notes that although collecting data is a mandatory step and enables everything else, it does not translate directly into value. R8 concur and note that:

“Data is an obvious important resource, not only for commercial aspects but for sustainability and CE in general. It is important that we collect data in order to operate these processes and concepts more efficiently.”

For the data to be useful, it needs to be trusted, for which respondents stressed the importance of data quality. Several solutions were presented on how to mitigate this challenge, such as R1, with their data quality framework of using ‘analytics on analytics’ to monitor the data with quantitative terms, catching problems, and visualizing the situation so that they can react swiftly. R4 also advised for collecting data as close to the source as possible to ensure it has not been tampered with. Further, R6 and R13 experienced that employing metadata preservation and visualization technologies were important to understand the context of the data and to ‘tell a story’ that people can trust.

Technology

Digital technologies and infrastructures were, by most all respondents, subject to large investments and focus. Overall, eight respondents reported to have implemented a satisfactory level of technologies, whilst three were partly satisfied with their current implementation level (see Table 4 for details). From the analysis, we were able to identify three themes: automated data collection, data integration and interoperability, and advanced analytics (see Table 5 for details).

Particularly, the respondents noted that the added complexity of CE value chains increased the need for automated data collection and integration. In general, the CE requires a shift from only looking at data from first-tier suppliers but also to second and third-tier suppliers. If this data is correctly managed and combined with advanced analytics, it can, for instance, prove vital for understanding and simulating alternative sourcing plans with details on how a change in material affects the whole supply chain. Furthermore, multiple respondents mentioned that circular strategies, specifically the ones involving services, were challenging to operate without advanced analytics software and high-resolution data with enough metadata to segment individual users and products. For instance, R5 shared their success in integrating gamification mechanisms in pay-as-you-throw business models for waste management:

“We have data with high resolution of each customer; this enables us to support different digital user experiences and communication strategies as well as add gamification and different tools of behavioral economics. We can make metadata from an individual customer’s recycling behavior available and, for instance, benchmark against the mean of the neighborhood to create behavioral incentives.”

However, R1, R5, R6, and R7 note that it is difficult to enable such advanced uses of analytics without having control of the basic technologies. R5 cite that one of their biggest challenge in implementing this solution was integrating all data points, vendor systems, and proprietary standards in a common cloud-based platform. R4 concur and note that:

“The challenge is to create infrastructures that are generic and static enough that you can support it with continuous update and new functionality without having to disrupt a large number of peer-to-peer nodes.”

In addition, R4 noted that it was important to include tools that better support the design of desirable systems dynamics of CE, such as STELLA (a systems thinking modelling package).

Basic resources

Financial resources were seen as imperative by most all respondents for the success of BA efforts for CE, with adequate funds reported for eight respondents and partly for three (see Table 4). From the analysis, we were able to identify three themes: non-value indicator, new costing models, and uncertain ROI and impact of lag effects (see Table 5 for details). Several respondents had experienced challenges with obtaining adequate funding for their efforts. Most all experiences could be traced back to a lack of top management buy-in due to the novelty of CE business models, lack of CE performance metrics, unclear ROI, and lag effects of circular strategies. Often, the lack of investment from top management could be linked to low systems thinking skills, resulting in a single bottom line where environmental and social value were not regarded as business success. R3 note:

“Top management buy-in is important; the challenge here is that they ask for ROI, which you often cannot provide upfront. Because the way you can get to a ROI is when you have indeed reshaped the business model by having brought all critical partners in the ecosystem together and shaping a scenario. It is a different approach; it is not plug-in solutions where you can come up with very clear indicators of success and monetary returns and ROI.”

Exacerbating this, the lack of key performance indicators (KPIs) to measure the progress towards CE was highlighted as a challenge. Meager improvements had been made by the respondents on this issue, and most based their calculations on crude approximations of resource optimizations, such as material intensity and amount of waste produced. However, the non-value indicator proposed by R4, when combined with automated pricing mechanisms and data collection, may prove fruitful as a pressure mechanism to incentivize companies to start sharing more data.

Intangible resources

The respondents mentioned that the CE sets greater demand for firms to collect, integrate, analyze, and share data across organizational boundaries, both upstream and downstream in the value chain. In terms of intangible resources, the general consensus was that this increases the

Table 5
Tangible resources subthemes, sample quotes, and takeaways.

Themes	Quotes	Key takeaways
<u>**Data**</u>		
Single-source-of-truth	R1: *"[...] consolidate all this information. We are working on having this in what we call a "single-point-of-truth" where anybody can access the data one is looking for, like lube oil consumption, fuel consumption, invoice, cost, savings, regulatory questions, health of an engine and onwards. And it is well presented, updated, and you can trust it."*	Data integration and availability is important for the data to be used and trusted.
Data quality and availability	R8: *"The biggest problem is in the quality of the underlying data. The tools and techniques are solid, so I think the biggest challenge is the availability and quality of data."*	Providing quality data is a bigger challenge than providing tools that use the data.
Metadata preservation	R6: *"You can easily get access to the data from different systems, but the system is created for different purposes than what we will use the data for. So, you often lose the context and the understanding of how data were created. The solution is metadata preservation."*	The lack of interoperability and preservation of metadata degrade the data quality.
<u>**Technology**</u>		
Automated data collection	R4: *"Automated process for moving data from one actor to another in the supply chain. [...] you have an automated approach for the core data for input products that carries the KPIs, and [...] you transfer what you could call the automated life cycle analysis result."*	Automating the collection of data throughout the supply chain could enable better life cycle analyses.
Data integration and interoperability	R9: *"It is critical to have data integration and sharing infrastructure, and it becomes more important when adopting a CE and it must happen throughout a product's lifecycle and the value chain in order for us as a society and economy to really realize the opportunities of circularity."*	Adopting CE requires more holistic data integration and sharing infrastructures.
Advanced analytics	R6: *"Without analytics, data is just data. What we want to extract is information, or even better, information for decision-making support. You need analytics to get the meaning out of the data and the context to tell a story so you can understand what to do."*	Analytics is critical for data to be interpreted, provide insights, and used.
<u>**Basic Resources**</u>		
Non-value indicator	R4: *"One vital KPI is the non-value indicator. What I mean is that is the lack of an indicator is an indicator in itself. If you see a product and if you have several sever information gaps in the product, that is an indication that you maybe should not trust it."*	The proportion of missing data is a valuable indication of integrity.
New costing models	R10: *"The total cost accounting model needs to be a critical foundation to any kind of digital tool or technology that can help really quickly analyze the impacts of producing something to the investor."*	The full lifecycle impact of a solution should be accounted for.
Uncertain ROI and impact of lag effects	R5: *"The investment in data collection infrastructure is expensive and uncertain, essentially to go from one paradigm to another, there is a lot of dark matter. The interesting thing is that you first discover the actual value of the data, long after it was collected. It is first when you can have the data that you can see the pattern. This puts up a challenge for the leaders and with investment."*	Lag effects and uncertain ROI make investments difficult and require a shift in mindset.

importance of trust, transparency, and collaborative relationships along with the need for organizations to foster both a data-driven and circular-oriented innovative culture to encourage change. Despite the importance of the aforementioned tangible resources, the respondents experienced a greater challenge with changing their work processes and organizational culture accordingly. Although many respondents illustrated great knowledge of the CE and a high degree of digital maturity within their organization, the intangible resources as culture, trust, and collaboration remained an issue.

Data-driven culture

Fostering a data-driven culture was seen as fundamental nearly all respondents for the success of BA efforts for CE, with 13 respondents reporting considerable efforts, as can be seen in Table 4. From the analysis, we were able to identify two themes: feedback loops and value-driven (see Table 6 for details). Although many respondents cited to have implemented advanced analytics in several of their company's projects, the vast majority reportedly struggled to effectively incorporate the extracted information in decision-making, as was mentioned for instance by R6:

"We have a tendency to take fast decisions, often on gut feeling. We are less experienced with being true to the organization's strategy, visions, and to work systematically with data. At the same time, we have a high degree of digitalization in general […], but our culture is a challenge, possibly one of the biggest."

R5 concur and note the importance of addressing both the technical and non-technical elements of becoming data-driven:

"The most important dimensions here is to create data-driven businesses and make decisions based on data. For this, you need sufficient data quality, and you have to change the culture in many organizations. One needs to address both the technical and cultural challenge of becoming data-driven."

Circular-oriented innovation culture

Concerning culture, there was a lot of discussion by the respondents on the potential of CE to heighten the data-driven culture to a value-driven culture. From the analysis, we were able to identify three themes: catalyst for change, open innovation, and CE as a source of innovation (see Table 6 for details). Overall, six respondents reported CE as important for innovation and had implemented measures to adopt a supportive culture whilst an additional six were only partly convinced

Table 6
Intangible resources subthemes, sample quotes, and takeaways.

Themes	Quotes	Key takeaways
Data-driven culture		
Feedback loops	R8: *"We are very much concerned with what we call feedback loops, we are interested in gathering signals on how our customers are using our technology to give feedback to the next generation of the product. We also do the same for our employees to figure out what works and what does not, where can we improve how our processes are working. We think of all this as feedback loops where we gather data, process, and analyze it to figure out how we can improve. We are very aware of this and how we control it."*	Using customer and employee feedback data to drive strategic decision-making improves organizational learning.
Value-driven	R10: *"I do see a more sophisticated use of data within the culture of organizations, but I do not think it will ever supplant value-driven culture from leadership. The mission and value of the organization should override the data-driven culture or make specific use of that data for a purpose."*	Pairing the data-driven culture with value-driven leadership is critical.
Circular-oriented innovation culture		
Catalyst for change	R7: *"Our CE vision is clear, both at a top strategy level and for individuals. It required a re-branding process, not by changing logo or anything, but changing our expression and communication. […] We have also made recruitments. The new people are employed based on our new expression and vision, which in itself has a catalyzing effect. The CE is a catalyst for change."*	Incorporating a CE vision throughout the firm is effective for stimulating change and making recruitments.
Open innovation	R3: *"A lot of our innovation lies on the edge of each vertical, it is when you cross each vertical that you get the potential. You need to cultivate a culture of open innovation, which is quite transformative for some organizations, but you could argue it is a cultural approach to see how you build value for the company with surrounding stakeholders."*	Crossing verticals and including multiple stakeholders trigger innovation.
CE as a source of innovation	R11: *"In our organization, our people definitely understand what the CE means and the opportunities it brings. It is definitely an innovation opportunity because, for instance, you are looking for different materials that is changing the line of production and business in the company."*	The CE brings new value propositions that spark innovation.
Openness and co-creation		
Data sharing	R5: *"One of the core challenges with the CE, is to be able to share and distribute data internally and externally. Most companies are not able to effectively share data internally and are reluctant to share data externally and with the environment. If one is to succeed within CE, you have to open up these models, but in a way that safeguards the actors in the supply chain."*	The CE requires more and new models for data sharing that safeguards the actors.
Removing silos and internal alignment	R10: *"It absolutely requires tremendous more collaboration internally and externally. The majority of companies are very siloed in their management regimes, and there is so much deficiency because of that and not a lot of understanding of synergies between different departments, people do not see the patterns or the interconnectedness or interdependencies. Lose sight of those and we lose value. I think assessing the organizational structure is really critical to identify where that collaboration leads to more value."*	Removing silos and encouraging more internal collaboration reduce deficiencies and the increase value potential.
Collaborative relationships	R3: *"What is underneath the CE is that you have to work in cooperative modus. Thus, orchestrating this ecosystem and collaborating becomes a vital success factor. This seems to be contradicting the competition mindset, but there is something about it. You have a digital enablement, but as an organization, you have to complement this through co-creation methodologies and facilitation."*	Collaborating and co-creating across firms are vital success criteria for the CE.

(see Table 4 for details). In contrast, three respondents mentioned that the CE did not drive their culture or innovation processes as a result of either counteractive compliance rules or regulation, low market readiness, or low CE concept maturity, as for instance mentioned by R12:

"I do not think the CE concept has enough of a foothold to directly influence how we operate. It will only be indirect, it is clear that a lot of the things we wish to do is connected to the sustainable development goals and what the customer want to do, but it does not drive us directly."

However, if incorporated, the value-driven vision of the CE can provide better purpose to digitalization efforts of the organization, leveraged through data-driven insights and decisions. For instance, R13 note that by, firstly, regarding CE as a source of innovation, one can turn circular strategies into hypotheses which in turn are used as questions for data collection and analysis:

"We have been trying to work within hypothesis-driven development. Essentially, you have a decision and a direction you want to go, let us turn this vision into a hypothesis and let us test it. This has been a very useful method. […] So instead of starting with what data do we have, start with what do you actually want to know. Essentially, figure out what are the key questions your company needs answers to now, and then whether we have the data for those answers and only look at that, not everything else."

Table 7
Human skills resources subthemes, sample quotes, and takeaways.

Themes	Quotes	Key takeaways
<u>Systems thinking skills</u>		
New criteria for success	R3: *"That is one thing we see, that those that are too short-termist asking for ROI, clear black numbers before taking action will probably end up disrupted in some industries. [...] You need to open up the company and go beyond just ROI for shareholders and bring in new indicators of success."*	Expanding the criteria and horizon for business success is important to remain competitive.
System dynamics	R4: *"They will need to utilize these additional tools, mainly the system dynamics to understanding their own processes because BA without yourself understanding what your organization is, the processes are and the consequences to different actions are, is useless. So, you have to build up a foundation of system dynamics thinking where you understand your own business."*	The capacity to utilize system dynamics tools is helpful in understanding the organizations processes, impacts, and role within the system.
Shifting mental models	R10: *"The big thing here is that the CE is a big mental model shift to how one should work through the world. That is the big tipping point; you have to have the right mental model, framework and governance before you can apply it effectively."*	Shifting the mental model to include a systems view of the organization is critical in order to facilitate the CE effectively.
<u>Data science skills</u>		
Tacit knowledge management	R5: *"The challenge is to combine the human inputs with what is machine-readable data. We have done this by systematically collecting this operational insights and fed this as background data for the algorithm to make better decisions. This is an example of the human-machine interface where you systematize the tacit knowledge of humans."*	Translating and combining tacit human knowledge with machine-readable data is crucial for developing analytics for decision-making support.
Data visualization	R10: *"It is crucial with data science and data visualization and interpretation of large quantity of data, not big data, but like edge data."*	Mastering data visualizations skills are essential in order to interpret large data sets and core to data science.
Setting goodness requirements	R1: *"Good stable requirements are difficult and require people to know what they want and getting exactly that. For the goodness requirement, we do not have a good solution. If you don't know what you want, asking you to write what you want is like looking for bacon in an empty fridge. If you don't have good requirements it is a long and difficult process."*	Domain knowledge and analytics and business understanding are important in order to set appropriate requirements for algorithm development.
Explainability	R8: *"Well, I think our leaders are quite good in using these tools and techniques. In general, I think they are good at communicating the outputs and understand the nuances in the data produced by analytics."*	Understanding the nuances of analytics is important in order to effectively communicate its outputs.

Table 8
Key quotes for resource orchestration capability, CE implementation, and competitive performance.

Themes	Quotes	Key takeaways
<u>Resource orchestration capability</u>		
Structuring	R5: *"You need to expand the overall skillset within the organization in order to recruit and address a series of new challenges, and they have to collaborate more interdisciplinary. You need to be both a human and technical leader and have the ability to project future technology trends and hit at the right time, because the cost of investing in legacy systems is very high, but also the cost of being too early is very high. So, you need to be able to target when the technology is sufficiently mature whilst not incurring technical debt."*	Addressing the challenges of BA and CE requires procuring new talent and resources at the right time to ensure competitiveness whilst not incurring technical debt.
Bundling	R5: *"The investment in data collection infrastructure is expensive and uncertain, essentially to go from one paradigm to another, there is a lot of dark matter. One thing to consider is that there's already been produced a lot of data, but that in an analytics context can be used in a different manner, essentially the repurposing of data. The interesting thing is that you first discover the actual value of the data, long after it was collected."*	Before acquiring new data resources, an assessment should be made if existing data sets within the firm can be bundled or enriched to fit the need.
Leveraging	R13: *"Having access to data and the facts have been a very helpful tool to answer the question of 'why are we actually doing this?' Just saying 'it is good for the world and times are changing' can be quite abstract, but with BA we can make it more concrete and how it can actually create value for the company."*	BA makes CE efforts more concrete and easier to understand, increasing strategic value and market opportunities.
<u>CE implementation</u>		
Net positive impact	R9: *"They understand from both a positive benefit standpoint as well from a negative cost, either financial, reputational, indirect or social. They realize the importance of these impacts."*	The wider effects of CE have a positive impact on business operation.
Brand reputation and differentiation	R10: *"CE brings corporations an advantage. It gives clarity for the community or customers you are engaging with or the government that you have an authentic commitment beyond business as usual. You are a different thinker*	CE increases customer and stakeholder relationships.

(*continued on next page*)

Table 8 (*continued*)

Themes	Quotes	Key takeaways
	if you are engaging with the CE."	
Competitive performance		
Improving planning	R1: *"Where we can create a competitive advantage is by improving planning, and we will do this through BA by improving transparency. […] essentially making better and more informed decisions. Knowing where you are, knowing where it hurts. The thing I would downplay a bit is BA's ability to predict. Being able to plan ahead, that is a competitive advantage."*	BA provides an enhanced ability to predict and plan ahead, improving firms' operations excellence.
Recruiting and retaining talent	R6: *"I think it is all about getting hold of and keeping the best individuals and be true to their own values. Today, it is a stronger demand by employees to identify oneself with the company and have good corporate values and their contribution to society. The focus should not be to only make money, because this does not motivate people. There is often a mutual gain that the organization gets to keep their employees (which again gives profitability over time). Finding this intersection will be very beneficial."*	CE strengthen firms' corporate vision and improves their ability to recruit and retain talent, promoting operations excellence.
Increased diversification and reduced risks, inefficiencies, and cost	R10: *"If you do it intelligently, it also saves you money and adds more value to what you are building or creating. It also brings a unique procurement ecosystem and partnership arrangements with other corporations."*	CE enables the reduction of risks and costs through diversification whilst providing new value propositions promoting firms' revenue growth.

Openness and co-creation

An MIT Sloan Management Review by Ransbotham and Kiron (2017) highlights that companies that share data and collaborate more intensively tend to be more innovative. Similarly, nearly all respondents reported having implemented measures to become more open as a firm and improve co-creation by increasing trust, transparency, and collaboration (as can be seen in Table 4). From the analysis, we were able to identify three themes: data sharing, removing silos and internal alignment, and collaborative relationships (see Table 6). Further, many respondents saw a close relationship between being data-driven and their ability to innovate for the CE. While CE requires an overall redesign of products, processes, and business models, it also demands companies to rethink their value chains and the degree to which stakeholders are involved. The respondents recognized that no single company could transition to the CE alone and pointed to the need for increased data sharing, collaboration, transparency, and trust internally and externally. Several respondents noted that external collaboration and co-creation was more difficult due to a lack of transparency and trust in the value chain, re-emphasizing the need for a single-source-of-truth and good data quality throughout. However, R2 mentioned that due to the novelty and lack of awareness of CE and sustainability, internal collaboration was, in fact, more challenging than external:

"Collaboration within one company is more important and to some degree even more challenging than collaboration between companies. It is easier for two sustainability directors of two different companies to collaborate than it is for a sustainability director to collaborate with a compliance director for example."

Table 9
Quality evaluation.

Criteria for quality	Methods and tactics used
Worthy topic	Utilizing BA for CE is an important topic of timely concern with significant relevance to research, industry, and policy.
Rich rigor	The study used rigorous theoretical frameworks (RBV and ROV) to ground the research.
Sincerity	The study is transparent about the methods used and tactics used to arrive at identified themes and concepts. The authors are reflective about their subjective values, biases and inclinations.
Credibility	The research is marked by concrete details and examples of how the data has been interpreted in the analysis. Triangulation of sources and cross-validation between the authors is employed.
Resonance	Based on thick descriptions of the themes identified with several graphical and tabular representations, transferability of findings is achieved.
Significant contribution	The research provides significant contributions of both academic and practical use. Propositions for future studies is provided and testing of the proposed conceptual model is possible.
Ethical	Appropriate ethical considerations were made throughout the interview process to ensure respondents about their anonymity and data protection rights.
Meaningful coherence	The study employs appropriate methodologies to reach its stated goals in the research questions and provides meaningful connections to extant literature and calls for action.

Human skills

Closely related to intangible resources, human skills were credited as being a crucial factor by most all the respondents in this study, but difficult to acquire. Effectively leveraging BA with circular strategies reportedly requires a different skillset for humans to master both the technical aspects of BA together with the system dynamics of CE through systems thinking skills. Thus, central to improvements of both tangible and intangible resources are managers with systems thinking skills and analytics acumen, as was mentioned by R9:

"Human skills are very important in terms of building those relationships within a value chain that has to be in place in order to able the flow of data necessary to close loops and design products differently. On the management and executive side, that is very much critical, because the idea of redesigning products' lifecycle to be circular is not something that can happen in one department of the firm. It is very much a large-scale effort that requires teams from design, procurement, EHS, waste management, etc. Where you need to have a management buy-in to be able to bring those internal teams together and show this is a priority as well as working on the outside on the value chain side with upstream suppliers as well as downstream customers."

When examining the human skills required for leveraging BA for CE, two primary resources were identified. The first was systems thinking skills, mainly encompassing a shift in managers' mental models in order to set new criteria of success and utilize tools for system dynamics. The second were data science skills, encompassing the requirements of technical-oriented roles for developing analytics models and more business-oriented roles to communicate requirements and the results of these models.

Systems thinking skills

Fourteen respondents cited efforts in developing systems thinking skills within their organization. However, only eight respondents reported that their managers showcased a satisfactory level of this skill, as can be seen in Table 4. The remaining respondents mentioned that most managers were not looking at the broader system that their organizations were operating in. Instead, many managers were rather focusing on smaller pieces of the system and optimizing them. From a CE perspective, this is often noted as focusing on efficiency rather than effectiveness and is often an outcome from working in silos. From the analysis, we were able to identify three themes: new criteria for success, system dynamics, and shifting mental models (see Table 7 for details). Together, these themes corroborate the general consensus of the respondents of the importance of systems thinking for CE implementation. R9 explains this by comparing the skill of systems thinking to the human vision:

"If you take the idea of your vision analogy, if you are looking at a linear product and only worry about price, performance, and esthetics. You are taking a very narrow front view. If you are trying to look at the unintended consequences and the hidden impacts and opportunities of a CE, you have to bring in your peripheral vision too."

Despite many respondents reporting a high level of systems thinking within their organization, actions were often still missing, suggestion knowledge of the CE and its implication is not enough as R2 note:

"Knowledge of it is not as important that acknowledgment that it is a central part of their job description. That is a bit of a problem."

Data science skills

Possessing, or having access to, analytics development talent is fundamental for organizations' capacity to realize the opportunities of BA. Overall, most all respondents cited having sufficient talent and skill within their organization, as can be seen in Table 4. From the analysis, we were able to identify four themes of: tacit knowledge management, data visualization, setting goodness requirements, and explainability (see Table 7 for details). With data science being a multidisciplinary field, often requiring extensive domain knowledge, managing tacit human knowledge together with machine learning algorithms was mentioned as particularly important. For instance, R7 explains how they combine hardware and reliability knowledge with machine learning skills to implement predictive maintenance:

"We see a need to shift more towards predictive maintenance. We are quite reliant on hardware and there will be parts that degrade and break. […] to be able to predict when a part might break so we can service it in advance has great value for us and our customers. […] we use all our domain knowledge and data on machine learning to get this up and running."

Furthermore, R5 highlight that it is crucial for data scientists to remember that you need an overall vision and to put the data into a context since it is not given that the most important insights are present in the dataset you are given:

"For those that are developing the algorithms, it requires a level of proactive thinking. It is important that leaders develop these individuals sufficiently and communicate this further."

Furthermore, as CE proposes a new paradigm for value generation and business model design, it sets greater demand for innovation and data on how these new products and services are operated. This increases the general demand for analytics acumen and particularly individuals mastering both the complex business landscape of CE and the technical challenges imposed by analytics, as for instance mentioned by R6:

"The combination of business and technical skills is difficult. It is also hard to find technologists that know business well. […] the leaders of tomorrow will need better knowledge of analytics and need the ability to understand how to use it. It is more a tool to ask good questions rather than finding the right answers. It is a new way of thinking."

However, only eight respondents experienced that their managers effectively communicated both the requirements for developing analytics and the outputs generated from the analysis, as can be seen in Table 4. R1 mentioned that their managers did not see the direct benefits of analytics and did not have a suitable educational background to become efficient at it.

