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The effects of business analytics capability on circular economy implementation, resource orchestration capability, and firm performance

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A R T I C L E I N F O

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A B S T R A C T

Today, most organizations are undergoing a digital transformation. At the same time, the gravity of environmental issues has put sustainability and the circular economy at the top of corporate agendas. To this end, information systems, in particular business analytics, are being highlighted as essential enablers of an accelerated circular economy transition. However, effectively managing this joint transformation is a challenge. Firms struggle to identify which organizational resources they should target and how those should be leveraged towards a firm-wide business analytics capability for circular economy. To address these questions, this study draws on recent literature dealing with smart circular economy and business analytics capabilities along with the resource-based and resource orchestration view to (1) create an instrument to measure firms' business analytics capability for circular economy, and (2) examine the relationship among a circular economy-specific business analytics capability, circular economy implementation, resource orchestration capability, and firm performance. The proposed research model was tested using partial least squares structural equation modeling of survey data from 125 top-level managers at companies across Europe. The results show that firms with a strong business analytics capability have an increased resource orchestration capability and a greater ability to excel in the circular economy, resulting in improved organizational performance in building a more sustainable competitive advantage in an increasingly competitive business landscape. The effect of business analytics capability on firm performance is not direct but fully mediated through resource orchestration capability and circular economy implementation. The results empirically validate the proposed research model and offer pathways to future information systems research streams to support the operationalization of circular strategies. The study provides the first empirical evidence of a business analytics capability for circular economy and its effect on firm performance.

1. Introduction

The concept of circular economy (CE) is rapidly gathering momentum in industry, policymaking, and academia as a way to boost economic performance without consuming resources at a rate that exceeds the Earth's capacity (European Commission, 2020a, 2020b; Stahel, 2010). The CE achieves this decoupling of value creation from the consumption of finite resources by leveraging a range of efficiency, productivity, and restorative-oriented strategies (known as circular strategies) to keep products, components, and materials in use for longer (EMF, 2015a; 2015b). As such, the CE holds great promise as a contributor to sustainability (Geissdoerfer et al., 2017; Ghisellini et al., 2016) and directly impacts multiple United Nations' Sustainable Development Goals (Schroeder et al., 2019). However, the adoption of CE and sustainable strategies by industry has so far been modest (Circle Economy, 2020; Haas et al., 2015; Planing, 2015; Sousa-Zomer et al., 2018), and scant progress is observed in the decoupling from linear resource consumption.

Simultaneously, digital tools and technologies such as the internet of things, big data, and artificial intelligence have prompted a paradigm shift in industrial production across all sectors. These technologies are seen as critical enablers for an accelerated transition to CE (EMF, 2016);

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they will play a crucial role in operationalizing it at scale (Kristoffersen et al., 2020) and are linked to the accomplishment of all 17 Sustainable Development Goals (Vinuesa et al., 2020). However, findings from research and practice highlight that the main challenges in realizing value from data and analytics are not technological but organizational (Vidgen et al., 2017). Several sources have voiced the need for an improved understanding of firms' digital and circular transition, also known as the *Smart CE* (Askoxylakis, 2018; Bianchini et al., 2018; Ingemarsdotter et al., 2019; Kristoffersen et al., 2019; Rosa et al., 2020; Ünal et al., 2018). Specifically, such calls have been heard in the areas of organizational capabilities (Gelhard and Von Delft, 2016; Prieto-Sandoval et al., 2019), corporate sustainability (Amui et al., 2017), big data analytics for sustainability (Zhang et al., 2019), and information systems (IS) research on CE (Zeiss et al., 2020).

