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

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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

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

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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

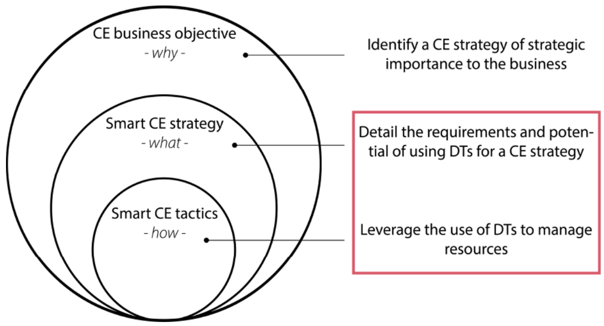

Fig. 1. Research scope.

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

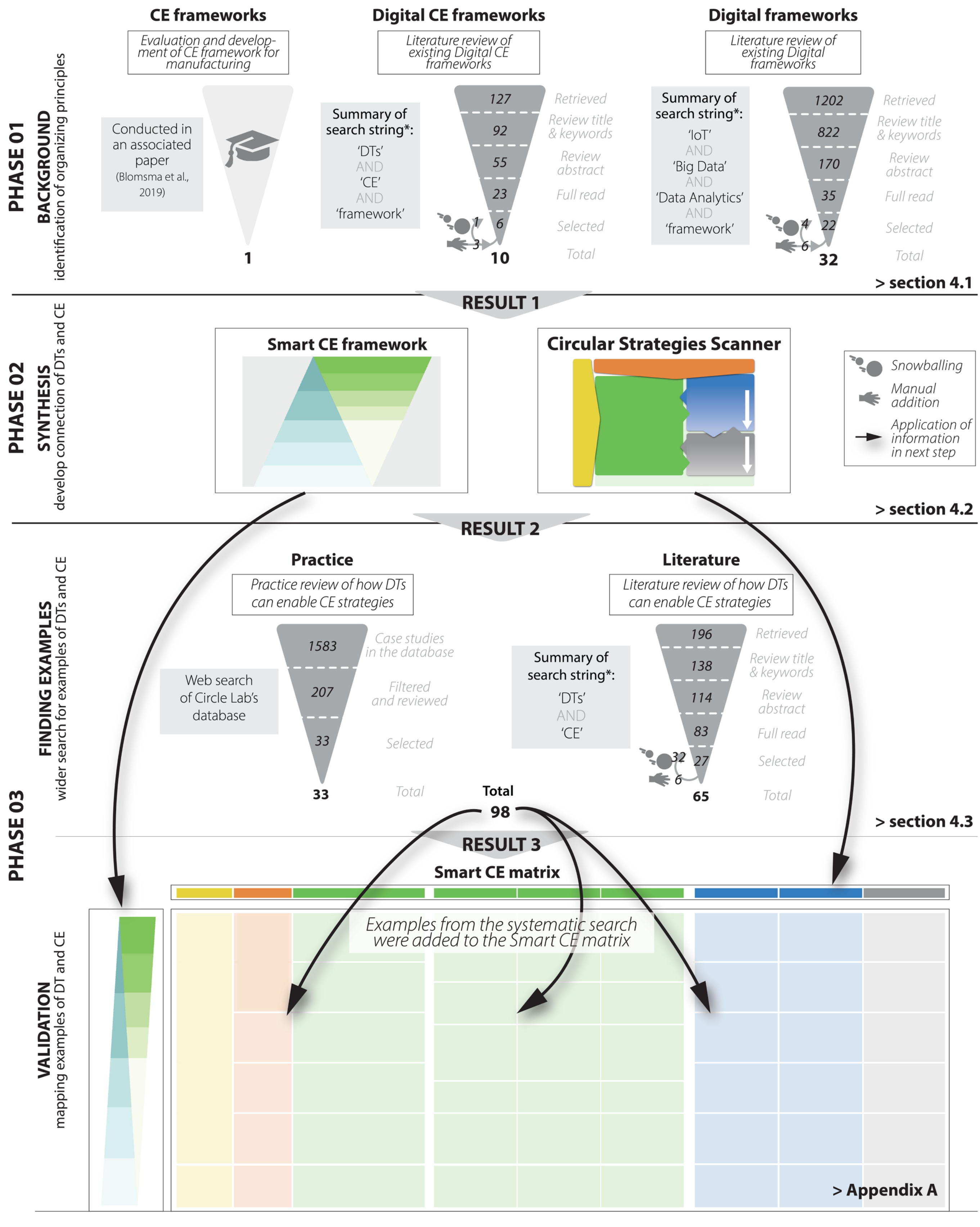

Fig. 2. Schematic illustration of the research approach that was followed to develop the Smart CE framework and matrix.