Leveraging business analytics for circular economy

Resource orchestration capability

According to RBV, resources that possess VRIN attributes (as the ones detailed above) tend to provide better opportunities for competitive performance (Eisenhardt and Martin, 2000; Mata et al., 1995). However, our findings corroborate previous studies arguing that merely possessing such resources without leveraging them is counterproductive for the firm Ahuja and Chan (2017). To this end, ROV argues that resources have to be structured, bundled, and leveraged in order to create new capabilities and enable them to generate business value (Wright et al., 2012). Once these capabilities have been internalized, they are difficult for competitors to imitate.

Overall, we observed a great discourse amongst the respondents on the importance of leveraging firms' BA for CE and competitive gains. In particular, managers were highlighted as crucial to the potential success, or failure, of developments under tangible resources and human skills, such as culture development and employee training. Given the variance in breadth and life cycle of the firms' covered (e.g., from waste management start-ups as R12 to large multinational IT service corporations as R8), the respondents experienced a difference in the approach and willingness of management to both adopt circular strategies and prioritize corresponding BA investments. This can be understood by drawing on the life cycle logic of the ROV which states that the start-up stage requires a greater degree of resource-structuring behavior to support the firm's business model when compared to firms in the mature stage (Miller and Friesen, 1984; Sirmon et al., 2011). Correspondingly, a mature firm's resources may exert a greater influence on its external environment (Smith et al., 1985). Despite variance in organizations' operating environment and development trajectory, the underlying capability development mechanism was conducive to the process of structuring, bundling, and leveraging, as detailed in ROV. However, the granularity of our data did not allow for the respective sub-processes to be fully identified, for instance, such as stabilizing, enriching, and pioneering for bundling.

Structuring

Corroborating the results of Wright et al. (2012), the selection and structuring of BA resources was seen as an important prerequisite for building a firm-wide BAC. Overall, the respondents reported numerous related activities, from identifying resources of strategic importance and making investments related to them (e.g., sensor data and data science talent) to creating new organizational structures and business models (e.g., horizontal departments and product-service systems). Despite receiving great attention to the importance of CE, some respondents cited several challenges related to the lack of top management support and willingness to acquire new resources. This was, for instance, the case for R3, where it could be traced back to lacking systems thinking skills of the managers, which in turn resulted in missing structuring behavior within the firm.

In contrast, R7 cited that both their top and lower management experienced great systems thinking skills and had recently started repositioning their firm towards a Smart CE. Correspondingly, the firm had made substantial investments into accumulating new digital technologies, recruited a new horizontal department of 10 CE experts, and divested in hardware-specific knowledge. However, despite their efforts, they still experienced challenges with effectively leveraging their new strategy at large, suggesting more focus should be put towards bundling their newly sought resources with existing ones to form new capabilities. R7 note:

"One internal challenge we have is connected to our history as a hardware producer. We have produced hardware with a great deal of customer

customization. This has given us great customer experience and appreciation, but now when we not only have software on the hardware itself but in the cloud, then all this hardware customization works against you. We have a large task to streamline our portfolio."

Bundling

Overall, the process of effectively bundling resources into capabilities was frequently reflected in the firms' governance practices, and choice of IT archetypes. Most respondents cited their current archetype and operation as functional silos where each unit handled its own resource allocation. However, this archetype was seen as somewhat incompatible with the lateral nature of circular strategies, and several efforts were suggested to remove unnecessary silos and align around common KPIs, as mentioned by R1:

"The main challenge we have is to align internally around KPIs. [...] sometimes we speak the same language and want the same things, sometimes we want the opposite things. Internally this is a major challenge because you try to strike a balance as you have to make someone else's KPI worse and yours better, and this is not good. [...] you need to have an honest discussion to make the best outcome. [...] it is management setting the direction and then a clear communication process taking into account the local flavor that irons out any disagreements or problems that might stand in the way."

Further, closely related to the intangible resource of trust, transparency, and collaborative relationships are the general consensus of the need to operate within an ecosystem in order to realize the value of CE. From the ROV, this can be seen as enriching internal capabilities with external capabilities to offer bundled services as a partnership between the firm and its suppliers, partners, and even competitors Ahuja and Chan (2017). Similar logic can be found in the literature on net-enabled business innovation cycles and value co-creation (Lenka et al., 2017; Zahra and George, 2002). Hence, bundling capabilities may result in increased customer value and provides more flexibility and options to the resources and capabilities offered by the firm, thereby making the overall value chain more robust against the competition, as for instance mentioned by R3:

"To be competitive in the future, you need to be part of this ecosystem or proactively shape your ecosystem. So, you shift from being value chain driven to value web or ecosystem based. The better you are at shaping or orchestrating your ecosystem to serve your purpose, the better you will be fit for the new environment. That is probably how companies that are not acting now will be disrupted because they are still functioning in a value chain approach, whilst what they really should be doing is repositioning themselves towards an ecosystem."

Leveraging

All the respondents were conscious that once the BA resources had been appropriately structured and bundled into a capability, it needs to be effectively leveraged in order to yield value. Nonetheless, many respondents reported challenges with effectively deploying this newly developed capability to capitalize on the investments and efforts made. For instance, an overall uncertainty was observed on how to mobilize such a capability to i) adopt an acceptable level of CE, ii) outperform rivals in the short term, and iii) maintain a competitive advantage in the long term. Many respondents pointed to this being a result of lacking market demand, internal awareness, and the overall fast-moving pace of the field. In other words, this can be summarized as environmental uncertainty, which can be defined as a general condition of ambiguity and unpredictability of customer needs and technology developments Pavlou and El Sawy (2006). According to the ROV, this can be understood as an information deficit that affects the type of resources and capabilities needed to outperform rivals and the leveraging strategies required to realize a competitive advantage (Sirmon et al., 2007). The respondents credited CE with strategic relevance for reducing overall risks and for building the material sourcing flexibility needed for a turbulent business environment. However, the respondents cited difficulties with generating societal value and evaluating the impact of their efforts, as for instance mentioned by R6:

"What is difficult is to take the last step from business value to social value. You have to think long enough for the business cases you create. You can easily evaluate the effect of a single solution, but what is difficult is evaluating the overall effect because you have a self-reinforcing effect over time that is exponential. But it takes time to measure it, and it takes time to change the behavior of humans."

Circular economy implementation

In line with the growing interest for sustainable solutions by researchers and industry alike, the respondents demonstrated a general consensus on the strategic importance and business opportunities of transitioning to the CE. Throughout the interviews, a number of prospective circular strategies leveraging insights from BA were presented, such as identification of optimal life cycle extending activity and timing of interventions for reduced production downtime through predictive maintenance, simulation of economic and environmental impacts in different life cycle scenarios, automated triggering, and scheduling of reverse logistics requests, optimization of product use for minimal product wear and degradation.

Furthermore, many respondents highlighted that they experienced an increasing number of firms making great strides to incorporate the UN Sustainable Development Goals, for which the CE could prove beneficial in generating business value from these efforts. From the analysis, apart from assisting with general competitive performance, were seen to improve firms' brand and reputation, provide new differentiation strategies, and had an indirect positive benefit for firms through social and environmental impacts (see Table 8). However, most all respondents experienced challenges with effectively scaling circular strategies because of barriers outside of the organization, such as:

- Lack of common reporting standard and database
- Missing regulatory alignment and CE frameworks
- Imprecise pricing of environmental externalities
- Conflicting micro- and macroeconomic targets for the CE

Competitive performance

Considerable discussion concerned the potential of BA and CE to increase the overall competitive performance of the firm. Notwithstanding the numerous comments on business value made throughout the findings, three themes, or leverage points, were found to be particularly relevant in improving firm performance and gaining a competitive advantage. First, gaining foresight and the ability to predict possible future outcomes for improved operational and strategic planning was seen as one of the main competitive drivers for investing in BA. This was repeated throughout most interviews and unfolded both in the choice of KPIs and goodness requirements. Second, the overall vision and societal contributions of the CE were seen to boost firms' appeal for new talent, both directly reducing costs for high employee turnover rates and operational excellence through attaining highly sought-after talent. Third, the unique procurement ecosystem and partnership arrangements enabled through the CE was seen to help firms diversify their portfolio and supply chain dependencies, reducing risks, inefficiencies, and cost.

Conceptual model

To structure our understanding and inform future studies on how BA can be leveraged towards CE, we synthesized our findings in a conceptual model (as seen in Fig. 2). The underlying logic of our model incorporates resource-picking (from the RBV) and capability-building (from the ROV) theory to demonstrate: i) how core BA resources are directly orchestrated through structuring, bundling, and leveraging activities into a BAC, and ii) how the hypothetical causal chain of the effects of BA on competitive performance is mediated through CE implementation and resource orchestration capability. As such, we theorize that by developing a strong BAC, firms are in a better position to strengthen existing circular strategies, implement new ones, improve their resource orchestration capability, and enhance their competitive performance. As such, the effect of BAC on competitive performance can be seen as a mediating effect by firms' resource orchestration capability and their degree of CE implementation. Support for this can be found in related empirical studies on the effect of BAC for improved sustainable supply chain management and circular strategy implementation (Dubey et al., 2016; Gupta et al., 2019; Hazen et al., 2016; Wang et al., 2016; Wu et al., 2017; Zhao et al., 2017). Accordingly, similar to studies on internal capabilities for realizing innovation and driving competitive performance (Barney, 1991; Chadwick et al., 2015; Chang, 2018; Sirmon et al., 2007), BAC can improve firms' resource orchestration capability. As such, BAC may reduce the risk of investing in CE implementation, increasing the overall effect on competitive performance.

Discussion

Correctly managing BA resources will be central for firms when navigating the CE transition and may even prove vital for obtaining a competitive advantage in this new business landscape. The impact of such as transition will far outreach mere financial gains for firms and can ultimately contribute to sustained environmental and social gains towards sustainable development. The respondents reported great strides being made by their firms and competitors in utilizing BA to connect material and information flows. This suggests competitive gains to be achieved by effectuating such a connection. Based on this, we theorize that the future control of the data translates to control of the material and subsequent market shares.

However, to reap these benefits, firms have to go beyond sheer incremental efficiency gains and take a holistic view of their firm and its value chain, re-assess both upstream and downstream impacts, and expand their criteria of business success. This requires firms to restructure existing organizational resources, make relevant recruitments and investments, and cultivate a new organizational culture of data-driven decision-making for circular-oriented innovation. While parallels can be made between the BA resources required for supply chain management and CE, the latter differs in particular on the degree of systems thinking skills required. Circular strategies span beyond the traditional supply chain and require a broader understanding of the context of the firm over a longer period of time. Companies need to look at new connections, patterns, and relationships throughout their value chain and increase their degree of data collection, integration, and sharing. While our work builds on previous related works from BA and CE theory, several additions and adjustments have been made towards the description of a firm-wide BAC for CE, as can be seen in Table 3.

Research implications

Effectively leveraging the hype around big data and BA is highlighted as pivotal for the operationalization of the CE. While practitioners seem to be leading the way for such novel uses of data, academics have only recently begun to investigate the synergies of BA and CE (Gupta et al., 2019; Kristoffersen et al., 2020). Consequently, gaps remain in the literature on defining the building blocks of a BAC for CE and how firms can create one. From a theoretical perspective, our study contributes both to the emerging literature on CE and strategic management literature on BAC and managers' role in resource orchestration (Ahuja and Chan, 2017; Kristoffersen et al., 2020; Lahti et al., 2018; Mikalef et al., 2018; Rialti et al., 2019; Sirmon et al., 2011). In particular, this work extends the Smart CE framework proposed by Kristoffersen et al. (2020) by providing empirical insights into the key organizational resources and practices needed to leverage the Smart CE.

Moreover, this study makes important contributions to the existing literature in five main areas. First, we propose eight constructs, as shown in Table 3, that make up the key resources of this capability. These constructs provide valuable insights for future studies by offering a lens to analyze both qualitative and quantitative data. Second, we further extend the ROV by explaining how the processes of structuring, bundling, and leveraging influence the conversion of organizational resources into firm-wide capabilities along with the effect of variance in firms' contexts. Third, we explore the role of managers for supporting these processes along with how their efforts interrelate to the resources present in the organization. Fourth, we provide a deeper understanding of how organizations leverage this capability to transition towards the CE and realize a competitive advantage. Finally, we present a theoretically grounded conceptual model to inform future quantitative studies on how to examine a BAC for CE, seen in Fig. 2. This extends the literature on RBV and ROV by combining them with BA and CE literature and empirical insights.

Practical implications

In terms of practical implications, managers may find this research useful in three main areas. First, to seek inspiration on how BA can leverage their organization's CE transition by i) understanding the conceptual relationship between BA, CE, and competitive performance (as seen in Fig. 2) and ii) gather insights from the experience of the respondents. Circular strategies supported by BA represent a new form of value creation and innovative and forward-looking business models. While practitioners may be paving the way in several new uses of analytics towards more sustainable business strategies, they lack support and examples of how to systematically innovate existing business strategies with BA and CE (Kristoffersen et al., 2020). Second, identify which artifacts, or organizational resources, are important leveraging BA for CE (as detailed in Section 4.1). As firms reposition and restructure their organization to meet new market and governance demands for sustainable operation, priorities have to be made that will be decisive for the future survival and competitiveness of firms. Hence, correctly identifying which resources to invest in and capabilities to build will be crucial. Third, understand how to appropriately structure, bundle, and leverage their organizational resources to build a firm-wide BAC to i) leverage their organization's CE transition and ii) realize competitive performance gains (as detailed in Section 4.2). As covered extensively in strategic management theory, only acquiring and holding resources of strategic relevance does not directly translate into competitive gains in itself. The resources first have to be appropriately managed to form firm-wide capabilities, which then needs to be effectively leveraged and deployed. Organizations may find this work useful for understanding how such a process can be orchestrated together with the role of managers for facilitating change.

Limitations and future research

This study is an early attempt to detail the organizational resources required to leverage BA for CE. As such, the work is not without limitations. First, while our purposeful sampling technique was successful in covering variance in breadth and life cycle of the firms, given the limited scope of our study, we were unable to cover variance in depth (levels of hierarchy) within the firm. This can, for instance, be addressed through an in-depth multiple case study with interviews of multiple levels of managers from the same firm, increasing the overall transferability of this work. Second, we recognize more longitudinal studies would be required to better understand and explicate how differences in firms' environmental uncertainty and the life cycle stage affect the structuring, bundling, and leveraging processes of resource orchestration. Further, while these processes can occur at the operational, tactical, and strategic levels in the firm, it is important to note that no such differentiation was made in this study. Third, we would like to emphasize that the conceptual model and constructs presented in this study were uncovered on the basis of 15 expert interviews. While this is a starting point, it can by no means be confirmed through a single qualitative analysis of such a sample. Addressing this, a large-scale quantitative analysis could be performed to test the validity of the constructs and generalizability of the conceptual model. This could also provide more granularity of the presented constructs and shed some light on the impact of contextual factors when leveraging BA for CE. Our propositions, to be tested empirically in future studies, are summarized below:

- Proposition 1: The resources identified are positively related to a firm-wide BAC for CE.
- Proposition 2: The structuring, bundling, and leveraging processes are positively related to forming BA capabilities.
- Proposition 3: The BAC identified is positively related to increased CE implementation, resource orchestration capability, and competitive advantage.
- Proposition 4: The effects of BA on competitive performance is mediated through obtaining a CE implementation and resource orchestration capability.

Building on the theoretical underpinnings and rich insights into the factors described in this study, the authors firmly believe that these issues may hold merit in contributing to future studies. The Smart CE strategies and enablers mapped by previous literature along with the empirical findings of this study clearly outline the novelty and pre-paradigmatic nature of this research stream. Hence future qualitative and quantitative studies should target the cause-and-effect relationship between BA and CE to leverage the transition towards sustainable development.

Validity and reliability

The amalgamation of the quantitative paradigm with qualitative research through validity and reliability have changed the traditional meaning of these terms and what constitutes quality research from the qualitative researcher's perspectives Golafshani (2003). Quantitative and qualitative studies are different in nature, while the former generally has a purpose of explaining, the latter has a purpose of understanding. This difference in purposes makes evaluating the quality of studies in quantitative and qualitative research dissimilar, Stenbacka (2001) even argues for the concept of reliability to be irrelevant and misleading in qualitative research. Similar arguments can be seen for the term of validity, but at the same time, qualitative researchers realize the need for some criteria of quality measures of their research Creswell and Miller (2000). As a result, several concepts for assessing the quality of qualitative studies have been proposed, such as credibility, neutrality, consistency, transferability, rigor, and trustworthiness (Davies and Dodd, 2002; Lincoln and Guba, 1990; Seale, 1999; Stenbacka, 2001). To discuss the validity and reliability of our study, we utilized the eight "big-tent" criteria for excellent qualitative research by Tracy (2010) (as seen in Table 9). The eight criteria are: worthy topic, rich rigor, sincerity, credibility, resonance, significant contribution, ethics, and meaningful coherence. These markers provide a rigorous conceptualization of qualitative quality and a common language to discuss the excellence of qualitative research recognizable across difference in paradigms and variety of audiences.

Conclusion

This work was motivated by the great interest in using data and analytics to leverage CE efforts by both practitioners and academics. It analyzed insight from 15 expert interviews along with theory from RBV, ROV, past BAC literature, and recently published work on the Smart CE. In summary, we have explored the role of BA resources and capabilities for adopting circular strategies using the lens of RBV, ROV, and the Smart CE. We have proposed a novel conceptual model that breaks down the process of developing a BAC into structuring, bundling, and leveraging and theorized how obtaining a competitive advantage are mediated through CE implementation and resource orchestration capability. Based on this, eight resources were suggested that, when combined, likely create a BAC for CE. Specifically, the three tangible resources of data, technology, and basic resources, the three intangible resources of data-driven culture, circular-oriented innovation culture, and openness and co-creation, and the two human skills of systems thinking and data science was suggested. In addition, the extensive and diverse industry experience of the respondents covered in this study enabled a deep understanding of how organizations and managers leverage this capability to gain CE and competitive advantage.

Declaration of Competing Interest

The authors declare no conflict of interests regarding the publication of this article.

Acknowledgements

The authors would like to thank the reviewers of this paper, Also, the authors would like to acknowledge that the work described in this article has been conducted as part of the research project CIRCit (Circular Economy Integration in the Nordic Industry for Enhanced Sustainability and Competitiveness), which is part of the Nordic Green Growth Research and Innovation Programme (grant number: 83144), and funded by NordForsk, Nordic Energy Research, and Nordic Innovation.

References

Abbasi, A., Sarker, S., Chiang, R.H.L., 2016. Big data research in information systems: toward an inclusive research agenda. J. AIS 17, 3.
Ahuja, S., Chan, Y.E., 2017. Resource orchestration for IT-enabled innovation. Kindai Manag. Rev. 5, 78–96.
Akter, S., Wamba, S.F., Gunasekaran, A., Dubey, R., Childe, S.J., 2016. How to improve firm performance using big data analytics capability and business strategy alignment? Int. J. Prod. Econ. 182, 113–131.
Alshenqeeti, H., 2014. Interviewing as a data collection method: a critical review. English Linguist. Res. 3, 39–45.
Amit, R., Schoemaker, P.J.H., 1993. Strategic assets and organizational rent. Strateg. Manag. J. 14, 33–46.
Antikainen, M., Uusitalo, T., Kivikytö-Reponen, P., 2018a. Digitalisation as an Enabler of Circular Economy. Procedia CIRP 73, 45–49.
Antikainen, M., Uusitalo, T., Kivikytö-Reponen, P., Maria Antikainena Päivi Kivikytö-Reponena, T.U., 2018b. Digitalisation as an enabler of circular economy. In: 10th CIRP Conference on Industrial Product-Service Systems. Linköping. https://doi.org/10.1016/j.procir.2018.04.027. IPS2 2018, 29-31 May 2018.
Arunachalam, D., Kumar, N., Kawalek, J.P., 2018. Understanding big data analytics capabilities in supply chain management: Unravelling the issues, challenges and implications for practice. Transp. Res. Part E Logist. Transp. Rev. 114, 416–436.
Askoxylakis, I., 2018. A framework for pairing circular economy and the internet of things. In: IEEE International Conference on Communications. https://doi.org/10.1109/ICC.2018.8422488.
Barney, J., 1991. Firm resources and sustained competitive advantage. J. Manage. 17, 99–120.
Barney, J.B., 2001. Resource-based theories of competitive advantage: a ten-year retrospective on the resource-based view. J. Manage. 27, 643–650.
Bharadwaj, A.S., 2000. A Resource-Based Perspective on Information Technology Capability and Firm Performance: An Empirical Investigation. MIS Q, pp. 169–196.
Bianchini, A., Pellegrini, M., Rossi, J., Saccani, C., 2018. A new productive model of circular economy enhanced by digital transformation in the fourth industrial revolution-an integrated framework and real case studies. XXIII Summer Sch. "Francesco Turco"–Industrial Syst. Eng 1–7.
Bin, S., Zhiquan, Y., Jonathan, L.S.C., Jiewei, D.K., Kurle, D., Cerdas, F., Herrmann, C., 2015. A big data analytics approach to develop industrial symbioses in large cities. Procedia CIRP 29, 450–455.
Blomsma, F., Brennan, G., 2017. The emergence of circular economy: a new framing around prolonging resource productivity. J. Ind. Ecol. https://doi.org/10.1111/jiec.12603.
Blomsma, F., Tennant, M., 2020. Circular economy: Preserving materials or products? Introducing the resource states framework. Resour. Conserv. Recycl. 156, 104698.
Bocken, N., Strupeit, L., Whalen, K., Nußholz, J., 2019. A review and evaluation of circular business model innovation tools. Sustainability 11, 2210.
Bocken, N.M.P., De Pauw, I., Bakker, C., van der Grinten, B., 2016. Product design and business model strategies for a circular economy. J. Ind. Prod. Eng. 33, 308–320.
Bocken, N.M.P., Short, S.W., 2016. Towards a sufficiency-driven business model: Experiences and opportunities. Environ. Innov. Soc. Transitions 18, 41–61. https://doi.org/10.1016/j.eist.2015.07.010.
Bogner, A., Littig, B., Menz, W., 2009. Interviewing Experts. Springer.
Braganza, A., Brooks, L., Nepelski, D., Ali, M., Moro, R., 2017. Resource management in big data initiatives: Processes and dynamic capabilities. J. Bus. Res. 70, 328–337.