Nevertheless, as the Smart CE represents an emergent field, the link between firms' organizational capabilities and their digital and circular strategies remains underdeveloped. Similarly, there is a limited body of work grounded in established management, IS, and CE theories (Lahti et al., 2018). As a result, there is a knowledge gap in the matter of which internal resources are required to effectively leverage data and analytics for the CE transition and the mechanisms through which this influences firms' performance. Addressing these critical gaps, this study is rooted in the IS field and grounded on the notion of a business analytics capability (BAC). The authors argue that to orchestrate and leverage business analytics (BA) toward increased CE implementation, companies need to develop an amalgamation of tangible, intangible, and human resources (Bag et al., 2021; Gupta et al., 2019; Kristoffersen et al., 2020; Modgil et al., 2021). With limited insight into how BACs create business value (Côrte-Real et al., 2017; Günther et al., 2017), further investigation is needed into how a CE-specific BAC improves firm performance through the mediating roles of CE implementation and resource orchestration capability (ROC) of information technology (IT) resources. Understanding this will have considerable implications for research, policy, and practice alike by highlighting the importance of taking a more holistic view of BA development, allowing firms to generate higher returns on their digital and circular investments, and setting directions for future Smart CE studies. To address this, the present study draws on the qualitative research model, CE-based BA resources, and propositions put forward by Kristoffersen et al. (2021), extending this with a quantitative survey to test the validity of the suggested constructs and relationships. Consequently, this paper seeks to answer the following research questions:

RQ1. What is the effect of business analytics capability on resource orchestration capability and circular economy implementation?

RQ2. What impact do resource orchestration capability and circular economy implementation have on firm performance?

These questions are addressed using the theoretical underpinnings of the resource-based view and the resource orchestration view, which are presented in the next section. Further, an instrument to measure the CE-specific BAC of firms is defined and used to illustrate how BA influences their CE implementation, IT ROC, and organizational performance. The authors hypothesize that BAC has a positive effect on firm performance and that this effect is fully mediated through CE implementation and IT ROC. A survey-based study is developed to examine the hypotheses and quantitatively assess each concept, as described in the subsequent sections. The findings from the empirical analysis are then presented, followed by a discussion of the results with implications for research, industry, and policy, along with the core limitations of this study.

2. Theoretical background

2.1. Smart circular economy

Despite the lack of a unified definition (Kirchherr et al., 2017), the CE can be understood as an *umbrella concept* in which multiple definitions and principles exist (Blomsma and Brennan, 2017). However, common throughout is the intention to address structural waste while constructing new value creation opportunities and reducing value loss and destruction. As the CE is still in a nascent stage of development, regulation continues to lag, and companies embracing circular strategies may be subject to risks such as fluctuating demand, supply, and quality of used assets, leading to uncertainties as to cost and return on investment (de Sousa Jabbour et al., 2018). As a result, assets (products, components, and materials) are recirculated at volumes far below their potential for value delivery.

Central to this untapped potential for recirculation and construction of closed-loop systems is the lack of information sharing and processing throughout the industrial life cycle (Wilts and Berg, 2018). If effectively leveraged, the abundant sources of information and data produced throughout the industrial life cycle of assets could connect the material and information flows towards a CE. Nevertheless, several operational barriers still exist in collecting, integrating, and processing information pertinent to the location, availability, and condition of assets (Su et al., 2013). Hence, increasing organizations' digital maturity and uptake of new digital technologies – particularly base technologies such as the Internet of Things, big data, cloud computing, and artificial intelligence – are highlighted as vital for the operationalization of circular strategies (Antikainen et al., 2018; Bressanelli et al., 2018; de Sousa Jabbour et al., 2018; EMF, 2016; 2019; Kristoffersen et al., 2019; Nobre and Tavares, 2017). In this study, the scope is limited to BA due to *i)* its function as a systems technology merging multiple base technologies (Frank et al., 2019) and *ii)* its potential to improve resource management and facilitate decision-making across different stages of the industrial life cycle of assets (Kristoffersen et al., 2020).