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.

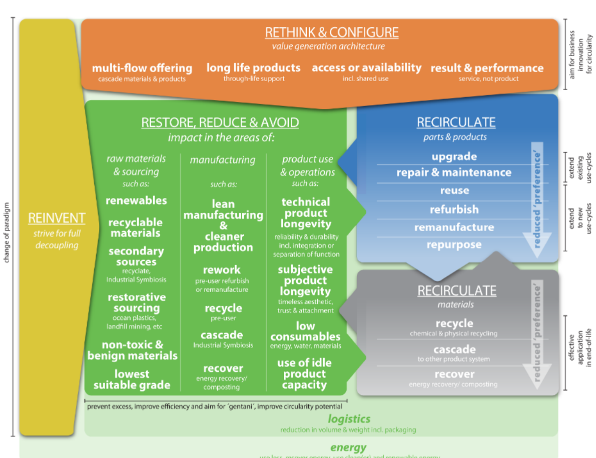

Fig. 3. The Circular Strategies Scanner.

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

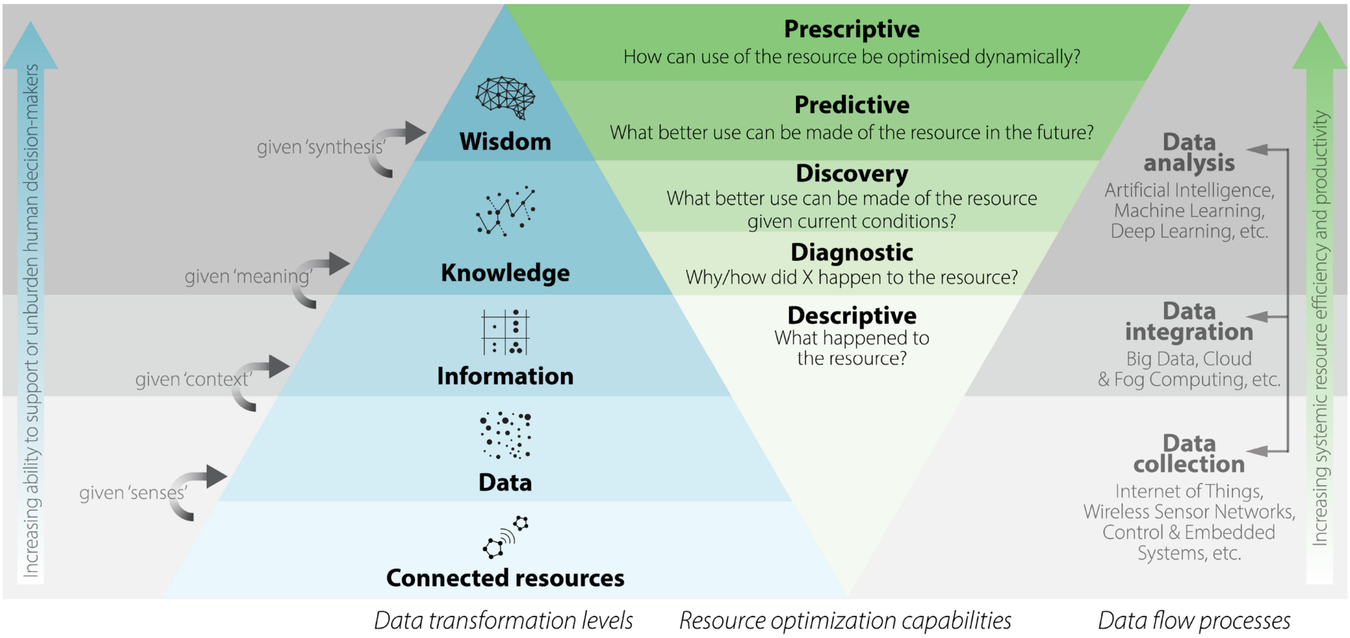

Fig. 4. The Smart CE framework.