Bressanelli, G., Adrodegari, F., Perona, M., Saccani, N., 2018a. The role of digital technologies to overcome circular economy challenges in PSS business models: an exploratory case study. Proc. CIRP 73, 216–221.
Bressanelli, G., Adrodegari, F., Perona, M., Saccani, N., Bressanelli, G., Adrodegari, F., Perona, M., Saccani, N., Perona, Bressanelli F.:, Saccani, M.:, N., G..A., 2018b. Exploring how usage-focused business models enable circular economy through digital technologies. Sustainability 10, 639. https://doi.org/10.3390/su10030639.
Brown, D.E., Famili, F., Paass, G., Smith-Miles, K., Thomas, L.C., Weber, R., Baeza-Yates, R., Bravo, C., L'Huillier, G., Maldonado, S., 2011. Future trends in business analytics and optimization. Intell. Data Anal. 15, 1001–1017.
Brown, P., Bocken, N., Balkenende, R., 2019. Why do companies pursue collaborative circular oriented innovation? Sustainability 11, 635. https://doi.org/10.3390/su11030635.
Chadwick, C., Super, J.F., Kwon, K., 2015. Resource orchestration in practice: CEO emphasis on SHRM, commitment-based HR systems, and firm performance. Strateg. Manag. J. https://doi.org/10.1002/smj.2217.
Chang, C.H., 2018. How to enhance green service and green product innovation performance? The Roles of Inward and Outward Capabilities. Corp. Soc. Responsib. Environ. Manag. https://doi.org/10.1002/csr.1469.
Chauhan, C., Sharma, A., Singh, A., 2019. A SAP-LAP linkages framework for integrating Industry 4.0 and circular economy. Benchmarking An Int. J.
Chen, H., Chiang, R.H.L., Storey, V.C., 2012. Business Intelligence and Analytics: From Big Data to Big Impact. MIS Q, pp. 1165–1188.
Choi, S.B., Lee, W.R., Kang, S.W., 2020. Entrepreneurial Orientation, Resource Orchestration Capability, Environmental Dynamics and Firm Performance: A Test of Three-Way Interaction. Sustain. https://doi.org/10.3390/su12135415.
Circle Economy, 2020. The Circularity Gap Report 2020. Circ. Econ. Amsterdam, Netherlands.
Commission on Environment and Development, 1987. Report of the World Commission on Environment and Development: Our common future. Accessed Feb 10.
Creswell, J.W., Miller, D.L., 2000. Determining validity in qualitative inquiry. Theory Pract 39, 124–130.
Crook, T.R., Ketchen Jr, D.J., Combs, J.G., Todd, S.Y., 2008. Strategic resources and performance: a meta-analysis. Strateg. Manag. J. 29, 1141–1154.
Davies, D., Dodd, J., 2002. Qualitative research and the question of rigor. Qual. Health Res. 12, 279–289.
de Sousa Jabbour, A.B.L., Jabbour, C.J.C., Godinho Filho, M., Roubaud, D., 2018. Industry 4.0 and the circular economy: a proposed research agenda and original roadmap for sustainable operations. Ann. Oper. Res. 1–14.
Dhar, V., 2013. Data science and prediction. Commun. ACM 56, 64–73.
Dubey, R., Gunasekaran, A., Childe, S.J., Papadopoulos, T., Luo, Z., Wamba, S.F., Roubaud, D., 2019. Can big data and predictive analytics improve social and environmental sustainability? Technol. Forecast. Soc. Change 144, 534–545. https://doi.org/10.1016/J.TECHFORE.2017.06.020.
Dubey, R., Gunasekaran, A., Childe, S.J., Wamba, S.F., Papadopoulos, T., 2016. The impact of big data on world-class sustainable manufacturing. Int. J. Adv. Manuf. Technol. 84, 631–645.
Eisenhardt, K.M., 1989. Building theories from case study research. Acad. Manag. Rev. 14, 532–550.
Eisenhardt, K.M., Graebner, M.E., 2007. Theory building from cases: opportunities and challenges. Acad. Manag. J. 50, 25–32.
Eisenhardt, K.M., Martin, J.A., 2000. Dynamic capabilities: what are they? Strateg. Manag. J. 21, 1105–1121.
EMF, 2019. Artificial Intelligence and the Circular Economy. Ellen MacArthur Found, Cowes, UK.
EMF, 2016. Intelligent Assets: Unlocking the Circular Economy Potential. Ellen MacArthur Found, Cowes, UK.
EMF, 2015a. Delivering the circular economy: A toolkit for policymakers. Ellen MacArthur Found, Cowes, UK.
EMF, 2015b. Growth within: A Circular Economy Vision for a Competitive Europea. Ellen MacArthur Found, Cowes, UK.
European Commission, 2020a. A New Industrial Strategy for Europe.
European Commission, 2020b. Circular Economy Action Plan.
Garmaki, M., Boughzala, I., Wamba, S.F., 2016. The Effect of Big Data Analytics Capability on Firm Performance. PACIS, p. 301.
Geissdoerfer, M., Savaget, P., Bocken, N.M.P., Hultink, E.J., 2017. The circular economy – a new sustainability paradigm? J. Clean. Prod. 143, 757–768. https://doi.org/10.1016/J.JCLEPRO.2016.12.048.
Ghisellini, P., Cialani, C., Ulgiati, S., 2016. A review on circular economy: the expected transition to a balanced interplay of environmental and economic systems. J. Clean. Prod. 114, 11–32. https://doi.org/10.1016/j.jclepro.2015.09.007.
Golafshani, N., 2003. Understanding reliability and validity in qualitative research. Qual. Rep. 8, 597–607.
Gupta, M., George, J.F., 2016. Toward the development of a big data analytics capability. Inf. Manag. 53, 1049–1064. https://doi.org/10.1016/j.im.2016.07.004.
Gupta, S., Chen, H., Hazen, B.T., Kaur, S., Santibañez Gonzalez, E.D.R., Gonzalez, E.D.S., 2019. Circular economy and big data analytics: a stakeholder perspective. Technol. Forecast. Soc. Change 144, 466–474. https://doi.org/10.1016/j.techfore.2018.06.030.
Haas, W., Krausmann, F., Wiedenhofer, D., Heinz, M., 2015. How circular is the global economy: an assessment of material flows, waste production, and recycling in the European Union and the world in 2005. J. Ind. Ecol. 19, 765–777.
Hazen, B.T., Skipper, J.B., Ezell, J.D., Boone, C.A., 2016. Big data and predictive analytics for supply chain sustainability: a theory-driven research agenda. Comput. Ind. Eng. 101, 592–598.
Hedberg, A., Sipka, S., Bjerkem, J., 2019. Creating a digital roadmap for a circular economy. Eur. Policy Cent.
Helfat, C.E., Finkelstein, S., Mitchell, W., Peteraf, M., Singh, H., Teece, D., Winter, S.G., 2009. Dynamic Capabilities: Understanding Strategic Change in Organizations. John Wiley & Sons.
Ingemarsdotter, E., Jamsin, E., Kortuem, G., Balkenende, R., 2019. Circular strategies enabled by the internet of things—a framework and analysis of current practice. Sustainability 11, 5689.
Janssen, M., van der Voort, H., Wahyudi, A., 2017. Factors influencing big data decision-making quality. J. Bus. Res. 70, 338–345. https://doi.org/10.1016/J.JBUSRES.2016.08.007.
Khan, O., Daddi, T., Iraldo, F., 2020. The role of dynamic capabilities in circular economy implementation and performance of companies. Corp. Soc. Responsib. Environ. Manag.
Kirchherr, J., Reike, D., Hekkert, M., 2017. Conceptualizing the circular economy: An analysis of 114 definitions. Resour. Conserv. Recycl. 127, 221–232.
Kraaijenbrink, J., Spender, J.-C., Groen, A.J., 2010. The resource-based view: a review and assessment of its critiques. J. Manage. 36, 349–372.
Kristoffersen, E., Aremu, O.O., Blomsma, F., Mikalef, P., Li, J., 2019. Exploring the relationship between data science and circular economy: an enhanced CRISP-DM process model. In: Conference on E-Business. Cham. Springer International Publishing, pp. 177–189. https://doi.org/10.1007/978-3-030-29374-1_15 e-Services and e-Society.
Kristoffersen, E., Blomsma, F., Mikalef, P., Li, J., 2020. The smart circular economy: a digital-enabled circular strategies framework for manufacturing companies. J. Bus. Res. 120, 241–261. https://doi.org/10.1016/j.jbusres.2020.07.044.
Kvale, S., Brinkmann, S., 2009. Interviews: Learning the Craft of Qualitative Research Interviewing. Sage.
Kwon, O., Lee, N., Shin, B., 2014. Data quality management, data usage experience and acquisition intention of big data analytics. Int. J. Inf. Manage. 34, 387–394.
Lahti, T., Wincent, J., Parida, V., 2018. A definition and theoretical review of the circular economy, value creation, and sustainable business models: where are we now and where should research move in the future? Sustainability 10, 2799.
Lenka, S., Parida, V., Wincent, J., 2017. Digitalization capabilities as enablers of value co-creation in servitizing firms. Psychol. Mark. 34, 92–100.
Lieder, M., Asif, F.M.A., Rashid, A., 2020. A choice behavior experiment with circular business models using machine learning and simulation modeling. J. Clean. Prod., 120894
Lincoln, Y.S., Guba, E.G., 1990. Judging the quality of case study reports. Int. J. Qual. Stud. Educ. 3, 53–59.
Low, J.S.C., Tjandra, T.B., Yunus, F., Chung, S.Y., Tan, D.Z.L., Raabe, B., Ting, N.Y., Yeo, Z., Bressan, S., Ramakrishna, S., Herrmann, C., 2018. A collaboration platform for enabling industrial symbiosis: application of the database engine for waste-to-resource matching. In: . https://doi.org/10.1016/j.procir.2017.11.075.
Makadok, R., 2001. Toward a synthesis of the resource-based and dynamic-capability views of rent creation. Strateg. Manag. J. 22, 387–401.
Mata, F.J., Fuerst, W.L., Barney, J.B., 1995. Information Technology and Sustained Competitive Advantage: A Resource-Based Analysis. MIS Q, pp. 487–505.
McAfee, A., Brynjolfsson, E., Davenport, T.H., Patil, D.J., Barton, D., 2012. Big data: the management revolution. Harv. Bus. Rev. 90, 60–68.
Mikalef, P., Framnes, V.A., Danielsen, F., Krogstie, J., Olsen, D., 2017. Big data analytics capability: antecedents and business value. In: Pacific Asia Conference on Information Systems (PACIS). Association For Information Systems.
Mikalef, P., Krogstie, J., Pappas, I.O., Pavlou, P., 2019. Exploring the Relationship Between Big Data Analytics Capability and Competitive Performance: The Mediating Roles of Dynamic and Operational Capabilities. Inf. Manag.
Mikalef, P., Pappas, I.O., Krogstie, J., Giannakos, M., 2018. Big data analytics capabilities: a systematic literature review and research agenda. Inf. Syst. E-bus. Manag. 16, 547–578.
Miles, M.B., Huberman, A.M., Huberman, M.A., Huberman, M., 1994. Qualitative Data Analysis: An Expanded Sourcebook. sage.
Miller, D., Friesen, P.H., 1984. A longitudinal study of the corporate life cycle. Manage. Sci. 30, 1161–1183.
Mortenson, M.J., Doherty, N.F., Robinson, S., 2015. Operational research from Taylorism to Terabytes: a research agenda for the analytics age. Eur. J. Oper. Res. 241, 583–595.
Munodawafa, R.T., Johl, S.K., 2019. Big data analytics capabilities and eco-innovation: a study of energy companies. Sustainability 11, 4254.
Myers, M.D., Newman, M., 2007. The qualitative interview in IS research: examining the craft. Inf. Organ. 17, 2–26.
Nobre, G.C., Tavares, E., 2017. Scientific literature analysis on big data and internet of things applications on circular economy: a bibliometric study. Scientometrics 111, 463–492. https://doi.org/10.1007/s11192-017-2281-6.
Okorie, O., Salonitis, K., Charnley, F., Moreno, M., Turner, C., Tiwari, A., 2018. Digitisation and the circular economy: a review of current research and future trends. ENERGIES 11. https://doi.org/10.3390/en11113009.
Pagoropoulos, A., Pigosso, D.C.A., McAloone, T.C., 2017. The emergent role of digital technologies in the circular economy: a review. Procedia CIRP 64, 19–24.
Patton, M.Q., 2014. Qualitative Research & Evaluation Methods: Integrating Theory and Practice. Sage publications.
Patton, M.Q., 1990. Qualitative Evaluation and Research Methods. SAGE Publications, inc.
Pauliuk, S., 2018. Critical appraisal of the circular economy standard BS 8001: 2017 and a dashboard of quantitative system indicators for its implementation in organizations. Resour. Conserv. Recycl. 129, 81–92.

Pavlou, P.A., El Sawy, O.A., 2006. From IT leveraging competence to competitive advantage in turbulent environments: the case of new product development. Inf. Syst. Res. 17, 198–227.
Planing, P., 2015. Business model innovation in a circular economy reasons for non-acceptance of circular business models. Open J. Bus. Model Innov. 1.
Power, D.J., 2016. Data science: supporting decision-making. J. Decis. Syst. 25, 345–356.
Prieto-Sandoval, V., Jaca, C., Santos, J., Baumgartner, R.J., Ormazabal, M., 2019. Key strategies, resources, and capabilities for implementing circular economy in industrial small and medium enterprises. Corp. Soc. Responsib. Environ. Manag. 26, 1473–1484.
Provost, F., Fawcett, T., 2013. Data Science for Business: What You Need to Know About Data Mining and Data-Analytic Thinking. O'Reilly Media, Inc.
Rai, A., Patnayakuni, R., Seth, N., 2006. Firm performance impacts of digitally enabled supply chain integration capabilities. MIS Q 225–246.
Ransbotham, S., Kiron, D., 2017. Analytics as a source of business innovation. MIT Sloan Manag. Rev. 58.
Rialti, R., Marzi, G., Ciappei, C., Busso, D., 2019. Big Data and Dynamic Capabilities: A Bibliometric Analysis and Systematic Literature Review. Manag. Decis.
Rosa, P., Sassanelli, C., Urbinati, A., Chiaroni, D., Terzi, S., 2020. Assessing relations between Circular Economy and Industry 4.0: a systematic literature review. Int. J. Prod. Res. 58, 1662–1687.
Rymaszewska, A., Helo, P., Gunasekaran, A., 2017. IoT powered servitization of manufacturing–an exploratory case study. Int. J. Prod. Econ. 192, 92–105.
Sarker, S., Xiao, X., Beaulieu, T., 2013. Guest Editorial: Qualitative Studies in Information Systems: A Critical Review and Some Guiding Principles, 37. MIS Q, pp. iii–xviii.
Savin-Baden, M., Howell-Major, C., 2013. Qualititative Research: the Essential Guide to Theory and Practice. Qual. Res. Essent. Guid. to Theory Pract., Routledge.
Seale, C., 1999. Quality in qualitative research. Qual. Inq. 5, 465–478.
Seddon, J.J.J.M., Currie, W.L., 2017. A model for unpacking big data analytics in high-frequency trading. J. Bus. Res. 70, 300–307.
Seddon, P.B., Constantinidis, D., Tamm, T., Dod, H., 2017. How does business analytics contribute to business value? Inf. Syst. J. https://doi.org/10.1111/isj.12101.
Shuradze, G., Wagner, H.-T., 2016. Towards a conceptualization of data analytics capabilities. In: 2016 49th Hawaii International Conference on System Sciences (HICSS), pp. 5052–5064.
Sirmon, D.G., Hitt, M.A., Ireland, R.D., 2007. Managing firm resources in dynamic environments to create value: looking inside the black box. Acad. Manag. Rev. 32, 273–292.
Sirmon, D.G., Hitt, M.A., Ireland, R.D., Gilbert, B.A., 2011. Resource orchestration to create competitive advantage: breadth, depth, and life cycle effects. J. Manage. 37, 1390–1412.
Smith, K.G., Mitchell, T.R., Summer, C.E., 1985. Top level management priorities in different stages of the organizational life cycle. Acad. Manag. J. 28, 799–820.
Sousa-Zomer, T.T., Magalhães, L., Zancul, E., Cauchick-Miguel, P.A., 2018. Exploring the challenges for circular business implementation in manufacturing companies: an empirical investigation of a pay-per-use service provider. Resour. Conserv. Recycl. 135, 3–13.
Stahel, W., 2010. The Performance Economy. Springer.
Stenbacka, C., 2001. Qualitative Research Requires Quality Concepts of its Own. Manag. Decis.
Su, B., Heshmati, A., Geng, Y., Yu, X., 2013. A review of the circular economy in China: moving from rhetoric to implementation. J. Clean. Prod. 42, 215–227.
The British Standards Institution, 2017. Framework for implementing the principles of the circular economy in organizations-Guide. Br. Stand. Inst. 26–31.
Tracy, S.J., 2010. Qualitative quality: Eight "big-tent" criteria for excellent qualitative research. Qual. Inq. 16, 837–851.
Ünal, E., Urbinati, A., Chiaroni, D., 2018. Circular Industry 4.0: an Integrative Framework.
Vidgen, R., Shaw, S., Grant, D.B., 2017. Management challenges in creating value from business analytics. Eur. J. Oper. Res. 261, 626–639. https://doi.org/10.1016/J.EJOR.2017.02.023.
Wamba, S.F., Gunasekaran, A., Akter, S., Ren, S.J.fan, Dubey, R., Childe, S.J., 2017. Big data analytics and firm performance: effects of dynamic capabilities. J. Bus. Res. 70, 356–365. https://doi.org/10.1016/j.jbusres.2016.08.009.
Wang, G., Gunasekaran, A., Ngai, E.W.T., Papadopoulos, T., 2016. Big data analytics in logistics and supply chain management: Certain investigations for research and applications. Int. J. Prod. Econ. 176, 98–110.
Wang, J., Xue, Y., Yang, J., 2020. Boundary-spanning search and firms' green innovation: The moderating role of resource orchestration capability. Bus. Strateg. Environ. 29, 361–374.
Webster, K., 2013. What might we say about a circular economy? Some temptations to avoid if possible. World Futures 69, 542–554.
Wernerfelt, B., 1984. A resource-based view of the firm. Strateg. Manag. J. 5, 171–180.
Wilts, C.H., Berg, H., 2018. The Digital Circular Economy: Can the Digital Transformation Pave the Way for Resource-Efficient Materials Cycles?.
Wright, M., Clarysse, B., Mosey, S., 2012. Strategic entrepreneurship, resource orchestration and growing spin-offs from universities. Technol. Anal. Strateg. Manag. 24, 911–927.
Wu, K.-J., Liao, C.-J., Tseng, M.-L., Lim, M.K., Hu, J., Tan, K., 2017. Toward sustainability: using big data to explore the decisive attributes of supply chain risks and uncertainties. J. Clean. Prod. 142, 663–676.
Yin, R.K., 2017. Case Study Research and Applications: Design and Methods. Sage publications.
Zahra, S.A., George, G., 2002. The net-enabled business innovation cycle and the evolution of dynamic capabilities. Inf. Syst. Res. 13, 147–150.
Zhao, R., Liu, Y., Zhang, N., Huang, T., 2017. An optimization model for green supply chain management by using a big data analytic approach. J. Clean. Prod. 142, 1085–1097.

Eivind Kristoffersen: Eivind Kristoffersen is a PhD candidate at the department of Computer Science at the Norwegian University of Science and Technology in the area of Information Systems, specializing on the connection between the digital and sustainable through the concept of a Smart Circular Economy.

Fenna Blomsma: Fenna Blomsma is a junior professor at the University of Hamburg and chair of Circular Economy and Systems Innovation, with a focus on innovation in circular business models, circular supply chains and business practices.

Patrick Mikalef: Patrick Mikalef is an associate professor at the department of Computer Science at the Norwegian University of Science and Technology in the area of big data analytics and business value, and a recipient of the Marie Skłodowska-Curie individual fellowship grant.

Jingyue Li: Jingyue Li is an associate professor at the department of Computer Science at the Norwegian University of Science and Technology in the area of software engineering and Artificial Intelligence.

Paper 5

The Effects of Business Analytics Capability on Circular Economy Implementation, Resource Orchestration Capability and Firm Performance.

Eivind Kristoffersen, Patrick Mikalef, Fenna Blomsma, and Jingyue Li.

In: International Journal of Production Economics, 239, 108205.

Int. J. Production Economics 239 (2021) 108205

Contents lists available at ScienceDirect

International Journal of Production Economics

journal homepage: www.elsevier.com/locate/ijpe

The effects of business analytics capability on circular economy implementation, resource orchestration capability, and firm performance

Eivind Kristoffersen [a,b,*], Patrick Mikalef [a,b], Fenna Blomsma [c], Jingyue Li [a]

[a] Department of Computer Science, Norwegian University of Science and Technology, Sem Sælandsvei 9, 7491, Trondheim, Norway
[b] SINTEF Digital, S. P. Andersens Veg 5, 7031, Trondheim, Norway
[c] University of Hamburg, 20146, Hamburg, Germany

ARTICLE INFO

Keywords:
Digital circular economy
Big data analytics
Circular economy capability
Sustainability
Policy implication
Digitalization

ABSTRACT

Today, most organizations are undergoing a digital transformation. At the same time, the gravity of environmental issues has put sustainability and the circular economy at the top of corporate agendas. To this end, information systems, in particular business analytics, are being highlighted as essential enablers of an accelerated circular economy transition. However, effectively managing this joint transformation is a challenge. Firms struggle to identify which organizational resources they should target and how those should be leveraged towards a firm-wide business analytics capability for circular economy. To address these questions, this study draws on recent literature dealing with smart circular economy and business analytics capabilities along with the resource-based and resource orchestration view to (1) create an instrument to measure firms' business analytics capability for circular economy, and (2) examine the relationship among a circular economy-specific business analytics capability, circular economy implementation, resource orchestration capability, and firm performance. The proposed research model was tested using partial least squares structural equation modeling of survey data from 125 top-level managers at companies across Europe. The results show that firms with a strong business analytics capability have an increased resource orchestration capability and a greater ability to excel in the circular economy, resulting in improved organizational performance in building a more sustainable competitive advantage in an increasingly competitive business landscape. The effect of business analytics capability on firm performance is not direct but fully mediated through resource orchestration capability and circular economy implementation. The results empirically validate the proposed research model and offer pathways to future information systems research streams to support the operationalization of circular strategies. The study provides the first empirical evidence of a business analytics capability for circular economy and its effect on firm performance.

1. Introduction

The concept of circular economy (CE) is rapidly gathering momentum in industry, policymaking, and academia as a way to boost economic performance without consuming resources at a rate that exceeds the Earth's capacity (European Commission, 2020a, 2020b; Stahel, 2010). The CE achieves this decoupling of value creation from the consumption of finite resources by leveraging a range of efficiency, productivity, and restorative-oriented strategies (known as circular strategies) to keep products, components, and materials in use for longer (EMF, 2015a; 2015b). As such, the CE holds great promise as a contributor to sustainability (Geissdoerfer et al., 2017; Ghisellini et al., 2016) and directly impacts multiple United Nations' Sustainable Development Goals (Schroeder et al., 2019). However, the adoption of CE and sustainable strategies by industry has so far been modest (Circle Economy, 2020; Haas et al., 2015; Planing, 2015; Sousa-Zomer et al., 2018), and scant progress is observed in the decoupling from linear resource consumption.

Simultaneously, digital tools and technologies such as the internet of things, big data, and artificial intelligence have prompted a paradigm shift in industrial production across all sectors. These technologies are seen as critical enablers for an accelerated transition to CE (EMF, 2016);

* Corresponding author.
E-mail addresses: eivind.kristoffersen@ntnu.no (E. Kristoffersen), patrick.mikalef@ntnu.no (P. Mikalef), fenna.blomsma@uni-hamburg.de (F. Blomsma), jingyue.li@ntnu.no (J. Li).

https://doi.org/10.1016/j.ijpe.2021.108205
Received 8 April 2021; Received in revised form 28 May 2021; Accepted 10 June 2021
Available online 12 June 2021

they will play a crucial role in operationalizing it at scale (Kristoffersen et al., 2020) and are linked to the accomplishment of all 17 Sustainable Development Goals (Vinuesa et al., 2020). However, findings from research and practice highlight that the main challenges in realizing value from data and analytics are not technological but organizational (Vidgen et al., 2017). Several sources have voiced the need for an improved understanding of firms' digital and circular transition, also known as the *Smart CE* (Askoxylakis, 2018; Bianchini et al., 2018; Ingemarsdotter et al., 2019; Kristoffersen et al., 2019; Rosa et al., 2020; Ünal et al., 2018). Specifically, such calls have been heard in the areas of organizational capabilities (Gelhard and Von Delft, 2016; Prieto-Sandoval et al., 2019), corporate sustainability (Amui et al., 2017), big data analytics for sustainability (Zhang et al., 2019), and information systems (IS) research on CE (Zeiss et al., 2020).

Nevertheless, as the Smart CE represents an emergent field, the link between firms' organizational capabilities and their digital and circular strategies remains underdeveloped. Similarly, there is a limited body of work grounded in established management, IS, and CE theories (Lahti et al., 2018). As a result, there is a knowledge gap in the matter of which internal resources are required to effectively leverage data and analytics for the CE transition and the mechanisms through which this influences firms' performance. Addressing these critical gaps, this study is rooted in the IS field and grounded on the notion of a business analytics capability (BAC). The authors argue that to orchestrate and leverage business analytics (BA) toward increased CE implementation, companies need to develop an amalgamation of tangible, intangible, and human resources (Bag et al., 2021; Gupta et al., 2019; Kristoffersen et al., 2020; Modgil et al., 2021). With limited insight into how BACs create business value (Côrte-Real et al., 2017; Günther et al., 2017), further investigation is needed into how a CE-specific BAC improves firm performance through the mediating roles of CE implementation and resource orchestration capability (ROC) of information technology (IT) resources. Understanding this will have considerable implications for research, policy, and practice alike by highlighting the importance of taking a more holistic view of BA development, allowing firms to generate higher returns on their digital and circular investments, and setting directions for future Smart CE studies. To address this, the present study draws on the qualitative research model, CE-based BA resources, and propositions put forward by Kristoffersen et al. (2021), extending this with a quantitative survey to test the validity of the suggested constructs and relationships. Consequently, this paper seeks to answer the following research questions:

RQ1. What is the effect of business analytics capability on resource orchestration capability and circular economy implementation?

RQ2. What impact do resource orchestration capability and circular economy implementation have on firm performance?

These questions are addressed using the theoretical underpinnings of the resource-based view and the resource orchestration view, which are presented in the next section. Further, an instrument to measure the CE-specific BAC of firms is defined and used to illustrate how BA influences their CE implementation, IT ROC, and organizational performance. The authors hypothesize that BAC has a positive effect on firm performance and that this effect is fully mediated through CE implementation and IT ROC. A survey-based study is developed to examine the hypotheses and quantitatively assess each concept, as described in the subsequent sections. The findings from the empirical analysis are then presented, followed by a discussion of the results with implications for research, industry, and policy, along with the core limitations of this study.