Acknowledging the potential of digitalizing the CE, numerous calls have been made for conducting more research into how companies can leverage their digital strategies towards a more efficient and effective CE (Chauhan et al., 2019; EMF, 2019; 2016; European Commission, 2020b; Okorie et al., 2018; Rosa et al., 2020; Zeiss et al., 2020). Given the breadth of both circular and digital strategies proposed in these calls, the present paper draws on the *Smart CE framework* by Kristoffersen et al. (2020) for consistency with the theoretical underpinnings of underlying base technologies and CE principles. Also known as the digital circular economy, the framework provides a much-needed link between the New Industrial Strategy for Europe and the European Green Deal (European Commission, 2020a, 2020b).

2.2. Resource-based view and resource orchestration

Developing and sustaining a competitive advantage is fundamental to strategic management literature (Amit and Schoemaker, 1993; Wernerfelt, 1984). Multiple frames exist to explain the details of firm performance, one of them being the resource-based view, which is often considered the most rigorous theory of firm performance explained through the resources that companies own and control (Barney, 2001). The resource-based view has also attracted considerable scholarly attention in IS research under the notion of IT capabilities (Bharadwaj, 2000). The theory argues that firms gain a competitive advantage by acquiring tangible and intangible organizational resources that are valuable, rare, inimitable, and non-substitutable (VRIN) (Barney, 1991). Despite several studies supporting the importance of these resources for firm performance, the theory has failed to adequately explain the difference between firms' performance and how they transform these resources into capabilities (Crook et al., 2008; Kraaijenbrink et al., 2010; Sirmon et al., 2011). The core assumptions of VRIN also pose a challenge when applied to BA since the core resource – in this case, data – is generally not rare (Braganza et al., 2017).

Extending the resource-based view, the resource orchestration view has been proposed to address the capability-building processes by explaining the role of managers in transforming resources into capabilities (Sirmon et al., 2011). The resource orchestration view has received significant attention in recent years and represents a promising area of research to understand how firms should best manage their resources for increased competitive performance (Gong et al., 2018; Teece, 2014; Wales et al., 2013; Wang et al., 2020). Recent studies have demonstrated the importance of a strong ROC for improving innovation when adapting to changing market conditions (Chadwick et al., 2015; Sirmon et al., 2007; Wales et al., 2013; Wong et al., 2018). For instance, Teece (2014) emphasizes that resource orchestration is essential for mitigating internal conflict and improving resource complementarities in the firm, supporting the dynamic capabilities needed to facilitate green innovation (Wang et al., 2020). Moreover, the research stream builds on both the resource-based view and the dynamic capabilities view by integrating the resource management framework of Sirmon et al. (2007) and the asset orchestration framework of Helfat et al. (2009). The joint framework presents a novel perspective on a robust management theory of how managers structure, bundle, and leverage their firms' resources for improved organizational performance. According to the framework, firms can only realize the full potential and value of their resources when those are deployed in a complementary manner together with capabilities and managerial acumen (Helfat et al., 2009; Sirmon et al., 2011).

As a result, the theory posits that the ROC is one of the most important competencies a firm can internalize, particularly in the case of organizations prone to suffering from resource-related liabilities. The capability can be seen as the proficiency of a firm in maximizing performance by effectively structuring, bundling, and leveraging existing and new resources (Choi et al., 2020; Wang et al., 2020). While studies have applied the framework to identify IT resources and capabilities for innovation (Ahuja and Chan, 2017), investigate the nature of e-commerce adoption (Cui and Pan, 2015), and understand how ambidexterity and IT competence can improve supply chain flexibility (Rojo Gallego Burin et al., 2020), resource orchestration remains inadequately researched in the context of BA and CE. As the resource orchestration view provides a more robust perspective of managers' specific roles in leveraging capabilities across differences in firm characteristics (e.g., firm size, industry type, and managerial hierarchy), the authors believe this theory proposes a novel perspective on the orchestration of BA that other theories do not. Therefore, the combined strengths of the resource-based view and the resource orchestration view are utilized as the theoretical underpinnings to establish a solid foundation for the survey.