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.
- **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.

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

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

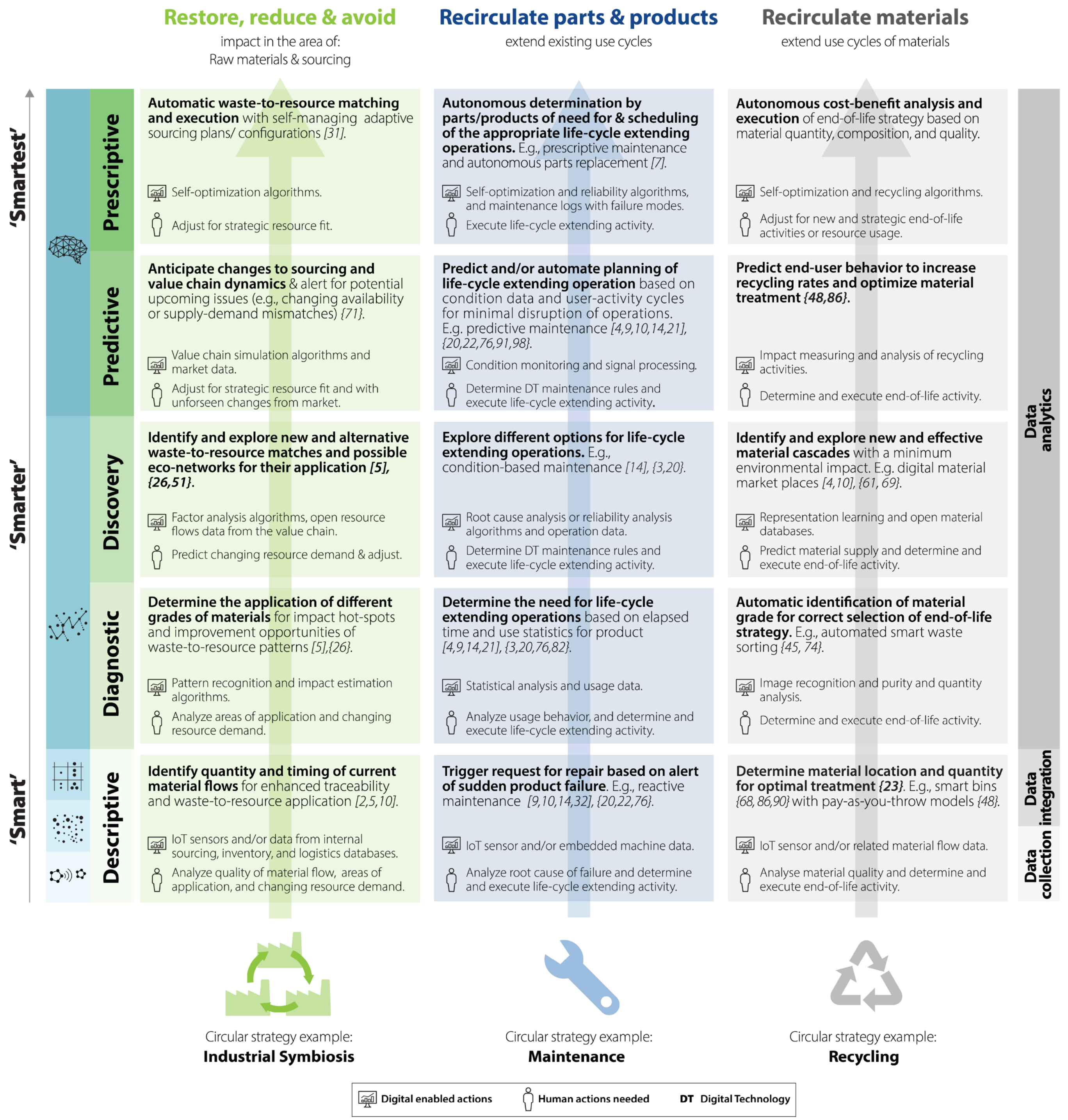

Fig. 5. Illustrative examples with representative requirements (see Figs. A.1–A.3 in Appendix A for further examples and details).

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, 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.

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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

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