2. Theoretical background

2.1. Smart circular economy

Despite the lack of a unified definition (Kirchherr et al., 2017), the CE can be understood as an *umbrella concept* in which multiple definitions and principles exist (Blomsma and Brennan, 2017). However, common throughout is the intention to address structural waste while constructing new value creation opportunities and reducing value loss and destruction. As the CE is still in a nascent stage of development, regulation continues to lag, and companies embracing circular strategies may be subject to risks such as fluctuating demand, supply, and quality of used assets, leading to uncertainties as to cost and return on investment (de Sousa Jabbour et al., 2018). As a result, assets (products, components, and materials) are recirculated at volumes far below their potential for value delivery.

Central to this untapped potential for recirculation and construction of closed-loop systems is the lack of information sharing and processing throughout the industrial life cycle (Wilts and Berg, 2018). If effectively leveraged, the abundant sources of information and data produced throughout the industrial life cycle of assets could connect the material and information flows towards a CE. Nevertheless, several operational barriers still exist in collecting, integrating, and processing information pertinent to the location, availability, and condition of assets (Su et al., 2013). Hence, increasing organizations' digital maturity and uptake of new digital technologies – particularly base technologies such as the Internet of Things, big data, cloud computing, and artificial intelligence – are highlighted as vital for the operationalization of circular strategies (Antikainen et al., 2018; Bressanelli et al., 2018; de Sousa Jabbour et al., 2018; EMF, 2016; 2019; Kristoffersen et al., 2019; Nobre and Tavares, 2017). In this study, the scope is limited to BA due to *i)* its function as a systems technology merging multiple base technologies (Frank et al., 2019) and *ii)* its potential to improve resource management and facilitate decision-making across different stages of the industrial life cycle of assets (Kristoffersen et al., 2020).

Acknowledging the potential of digitalizing the CE, numerous calls have been made for conducting more research into how companies can leverage their digital strategies towards a more efficient and effective CE (Chauhan et al., 2019; EMF, 2019; 2016; European Commission, 2020b; Okorie et al., 2018; Rosa et al., 2020; Zeiss et al., 2020). Given the breadth of both circular and digital strategies proposed in these calls, the present paper draws on the *Smart CE framework* by Kristoffersen et al. (2020) for consistency with the theoretical underpinnings of underlying base technologies and CE principles. Also known as the digital circular economy, the framework provides a much-needed link between the New Industrial Strategy for Europe and the European Green Deal (European Commission, 2020a, 2020b).

2.2. Resource-based view and resource orchestration

Developing and sustaining a competitive advantage is fundamental to strategic management literature (Amit and Schoemaker, 1993; Wernerfelt, 1984). Multiple frames exist to explain the details of firm performance, one of them being the resource-based view, which is often considered the most rigorous theory of firm performance explained through the resources that companies own and control (Barney, 2001). The resource-based view has also attracted considerable scholarly attention in IS research under the notion of IT capabilities (Bharadwaj, 2000). The theory argues that firms gain a competitive advantage by acquiring tangible and intangible organizational resources that are valuable, rare, inimitable, and non-substitutable (VRIN) (Barney, 1991). Despite several studies supporting the importance of these resources for firm performance, the theory has failed to adequately explain the difference between firms' performance and how they transform these resources into capabilities (Crook et al., 2008; Kraaijenbrink et al., 2010; Sirmon et al., 2011). The core assumptions of VRIN also pose a challenge when applied to BA since the core resource – in this case, data – is generally not rare (Braganza et al., 2017).

Extending the resource-based view, the resource orchestration view has been proposed to address the capability-building processes by explaining the role of managers in transforming resources into capabilities (Sirmon et al., 2011). The resource orchestration view has received significant attention in recent years and represents a promising area of research to understand how firms should best manage their resources for increased competitive performance (Gong et al., 2018; Teece, 2014; Wales et al., 2013; Wang et al., 2020). Recent studies have demonstrated the importance of a strong ROC for improving innovation when adapting to changing market conditions (Chadwick et al., 2015; Sirmon et al., 2007; Wales et al., 2013; Wong et al., 2018). For instance, Teece (2014) emphasizes that resource orchestration is essential for mitigating internal conflict and improving resource complementarities in the firm, supporting the dynamic capabilities needed to facilitate green innovation (Wang et al., 2020). Moreover, the research stream builds on both the resource-based view and the dynamic capabilities view by integrating the resource management framework of Sirmon et al. (2007) and the asset orchestration framework of Helfat et al. (2009). The joint framework presents a novel perspective on a robust management theory of how managers structure, bundle, and leverage their firms' resources for improved organizational performance. According to the framework, firms can only realize the full potential and value of their resources when those are deployed in a complementary manner together with capabilities and managerial acumen (Helfat et al., 2009; Sirmon et al., 2011).

As a result, the theory posits that the ROC is one of the most important competencies a firm can internalize, particularly in the case of organizations prone to suffering from resource-related liabilities. The capability can be seen as the proficiency of a firm in maximizing performance by effectively structuring, bundling, and leveraging existing and new resources (Choi et al., 2020; Wang et al., 2020). While studies have applied the framework to identify IT resources and capabilities for innovation (Ahuja and Chan, 2017), investigate the nature of e-commerce adoption (Cui and Pan, 2015), and understand how ambidexterity and IT competence can improve supply chain flexibility (Rojo Gallego Burin et al., 2020), resource orchestration remains inadequately researched in the context of BA and CE. As the resource orchestration view provides a more robust perspective of managers' specific roles in leveraging capabilities across differences in firm characteristics (e.g., firm size, industry type, and managerial hierarchy), the authors believe this theory proposes a novel perspective on the orchestration of BA that other theories do not. Therefore, the combined strengths of the resource-based view and the resource orchestration view are utilized as the theoretical underpinnings to establish a solid foundation for the survey.

2.3. *Business analytics capability*

Emerging in the 2000s, BA can be regarded as a collection of technologies, methods, and applications that enable the analysis of business data to promote more sound and data-driven decisions (Chen et al., 2012; Seddon and Currie, 2017). Related to BA, the term *big data analytics* describes the new methods and applications used for (big) data sets that are too large and complex for traditional methods (Chen et al., 2012). In this study, big data analytics and BA are regarded as a unified term (Mikalef et al., 2018). Effectively leveraging business data for value creation requires companies to focus beyond the mere technical aspects of implementing BA (Vidgen et al., 2017). Becoming data-driven is complex and multifaceted, necessitating changes to multiple organizational resources with involvement from several managerial levels. Addressing this, the concept of a *business analytics capability* has emerged to indicate a firm's proficiency in effectively leveraging its data, technology, and talent towards the generation of data-driven insight (Mikalef et al., 2018; Shuradze and Wagner, 2016).

While several studies have explored the role of BAC in improving firm performance through the lens of the resource-based view and dynamic capabilities, research has mostly disregarded its impact beyond the confines of competitive performance, leaving largely untouched the effects on sustainability, CE, and the role of resource orchestration (Rialti et al., 2019; Sirmon et al., 2011). While acknowledging recent research into the role of BAC in sustainable supply chain management (Dubey et al., 2016; Hazen et al., 2016; Wang et al., 2016; Wu et al., 2017; Zhao et al., 2017) and circular supply chain management (Gupta et al., 2019), these studies fall short when considering a broader range of circular strategies. Through a series of interviews, Kristoffersen et al. (2021) address this issue and propose a classification of BAC for CE (see Fig. 1). The study hypothesizes that companies need eight different BA resources that, in combination, build a BAC applicable to multiple circular strategies. However, a gap remains in examining this hypothesis and quantitatively assessing how firms leverage BA for CE. Addressing this gap, the present study operationalizes the notion of a CE-specific BAC to test its validity and suitability in explaining how BA affects IT ROC and CE implementation and how this, in turn, affects the different mechanisms of firm performance.

3. Research model

Drawing on the resource-based view and the resource orchestration view of the firm, this study proposes the research model shown in Fig. 2. In IS research, both tangible assets (like data and technology) and intangible and human assets (like data-driven culture and managerial skills) are regarded as resources based on the definition of Piccoli and Ives (2005). These resources are also specifically mentioned in the widely used classification of BA resources by Gupta and George (2016) and expands upon the highly influential work by Mata et al. (1995) and Wixom and Watson (2001). BAC is conceptualized as a higher-order construct, with each dimension comprising more than one sub-dimension (see definitions in Table 1). This classification (see Fig. 1) is consistent with the framework of Grant (1991), and the dimensions of human skills, tangible resources, and intangible resources are widely used in IT capability literature (Bharadwaj, 2000; Chae et al., 2014; Mikalef et al., 2020; Santhanam and Hartono, 2003).

The authors argue that in order to develop a strong BAC, organizations have to invest in all three types of resources. In doing so, they obtain the capacity to strengthen existing circular strategies, implement new ones, improve their IT ROC, and enhance their overall performance. As such, the effect of BAC on firm performance is fully mediated by firms' IT ROC and degree of CE implementation.

In today's competitive business environment, firms have to constantly update the means through which they deliver value. Complicating the situation is the increasing pressure on them from customers, shareholders, and governments to transition to a more sustainable mode of business operation. Companies utilizing insights generated through BA are better positioned to identify emerging opportunities and threats and transform their operation accordingly (Wamba et al., 2017). Specifically, BAC helps companies expand the locus of decision-making by providing previously unavailable insights and options (Abbasi et al., 2016; Drnevich and Kriauciunas, 2011) and improving response time, effectiveness, and efficiency when dealing with environmental changes (Popovič et al., 2018). Acknowledging the potential of BA to play a role in addressing critical societal challenges, a growing number of studies have noted its positive relationship to sustainable development and CE (Chen et al., 2012; Kristoffersen et al., 2021; Del Giudice et al., 2020; Gupta et al., 2018, 2019; Hashem et al., 2016; Kristoffersen et al, 2020; Patwa et al., 2020; Rajput and Singh, 2019; Singh and El-Kassar, 2019; Song et al., 2017; Zhang et al., 2019). Zeiss et al. (2020) detail the problem-solution pairing of CE and IS as a prolific relationship where digital technologies such as BA have the potential to connect the material and information flows needed to help understand and enact circular material flows, intensify and extend the use of products and components, and recycle waste materials. Data and information flow tracking plays an important role in the transition to a more sustainable economy (Jabbour et al., 2019), providing essential insights for enabling CE adoption and evolution for both large (Geng et al., 2013) and emerging economies (Patwa et al., 2020). Therefore,

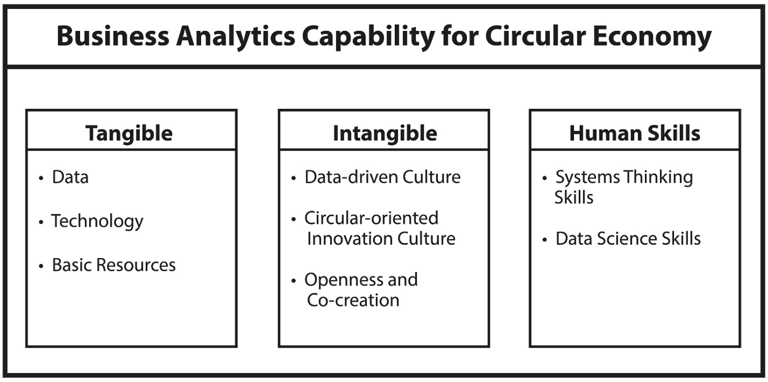


Fig. 1. Classification of business analytics capability (BAC) for circular economy (CE) (Kristoffersen et al., 2021).

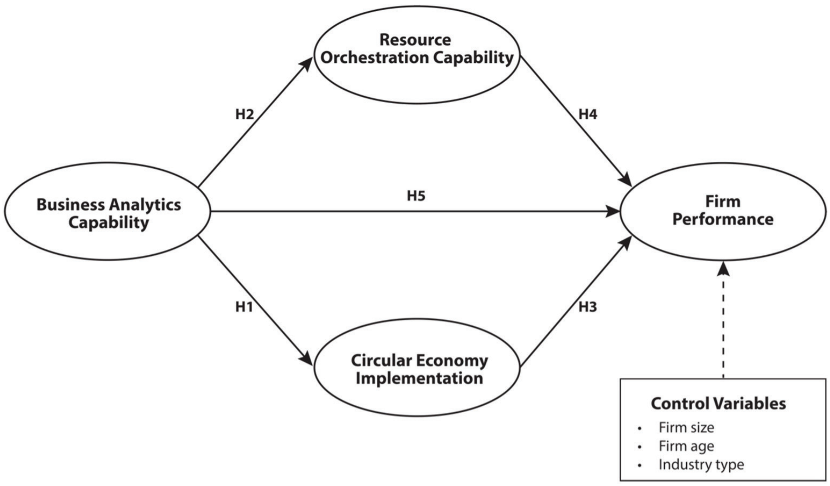


Fig. 2. Research model.

BAC can improve firms' ability to operationalize circular strategies and overall CE implementation. Extensive support for this can be found in related empirical studies on the effect of BAC for improved sustainable supply chain management and circular strategy implementation (Dubey et al., 2016; Gupta et al., 2019; Hazen et al., 2016; Kristoffersen et al., 2021; Wang et al., 2016; Wu et al., 2017; Zhao et al., 2017). From the preceding discussion, it is hypothesized that:

H1. BAC will have a positive effect on CE implementation.

Transforming the current mode of business operation requires that companies go beyond focusing solely on technology (Janssen et al., 2017). For instance, Raut et al. (2019) found that management and leadership style, supplier and customer integration, and internal business processes significantly influence the ability of BAC to support sustainable practices. Chauhan et al. (2019) supports this and highlights top-level management as the most essential agent of enablement. With several studies showcasing how a strong BAC can help firms identify threats, seize opportunities, and transform their operation to meet emerging market needs (Braganza et al., 2017; LaValle et al., 2011; Ransbotham and Kiron, 2017; Winig, 2017), the strength of dynamic capabilities and decision-making quality are largely dependent upon the BAC an organization can develop (Conboy et al., 2020; Janssen et al., 2017; Mikalef et al., 2020). Therefore, targeted BAC development may improve the value retention of investments, predictive decision-making quality, and the ability to respond to external needs and opportunities (Bharadwaj et al., 2013). Accordingly, with support from studies on internal capabilities for realizing innovation and driving competitive performance (Barney, 1991; Chadwick et al., 2015; Chang, 2018; Sirmon et al., 2007), BAC can improve firms' ROC. Thus, it is hypothesized that:

H2. BAC will have a positive effect on ROC.

With the launch of a new European CE action plan (European Commission, 2020b) and previously estimated economic benefits of up to €1.8 trillion by 2030 for Europe alone (EMF, 2015b), there is a great promise of value creation for organizations adopting the CE model. Often remarking on the ability to provide a sustainable competitive advantage through the concept of resource efficiency, or "producing more with less" (Linder and Williander, 2017), scholars generally agree that circular strategies lead to improved firm performance (Khan et al., 2020a; Scarpellini et al., 2020a; Zhu et al., 2010). Seeing it as a win-win situation, numerous studies have emphasized the economic benefits of adopting environmental solutions (Miroshnychenko et al., 2017). In the study by Gusmerotti et al. (2019), multiple advantages for companies

Table 1
Constructs and definitions.

Construct	Definition	Source(s)
Business Analytics Capability	Business analytics capability (BAC) is the ability of a firm to effectively mobilize, deploy, and utilize BA resources and align BA planning with its strategy to improve its performance.	(Gupta and George, 2016; Wamba et al., 2017)
Resource Orchestration Capability	Resource orchestration capability (ROC) is the ability of a firm to effectively structure, bundle, and leverage the resource portfolio towards firm performance.	(Choi et al., 2020; Sirmon et al., 2011; Wang et al., 2020)
Circular Economy Implementation	Circular economy (CE) implementation is the degree to which a firm effectively leverages circular strategies for value creation and capture as relevant to its perspective.	(Bocken et al., 2016; Khan et al., 2020a)
Firm performance	Firm performance is the degree to which a firm has superior performance relative to its competition in areas of environmental performance, financial performance, competitiveness, and corporate reputation.	(Khan et al., 2020a; Rai et al., 2006)

adopting CE were identified, among them improved brand reputation and customer satisfaction (Ambec and Lanoie, 2008; Darnall and Sides, 2008), current and future legal compliance (Bansal et al., 2018; Gusmerotti et al., 2012), reduced environmental impact (Manninen et al., 2018; Nuβholz, 2018), increased competitive performance (Iraldo et al., 2009), and reduced dependence on the supply of raw materials along with lower exposure to the risk associated with it (Kalaitzi et al., 2018; Winn and Pogutz, 2013). Driven by a business frame (Hahn et al., 2014), several managers see reducing the environmental impact of their products and services as a way to differentiate their offerings from competitors' (Darnall and Sides, 2008) and to lower costs (Iraldo et al., 2009) through more efficient resource use (Heras-Saizarbitoria, 2011). While prior empirical research has shown that CE can improve firm performance, the studies have mainly focused on a narrow subset of circular strategies (Khan et al., 2020a; Zeng et al., 2017), such as reduce, reuse, and recycle or targeting specific life cycle stages. Hence, the need exists for empirical investigation into a broad range of strategies in firms' CE implementation. Thus, the following is hypothesized:

H3. CE implementation will have a positive effect on firm performance.

Addressing the shortcomings of the resource-based view, the theory of resource orchestration has experienced a surge in quantitative studies into its effects on IT resources and capabilities and firm performance (Ahuja and Chan, 2017; Choi et al., 2020; Cui and Pan, 2015; Rojo Gallego Burin et al., 2020). Similarly, a growing number of studies have investigated the importance of dynamic capabilities for corporate sustainability (Annunziata et al., 2018; Hofmann et al., 2012; Wu et al., 2013), environmental management (Daddi et al., 2017), and CE (Kabongo and Boiral, 2017; Khan et al, 2020a, 2020b; Scarpellini et al., 2020b). Therefore, firms whose IT portfolios have a strong ROC are arguably better equipped to support circular and sustainable activities by covering *blind spots* in BA applications and more effectively realize value on their BA investments, which, in turn, influences performance. With studies supporting the strength of the resource orchestration theory in understanding managers' role in structuring, bundling, and leveraging organizational resources towards performance (Collis and Anand, 2019), the importance of optimal resource orchestration for increased competitive performance (Ahuja and Chan, 2017; Gong et al., 2018; Teece, 2014; Wales et al., 2013; Wang et al., 2020), and its complementary role in explaining how firms transition towards a CE (Kiefer et al., 2018), the following is hypothesized:

H4. ROC will have a positive effect on firm performance.

Furthermore, firms' IT ROC, together with CE implementation, may play an important role in fully mediating the relationship between their CE-specific BAC and firm performance. Support for this can be seen in the mediating role of dynamic capabilities between BAC and competitive performance (Mikalef et al., 2020), in CE implementation (Khan et al., 2020a), and the role of ROC in firms' boundary-spanning search for green innovation (Wang et al., 2020) and entrepreneurial orientation towards firm performance (Choi et al., 2020). Specifically, expanding on related studies into the importance of ROC in facilitating green innovation (Luo et al., 2017; Wales et al., 2013; Wang et al., 2020), firms with a strong ROC may be better equipped to structure, bundle, and leverage valuable CE-based BA resources for enhanced firm performance. Conversely, studies indicate that a weak ROC may lead to firms failing to explore and recognize useful knowledge (Zhou and Li, 2012), create novel ideas (Inkpen and Wang, 2006; Lane et al., 2006), and facilitate green innovation (Wang et al., 2020). This hampers their ability to effectively manage internal resources and capabilities, reducing the positive effect of BAC on firm performance. Hence, the main argument of this paper is that BAC improves firms' ROC and helps reduce the risk of investing in CE implementation, increasing the overall effect on firm performance. In other words, BA can support firms' overall CE transition and firm performance in two ways: directly through operationalization of circular strategies and through more efficient orchestration of IT resources. From the discussion above, it is hypothesized that:

H5. BAC will have a positive indirect effect on firm performance, which will be fully mediated by a positive effect on CE implementation and ROC.

4. Empirical study

4.1. Survey, administration, and data

For the purpose of this study, a questionnaire-based survey method was adopted to allow for generalizability and replication of the results and to facilitate a simultaneous investigation of several factors (Pinsonneault and Kraemer, 1993). The methodology is well-documented in exploratory settings and a robust way of identifying the general tendency and associations in a sample with predictive theory for generalization of results (Straub and Gefen, 2004). The recommended guidelines for questionnaire development (Churchill, 1979; Recker and Rosemann, 2010) and construct measurement (MacKenzie et al., 2011) were employed. In addition, the recommendations and tactics (i.e., personalization, consent screening, and anonymity) by Cycyota and Harrison (2006) to improve response rates were followed. Relevant literature to identify suitable indicators for the constructs under investigation was reviewed, and previously published latent variables with psychometric properties to support their validity were sought. Where this was not possible, new indicators were created based on qualitative and conceptual studies. On the basis of this, a trial questionnaire was drafted and shared with a panel of experts for careful assessment and refinement of indicators, questions, and wording. All items were measured on a 7-point Likert scale due to its suitability for quantifying constructs such as organizational resources and capabilities (Kumar et al., 1993). Following the panel review, a pretest was conducted in a small sample of 11 firms (see Table 2 for details) to test the statistical properties of the constructs and assess the face and content validity of items to ensure respondents interpreted the questions as intended. After completing the pretest, the respondents were contacted by email and asked to comment on the quality of the questionnaire and to provide suggestions for improving the clarity of the questions. The

Table 2
Pretest characteristics.

Factors	Sample (N = 11)
Country	
Norway	3
Sweden	2
Other	6
Industry	
Manufacturing	2
Consultancy	2
Information technology	3
Other	4
Firm size (number of employees)	
1–9	3
10–49	1
50–249	2
250+	5
Age of company	
1–4 years	2
5–9 years	2
10–49 years	5
50+ years	2
Respondent position	
Head of digital strategy	2
Head of circular economy/sustainability strategy	2
Director	2
Manager	1
Other	4

aforementioned step satisfied the psychometric properties for suitability and validity of the questionnaire.

For the main sample, the names and details of senior executives engaged in digital and CE activities were obtained from personal contacts, corporate directories, and professional forums. From this, 180 relevant executives and 11 industry networks with European companies were used to disseminate an electronic survey via Nettskjema (an online survey tool developed and operated by the University of Oslo, Norway). The respondents were invited by email, which was followed up by two reminders spaced two weeks apart. The data collection phase lasted for approximately two months (October 2020–December 2020). The sample comprised 64 responses, 56 of which were complete and retained for further analysis. Due to the inadequate number of responses, a second data collection phase was completed. It lasted for approximately one month (January 2021) and used a panel service company to disseminate the questionnaire. To ensure quality responses and consistency with the sample in phase one, the panel service was given strict criteria (guided by the control questions in Appendix A) on what would qualify a respondent for the survey. The second data collection phase resulted in 123 responses, 75 of which qualified for the survey with 69 complete responses. In total, the final sample consisted of 125 responses with an average completion time of 13 min.

The responses in the sample represented a broad set of companies from a variety of countries (see Table 3 for details). The largest proportion of them operated from Norway (23.2%), Poland (9.6%), the United Kingdom (8.8%), Spain (8.8%), and Germany (8.8%). The majority of the companies were medium and large in size (33.6% and 38.4% respectively) from the industries of manufacturing (33.5%), retail and consumer goods (20.8%), information technology (13.6%), and energy, utilities, and resources (10.4%). The questionnaire was targeted at senior managers with knowledge of both the digital and the circular strategies of their organization. To ensure a collective response from the company, the survey participants were encouraged to confer with colleagues in areas outside of their expertise. Most companies had several years of experience using BA and were either somewhat or entirely targeting the CE in their strategy.

Given that each data point was collected from a single source at a single point in time, the possibility of bias exists. The risk of bias in the sample was investigated using a series of statistical tests. First, to reduce the risk of informant bias, the responses from the two data collection

Table 3
Sample characteristics.