2.3. Business analytics capability

Emerging in the 2000s, BA can be regarded as a collection of technologies, methods, and applications that enable the analysis of business data to promote more sound and data-driven decisions (Chen et al., 2012; Seddon and Currie, 2017). Related to BA, the term *big data analytics* describes the new methods and applications used for (big) data sets that are too large and complex for traditional methods (Chen et al., 2012). In this study, big data analytics and BA are regarded as a unified term (Mikalef et al., 2018). Effectively leveraging business data for value creation requires companies to focus beyond the mere technical aspects of implementing BA (Vidgen et al., 2017). Becoming data-driven is complex and multifaceted, necessitating changes to multiple organizational resources with involvement from several managerial levels. Addressing this, the concept of a *business analytics capability* has emerged to indicate a firm's proficiency in effectively leveraging its data, technology, and talent towards the generation of data-driven insight (Mikalef et al., 2018; Shuradze and Wagner, 2016).

While several studies have explored the role of BAC in improving firm performance through the lens of the resource-based view and dynamic capabilities, research has mostly disregarded its impact beyond the confines of competitive performance, leaving largely untouched the effects on sustainability, CE, and the role of resource orchestration (Rialti et al., 2019; Sirmon et al., 2011). While acknowledging recent research into the role of BAC in sustainable supply chain management (Dubey et al., 2016; Hazen et al., 2016; Wang et al., 2016; Wu et al., 2017; Zhao et al., 2017) and circular supply chain management (Gupta et al., 2019), these studies fall short when considering a broader range of circular strategies. Through a series of interviews, Kristoffersen et al. (2021) address this issue and propose a classification of BAC for CE (see Fig. 1). The study hypothesizes that companies need eight different BA resources that, in combination, build a BAC applicable to multiple circular strategies. However, a gap remains in examining this hypothesis and quantitatively assessing how firms leverage BA for CE. Addressing this gap, the present study operationalizes the notion of a CE-specific BAC to test its validity and suitability in explaining how BA affects IT ROC and CE implementation and how this, in turn, affects the different mechanisms of firm performance.

3. Research model

Drawing on the resource-based view and the resource orchestration view of the firm, this study proposes the research model shown in Fig. 2. In IS research, both tangible assets (like data and technology) and intangible and human assets (like data-driven culture and managerial skills) are regarded as resources based on the definition of Piccoli and Ives (2005). These resources are also specifically mentioned in the widely used classification of BA resources by Gupta and George (2016) and expands upon the highly influential work by Mata et al. (1995) and Wixom and Watson (2001). BAC is conceptualized as a higher-order construct, with each dimension comprising more than one sub-dimension (see definitions in Table 1). This classification (see Fig. 1) is consistent with the framework of Grant (1991), and the dimensions of human skills, tangible resources, and intangible resources are widely used in IT capability literature (Bharadwaj, 2000; Chae et al., 2014; Mikalef et al., 2020; Santhanam and Hartono, 2003).

The authors argue that in order to develop a strong BAC, organizations have to invest in all three types of resources. In doing so, they obtain the capacity to strengthen existing circular strategies, implement new ones, improve their IT ROC, and enhance their overall performance. As such, the effect of BAC on firm performance is fully mediated by firms' IT ROC and degree of CE implementation.

In today's competitive business environment, firms have to constantly update the means through which they deliver value. Complicating the situation is the increasing pressure on them from customers, shareholders, and governments to transition to a more sustainable mode of business operation. Companies utilizing insights generated through BA are better positioned to identify emerging opportunities and threats and transform their operation accordingly (Wamba et al., 2017). Specifically, BAC helps companies expand the locus of decision-making by providing previously unavailable insights and options (Abbasi et al., 2016; Drnevich and Kriauciunas, 2011) and improving response time, effectiveness, and efficiency when dealing with environmental changes (Popovič et al., 2018). Acknowledging the potential of BA to play a role in addressing critical societal challenges, a growing number of studies have noted its positive relationship to sustainable development and CE (Chen et al., 2012; Kristoffersen et al., 2021; Del Giudice et al., 2020; Gupta et al., 2018, 2019; Hashem et al., 2016; Kristoffersen et al, 2020; Patwa et al., 2020; Rajput and Singh, 2019; Singh and El-Kassar, 2019; Song et al., 2017; Zhang et al., 2019). Zeiss et al. (2020) detail the problem-solution pairing of CE and IS as a prolific relationship where digital technologies such as BA have the potential to connect the material and information flows needed to help understand and enact circular material flows, intensify and extend the use of products and components, and recycle waste materials. Data and information flow tracking plays an important role in the transition to a more sustainable economy (Jabbour et al., 2019), providing essential insights for enabling CE adoption and evolution for both large (Geng et al., 2013) and emerging economies (Patwa et al., 2020). Therefore,

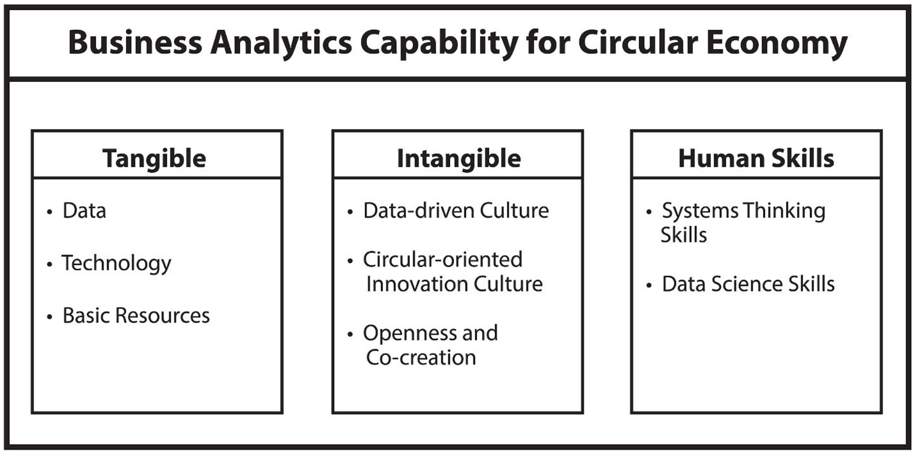

Fig. 1. Classification of business analytics capability (BAC) for circular economy (CE) (Kristoffersen et al., 2021).

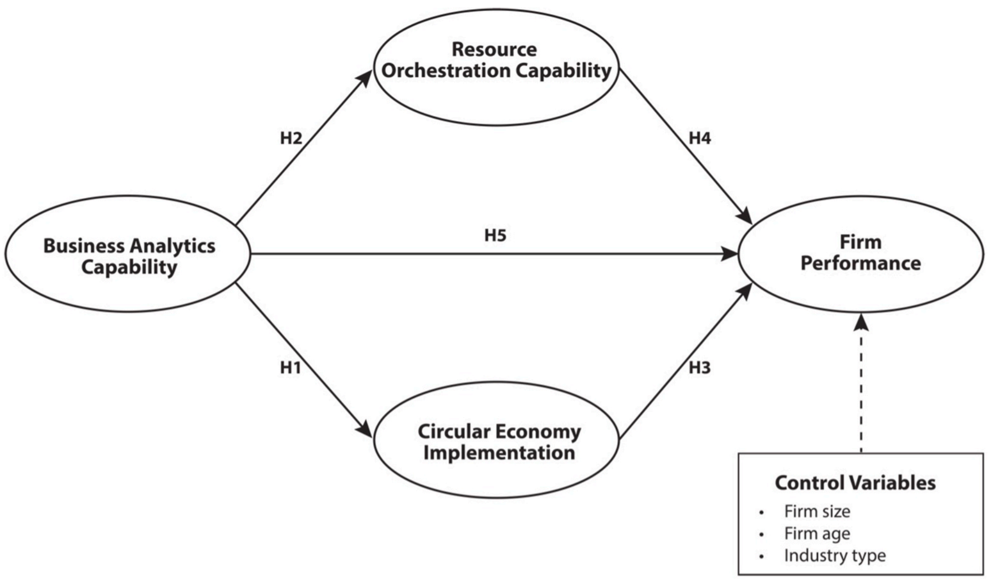

Fig. 2. Research model.