Factors	Sample (N = 125)	Percentage (%)
Country		
Norway	29	23.2%
Poland	12	9.6%
United Kingdom	11	8.8%
Spain	11	8.8%
Germany	11	8.8%
Italy	10	8%
France	9	7.2%
Netherlands	8	6.4%
Denmark	6	4.8%
Finland	6	4.8%
Sweden	5	4%
Other	7	5.6%
Industry		
Manufacturing	42	33.6%
Service provider	9	7.2%
Consultancy	7	5.6%
Energy, utilities, and resources	13	10.4%
Retail and consumer goods	26	20.8%
Information technology	17	13.6%
Other	11	8.8%
Firm size (number of employees)		
1–9	15	12%
10–49	20	16%
50–249	42	33.6%
250+	48	38.4%
Years of business analytics experience		
<1 year	16	12.8%
1–2 years	21	16.8%
3–4 years	36	28.8%
4+ years	52	41.6%
Extent to which firm strategy targets the circular economy		
Not at all	5	4%
A little	21	16.8%
Somewhat	50	40%
Entirely	49	39.2%
Age of company		
<1 year	1	0.8%
1–4 years	13	10.4%
5–9 years	24	19.2%
10–49 years	67	53.6%
50+ years	20	16%
Respondent position		
CEO/president	21	16.8%
CIO	10	8%
Head of digital strategy	5	4%
Head of circular economy/sustainability strategy	14	11.2%
Director	19	15.2%
Manager	49	39.2%
Other	7	5.6%

phases were divided into two groups, one for each phase. To compare the two groups a Mann-Whitney *U* test was run of the dependent variable measures using the SPSS software package. The test showed no significant difference between the groups, meaning response bias between the two data collection phases was not an issue (see Table 4 for the results). Second, to control for common method bias ex ante and post ante, the guidelines by Chang et al. (2010) and Podsakoff et al. (2003) were followed. With a view to encouraging the free flow of responses and reducing social desirability bias, the respondents were informed about the purpose of the survey and their data protection rights, receiving assurance that they would remain fully anonymous (Hossain et al., 2020). To test if common method bias was present, a collinearity assessment and Harman's single factor test were performed. For the collinearity assessment approach, VIF values were below 3.3 (at the factor-level), indicating that pathological collinearity was absent and the model was not contaminated by common method bias (Kock, 2015). Similarly, the results for Harman's single factor test indicated an absence of common method bias with a maximum variance by any factor

Table 4
Mann-Whitney *U* test.

Measure	Mann-Whitney U	Significance
PER-EN1	1952.5	0.800
PER-EN2	1832.0	0.707
PER-EN3	1920.0	0.934
PER-F1	1839.5	0.738
PER-F2	1657.5	0.203
PER-F3	1947.5	0.822
PER-CO1	1744.5	0.405
PER-CO2	1588.0	0.099
PER-CO3	1676.5	0.236
PER-CO4	1816.0	0.648
PER-CR1	1708.0	0.306
PER-CR2	1763.5	0.574
PER-CR3	1803.0	0.860
PER-CR4	1910.0	0.975

of 38.8%, meaning that not a single construct accounted for the majority of the variance (Fuller et al., 2016). This suggests that the research model and questionnaire were not contaminated by common method bias.

4.2. Measurements

The main constructs of the study were operationalized using a hierarchical component model with respective sub-constructs for each main construct (Sarstedt et al., 2019). *BAC* was put together as a third-order formative construct consisting of tangible, intangible, and human skills resources as second-order formative constructs, each incorporating three first-order constructs. First, the tangible BA-related resources – consisting of data, technology, and basic resources – were represented as formative first-order constructs. Second, the intangible resources of data-driven culture, circular-oriented innovation (COI) culture, and openness and co-creation were represented as reflective first-order constructs. Third, the human skills components of systems thinking and data science were represented as reflective first-order constructs (See Table 5 for the development and dimension structure of the BAC construct and Table 6 for definitions.). Respondents were asked to what degree they agreed with the listed questions (see Appendix A) on a 7-point Likert scale (1 – Totally disagree; 7 – Totally agree).

CE implementation was developed as a second-order formative construct with three first-order formative constructs. The second-order construct was based on the empirical study by Khan et al. (2020), whereas the first-order constructs and indicators were adapted from the *Circular strategies framework* by Blomsma et al. (2019). The framework presents seven categories of circular strategies (reinvent, rethink and reconfigure, restore, reduce and avoid, recirculate parts and products, recirculate materials, logistics, and energy), each with several sub-categories or areas of application. Informed by the *Smart CE framework* of Kristoffersen et al. (2020) of how BA relates to CE, the logistics and energy categories were omitted, and four of the remaining categories were combined into two. This was done for three reasons: to reduce the total number of survey questions for the sake of brevity, to maintain a formative structure with low indicator correlation, and to avoid first-order constructs with only one indicator. The outcome of the above was the three dimensions of circular strategies, namely reinvent and rethink (strategic activities), restore, reduce and avoid (operational activities), and recirculate (operational activities). Respondents were asked to indicate the level they had implemented or contributed to circular strategies on behalf of another stakeholder on a 7-point Likert scale (1 – Totally disagree; 7 – Totally agree).

ROC was established as a second-order formative construct with three first-order formative constructs: structuring, bundling, and leveraging. The measurements were adopted from prior conceptual research on resource orchestration (Sirmon et al., 2011) and empirical research on ROC (Choi et al., 2020; Wang et al., 2020). As the resource orchestration view is a generic theory, essentially all types of organizational resources all relevant. Therefore, to narrow the scope and ensure consistency with the BAC, respondents were asked to assess the current situation in their firm concerning IT resources and assets only. Questions were measured on a 7-point Likert scale (1 – Totally disagree; 7 – Totally agree).

Firm performance was devised as a second-order formative construct with four first-order formative constructs, specifically environmental performance, financial performance, competitiveness, and corporate reputation. The measurements were based on the scale of Khan et al. (2020) and build upon established indicators from previous studies (Bagur-Femenias et al., 2013; Eurostat, 2014; Zhu et al., 2010). Respondents were asked to assess the degree to which their firm had improved in different areas of organizational performance in the last five years. Questions were measured on a 7-point Likert scale (1 – Totally disagree; 7 – Totally agree). For *control variables,* descriptive information was collected on firm size and age, industry sector, country, ownership structure, experience levels with BA and CE, and the respondents' position within the firm.

5. Analysis

To conduct the analysis and assess the validity and reliability of the research model, partial least squares-based structural equation modeling (PLS-SEM) was employed using the SmartPLS 3 software package

Table 5
Latent constructs and sub-dimensions.

Third-order	Type	Second-order	Type	First-order	Type
BAC	Formative	Tangible resources	Formative	Data	Formative
				Technology	Formative
				Basic resources	Formative
		Intangible resources	Formative	Data-driven culture	Reflective
				COI culture	Reflective
				Openness and co-creation	Reflective
		Human skills	Formative	Systems thinking skills	Reflective
				Data science skills	Reflective
		CE implementation	Formative	Reinvent and rethink	Formative
				Restore, reduce and avoid	Formative
				Recirculate	Formative
		ROC	Formative	Structuring	Formative
				Bundling	Formative
				Leveraging	Formative
		Firm performance	Formative	Environmental	Formative
				Financial	Formative
				Competitiveness	Formative
				Corporate reputation	Formative

Table 6
Business analytics resources.

Second-order construct	First-order construct	Definition	Source(s)
Tangible	Data	Organizations utilizing BA for CE need to capture both internal and external data from multiple sources, independently of structures and on a continuous basis. Further, aspects concerning data (such as quality, sources, availability, and methods for curating) need handling.	(Arunachalam et al., 2018; Gupta and George, 2016; Hedberg et al., 2019; Janssen et al., 2017; Kwon et al., 2014; Mikalef et al., 2017)
	Technology	Novel digital technologies are necessary for handling the large volume, diversity, and speed of data accumulated throughout circular value chains. The complexity of these value chains increases the need for firms to deploy advanced data generation, integration, analysis, and sharing infrastructures.	(Arunachalam et al., 2018; Gupta and George, 2016; Gupta et al., 2019; Hedberg et al., 2019; Mikalef et al., 2017)
	Basic resources	This refers to an organization's investment of time and funds. It includes financial resources as direct investments in support of these technologies and working hours allocated to experimentation with utilizing the potential of BA.	(Gupta and George, 2016; Mikalef et al., 2017; Wamba et al., 2017)
Intangible	Data-driven culture	This describes the extent to which organizational members are committed to BA and make decisions based on insights derived from data.	(Arunachalam et al., 2018; Dubey et al., 2019; Gupta and George, 2016; Mikalef et al., 2020)
	COI culture	This describes the extent to which CE goals, principles, and strategies are integrated into technical and market-based innovations to create value by enabling the sustainable management of resources throughout the design of processes, products/services, and business models.	(Brown et al., 2019; Gupta et al., 2019; Munodawafa and Johl, 2019; Pauliuk, 2018; Prieto-Sandoval et al., 2019; The British Standards Institution, 2017)
	Openness and co-creation	This describes the extent to which organizational members are mutually open about decisions and activities that affect the society/economy/environment and willing to communicate these in a clear, accurate, timely, honest, and complete manner to enhance formal and/or informal arrangements internally and externally to create mutual value.	(Akter et al., 2021; Gupta et al., 2019; Hedberg et al., 2019; Pauliuk, 2018; The British Standards Institution, 2017)
Human skills	Systems thinking skills	This refers to the competencies of employees to take a holistic approach to understanding larger contexts over longer periods of time, looking at connections and patterns of how individual decisions and activities impact environmental, economic, and social issues beyond the immediate first-tier scope.	(Bocken et al., 2019; Gupta et al., 2019; Pauliuk, 2018; The British Standards Institution, 2017; Webster, 2013)
	Data science skills	This refers to the competencies of employees to formulate and solve machine learning problems, utilizing data analytics skills such as statistics, computing, and knowledge about correlation and causation.	(Dhar, 2013; Dubey et al., 2019; Gupta and George, 2016; Power, 2016)

(Ringle et al., 2015). The analysis followed the updated guidelines by Benitez et al. (2020) on how to perform and report on PLS analyses in IS research. Given that the proposed research model is targeted towards exploratory theory building as opposed to theory testing, PLS-SEM is seen as a better option than covariance-based SEM. Further, PLS-SEM allows the use of mixed model specification methods (i.e., simultaneous use of formative and reflective constructs in higher-order latent constructs), while covariance-based SEM methods do not (Akter et al., 2017). PLS-SEM is regarded as a robust and powerful statistical tool and has been applied across various disciplines (Joseph F. Joseph F. Hair et al., 2012a, 2012b), including BA and CE research (Akter et al., 2019; Khan et al., 2020a; Mikalef et al., 2020). Moreover, PLS-SEM is recommended when the research is exploratory, focusing on theory building and predicting target constructs for complex structural models, and allows for simultaneous estimation of multiple relationships between one or more independent and dependent variables (Henseler et al., 2016). Categorized as a variance-based soft modeling technique, PLS-SEM can be used to estimate both reflective and formative constructs and is a well-suited predictive tool for theory building in complex models using smaller samples (Nair et al., 2018). In terms of sample size requirements, the total of 125 respondents meant that the sample exceeded both requirements of *i)* ten times the largest number of formative indicators used to measure one construct and *ii)* ten times the largest number of structural paths directed at a particular latent construct in the model (Hair et al., 2011).

5.1. Measurement model

As the measurement model consisted of both formative and reflective constructs, several different assessment criteria were applied to examine their validity and reliability. The reflective measures, specifically first-order reflective constructs, were tested for discriminant validity, reliability, and convergent validity. Discriminant validity was assessed by calculating the Heterotrait-Monotrait ratio (HTMT). HTMT is seen as a more robust criterion for assessing discriminant validity compared to, for instance, the Fornell-Larcker criterion and assessment of cross-loadings between constructs (Benitez et al., 2020; Henseler et al., 2015). The test measures similarity between constructs by using the multitrait-multimethod matrix and calculating the average correlation of indicators across constructs, measuring different elements of the model relative to the average of the correlation of indicators within the same construct (Benitez et al., 2020). The HTMT should be below the 0.85 (stricter) or 0.9 (more tolerant) thresholds. In this case, all values were below the more stringent thresholds, indicating sufficient discriminant validity (see Table 7). Reliability was examined at the indicator and construct level. For indicator reliability, the construct-to-item loadings were confirmed to be above the threshold of 0.707 and significant (see Table 8). At the construct level, the Cronbach's alpha and composite reliability values were calculated, and it was confirmed that both values greatly exceeded the threshold of 0.70 (Nunnally, 1978). For composite reliability, Benitez et al. (2020) recommend using the Dikjstra-Henseler's indicator. Values over 0.70 indicate that more than 50% of the variance in the construct scores can be explained by the latent variable. For convergent validity, the average variance extracted (AVE) was calculated, and it was confirmed that all values were above the 0.50 threshold. The abovementioned results (see Table 9) suggest that the reflective measures are valid as all items are good indicators of their respective first-order constructs.

For formative measures, the weights and significance levels of each item were calculated first. Although most weights of the indicators were statistically significant, some were found to be non-significant at the first or second-order level (e.g., T2 to T5 of Technology, CE-INV1 to CE-INV3 of Reinvent and Rethink, and PER-CO2 to PER-CO4 of Competitiveness). However, Cenfetelli and Bassellier (2009) argue that formative constructs are likely to have indicators with non-significant weights. This is exasperated with the number indicators. Their recommendation is to keep non-significant indicators in the model provided that there is strong theoretical justification for their inclusion. This contrasts with the approach for reflective indicators, the reason being that reflective measures focus on maximizing the overlap between interchangeable indicators, whereas formative measures focus on minimizing the overlap between complementary indicators. Therefore, removing a formative measure would potentially remove a distinct and important characteristic from the phenomenon under investigation. As the non-significant dimensions and indicators developed to measure them are all based on rigorous theories and capture different critical factors, it is necessary to retain them in the model. Similar justifications can be found in related BAC studies by Gupta and George (2016) and Mikalef and Gupta (2021).

Next, the validity of the formative constructs was evaluated using Edwards' (2001) adequacy coefficient (R2a), following the guidelines of MacKenzie et al. (2011) Schmiedel et al. (2014). The R2a value is calculated by summing the squared correlation between indicators and their respective construct and dividing by the number of items. All values exceeded the threshold of 0.50, indicating that the items are a

Table 7
Discriminant validity (HTMT) of reflective constructs.

	COI culture	Data science skills	Data-driven culture	Openness and co-creation	Systems thinking
COI culture					
Data science skills	0.526				
Data-driven culture	0.692	0.700			
Openness and co-creation	0.809	0.628	0.602		
Systems thinking	0.847	0.595	0.607	0.775	

Table 8
Reflective constructs loadings.

Construct	Measure	Loading	Significance
COI culture			
	COI1	0.83	$p < 0.001$
	COI2	0.72	$p < 0.001$
	COI3	0.82	$p < 0.001$
	COI4	0.76	$p < 0.001$
Data science skills			
	DS1	0.86	$p < 0.001$
	DS2	0.91	$p < 0.001$
	DS3	0.85	$p < 0.001$
	DS4	0.81	$p < 0.001$
Data-driven culture			
	DD1	0.73	$p < 0.001$
	DD2	0.71	$p < 0.001$
	DD3	0.74	$p < 0.001$
	DD4	0.71	$p < 0.001$
Openness and co-creation			
	OCC1	0.81	$p < 0.001$
	OCC2	0.70	$p < 0.001$
	OCC3	0.79	$p < 0.001$
System thinking skills			
	ST1	0.71	$p < 0.001$
	ST2	0.80	$p < 0.001$
	ST3	0.84	$p < 0.001$

valid representation of the construct as most of the variance in the indicators is shared with the construct. The same approach was followed for the higher-order constructs, and all R2a values were above 0.50. Lastly, the presence of multicollinearity was examined using Variance Inflation Factor (VIF) values. While multicollinearity is encouraged for reflective constructs as they focus on maximizing overlap, it can be problematic for formative constructs. The threshold for VIF is typically set at values below 10 (MacKenzie et al., 2011), while Petter et al. (2007) recommend a more conservative cutoff at 3.3. Four items were observed to be above the conservative threshold, with the highest VIF value being 3.593. However, as these values are only slightly above the more strict cutoff, it is believed that multicollinearity is not a concern in this study (Cenfetelli and Bassellier, 2009). The above-mentioned results (see Table 10) suggest that the formative measures are valid as all items are good indicators of their respective constructs. Overall, both reflective and formative constructs demonstrated satisfactory psychometric properties.

5.2. Confirmatory composite analysis

To assess the overall fit of the model, a confirmatory composite analysis of the saturated model was performed, following the recommendations of Gefen et al. (2011), Hair et al. (2020), and Henseler (2017). The saturated model allows all constructs to be freely correlated, while the concept's operationalization is as specified by the analyst. This is useful when assessing the model fit and the validity of the measurement and composite model because it helps determine potential misspecifications in the model (Benitez et al., 2020). This is done by comparing the empirical correlation matrix with the model-implied correlation matrix. Benitez et al. (2020) recommend using the standardized root means square residual (SRMR), unweighted least squares discrepancy (d_{ULS}), and geodesic discrepancy (d_g) for evaluating the goodness of fit for the saturated model. As a whole, the analysis provides empirical support to whether or not the indicators form a construct and if the latent variables exist. For SRMR, a value of 0.036 was observed, which is lower than the 0.080 threshold (Henseler et al., 2014; Hu et al., 1992). SRMR measures the average magnitude of the discrepancies between the observed and the expected correlations. The discrepancy indicators (d_{ULS} and d_G) were both below their corresponding 95% quantile reference distributions. Thus, empirical evidence for the latent variables was obtained (see Table 11).

Table 9
Assessment of reliability and convergent validity of reflective constructs.

Construct	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1) Basic resources	n/a																	
(2) Bundling	0,636	n/a																
(3) Reinvent and rethink	0,651	0461	n/a															
(4) Recirculate	0,677	0438	0,575	n/a														
(5) Restore, reduce, and avoid	0,560	0419	0,549	0646	n/a													
(6) COI culture	0,750	0566	0,659	0731	0,521	0780												
(7) Competitiveness	0,437	0464	0,298	0452	0,348	0547	n/a											
(8) Corporate reputation	0,590	0650	0,435	0525	0,461	0656	0,728	n/a										
(9) Data	0,639	0656	0,462	0553	0,544	0479	0,356	0509	n/a									
(10) Data science skills	0,641	0668	0,374	0537	0,417	0524	0,346	0508	0,640	0858								
(11) Data-driven culture	0,739	0784	0,452	0531	0,452	0693	0,500	0700	0,636	0700	0,721							
(12) Environmental performance	0,532	0475	0,415	0501	0,532	0611	0,573	0661	0,434	0451	0,503	n/a						
(13) Financial performance	0,336	0433	0,212	0318	0,407	0369	0,648	0569	0,396	0300	0,313	0583	n/a					
(14) Leveraging	0,688	0798	0,448	0483	0,443	0604	0,474	0620	0,650	0684	0,747	0455	0,375	n/a				
(15) Openness and co-creation	0,711	0521	0,633	0740	0,551	0808	0,510	0625	0,493	0630	0,609	0522	0,303	0548	0,768			
(16) Structuring	0,642	0785	0,433	0428	0,482	0483	0,414	0591	0,678	0698	0,771	0517	0,401	0807	0,485	n/a		
(17) Systems thinking skills	0,760	0643	0,624	0694	0,566	0849	0,576	0697	0,594	0595	0,612	0541	0,368	0632	0,773	0522	0,786	
(18) Technology	0,643	0731	0,492	0478	0,524	0409	0,356	0492	0,749	0750	0,660	0416	0,384	0669	0,549	0716	0,538	n/a
Mean	5.00	5.03	4.84	5.39	5.44	5.16	5.56	5.46	5.10	5.27	4.99	5.49	5.29	5.06	5.27	4.98	5.38	5.23
Standard Deviation	1.32	1.27	1.00	1.24	1.00	1.27	0.99	0.98	1.23	1.26	1.11	1.12	1.11	1.16	1.17	1.18	1.17	1.19
AVE	n/a	n/a	n/a	n/a	n/a	0.608	n/a	n/a	n/a	0.735	0.520	n/a	n/a	n/a	0.589	n/a	0.618	n/a
Cronbach's Alpha	n/a	n/a	n/a	n/a	n/a	0.860	n/a	n/a	n/a	0.917	0.811	n/a	n/a	n/a	0.813	n/a	0.827	n/a
Composite Reliability	n/a	n/a	n/a	n/a	n/a	0.861	n/a	n/a	n/a	0.917	0.812	n/a	n/a	n/a	0.811	n/a	0.829	n/a

178

5.3. *Structural model*

The structural model from the PLS analysis is depicted in Fig. 3 and presents the results of the structural model explained by the variance of endogenous variables (R^2) and the standardized path coefficient (β). The model was verified by assessing the coefficient of determination (R^2) values, path coefficients, and effect size of the predictor variable (f^2). To obtain significance levels of the estimates (t-statistics), a bootstrap analysis using 5000 resamples was performed. Since PLS-SEM does not require the data to meet any particular assumptions about sample distribution, parametric significance tests cannot be applied. Instead, PLS-SEM relies on the non-parametric bootstrap resampling approach where randomly drawn sub-samples are used to derive standard errors, t-values, p-values, and confidence intervals (Hair et al., 2016; Preacher and Hayes, 2008). The structural model explained 59.3% of variance in CE implementation ($R^2 = 0.593$), 70.1% in ROC ($R^2 = 0.701$), and 52.2% of variance in firm performance ($R^2 = 0.522$). The expected magnitude of R^2 values is dependent on the phenomenon under investigation and should be judged relative to studies that investigate the same dependent variable (Benitez et al., 2020). In this case, all values exceeded the coefficient of determination in the Khan et al. (2020a) study on CE implementation and firm performance (reporting 0.180 and 0.409, respectively). Furthermore, as the R^2 values represent moderate to substantial predictive power (Henseler et al., 2009), all values are seen as satisfactory.

For the path coefficients, firms' BAC was found to have a significant direct impact on CE implementation ($\beta = 0.770$, $T = 17.738$, $p < 0.001$) and ROC ($\beta = 0.837$, $T = 29.497$, $p < 0.001$). The direct impact of BAC on firm performance was not significant ($\beta = 0.206$, $T = 1.178$, $p > 0.05$), as expected for mediation (see Subsection 5.4). Furthermore, both the impact of CE implementation on firm performance ($\beta = 0.253$, $T = 2.141$, $p < 0.05$) and ROC on firm performance ($\beta = 0.345$, $T = 2.561$, $p < 0.05$) were significant. In the model, the f^2 values from BAC to CE implementation (1.454) and ROC (2.349) indicated a strong effect size, while the effect from CE implementation (0.051) and ROC (0.070) on firm performance indicated a weak effect size (Cohen, 1988). The effect size is useful in measuring the practical relevance of relationships between constructs by indicating the extent to which the path coefficient exists in the population. The influence of control variables on the dependent variable, firm performance, was examined using dummy variables. All variables were found to have non-significant relationships to firm performance, with the exception of information technology companies ($\beta = 0.129$, $T = 2.204$, $p < 0.05$). Despite having a significant path coefficient, the change in explained variance ($\Delta R^2 = 0.015$) was small and the effect size ($f^2 = 0.034$, $T = 0.933$, $p = 0.351$) weak and non-significant. Furthermore, this is believed to have no practical relevance for the model due to when the data was collected (during the COVID-19 pandemic). Information technology companies might have been less affected, and this can be why they are more strongly correlated with firm performance.

5.4. *Test for mediation*

Mediation is the sequence in which a change in an exogenous variable causes a change in a mediator variable, which then affects the endogenous variable (Nitzl et al., 2016). In other words, it helps explain the underlying process, or mechanism, of the relationship between two constructs. Following the recommendations of Hair et al. (2016), the model was examined for mediation by comparing the direct and indirect effects between BAC and firm performance. As seen in Table 12, both indirect or mediated paths (BAC → CE implementation → firm performance and BAC → ROC → firm performance) were significant, and the direct path (BAC → firm performance) was non-significant. Thus, as the direct path from BAC to firm performance was non-significant while the indirect paths were significant, it is concluded that CE implementation and ROC fully mediate the effect of BAC on firm performance.

Table 10
Formative construct validation.