BAC can improve firms' ability to operationalize circular strategies and overall CE implementation. Extensive support for this can be found in related empirical studies on the effect of BAC for improved sustainable supply chain management and circular strategy implementation (Dubey et al., 2016; Gupta et al., 2019; Hazen et al., 2016; Kristoffersen et al., 2021; Wang et al., 2016; Wu et al., 2017; Zhao et al., 2017). From the preceding discussion, it is hypothesized that:

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

Transforming the current mode of business operation requires that companies go beyond focusing solely on technology (Janssen et al., 2017). For instance, Raut et al. (2019) found that management and leadership style, supplier and customer integration, and internal business processes significantly influence the ability of BAC to support sustainable practices. Chauhan et al. (2019) supports this and highlights top-level management as the most essential agent of enablement. With several studies showcasing how a strong BAC can help firms identify threats, seize opportunities, and transform their operation to meet emerging market needs (Braganza et al., 2017; LaValle et al., 2011; Ransbotham and Kiron, 2017; Winig, 2017), the strength of dynamic capabilities and decision-making quality are largely dependent upon the BAC an organization can develop (Conboy et al., 2020; Janssen et al., 2017; Mikalef et al., 2020). Therefore, targeted BAC development may improve the value retention of investments, predictive decision-making quality, and the ability to respond to external needs and opportunities (Bharadwaj et al., 2013). Accordingly, with support from studies on internal capabilities for realizing innovation and driving competitive performance (Barney, 1991; Chadwick et al., 2015; Chang, 2018; Sirmon et al., 2007), BAC can improve firms' ROC. Thus, it is hypothesized that:

H2. BAC will have a positive effect on ROC.

With the launch of a new European CE action plan (European Commission, 2020b) and previously estimated economic benefits of up to €1.8 trillion by 2030 for Europe alone (EMF, 2015b), there is a great promise of value creation for organizations adopting the CE model. Often remarking on the ability to provide a sustainable competitive advantage through the concept of resource efficiency, or "producing more with less" (Linder and Williander, 2017), scholars generally agree that circular strategies lead to improved firm performance (Khan et al., 2020a; Scarpellini et al., 2020a; Zhu et al., 2010). Seeing it as a win-win situation, numerous studies have emphasized the economic benefits of adopting environmental solutions (Miroshnychenko et al., 2017). In the study by Gusmerotti et al. (2019), multiple advantages for companies

Table 1
Constructs and definitions.

Construct	Definition	Source(s)
Business Analytics Capability	Business analytics capability (BAC) is the ability of a firm to effectively mobilize, deploy, and utilize BA resources and align BA planning with its strategy to improve its performance.	(Gupta and George, 2016; Wamba et al., 2017)
Resource Orchestration Capability	Resource orchestration capability (ROC) is the ability of a firm to effectively structure, bundle, and leverage the resource portfolio towards firm performance.	(Choi et al., 2020; Sirmon et al., 2011; Wang et al., 2020)
Circular Economy Implementation	Circular economy (CE) implementation is the degree to which a firm effectively leverages circular strategies for value creation and capture as relevant to its perspective.	(Bocken et al., 2016; Khan et al., 2020a)
Firm performance	Firm performance is the degree to which a firm has superior performance relative to its competition in areas of environmental performance, financial performance, competitiveness, and corporate reputation.	(Khan et al., 2020a; Rai et al., 2006)