Construct	Measures	Weight	Significance	VIF	R^2_a
Data	D1	0.221	*Ns*	1.781	0.64
	D2	0.158	*Ns*	1.856	
	D3	0.480	$p < 0.01$	2.013	
	D4	0.351	$p < 0.01$	1.896	
Basic resources	BR1	0.330	$p < 0.01$	1.637	0.73
	BR2	0.551	$p < 0.001$	1.974	
	BR3	0.275	$p < 0.05$	2.145	
Technology	T1	0.434	$p < 0.001$	1.895	0.66
	T2	0.125	*Ns*	2.565	
	T3	0.219	*Ns*	2.454	
	T4	0.197	*ns*	2.542	
	T5	0.239	*ns*	2.086	
Tangible	Data	0.187	$p < 0.05$	2.629	0.76
	Basic resources	0.663	$p < 0.001$	2.012	
	Technology	0.255	$p < 0.01$	2.557	
Intangible	Data-driven culture	0.487	$p < 0.001$	1.557	0.72
	COI culture	0.327	$p < 0.01$	2.173	
	Openness and co-creation	0.365	$p < 0.001$	1.907	
Human skills	Systems thinking skills	0.625	$p < 0.001$	1.374	0.76
	Data science skills	0.520	$p < 0.001$	1.374	
BAC	Tangible	0.407	$p < 0.001$	3.171	0.85
	Intangible	0.476	$p < 0.001$	2.940	
	Human skills	0.198	$p < 0.05$	3.461	
Structuring	ROS1	0.290	$p < 0.05$	1.905	0.74
	ROS2	0.420	$p < 0.01$	2.027	
	ROS3	0.434	$p < 0.001$	1.830	
Bundling	ROB1	0.531	$p < 0.001$	2.465	0.79
	ROB2	0.378	$p < 0.01$	2.578	
	ROB3	0.194	$p < 0.05$	2.171	
Leveraging	ROL1	0.471	$p < 0.001$	2.246	0.78
	ROL2	0.229	$p < 0.05$	2.177	
	ROL3	0.416	$p < 0.001$	2.472	
ROC	Structuring	0.249	*ns*	3.473	0.86
	Bundling	0.430	$p < 0.05$	3.351	
	Leveraging	0.393	$p < 0.01$	3.593	
Reinvent and rethink	CE-INV1	0.317	*ns*	2.133	0.63
	CE-INV2	0.260	*ns*	1.360	
	CE-INV3	0.157	*ns*	2.430	
	CE-INV4	0.507	$p < 0.01$	1.963	
Restore, reduce, and avoid	CE-RRA1	0.437	$p < 0.01$	1.218	0.57
	CE-RRA2	0.364	$p < 0.05$	1.227	
	CE-RRA3	0.513	$p < 0.001$	1.269	
Recirculate	CE-REC1	0.524	$p < 0.001$	1.352	0.66
	CE-REC2	0.344	$p < 0.05$	1.615	
	CE-REC3	0.361	$p < 0.01$	1.592	
CE implementation	Reinvent and rethink	0.334	$p < 0.01$	1.755	0.73
	Restore, reduce, and avoid	0.199	*ns*	2.041	
	Recirculate	0.608	$p < 0.001$	1.991	
Environmental	PER-EN1	0.314	$p < 0.05$	2.247	0.73
	PER-EN2	0.473	$p < 0.01$	2.351	
	PER-EN3	0.380	$p < 0.05$	1.476	
Financial	PER-F1	0.475	$p < 0.01$	1.305	0.63
	PER-F2	−0.038	*ns*	2.045	
	PER-F3	0.724	$p < 0.01$	2.029	
Competitiveness	PER-CO1	0.577	$p < 0.01$	1.733	0.67
	PER-CO2	0.354	*ns*	2.199	
	PER-CO3	0.141	*ns*	2.338	
	PER-CO4	0.097	*ns*	2.180	
Corporate reputation	PER-CR1	0.161	*ns*	2.706	0.65
	PER-CR2	0.388	$p < 0.01$	2.097	
	PER-CR3	−0.002	*ns*	2.258	
	PER-CR4	0.603	$p < 0.001$	1.833	
Firm performance	Environmental	0.360	$p < 0.01$	2.028	0.62
	Financial	−0.085	*ns*	1.992	
	Competitiveness	0.002	*ns*	2.724	
	Corporate reputation	0.777	$p < 0.001$	2.827	

5.5. Predictive validity

Lastly, the predictive validity of the model was examined. Predictive validity can be assessed through sample re-use by computing the predictive relevance of constructs and evaluating how well values are reproduced by the model and its parameter estimates (Chin, 1998; Woodside, 2013). Known as the Stone-Geisser (Q^2) indicator, the method is a combination of function fitting and cross-validation, which omits certain inner model relationships and examines each construct's predictive relevance by changes in the criterion estimates (Joe F. Joe F. Hair et al., 2012a, 2012b). Values above 0 indicate predictive relevance, with values above 0.35 indicating a high effect, and contrary values

Table 11
Results of the confirmatory composite analysis.

Discrepancy	Saturated model fit		
	Value	HI_{95}	Conclusion
SRMR	0.036	0.042	Supported
d_{ULS}	0.117	0.163	Supported
d_G	0.129	0.167	Supported

below 0 indicate insufficient predictive relevance (Hair et al., 2016). It was found from the analysis that ROC ($Q^2 = 0.697$), CE implementation ($Q^2 = 0.573$), and firm performance ($Q^2 = 0.502$) all had satisfactory and high predictive relevance. Overall, the proposed nomological network fits the data quite well based on consistency in the analysis results, and all five hypotheses were empirically supported, reinforcing the validity of the findings.

6. Discussion

While real examples of information flows enabling circularity exist, and researchers' theoretical understanding of the relationship between BA and CE has been improving (Nobre and Tavares, 2019; Rosa et al., 2020), the mechanisms and conditions under which BA can accelerate firms' CE implementation remain largely unexplored in empirical research. Notwithstanding the number of empirical studies on BA for general business operation and supply chain management (Akter et al., 2016; Wamba et al., 2020), these are all rooted in the linear economic model and way of thinking. In other words, they lack alignment with more holistic information management and sustainable principles core to the CE (Gupta et al., 2019). Furthermore, little is known about the orchestration process required to leverage these BA investments towards firm performance (Mikalef et al., 2018).

6.1. Research implications

This study addresses the issue in an attempt to understand if BA can aid in firms' CE implementation and resource orchestration and how their effects on several facets of organizational performance can be measured. To this end, four main contributions are made in terms of research implications: (1) a construct for capturing CE-specific BAC is developed, (2) the importance of having this capability is demonstrated, not just circular strategies to operationalize it (H1), thus differentiating between strategy and its enactment, (3) the effect BAC has on ROC is highlighted (H2), which is an assumption many studies carry but has not been empirically validated, and (4) it is demonstrated how this affects different mechanisms of firm performance (H3-H5).

The measurement model was established with a BAC construct adapted explicitly for the CE context alongside operationalization of the resource orchestration theory and circular strategies as higher-order constructs. The model was grounded in both established (the resource-based and resource orchestration views) and emergent (the Smart CE framework of Kristoffersen et al. (2020)) theories and enacted through a questionnaire-based survey for empirical investigation with PLS-SEM for analysis. By analyzing survey data from 125 European companies, important contributions are made to both the IS and organizational sustainability research fields by exploring the inner mechanisms of how BA improves CE implementation, along with their combined effect on firm performance. For research on how firms transition towards the CE,

Table 12
Summary of hypotheses and results.

Structural path	Effect	t-value[a]	Bias corrected 95% confidence interval	Conclusion
BAC → CE impl.	0.770	17.738***	[0.670–0.840]	H1 supported
CE impl. → firm performance	0.253	2.141*	[0.021–0.476]	H3 supported
BAC → ROC	0.837	29.497***	[0.772–0.888]	H2 supported
ROC → firm performance	0.345	2.561*	[0.057–0.586]	H4 supported
BAC → firm performance	0.206	1.178	[-0.111 – 0.581]	(Full mediation)
BAC → CE impl. → firm performance	0.195	2.114*	[0.026–0.389]	H5 supported
BAC → ROC → firm performance	0.289	2.529*	[0.064–0.499]	H5 supported
Total indirect effect	0.483	3.164**	[0.172–0.766]	

[a] * significant at $p < 0.05$; ** significant at $p < 0.01$; *** significant at $p < 0.001$ (two-tailed test).

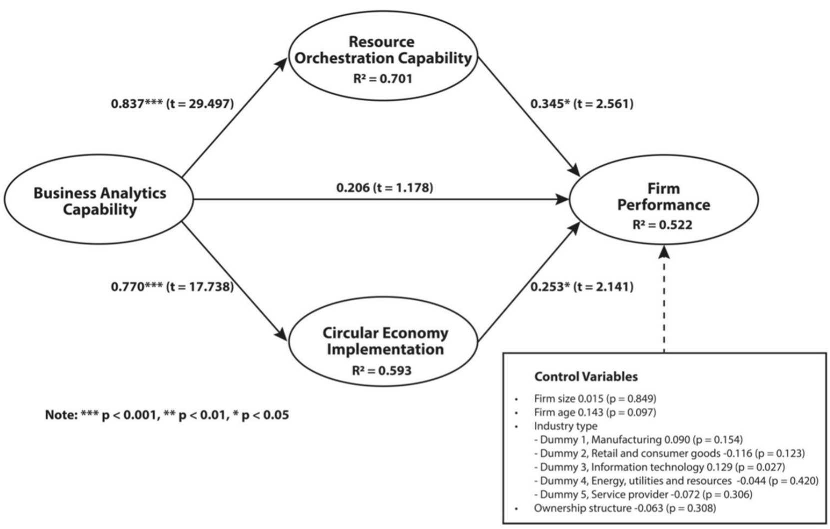


Fig. 3. Results and estimated relationships of the structural model.

the importance of developing a strong BAC is demonstrated by showing it to *i)* enable the operationalization of circular strategies and *ii)* promote better leveraging of such strategies for improved value generation and firm performance. Furthermore, this study contributes to the strategic management theory on the resource-based and resource orchestration views by developing and empirically validating an instrument to measure the IT-based ROC of firms. This builds on previous literature showcasing the importance of BACs for developing dynamic capabilities and supporting decision-making across different stages of the industrial life cycle of assets (Mikalef et al., 2018; Wamba et al., 2017; Wang et al., 2016). The latter put forward interesting propositions on the role of ROC and CE implementation in mediating the effect of BAC on firm performance.

The results are consistent with related BA and CE studies. For instance, the findings of Gupta et al. (2019) and Kristoffersen et al. (2021) on the importance of BA for CE, the effect of CE implementation on firm performance in Khan et al. (2020a), and Mikalef et al. (2020) result in the contingent role of dynamic and operational capabilities in the effect of BAC on firm performance. The present study has several implications for research. Specifically, it highlights the role of digital transformation in sustainable development, explained through the role of BA in accelerating firms' CE adoption and realizing business value. While the development of a BAC is not a prerequisite for CE implementation, it can help organizations generate faster returns and make a more significant impact on their CE investments. Notwithstanding the direct effects of BAC on firm performance for general business operation (Akter et al., 2016), emphasis is placed on the importance of IS research to examine the impact of IT beyond firm performance and strengthen research in the areas of CE and sustainability.

6.2. Practical implications

In terms of practical relevance, firms may find this research useful in three main areas. First, it can provide motivation for transitioning towards the Smart CE. It was found that BA strengthened firms' implementation of circular strategies and organizational performance in terms of competitiveness, corporate reputation, financial results, and environmental efforts. These are valuable findings for companies as they provide a business rationale for implementing circular strategies and ways of capitalizing on BA investments. Furthermore, this research offers strategic justifications for transitioning to a more sustainable mode of business operation. This may be particularly useful for forward-thinking managers and early CE adopters lacking arguments or proof to support a corporate strategy change. Second, it can help companies understand which organizational resources and capabilities are important for leveraging BA for CE. As firms reposition their business to meet new customer needs and sustainability requirements, the investments they make will be crucial for their survival and lasting competitiveness. Therefore, correctly identifying which resources to invest in and which capabilities to develop will be critical. The study also shows that leveraging BA for CE requires investments across talent, culture, and technology. As evident from the eight distinct factors comprising the BAC for CE, companies should be wary of focusing only on tangible assets like data and IT infrastructure, making sure to target investment in their human capital as well, for instance, by improving managers' systems thinking skills and commitment to establishing a data-driven culture. By untangling the relationship between BA and CE, this study advocates for more holistic information management, encouraging a greater focus on 'green digital transformation' within companies. These findings can support the development of more constructive guidelines for implementing circular strategies and aid organizations in making more cost-effective BA investments, for example, by developing the BAC into a benchmarking tool to map a firm's maturity and guide its investments through customized roadmaps. Third, by establishing the ROC, the study demonstrates the importance of managing BA resources to seize business value and the performance returns of BACs. For instance, the ROC can be integrated in the BAC benchmarking tool and roadmap to facilitate SWOT (strengths, weaknesses, opportunities, and threats) analyses and help companies understand where and how to target development activities. The ROC is confluent with previous strategic management theory, arguing that merely procuring and holding valuable resources does not translate into business value or performance gains. Instead, organizations should focus on developing internal capabilities to orchestrate such resources better. Thus, they may find this study useful as a guide to better managing their employees at various levels around the structuring, bundling, and leveraging processes of resource orchestration. Through improved understanding of the relationship between BAC, firm performance, and the mechanisms in-between, companies become better equipped to facilitate change.

6.3. Policy implications

Notwithstanding the growing interest from industry and academia alike, CE as a concept is still in its infancy. As a result, multiple frameworks and definitions co-exist (Blomsma et al., 2019; Kirchherr et al., 2017), and international standardization efforts have recently been initiated (ISO, 2021). Despite the barriers of conflicting definitions and lack of standardization, this also presents an array of opportunities for developed and developing economies to establish unique positions. Studies have suggested a total annual benefit of €1.8 trillion from a complete CE transition for Europe by 2030 (EMF, 2015b). Additionally, with the unprecedented amount of data available in the modern age (McAfee et al., 2012), data itself is becoming a key source of value generation for countries and may even emerge as the most prominent commodity traded in the future (Xiao et al., 2014). For example, the Confederation of Norwegian Enterprise recently estimated the value creation potential of data for Norway to surpass that of oil and gas by 2030 for a total of €30 billion annually (Skogli et al., 2019).

Despite the significant economic benefits to be found in a complete transition to the nexus of these developments, the Smart CE, the challenges facing businesses and policymakers are diverse. This study focused on the perspective of a single company's transition and performance gains; hence, it did not consider issues typical of policy development, such as dealing with a multitude of stakeholders and their joint competitiveness for a fair value distribution in the CE. However, based on the factors identified in the research model, the authors believe that maintaining an open and transparent digital ecosystem where data and services can be made available and shared in an environment of trust will be more important than ever before with the CE. The core success criteria of the Smart CE being its ability to connect material flow with information flow, a framework and data governance model is needed for the free flow of non-personal data. For instance, data on the location, availability, and condition of assets alongside guidelines for tracking products, parts, and materials across value chains should be made available. In this respect, a set of criteria for the minimum amount of data to be shared for circular activities should be established. A balance between data sharing and protection of commercial and strategic information could support collaborative efforts and trust between companies, improving their ability to adopt circular strategies.

Policies and regulations should both be investigated within (e.g., how digitally enabled solutions can be used to improve the extended producer responsibility scheme for electronics or the data associated with waste streams) and across sectors (e.g., raising awareness and enhancing knowledge and competencies in government, industry, and consumers). To enable this, collaborative projects among authorities, industry, and academia should be launched to improve knowledge and develop inspirational best-case scenarios. Pilot projects can be run in selected value chains to create an overview of how to effectively connect information flow with material flow and establish a first-version data governance model and framework for non-personal data sharing.

6.4. Limitations and future research

As with any research, the present study is constrained by certain limitations. To structure the reflection, this is discussed in terms of threats to construct validity and external validity.

6.4.1. Threats to construct validity

Construct validity refers to the adherence of inference made based on the measurements in the study, in other words, whether the study measures what it claims to be measuring. Firstly, the survey relies on self-reported data. Despite this being a common approach to collecting data in several disciplines, people are often biased when reporting on their own experience, meaning factual data may not coincide with respondents' perceptions (Devaux and Sassi, 2016). Reasons can include the interpretation of questions, honesty, introspective ability, and knowledge. To remedy this, the respondents were informed about data protection and anonymity and encouraged to consult with colleagues when answering questions. Despite the researchers' considerable efforts to reduce the potential of bias and ensure good data quality, the occurrence of bias cannot be excluded. Future studies could explore the topic for variance in levels of hierarchy and discrepancies between BA and CE expertise, for instance, by interviewing multiple levels and types of managers from the same firm, checking for interrater validity, and improving internal validity. Secondly, since a different and objective data source (i.e., for firm performance) was not included, there is a risk of mono-method bias in the study. Given its operational scope, with companies from multiple countries and alternatives for complete anonymity (meaning the submission of company name and/or contact details were optional), the authors were unable to collect adequate data on objective firm performance. Establishing firm performance as a higher-order construct addresses this issue to some extent as it provides multiple measures of performance. However, future studies should include an objective measure of both firm performance and CE implementation (e.g., using the circular transition indicators (WBCSD, 2021)).

6.5. Threats to external validity

External validity refers to the extent to which the results of the study can be applied or generalized to other situations or population groups. Despite efforts to develop an inclusive model and generic constructs, the model cannot be considered universal and fully applicable to all companies and applications. Some firms may likely need to develop different BA resources and/or resource orchestration processes to improve their performance and effectively leverage their circular strategies. In particular, CE research has established that firms require many different circular strategies and business model configurations, highly contingent on their size, industry setting, and individual value chain (Bocken et al., 2014). Additionally, paradigm shifts such as those the CE introduces require a change in people's mindset as well as system changes and take decades to unfold (Koschmann, 1996). The concept of CE is still in its early stages, and adoption by industry is modest (Circle Economy, 2020). As this study is only a snapshot in time, longitudinal studies (e.g., a panel survey) could help alleviate endogeneity concerns and provide interesting findings on firms' development and stage-wise adoption of circular strategies. Nevertheless, this is an important and much-needed first step towards a BA construct for CE. By crystallizing related IS theories, the study lays a solid foundation for future studies to extend the application of the model.

7. Conclusion

Now more than ever, implementing circular strategies is dependent on the use of digital technologies like BA. Thus, firms must develop a capability to utilize BA for CE purposes, which can improve their ability to pursue circular strategies, boost value creation, and achieve higher performance returns. Motivated by this prolific BA-CE relationship, the present study utilized PLS-SEM to analyze survey data from 125 European companies. It developed and empirically validated several higher-order constructs alongside a conceptual model for the relationship between a CE-specific BAC, IT ROC, CE implementation, and firm performance. The study was built on the resource-based and resource orchestration views and emergent theory on the Smart CE. The empirical results highlight the importance of taking a more holistic view of BA development. By doing so, firms can better manage their CE implementation and ROC of their IT portfolio, which, in turn, results in improved organizational performance, yielding higher returns on BA investments.

A. Survey instrument.

Measure	Item
Control variables (C) (Mikalef et al., 2020)	
	C1. In which industry sector does your company operate in? (Manufacturing, Service provider, Consultancy, Financial services, Energy, utilities and resources, Retail and consumer goods, Information technology, Media and communication services, Transport, Other)
	C2. What is the approximate number of employees in your company? (1–9, 10–49, 50–249, 250+)
	C3. What is the approximate age of your company? (<1 year, 1–4 years, 5–9 years, 10–49 years, 50+ years)
	C4. What is your position within the company (CEO/President, CIO, Head of digital strategy, Head of circular economy/sustainability strategy, Director, Manager, Other)
	C5. For how many years, if any, has your company employed business analytics? (<1 year, 1–2 years, 3–4 years, 4+ years)
	C6. To what extent does your company's strategy involve circular economy? (Not at all, A little, Somewhat, Entirely)
	C7. For how many years has your company worked with circular economy? (<1 year, 1–2 years, 3–4 years, 4+ years)
	C8. In which country is your company registered?
	C9. What is the ownership structure of your firm? (Public, Private)
Business analytics capability (Gupta and George, 2016; Kristoffersen et al., 2021; Mikalef et al., 2020; Wamba et al., 2017)	
In connection to your circular economy strategies, to what extent do the following statements reflect the situation in your firm? On a scale of (1. Strongly disagree, 2. Disagree, 3. Somewhat disagree, 4. Neither agree or disagree, 5. Somewhat agree, 6. Agree, 7. Strongly agree)	
<u>Tangible</u>	
Data (D)	D1. We have access to high quality data on products/services such as location, availability, and condition data
	D2. We have access to data throughout the life cycle of products/services
	D3. We integrate data from multiple sources into a data warehouse for easy access
	D4. We integrate external data with internal to facilitate analysis of business environment
Basic resources (BR)	BR1. Our 'business analytics' projects are adequately staffed
	BR2. Our 'circular economy' projects are adequately staffed
	BR3. Our joint 'business analytics and circular economy' projects are adequately staffed
Technology (T)	T1. We have implemented different data visualization tools
	T2. We have implemented cloud-based services for processing data and performing analytics
	T3. We have implemented software for business analytics
	T4. We have implemented different data integration technologies
	T5. We have implemented automated data collection technologies (e.g. IoT)
<u>Human Skills</u>	
Systems Thinking skills (ST)	

(continued on next page)

(*continued*)

Measure	Item
	ST1. Our managers take a holistic view of the firm and its value chain, understanding both upstream and downstream impacts over longer periods of time ST2. Our managers understand how individual decisions and activities impact economic, environmental as well as social issues ST3. Our managers view the firm as a collection of parts and relationships within a wider environment
Data science skills (DS)	DS1. Our 'data scientist' staff have the necessary skills to accomplish their jobs successfully (e.g., statistics and computing) DS2. Our 'data scientist' staff are well trained DS3. Our 'data scientist' staff effectively process complex data sets (e.g. through machine learning, data mining, or statistical analyses) DS4. Our 'data scientist' staff are able to understand the business needs and impact of business analytics
Intangible	
Data-driven Culture (DD)	DD1. We base our decisions on data rather than on instinct DD2. We are willing to override our own intuition when data contradict our viewpoints DD3. We continuously coach our employees to make decisions based on data DD4. We offer training on analytics and data-driven decision making to our employees
Circular-oriented innovation culture (COI)	COI1. We have a clear vision of the circular economy and have aligned our corporate strategy accordingly COI2. We integrate circular economy objectives into our innovation process COI3. We continuously coach our employees to make decisions based on circular economy principles COI4. We offer training on circular economy and/or sustainability to our employees
Openness and co-creation (OCC)	OCC1. We actively share data OCC2. We actively promote working across departments and in multi-skilled teams OCC3. We continuously look for ways to support co-creation by developing, experimenting with, and demonstrating, new business models together with end-users, suppliers, and partners
Resource orchestration capability (Choi et al., 2020; Sirmon et al., 2011; Wang et al., 2020) Please indicate to what extent the following statements reflect the current situation in your firm related to IT resources or assets on a scale of (1. Strongly disagree, 2. Disagree, 3. Somewhat disagree, 4. Neither agree or disagree, 5. Somewhat agree, 6. Agree, 7. Strongly agree)	
Structuring (ROS)	ROS1. We are effective at purchasing valuable IT resources/assets from suppliers ROS2. We are effective at developing valuable IT resources/assets internally ROS3. We are effective at decommission less-valuable IT resources/assets
Bundling (ROB)	ROB1. We are effective at integrating IT resources/assets to build IT capabilities ROB2. We are effective at enriching, or extending, existing IT capabilities with new IT resources/assets ROB3. We are effective at pioneering, or creating, new IT capabilities
Leveraging (ROL)	ROL1. We are effective at mobilizing our IT capabilities towards a common vision ROL2. We are effective at coordinating, or integrating, our IT capabilities ROL3. We are effective at deploying our joint IT capabilities to take advantage of specific market opportunities
Circular Economy implementation (Blomsma et al., 2019) Please indicate whether you have implemented the listed circular economy strategies in your company, or contributed to its implementation for another stakeholder (e.g. if you are a service provider, consultancy or similar), on a scale of (1. Strongly disagree, 2. Disagree, 3. Somewhat disagree, 4. Neither agree or disagree, 5. Somewhat agree, 6. Agree, 7. Strongly agree)	
Reinvent and rethink (CE-INV)	CE-INV1. We provide value offerings that are decoupled from material use (e.g. abandoning physical product for digital service) CE-INV2. We support products during their lifetime through providing spare parts and/or repair services as separate sales offerings CE-INV3. We provide the result or performance of a product as a service instead of selling the physical product (e.g. performance-based business models) CE-INV4. We provide the access or usage of a product as a service instead of selling the physical product (e.g. usage-based business models)
Restore, reduce and avoid (CE-RRA)	CE-RRA1. We source secondary, recycled and/or renewable materials (e.g. industrial symbiosis, using ocean plastics or non-toxic materials) CE-RRA2. We run a lean and clean production (e.g. use less energy and materials, treat wastes, rework) CE-RRA3. We optimize product use and operation to extend the product life, minimize energy use, and/or increase product utilization.
Recirculate (CE-REC)	CE-REC1. We provide activities for extending the existing use-cycles of products and parts (e.g. upgrade, repair, maintenance) CE-REC2. We provide activities for extending products and parts to new use-cycles (e.g. reuse, refurbish, remanufacture) CE-REC3. We provide activities for extending the lifespan of materials (e.g. recycle, cascade, energy recovery)
Firm Performance (Khan et al., 2020a) In comparison to your firm's overall performance 5 years ago, please indicate your level of agreement to the following statements, on a scale of (1. Strongly disagree, 2. Disagree, 3. Somewhat disagree, 4. Neither agree or disagree, 5. Somewhat agree, 6. Agree, 7. Strongly agree)	
Environmental (PER-EN)	PER-EN1. We reduced energy consumption PER-EN2. We reduced waste generation PER-EN3. We reduced atmospheric pollution
Financial (PER-F)	PER-F1. We decreased manufacturing/operational costs PER-F2. We increased annual turnover PER-F3. We increased market share
Competitiveness (PER-CO)	PER-CO1. We increased capability to introduce innovative products/services PER-CO2. We improved quality of products/services PER-CO3. We improved brand value of products/services PER-CO4. We increased accessibility to new markets
Corporate reputation (PER-CR)	PER-CR1. We improved corporate image among customers PER-CR2. We improved relationship with suppliers/local community/regulatory organization PER-CR3. We increased satisfaction and support from investors/partners PER-CR4. We increased satisfaction and loyalty of employees

Declaration of competing interest

The authors declare no conflict of interests regarding the publication of this article.

Acknowledgements

The authors would like to thank the reviewers of this paper, Also, the authors would like to acknowledge that the work described in this article has been conducted as part of the research project CIRCit (Circular Economy Integration in the Nordic Industry for Enhanced Sustainability and Competitiveness), which is part of the Nordic Green Growth Research and Innovation Programme (grant number: 83144), and funded by NordForsk, Nordic Energy Research, and Nordic Innovation.

References

Abbasi, A., Sarker, S., Chiang, R.H.L., 2016. Big data research in information systems: toward an inclusive research agenda. J. Assoc. Inf. Syst. Online. https://doi.org/10.17705/1jais.00423.

Ahuja, S., Chan, Y.E., 2017. Resource orchestration for IT-enabled innovation. Kindai Manag. Rev. 5, 78–96.

Akter, S., Wamba, S.F., Gunasekaran, A., Dubey, R., Childe, S.J., 2016. How to improve firm performance using big data analytics capability and business strategy alignment? Int. J. Prod. Econ. 182, 113–131.

Akter, S., Fosso Wamba, S., Dewan, S., 2017. Why PLS-SEM is suitable for complex modelling? An empirical illustration in big data analytics quality. Prod. Plann. Contr. 28, 1011–1021.

Akter, S., Wamba, S.F., D'Ambra, J., 2019. Enabling a transformative service system by modeling quality dynamics. Int. J. Prod. Econ. 207, 210–226.

Akter, S., Mohiuddin Babu, M., Hossain, M.A., Hani, U., 2021. How does value co-creation transform quality of life at the bottom of the pyramid? J. Market. Manag. 1–31.

Ambec, S., Lanoie, P., 2008. Does it pay to be green? A systematic overview. Acad. Manag. Perspect. https://doi.org/10.5465/amp.2008.35590353.

Amit, R., Schoemaker, P.J.H., 1993. Strategic assets and organizational rent. Strat. Manag. J. 14, 33–46.

Amui, L.B.L., Jabbour, C.J.C., de Sousa Jabbour, A.B.L., Kannan, D., 2017. Sustainability as a dynamic organizational capability: a systematic review and a future agenda toward a sustainable transition. J. Clean. Prod. 142, 308–322.

Annunziata, E., Pucci, T., Frey, M., Zanni, L., 2018. The role of organizational capabilities in attaining corporate sustainability practices and economic performance: evidence from Italian wine industry. J. Clean. Prod. https://doi.org/10.1016/j.jclepro.2017.10.035.

Antikainen, M., Uusitalo, T., Kivikytö-Reponen, P., 2018. Digitalisation as an enabler of circular economy. Procedia CIRP 73, 45–49.

Arunachalam, D., Kumar, N., Kawalek, J.P., 2018. Understanding big data analytics capabilities in supply chain management: unravelling the issues, challenges and implications for practice. Transp. Res. Part E Logist. Transp. Rev. 114, 416–436.

Askoxylakis, I., 2018. A framework for pairing circular economy and the internet of things. IEEE Int. Conf. Commun. https://doi.org/10.1109/ICC.2018.8422488.

Bag, S., Gupta, S., Kumar, S., 2021. Industry 4.0 adoption and 10R advance manufacturing capabilities for sustainable development. Int. J. Prod. Econ. 231, 107844.

Bagur-Femenias, L., Llach, J., Alonso-Almeida, M. del M., 2013. Is the adoption of environmental practices a strategical decision for small service companies?: an empirical approach. Manag. Decis. https://doi.org/10.1108/00251741311291300.

Bansal, P., Anna, K.I.M., Wood, M.O., 2018. Hidden in plain sight: the importance of scale in organizations' attention to issues. Acad. Manag. Rev. https://doi.org/10.5465/amr.2014.0238.

Barney, J., 1991. Firm resources and sustained competitive advantage. J. Manag. 17, 99–120.

Barney, J.B., 2001. Resource-based theories of competitive advantage: a ten-year retrospective on the resource-based view. J. Manag. 27, 643–650.

Benitez, J., Henseler, J., Castillo, A., Schuberth, F., 2020. How to perform and report an impactful analysis using partial least squares: guidelines for confirmatory and explanatory IS research. Inf. Manag. https://doi.org/10.1016/j.im.2019.05.003.

Bharadwaj, A.S., 2000. A resource-based perspective on information technology capability and firm performance: an empirical investigation. MIS Q. 169–196.

Bharadwaj, A., El Sawy, O.A., Pavlou, P.A., Venkatraman, N., 2013. Digital business strategy: toward a next generation of insights. MIS Q. Manag. Inf. Syst. https://doi.org/10.25300/MISQ/2013/37:2.3.

Bianchini, A., Pellegrini, M., Rossi, J., Saccani, C., 2018. A new productive model of circular economy enhanced by digital transformation in the Fourth Industrial Revolution-An integrated framework and real case studies. XXIII Summer Sch. "Francesco Turco"–Indus. Syst. Eng. 1–7.

Blomsma, F., Brennan, G., 2017. The emergence of circular economy: a new framing around prolonging resource productivity. J. Ind. Ecol. https://doi.org/10.1111/jiec.12603.

Blomsma, F., Pieroni, M., Kravchenko, M., Pigosso, D.C.A., Hildenbrand, J., Kristinsdottir, A.R., Kristoffersen, E., Shabazi, S., Nielsen, K.D., Jönbrink, A.-K., Li, J., Wiik, C., McAloone, T.C., 2019. Developing a circular strategies framework for manufacturing companies to support circular economy-oriented innovation. J. Clean. Prod. 241 https://doi.org/10.1016/j.jclepro.2019.118271.

Bocken, N.M.P., Short, S.W., Rana, P., Evans, S., 2014. A literature and practice review to develop sustainable business model archetypes. J. Clean. Prod. 65, 42–56.

Bocken, N.M.P., De Pauw, I., Bakker, C., van der Grinten, B., 2016. Product design and business model strategies for a circular economy. J. Ind. Prod. Eng. 33, 308–320.

Bocken, N., Strupeit, L., Whalen, K., Nußholz, J., 2019. A review and evaluation of circular business model innovation tools. Sustainability 11, 2210.

Braganza, A., Brooks, L., Nepelski, D., Ali, M., Moro, R., 2017. Resource management in big data initiatives: processes and dynamic capabilities. J. Bus. Res. 70, 328–337.

Bressanelli, G., Adrodegari, F., Perona, M., Saccani, N., 2018. The role of digital technologies to overcome Circular Economy challenges in PSS Business Models: an exploratory case study. Procedia CIRP 73, 216–221.

Brown, P., Bocken, N., Balkenende, R., 2019. Why do companies pursue collaborative circular oriented innovation? Sustainability 11, 635. https://doi.org/10.3390/su11030635.

Cenfetelli, R.T., Bassellier, G., 2009. Interpretation of formative measurement in information systems research. MIS Q. Manag. Inf. Syst. https://doi.org/10.2307/20650323.

Chadwick, C., Super, J.F., Kwon, K., 2015. Resource orchestration in practice: CEO emphasis on SHRM, commitment-based HR systems, and firm performance. Strat. Manag. J. https://doi.org/10.1002/smj.2217.

Chae, H.-C., Koh, C.E., Prybutok, V.R., 2014. Information technology capability and firm performance: contradictory findings and their possible causes. MIS Q. 38, 305–326.

Chang, C.H., 2018. How to enhance green service and green product innovation performance? The roles of inward and outward capabilities. Corp. Soc. Responsib. Environ. Manag. https://doi.org/10.1002/csr.1469.

Chang, S.J., Van Witteloostuijn, A., Eden, L., 2010. From the Editors: common method variance in international business research. J. Int. Bus. Stud. https://doi.org/10.1057/jibs.2009.88.

Chauhan, C., Sharma, A., Singh, A., 2019. A SAP-LAP linkages framework for integrating Industry 4.0 and circular economy. Benchmark Int. J.

Chen, H., Chiang, R.H.L., Storey, V.C., 2012. Business intelligence and analytics: from big data to big impact. MIS Q. 1165–1188.

Chin, W.W., 1998. The Partial Least Squares Approach for Structural Equation modeling., in: Modern Methods for Business Research.

Choi, S.B., Lee, W.R., Kang, S.W., 2020. Entrepreneurial orientation, resource orchestration capability, environmental dynamics and firm performance: a test of three-way interaction. Sustain. Times. https://doi.org/10.3390/su12135415.

Churchill, G.A., 1979. A paradigm for developing better measures of marketing constructs. J. Mar. Res. https://doi.org/10.2307/3150876.

Cohen, J., 1988. Statistical Power Analysis for the Behavioural Science, second ed. Statistical Power Anaylsis for the Behavioral Sciences.

Collis, D., Anand, B.N., 2019. The Limitations of Dynamic Capabilities. Harvard Business School.

Conboy, K., Mikalef, P., Dennehy, D., Krogstie, J., 2020. Using business analytics to enhance dynamic capabilities in operations research: a case analysis and research agenda. Eur. J. Oper. Res. 281, 656–672.

Côrte-Real, N., Oliveira, T., Ruivo, P., 2017. Assessing business value of big data analytics in European firms. J. Bus. Res. https://doi.org/10.1016/j.jbusres.2016.08.011.

Crook, T.R., Ketchen Jr., D.J., Combs, J.G., Todd, S.Y., 2008. Strategic resources and performance: a meta-analysis. Strat. Manag. J. 29, 1141–1154.

Cui, M., Pan, S.L., 2015. Developing focal capabilities for e-commerce adoption: a resource orchestration perspective. Inf. Manag. https://doi.org/10.1016/j.im.2014.08.006.

Cycyota, C.S., Harrison, D.A., 2006. What (not) to expect when surveying executives: a meta-analysis of top manager response rates and techniques over time. Organ. Res. Methods 9, 133–160.

Daddi, T., Nucci, B., Iraldo, F., 2017. Using Life Cycle Assessment (LCA) to measure the environmental benefits of industrial symbiosis in an industrial cluster of SMEs. J. Clean. Prod. https://doi.org/10.1016/j.jclepro.2017.01.090.

Darnall, N., Sides, S., 2008. Assessing the performance of coluntary environmental programs: does certification matter? Pol. Stud. J. https://doi.org/10.1111/j.1541-0072.2007.00255.x.

de Sousa Jabbour, A.B.L., Jabbour, C.J.C., Godinho Filho, M., Roubaud, D., 2018. Industry 4.0 and the circular economy: a proposed research agenda and original roadmap for sustainable operations. Ann. Oper. Res. 1–14.

Del Giudice, M., Chierici, R., Mazzucchelli, A., Fiano, F., 2020. Supply chain management in the era of circular economy: the moderating effect of big data. Int. J. Logist. Manag.

Devaux, M., Sassi, F., 2016. Social disparities in hazardous alcohol use: self-report bias may lead to incorrect estimates. Eur. J. Publ. Health. https://doi.org/10.1093/eurpub/ckv190.

Dhar, V., 2013. Data science and prediction. Commun. ACM 56, 64–73.

Drnevich, P.L., Kriauciunas, A.P., 2011. Clarifying the conditions and limits of the contributions of ordinary and dynamic capabilities to relative firm performance. Strat. Manag. J. https://doi.org/10.1002/smj.882.

Dubey, R., Gunasekaran, A., Childe, S.J., Wamba, S.F., Papadopoulos, T., 2016. The impact of big data on world-class sustainable manufacturing. Int. J. Adv. Manuf. Technol. 84, 631–645.

Dubey, R., Gunasekaran, A., Childe, S.J., Papadopoulos, T., Luo, Z., Wamba, S.F., Roubaud, D., 2019. Can big data and predictive analytics improve social and environmental sustainability? Technol. Forecast. Soc. Change 144, 534–545. https://doi.org/10.1016/J.TECHFORE.2017.06.020.

Economy, Circle, 2020. The Circularity Gap Report 2020. Circ. Econ., Amsterdam, Netherlands.

Edwards, J.R., 2001. Multidimensional constructs in organizational behavior research: an integrative analytical framework. Organ. Res. Methods. https://doi.org/10.1177/109442810142004.

EMF, 2015a. Delivering the Circular Economy: A Toolkit for Policymakers. Ellen MacArthur Found. Cowes, UK.

EMF, 2015b. Growth within: a Circular Economy Vision for a Competitive Europea. Ellen MacArthur Found. Cowes, , UK.

EMF, 2016. Intelligent Assets: Unlocking the Circular Economy Potential. Ellen MacArthur Found, Cowes, UK.

EMF, 2019. Artificial Intelligence and the Circular Economy. Ellen MacArthur Found. Cowes, UK.

European Commission, 2020a. A New Industrial Strategy for Europe.

European Commission, 2020b. Circular Economy Action Plan.

Eurostat, 2014. The Community Innovation Survey (CIS) - the Harmonized Survey Questionnaire [WWW Document] (accessed 9.30.2020). https://ec.europa.eu/eurostat/web/microdata/community-innovation-survey.

Frank, A.G., Dalenogare, L.S., Ayala, N.F., 2019. Industry 4.0 technologies: implementation patterns in manufacturing companies. Int. J. Prod. Econ. 210, 15–26. https://doi.org/10.1016/j.ijpe.2019.01.004.
Fuller, C.M., Simmering, M.J., Atinc, G., Atinc, Y., Babin, B.J., 2016. Common methods variance detection in business research. J. Bus. Res. https://doi.org/10.1016/j.jbusres.2015.12.008.
Gefen, D., Rigdon, E.E., Straub, D., 2011. An update and extension to SEM guidelines for administrative and social science research. MIS Q. Manag. Inf. Syst. https://doi.org/10.2307/23044042.
Geissdoerfer, M., Savaget, P., Bocken, N.M.P., Hultink, E.J., 2017. The Circular Economy – a new sustainability paradigm? J. Clean. Prod. 143, 757–768. https://doi.org/10.1016/J.JCLEPRO.2016.12.048.
Gelhard, C., Von Delft, S., 2016. The role of organizational capabilities in achieving superior sustainability performance. J. Bus. Res. 69, 4632–4642.
Geng, Y., Sarkis, J., Ulgiati, S., Zhang, P., 2013. Measuring China's circular economy. Science 80. https://doi.org/10.1126/science.1227059.
Ghisellini, P., Cialani, C., Ulgiati, S., 2016. A review on circular economy: the expected transition to a balanced interplay of environmental and economic systems. J. Clean. Prod. 114, 11–32. https://doi.org/10.1016/j.jclepro.2015.09.007.
Gong, Y., Jia, F., Brown, S., Koh, L., 2018. Supply chain learning of sustainability in multi-tier supply chains: a resource orchestration perspective. Int. J. Oper. Prod. Manag. https://doi.org/10.1108/IJOPM-05-2017-0306.
Grant, R.M., 1991. The resource-based theory of competitive advantage: implications for strategy formulation. Calif. Manag. Rev. 33, 114–135.
Günther, W.A., Rezazade Mehrizi, M.H., Huysman, M., Feldberg, F., 2017. Debating big data: a literature review on realizing value from big data. J. Strat. Inf. Syst. 26, 191–209. https://doi.org/10.1016/j.jsis.2017.07.003.
Gupta, M., George, J.F., 2016. Toward the development of a big data analytics capability. Inf. Manag. 53, 1049–1064. https://doi.org/10.1016/j.im.2016.07.004.
Gupta, A., Deokar, A., Iyer, L., Sharda, R., Schrader, D., 2018. Big data & analytics for societal impact: recent research and trends. Inf. Syst. Front. https://doi.org/10.1007/s10796-018-9846-7.
Gupta, S., Chen, H., Hazen, B.T., Kaur, S., Santibañez Gonzalez, E.D.R., Gonzalez, E.D.S., 2019. Circular economy and big data analytics: a stakeholder perspective. Technol. Forecast. Soc. Change 144, 466–474. https://doi.org/10.1016/j.techfore.2018.06.030.
Gusmerotti, N.M., Testa, F., Amirante, D., Frey, M., 2012. The role of negotiating tools in the environmental policy mix instruments: determinants and effects of the Environmental Agreement. J. Clean. Prod. https://doi.org/10.1016/j.jclepro.2012.05.036.
Gusmerotti, N.M., Testa, F., Corsini, F., Pretner, G., Iraldo, F., 2019. Drivers and approaches to the circular economy in manufacturing firms. J. Clean. Prod. 230, 314–327.
Haas, W., Krausmann, F., Wiedenhofer, D., Heinz, M., 2015. How circular is the global economy: an assessment of material flows, waste production, and recycling in the European Union and the world in 2005. J. Ind. Ecol. 19, 765–777.
Hahn, T., Preuss, L., Pinkse, J., Figge, F., 2014. Cognitive frames in corporate sustainability: managerial sensemaking with paradoxical and business case frames. Acad. Manag. Rev. https://doi.org/10.5465/amr.2012.0341.
Hair, J.F., Ringle, C.M., Sarstedt, M., 2011. PLS-SEM: indeed a silver bullet. J. Mark. Theor. Pract. 19, 139–152.
Hair, Joseph F., Sarstedt, M., Pieper, T.M., Ringle, C.M., 2012. The Use of Partial Least Squares Structural Equation Modeling in Strategic Management Research: A Review of Past Practices and Recommendations for Future Applications. Long Range Plann. https://doi.org/10.1016/j.lrp.2012.09.008.
Hair, Joe F., Sarstedt, M., Ringle, C.M., Mena, J.A., 2012. An assessment of the use of partial least squares structural equation modeling in marketing research. J. Acad. Market. Sci. https://doi.org/10.1007/s11747-011-0261-6.
Hair Jr., J.F., Hult, G.T.M., Ringle, C., Sarstedt, M., 2016. A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). Sage publications.
Hair Jr., J.F., Howard, M.C., Nitzl, C., 2020. Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. J. Bus. Res. 109, 101–110.
Hashem, I.A.T., Chang, V., Anuar, N.B., Adewole, K., Yaqoob, I., Gani, A., Ahmed, E., Chiroma, H., 2016. The role of big data in smart city. Int. J. Inf. Manag. https://doi.org/10.1016/j.ijinfomgt.2016.05.002.
Hazen, B.T., Skipper, J.B., Ezell, J.D., Boone, C.A., 2016. Big data and predictive analytics for supply chain sustainability: a theory-driven research agenda. Comput. Ind. Eng. 101, 592–598.
Hedberg, A., Sipka, S., Bjerkem, J., 2019. Creating a digital roadmap for a circular economy. Eur. Policy Cent.
Helfat, C.E., Finkelstein, S., Mitchell, W., Peteraf, M., Singh, H., Teece, D., Winter, S.G., 2009. Dynamic Capabilities: Understanding Strategic Change in Organizations. John Wiley & Sons.
Henseler, J., 2017. Bridging design and behavioral research with variance-based structural equation modeling. J. Advert. https://doi.org/10.1080/00913367.2017.1281780.
Henseler, J., Ringle, C.M., Sinkovics, R.R., 2009. The use of partial least squares path modeling in international marketing. Adv. Int. Market. https://doi.org/10.1108/S1474-7979(2009)0000020014.
Henseler, J., Dijkstra, T.K., Sarstedt, M., Ringle, C.M., Diamantopoulos, A., Straub, D.W., Ketchen, D.J., Hair, J.F., Hult, G.T.M., Calantone, R.J., 2014. Common beliefs and reality about partial least squares: comments on Rönkkö & Evermann (2013),. Organ. Res. Methods.
Henseler, J., Ringle, C.M., Sarstedt, M., 2015. A new criterion for assessing discriminant validity in variance-based structural equation modeling. J. Acad. Market. Sci. https://doi.org/10.1007/s11747-014-0403-8.
Henseler, J., Hubona, G., Ray, P.A., 2016. Using PLS path modeling in new technology research: updated guidelines. Ind. Manag. Data Syst.
Heras-Saizarbitoria, I., 2011. Mapping out ISO 9001, ISO 14001 and other management system standards. Int. J. Prod. Qual. Manag. https://doi.org/10.1504/IJPQM.2011.041096.
Hofmann, K.H., Theyel, G., Wood, C.H., 2012. Identifying firm capabilities as drivers of environmental management and sustainability practices - evidence from small and medium-sized manufacturers. Bus. Strat. Environ. https://doi.org/10.1002/bse.739.
Hossain, T.M.T., Akter, S., Kattiyapornpong, U., Dwivedi, Y., 2020. Reconceptualizing integration quality dynamics for omnichannel marketing. Ind. Market. Manag. 87, 225–241.
Hu, L. tze, Bentler, P.M., Kano, Y., 1992. Can test statistics in covariance structure analysis Be trusted? Psychol. Bull. https://doi.org/10.1037/0033-2909.112.2.351.
Ingemarsdotter, E., Jamsin, E., Kortuem, G., Balkenende, R., 2019. Circular strategies enabled by the internet of things—a framework and analysis of current practice. Sustainability 11, 5689.
Inkpen, A.C., Wang, P., 2006. An examination of collaboration and knowledge transfer: China-Singapore Suzhou industrial park. J. Manag. Stud. https://doi.org/10.1111/j.1467-6486.2006.00611.x.
Iraldo, F., Testa, F., Frey, M., 2009. Is an environmental management system able to influence environmental and competitive performance? The case of the eco-management and audit scheme (EMAS) in the European Union. J. Clean. Prod. https://doi.org/10.1016/j.jclepro.2009.05.013.
ISO, 2021. ISO/TC 323 Circular Economy [WWW Document]. https://www.iso.org/committee/7203984.html. (Accessed 4 February 2021).
Jabbour, C.J.C., de Sousa Jabbour, A.B.L., Sarkis, J., Godinho Filho, M., 2019. Unlocking the circular economy through new business models based on large-scale data: an integrative framework and research agenda. Technol. Forecast. Soc. Change 144, 546–552.
Janssen, M., van der Voort, H., Wahyudi, A., 2017. Factors influencing big data decision-making quality. J. Bus. Res. 70, 338–345. https://doi.org/10.1016/J.JBUSRES.2016.08.007.
Kabongo, J.D., Boiral, O., 2017. Doing more with less: building dynamic capabilities for eco-efficiency. Bus. Strat. Environ. https://doi.org/10.1002/bse.1958.
Kalaitzi, D., Matopoulos, A., Bourlakis, M., Tate, W., 2018. Supply chain strategies in an era of natural resource scarcity. Int. J. Oper. Prod. Manag. https://doi.org/10.1108/IJOPM-05-2017-0309.
Khan, O., Daddi, T., Iraldo, F., 2020a. The role of dynamic capabilities in circular economy implementation and performance of companies. Corp. Soc. Responsib. Environ. Manag.
Khan, O., Daddi, T., Iraldo, F., 2020b. Microfoundations of dynamic capabilities: insights from circular economy business cases. Bus. Strat. Environ. https://doi.org/10.1002/bse.2447.
Kiefer, C.P., Del Río González, P., Carrillo-Hermosilla, J., 2018. Drivers and barriers of eco-innovation types for sustainable transitions: a quantitative perspective. Bus. Strat. Environ. https://doi.org/10.1002/bse.2246.
Kirchherr, J., Reike, D., Hekkert, M., 2017. Conceptualizing the circular economy: an analysis of 114 definitions. Resour. Conserv. Recycl. 127, 221–232.
Kock, N., 2015. Common method bias in PLS-SEM: a full collinearity assessment approach. Int. J. e-Collaboration 11, 1–10.
Koschmann, T., 1996. Paradigm shifts and instructional technology. CSCL Theor. Pract. Emerg. Paradig.
Kraaijenbrink, J., Spender, J.-C., Groen, A.J., 2010. The resource-based view: a review and assessment of its critiques. J. Manag. 36, 349–372.
Kristoffersen, E., Aremu, O.O., Blomsma, F., Mikalef, P., Li, J., 2019. Exploring the relationship between data science and circular economy: an enhanced CRISP-DM process model. In: Conference on E-Business, E-Services and E-Society. Springer International Publishing, Cham, pp. 177–189. https://doi.org/10.1007/978-3-030-29374-1_15.
Kristoffersen, E., Blomsma, F., Mikalef, P., Li, J., 2020. The smart circular economy: a digital-enabled circular strategies framework for manufacturing companies. J. Bus. Res. 120, 241–261. https://doi.org/10.1016/j.jbusres.2020.07.044.
Kristoffersen, Eivind, Mikalef, Patrick, Blomsma, Fenna, Li, Jingyue, 2021. Towards a business analytics capability for the circular economy. Technol. Forecast. Soc. Change 171 (120957). https://doi.org/10.1016/j.techfore.2021.120957.
Kumar, N., Stern, L.W., Anderson, J.C., 1993. Conducting interorganizational research using key informants. Acad. Manag. J. https://doi.org/10.2307/256824.
Kwon, O., Lee, N., Shin, B., 2014. Data quality management, data usage experience and acquisition intention of big data analytics. Int. J. Inf. Manag. 34, 387–394.
Lahti, T., Wincent, J., Parida, V., 2018. A definition and theoretical review of the circular economy, value creation, and sustainable business models: where are we now and where should research move in the future? Sustainability 10, 2799.
Lane, P.J., Koka, B.R., Pathak, S., 2006. The reification of absorptive capacity: a critical review and rejuvenation of the construct. Acad. Manag. Rev. https://doi.org/10.5465/AMR.2006.22527456.
LaValle, S., Lesser, E., Shockley, R., Hopkins, M.S., Kruschwitz, N., 2011. Big data, analytics and the path from insights to value. MIT Sloan Manag. Rev. 52, 21–32.
Linder, M., Williander, M., 2017. Circular business model innovation: inherent uncertainties. Bus. Strat. Environ. 26, 182–196.
Luo, B.N., Lui, S.S., Kim, Y., 2017. Revisiting the relationship between knowledge search breadth and firm innovation: a knowledge transfer perspective. Manag. Decis. https://doi.org/10.1108/MD-07-2015-0327.
MacKenzie, S.B., Podsakoff, P.M., Podsakoff, N.P., 2011. Construct measurement and validation procedures in MIS and behavioral research: integrating new and existing techniques. MIS Q. Manag. Inf. Syst. https://doi.org/10.2307/23044045.

Manninen, K., Koskela, S., Antikainen, R., Bocken, N., Dahlbo, H., Aminoff, A., 2018. Do circular economy business models capture intended environmental value propositions? J. Clean. Prod. https://doi.org/10.1016/j.jclepro.2017.10.003.
Mata, F.J., Fuerst, W.L., Barney, J.B., 1995. Information technology and sustained competitive advantage: a resource-based analysis. MIS Q. 487–505.
McAfee, A., Brynjolfsson, E., Davenport, T.H., Patil, D.J., Barton, D., 2012. Big data: the management revolution. Harv. Bus. Rev. 90, 60–68.
Mikalef, P., Gupta, M., 2021. Artificial intelligence capability: conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. Inf. Manag. https://doi.org/10.1016/j.im.2021.103434.
Mikalef, P., Framnes, V.A., Danielsen, F., Krogstie, J., Olsen, D., 2017. Big data analytics capability: antecedents and business value. In: Pacific Asia Conference on Information Systems (PACIS). Association For Information Systems.
Mikalef, P., Pappas, I.O., Krogstie, J., Giannakos, M., 2018. Big data analytics capabilities: a systematic literature review and research agenda. Inf. Syst. E-bus. Manag. 16, 547–578.
Mikalef, P., Krogstie, J., Pappas, I.O., Pavlou, P., 2020. Exploring the relationship between big data analytics capability and competitive performance: the mediating roles of dynamic and operational capabilities. Inf. Manag. 57, 103169.
Miroshnychenko, I., Barontini, R., Testa, F., 2017. Green practices and financial performance: a global outlook. J. Clean. Prod. https://doi.org/10.1016/j.jclepro.2017.01.058.
Modgil, S., Gupta, S., Sivarajah, U., Bhushan, B., 2021. Technological Forecasting & Social Change Big data-enabled large-scale group decision making for circular economy : an emerging market context. Technol. Forecast. Soc. Change 166, 120607. https://doi.org/10.1016/j.techfore.2021.120607.
Munodawafa, R.T., Johl, S.K., 2019. Big data analytics capabilities and eco-innovation: a study of energy companies. Sustainability 11, 4254.
Nair, S.R., Demirbag, M., Mellahi, K., Pillai, K.G., 2018. Do parent units benefit from reverse knowledge transfer? Br. J. Manag. https://doi.org/10.1111/1467-8551.12234.
Nitzl, C., Roldan, J.L., Cepeda, G., 2016. Mediation analysis in partial least squares path modelling, Helping researchers discuss more sophisticated models. Ind. Manag. Data Syst. https://doi.org/10.1108/IMDS-07-2015-0302.
Nobre, G.C., Tavares, E., 2017. Scientific literature analysis on big data and internet of things applications on circular economy: a bibliometric study. Scientometrics 111, 463–492. https://doi.org/10.1007/s11192-017-2281-6.
Nobre, G.C., Tavares, E., 2019. Assessing the role of big data and the internet of things on the transition to circular economy: Part I-ii. Johnson Matthey Technol. Rev.
Nunnally, J.C., 1978. Phychometric theory. Psychom. theory.
Nußholz, J.L.K., 2018. A circular business model mapping tool for creating value from prolonged product lifetime and closed material loops. J. Clean. Prod. https://doi.org/10.1016/j.jclepro.2018.06.112.
Okorie, O., Salonitis, K., Charnley, F., Moreno, M., Turner, C., Tiwari, A., 2018. Digitisation and the circular economy: a review of current research and future trends. ENERGIES 11. https://doi.org/10.3390/en11113009.
Patwa, N., Sivarajah, U., Seetharaman, A., Sarkar, S., Maiti, K., Hingorani, K., 2020. Towards a circular economy: an emerging economies context. J. Bus. Res.
Pauliuk, S., 2018. Critical appraisal of the circular economy standard BS 8001: 2017 and a dashboard of quantitative system indicators for its implementation in organizations. Resour. Conserv. Recycl. 129, 81–92.
Petter, S., Straub, D., Rai, A., 2007. Specifying formative constructs in information systems research. MIS Q. Manag. Inf. Syst. https://doi.org/10.2307/25148814.
Piccoli, G., Ives, B., 2005. IT-dependent strategic initiatives and sustained competitive advantage: a review and synthesis of the literature. MIS Q. 747–776.
Pinsonneault, A., Kraemer, K.L., 1993. Survey research methodology in management information systems: an assessment. J. Manag. Inf. Syst. https://doi.org/10.1080/07421222.1993.11518001.
Planing, P., 2015. Business model innovation in a circular economy reasons for non-acceptance of circular business models. Open J. Bus. Model Innov. 1.
Podsakoff, P.M., MacKenzie, S.B., Lee, J.Y., Podsakoff, N.P., 2003. Common method biases in behavioral research: a critical review of the literature and recommended remedies. J. Appl. Psychol. https://doi.org/10.1037/0021-9010.88.5.879.
Popovič, A., Hackney, R., Tassabehji, R., Castelli, M., 2018. The impact of big data analytics on firms' high value business performance. Inf. Syst. Front. https://doi.org/10.1007/s10796-016-9720-4.
Power, D.J., 2016. Data science: supporting decision-making. J. Decis. Syst. 25, 345–356.
Preacher, K.J., Hayes, A.F., 2008. Asymptotic and Resampling Strategies for Assessing and Comparing Indirect Effects in Multiple Mediator Models, in: Behavior Research Methods. https://doi.org/10.3758/BRM.40.3.879.
Prieto-Sandoval, V., Jaca, C., Santos, J., Baumgartner, R.J., Ormazabal, M., 2019. Key strategies, resources, and capabilities for implementing circular economy in industrial small and medium enterprises. Corp. Soc. Responsib. Environ. Manag. 26, 1473–1484.
Rai, A., Patnayakuni, R., Seth, N., 2006. Firm performance impacts of digitally enabled supply chain integration capabilities. MIS Q. 225–246.
Rajput, S., Singh, S.P., 2019. Connecting circular economy and industry 4.0. Int. J. Inf. Manag. 49, 98–113. https://doi.org/10.1016/J.IJINFOMGT.2019.03.002.
Ransbotham, S., Kiron, D., 2017. Analytics as a source of business innovation. MIT Sloan Manag. Rev. 58.
Raut, R.D., Mangla, S.K., Narwane, V.S., Gardas, B.B., Priyadarshinee, P., Narkhede, B.E., 2019. Linking big data analytics and operational sustainability practices for sustainable business management. J. Clean. Prod. https://doi.org/10.1016/j.jclepro.2019.03.181.
Recker, J., Rosemann, M., 2010. A measurement instrument for process modeling research : development, test and procedural model. Scand. J. Inf. Syst.
Rialti, R., Marzi, G., Ciappei, C., Busso, D., 2019. Big data and dynamic capabilities: a bibliometric analysis and systematic literature review. Manag. Decis.
Ringle, C.M., Wende, S., Becker, J.M., 2015. SmartPLS 3 [computer Software]. http://www.smartpls.com. Retrived from.
Rojo Gallego Burin, A., Perez-Arostegui, M.N., Llorens-Montes, J., 2020. Ambidexterity and IT competence can improve supply chain flexibility? A resource orchestration approach. J. Purch. Supply Manag. https://doi.org/10.1016/j.pursup.2020.100610.
Rosa, P., Sassanelli, C., Urbinati, A., Chiaroni, D., Terzi, S., 2020. Assessing relations between Circular Economy and Industry 4.0: a systematic literature review. Int. J. Prod. Res. 58, 1662–1687.
Santhanam, R., Hartono, E., 2003. Issues in linking information technology capability to firm performance. MIS Q. 125–153.
Sarstedt, M., Hair, J.F., Cheah, J.H., Becker, J.M., Ringle, C.M., 2019. How to specify, estimate, and validate higher-order constructs in PLS-SEM. Australas. Mark. J. https://doi.org/10.1016/j.ausmj.2019.05.003.
Scarpellini, S., Marín-Vinuesa, L.M., Aranda-Usón, A., Portillo-Tarragona, P., 2020a. Dynamic capabilities and environmental accounting for the circular economy in businesses. Sustain. Acc. Manag. Pol. J. https://doi.org/10.1108/SAMPJ-04-2019-0150.
Scarpellini, S., Valero-Gil, J., Moneva, J.M., Andreaus, M., 2020b. Environmental management capabilities for a "circular eco-innovation. Bus. Strat. Environ. https://doi.org/10.1002/bse.2472.
Schmiedel, T., Vom Brocke, J., Recker, J., 2014. Development and validation of an instrument to measure organizational cultures' support of Business Process Management. Inf. Manag. https://doi.org/10.1016/j.im.2013.08.005.
Schroeder, P., Anggraeni, K., Weber, U., 2019. The relevance of circular economy practices to the sustainable development Goals. J. Ind. Ecol. 23, 77–95. https://doi.org/10.1111/jiec.12732.
Seddon, J.J.J.M., Currie, W.L., 2017. A model for unpacking big data analytics in high-frequency trading. J. Bus. Res. 70, 300–307.
Shuradze, G., Wagner, H.-T., 2016. Towards a conceptualization of data analytics capabilities. In: 2016 49th Hawaii International Conference on System Sciences (HICSS), pp. 5052–5064.
Singh, S.K., El-Kassar, A.N., 2019. Role of big data analytics in developing sustainable capabilities. J. Clean. Prod. https://doi.org/10.1016/j.jclepro.2018.12.199.
Sirmon, D.G., Hitt, M.A., Ireland, R.D., 2007. Managing firm resources in dynamic environments to create value: looking inside the black box. Acad. Manag. Rev. 32, 273–292.
Sirmon, D.G., Hitt, M.A., Ireland, R.D., Gilbert, B.A., 2011. Resource orchestration to create competitive advantage: breadth, depth, and life cycle effects. J. Manag. 37, 1390–1412.
Skogli, A.E., Stokke, O.M., Hveem, E.B., Aamo, A.W., Scheffer, M., Jakobsen, E.W., 2019. ER VERDISKAPING med data NOE NORGE KAN LEVE AV? Menon Econ.
Song, M., Cen, L., Zheng, Z., Fisher, R., Liang, X., Wang, Y., Huisingh, D., 2017. How would big data support societal development and environmental sustainability? Insights and practices. J. Clean. Prod. https://doi.org/10.1016/j.jclepro.2016.10.091.
Sousa-Zomer, T.T., Magalhães, L., Zancul, E., Cauchick-Miguel, P.A., 2018. Exploring the challenges for circular business implementation in manufacturing companies: an empirical investigation of a pay-per-use service provider. Resour. Conserv. Recycl. 135, 3–13.
Stahel, W., 2010. The Performance Economy. Springer.
Straub, D., Gefen, D., 2004. Validation Guidelines for IS Positivist Research. Commun. Assoc. Inf. Syst. https://doi.org/10.17705/1cais.01324.
Su, B., Heshmati, A., Geng, Y., Yu, X., 2013. A review of the circular economy in China: moving from rhetoric to implementation. J. Clean. Prod. 42, 215–227.
Teece, D.J., 2014. A dynamic capabilities-based entrepreneurial theory of the multinational enterprise. J. Int. Bus. Stud. https://doi.org/10.1057/jibs.2013.54.
The British Standards Institution, 2017. Framework for implementing the principles of the circular economy in organizations-Guide. Br. Stand. Inst. 26–31.
Ünal, E., Urbinati, A., Chiaroni, D., 2018. Circular Industry 4.0: an Integrative Framework.
Vidgen, R., Shaw, S., Grant, D.B., 2017. Management challenges in creating value from business analytics. Eur. J. Oper. Res. 261, 626–639. https://doi.org/10.1016/J.EJOR.2017.02.023.
Vinuesa, R., Azizpour, H., Leite, I., Balaam, M., Dignum, V., Domisch, S., Felländer, A., Langhans, S.D., Tegmark, M., Nerini, F.F., 2020. The role of artificial intelligence in achieving the Sustainable Development Goals. Nat. Commun. 11, 1–10.
Wales, W.J., Patel, P.C., Parida, V., Kreiser, P.M., 2013. Nonlinear effects of entrepreneurial orientation on small firm performance: the moderating role of resource orchestration capabilities. Strateg. Entrep. J. https://doi.org/10.1002/sej.1153.
Wamba, S.F., Gunasekaran, A., Akter, S., Ren, S.J. fan, Dubey, R., Childe, S.J., 2017. Big data analytics and firm performance: effects of dynamic capabilities. J. Bus. Res. 70, 356–365. https://doi.org/10.1016/j.jbusres.2016.08.009.
Wamba, S.F., Dubey, R., Gunasekaran, A., Akter, S., 2020. The performance effects of big data analytics and supply chain ambidexterity: the moderating effect of environmental dynamism. Int. J. Prod. Econ. https://doi.org/10.1016/j.ijpe.2019.09.019.
Wang, G., Gunasekaran, A., Ngai, E.W.T., Papadopoulos, T., 2016. Big data analytics in logistics and supply chain management: certain investigations for research and applications. Int. J. Prod. Econ. 176, 98–110.

Wang, J., Xue, Y., Yang, J., 2020. Boundary-spanning search and firms' green innovation: the moderating role of resource orchestration capability. Bus. Strat. Environ. 29, 361–374.
WBCSD, 2021. Circular Transition Indicators v2.0 – Metrics for Business, by Business.
Webster, K., 2013. What might we say about a circular economy? Some temptations to avoid if possible. World Fut. 69, 542–554.
Wernerfelt, B., 1984. A resource-based view of the firm. Strat. Manag. J. 5, 171–180.
Wilts, C.H., Berg, H., 2018. The Digital Circular Economy: Can the Digital Transformation Pave the Way for Resource-Efficient Materials Cycles?.
Winig, L., 2017. A Data-Driven Approach to Customer Relationships: A Case Study of Nedbank's Data Practices in South Africa. MIT Sloan Manag. Rev.
Winn, M.I., Pogutz, S., 2013. Business, ecosystems, and biodiversity: new horizons for management research. Organ. Environ. https://doi.org/10.1177/1086026613490173.
Wixom, B.H., Watson, H.J., 2001. An empirical investigation of the factors affecting data warehousing success. MIS Q. 17–41.
Wong, C.W.Y., Wong, C.Y., Boon-itt, S., 2018. How does sustainable development of supply chains make firms lean, green and profitable? A resource orchestration perspective. Bus. Strat. Environ. https://doi.org/10.1002/bse.2004.
Woodside, A.G., 2013. Moving beyond multiple regression analysis to algorithms: calling for adoption of a paradigm shift from symmetric to asymmetric thinking in data analysis and crafting theory. J. Bus. Res. https://doi.org/10.1016/j.jbusres.2012.12.021.
Wu, Q., He, Q., Duan, Y., 2013. Explicating dynamic capabilities for corporate sustainability. EuroMed J. Bus. https://doi.org/10.1108/EMJB-05-2013-0025.
Wu, K.-J., Liao, C.-J., Tseng, M.-L., Lim, M.K., Hu, J., Tan, K., 2017. Toward sustainability: using big data to explore the decisive attributes of supply chain risks and uncertainties. J. Clean. Prod. 142, 663–676.
Xiao, Y., Lu, L.Y.Y., Liu, J.S., Zhou, Z., 2014. Knowledge diffusion path analysis of data quality literature: a main path analysis. J. Informetr. 8, 594–605.
Zeiss, R., Ixmeier, A., Recker, J., Kranz, J., 2020. Mobilising information systems scholarship for a circular economy: review, synthesis, and directions for future research. Inf. Syst. J. 1–36. https://doi.org/10.1111/isj.12305.
Zeng, H., Chen, X., Xiao, X., Zhou, Z., 2017. Institutional pressures, sustainable supply chain management, and circular economy capability: empirical evidence from Chinese eco-industrial park firms. J. Clean. Prod. https://doi.org/10.1016/j.jclepro.2016.10.093.
Zhang, D., Pan, S.L., Yu, J., Liu, W., 2019. Orchestrating big data analytics capability for sustainability: a study of air pollution management in China. Inf. Manag. https://doi.org/10.1016/j.im.2019.103231.
Zhao, R., Liu, Y., Zhang, N., Huang, T., 2017. An optimization model for green supply chain management by using a big data analytic approach. J. Clean. Prod. 142, 1085–1097.
Zhou, K.Z., Li, C.B., 2012. How knowledge affects radical innovation: knowledge base, market knowledge acquisition, and internal knowledge sharing. Strat. Manag. J. https://doi.org/10.1002/smj.1959.
Zhu, Q., Geng, Y., Lai, K. hung, 2010. Circular economy practices among Chinese manufacturers varying in environmental-oriented supply chain cooperation and the performance implications. J. Environ. Manag. https://doi.org/10.1016/j.jenvman.2010.02.013.

Secondary Paper 1

Big Data and Firm Marketing Performance: Findings from Knowledge-Based View.

Shivam Gupta, Theo Justy, Kamboj Shampy, Ajay Kumar, and Eivind Kristoffersen

In: Technological Forecasting and Social Change, 171, 120986.

Abstract: A universal trend in advanced manufacturing countries is defining Industry 4.0, industrialized internet and future factories as a recent wave, which may transform the production and its related services. Further, big data analytics has emerged as a game changer in the business world due to its uses for increasing accuracy in decision-making and enhancing performance of sustainable industry 4.0 applications. This study intends to emphasize on how to support Industry 4.0 with knowledge based view. For the same, a conceptual model is framed and presented with essential components that are required for a real world implementation. The study used qualitative analysis and was guided by a knowledge-based theoretical framework. Thematic analysis resulted in the identification of a number of emergent categories. Key findings highlight significant gaps in conventional decision-making systems and demonstrate how big data enhances firms' strategic and operational decisions as well as facilitates informational access for improved marketing performance. The resulting proposed model can provide managers with a reference point for using big data to line up firms' activities for more effective marketing efforts, and presents a conceptual basis for further empirical studies in this area.

Secondary Paper 2

A taxonomy and survey of deep learning driven approaches for predictive maintenance.

Zhe Li, Eivind Kristoffersen, and Jingyue Li

Manuscript complete

Abstract: Industry 4.0 and sustainable manufacturing has gained increasing attention and encouraged an accelerated use of the Internet of Things and deep learning methods to capture and analyze data through all stages of production in recent years. Particularly, companies are investigating how to gain foresight of their production through predicting product behavior and performance – as seen with the strategy of predictive maintenance. The aspiration of predictive maintenance is to perform maintenance only when necessary, meaning only after certain analytical models forecast impending failures or degradations. The purpose is to minimize unnecessary maintenance interruptions and extend the remaining useful life of products. However, it is difficult to realize this potential without the correct selection and use of deep learning methods. To address this gap, this paper presents a survey and taxonomy of deep learning driven approaches in the application of predictive maintenance and summarizes the superiorities, limitations, and application scopes of the five most widely used deep learning architectures. The aim is to provide an overall understanding and guide for researchers and practitioners to select proper deep learning approaches for predictive maintenance.

Secondary Paper 3

Using Deep Transfer Learning to Predict Failures with Insufficient Data.

Zhe Li, Eivind Kristoffersen, and Jingyue Li

Manuscript complete

Abstract: Recently, with the increasing development in Artificial Intelligence (AI) technologies for sustainable manufacturing, deep learning-driven approaches are widely and successfully applied to various predictive maintenance tasks. One typical predictive maintenance task is to predict different types of failures of machinery. In practice, the challenge is to collect sufficient data, especially data of various failure types, to train the data-driven models for failure identification, classification, or prediction. Literature shows that knowledge about failure among similar equipment is transferable. In this study, we hypothesize that knowledge about failure among similar failure types is transferable. If the hypothesis holds, it means that companies may no longer require a large amount of all types of failure data for predictive maintenance, which will increase companies' overall implementation feasibility and productivity gains. In this paper, we test our hypothesis about knowledge transferability for predictive maintenance in an experiment performed on rotating machinery with vibration signals. During the experiment, we first calibrated the performance of the trained deep neural network in each impending failure type. Afterward, we leveraged the network trained from one type of failure as the initial weights and further fine-tuned the network with another type of failure. According to the comparison between the performance in calibration and transfer learning, we found that by transferring knowledge obtained from one failure could largely improve the performance of the other failure and reduce the indispensable amount of data for failure identification.

Secondary Paper 4

Smart Circular Economy: CIRCit Workbook 4.

Eivind Kristoffersen, Zhe Li, Jingyue Li, Thomas H. Jensen, Daniela C.A. Pigosso, Tim C. McAloone

Technical University of Denmark

Abstract: This workbook provides insights into which technologies to focus on, depending on the level of organisational readiness and Circular Economy strategies to be adopted. Acknowledging that the workbook covers two emerging and complex fields (Circular Economy and Digitalisation), this workbook attempts to make sense of the many terms and digital buzzwords (that may or may not mean the same). The workbook should be seen as a supplement to many other readings about potential smart solutions to support Circular Economy. Our aim is to go one step deeper into: (i) the terminology and how to understand it; and (ii) provide some examples of how to proceed with smart Circular Economy strategies in real life cases.

Secondary Paper 5

Digital circular economy as a cornerstone of a sustainable European industry transformation.

Holger Berg, Kevin Le Blévennec, Eivind Kristoffersen, Bernard Strée, Arnaud Witomski, Nicole Stein, Ton Bastein, Stephan Ramesohl, and Karl Vrancken

Global Sustainable Technology and Innovation Community Conference 2020

Abstract:

The circular economy is a cornerstone of the European Green Deal. Aimed at renewing existing production and consumption systems, circular economy focuses on optimising the functionality of products and materials, maintaining this functionality for as long as possible and minimising the production of waste and residues. As digital technologies allow to create and process data and information required for circular business models and the complex demands of circular supply chains, they are an enabler for upscaling the circular economy. The circular goals of optimising functionality on the one hand and developing products-as-a-service, on the other hand, call directly upon digital technologies such as functional electronics, distributed ledger and Internet of Things. The aim of dematerialisation is closely related to the development of digital technologies such as digital twins, artificial intelligence and virtual reality. At the same time, the circular economy provides the necessary long-term sustainability vision that is needed to upscale the digital industry. In the run-up to the 2020 edition of the G-STIC conference, we worked closely together with experts from research and technology organisations that are part of ECERA, the European Circular Economy Research Alliance. ECERA is a voluntary collaboration network that aims to strengthen and integrate scientific knowledge and expertise in the field of Circular Economy from an interdisciplinary perspective. As a meeting place for circular economy experts, ECERA provided us with the proper setting for writing a white paper on the digital circular economy. With this white paper, we want to strengthen the link between the digital and circular expert communities, and, as a first critical step, provide a common vocabulary.

ISBN 978-82-326-6505-1 (printed ver.)
ISBN 978-82-326-5669-1 (electronic ver.)
ISSN 1503-8181 (printed ver.)
ISSN 2703-8084 (online ver.)

NTNU
Norwegian University of
Science and Technology