adopting CE were identified, among them improved brand reputation and customer satisfaction (Ambec and Lanoie, 2008; Darnall and Sides, 2008), current and future legal compliance (Bansal et al., 2018; Gusmerotti et al., 2012), reduced environmental impact (Manninen et al., 2018; Nuβholz, 2018), increased competitive performance (Iraldo et al., 2009), and reduced dependence on the supply of raw materials along with lower exposure to the risk associated with it (Kalaitzi et al., 2018; Winn and Pogutz, 2013). Driven by a business frame (Hahn et al., 2014), several managers see reducing the environmental impact of their products and services as a way to differentiate their offerings from competitors' (Darnall and Sides, 2008) and to lower costs (Iraldo et al., 2009) through more efficient resource use (Heras-Saizarbitoria, 2011). While prior empirical research has shown that CE can improve firm performance, the studies have mainly focused on a narrow subset of circular strategies (Khan et al., 2020a; Zeng et al., 2017), such as reduce, reuse, and recycle or targeting specific life cycle stages. Hence, the need exists for empirical investigation into a broad range of strategies in firms' CE implementation. Thus, the following is hypothesized:

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

Addressing the shortcomings of the resource-based view, the theory of resource orchestration has experienced a surge in quantitative studies into its effects on IT resources and capabilities and firm performance (Ahuja and Chan, 2017; Choi et al., 2020; Cui and Pan, 2015; Rojo Gallego Burin et al., 2020). Similarly, a growing number of studies have investigated the importance of dynamic capabilities for corporate sustainability (Annunziata et al., 2018; Hofmann et al., 2012; Wu et al., 2013), environmental management (Daddi et al., 2017), and CE (Kabongo and Boiral, 2017; Khan et al, 2020a, 2020b; Scarpellini et al., 2020b). Therefore, firms whose IT portfolios have a strong ROC are arguably better equipped to support circular and sustainable activities by covering *blind spots* in BA applications and more effectively realize value on their BA investments, which, in turn, influences performance. With studies supporting the strength of the resource orchestration theory in understanding managers' role in structuring, bundling, and leveraging organizational resources towards performance (Collis and Anand, 2019), the importance of optimal resource orchestration for increased competitive performance (Ahuja and Chan, 2017; Gong et al., 2018; Teece, 2014; Wales et al., 2013; Wang et al., 2020), and its complementary role in explaining how firms transition towards a CE (Kiefer et al., 2018), the following is hypothesized:

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

Furthermore, firms' IT ROC, together with CE implementation, may play an important role in fully mediating the relationship between their CE-specific BAC and firm performance. Support for this can be seen in the mediating role of dynamic capabilities between BAC and competitive performance (Mikalef et al., 2020), in CE implementation (Khan et al., 2020a), and the role of ROC in firms' boundary-spanning search for green innovation (Wang et al., 2020) and entrepreneurial orientation towards firm performance (Choi et al., 2020). Specifically, expanding on related studies into the importance of ROC in facilitating green innovation (Luo et al., 2017; Wales et al., 2013; Wang et al., 2020), firms with a strong ROC may be better equipped to structure, bundle, and leverage valuable CE-based BA resources for enhanced firm performance. Conversely, studies indicate that a weak ROC may lead to firms failing to explore and recognize useful knowledge (Zhou and Li, 2012), create novel ideas (Inkpen and Wang, 2006; Lane et al., 2006), and facilitate green innovation (Wang et al., 2020). This hampers their ability to effectively manage internal resources and capabilities, reducing the positive effect of BAC on firm performance. Hence, the main argument of this paper is that BAC improves firms' ROC and helps reduce the risk of investing in CE implementation, increasing the overall effect on firm performance. In other words, BA can support firms' overall CE transition and firm performance in two ways: directly through operationalization of circular strategies and through more efficient orchestration of IT resources. From the discussion above, it is hypothesized that:

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

4. Empirical study

4.1. Survey, administration, and data

For the purpose of this study, a questionnaire-based survey method was adopted to allow for generalizability and replication of the results and to facilitate a simultaneous investigation of several factors (Pinsonneault and Kraemer, 1993). The methodology is well-documented in exploratory settings and a robust way of identifying the general tendency and associations in a sample with predictive theory for generalization of results (Straub and Gefen, 2004). The recommended guidelines for questionnaire development (Churchill, 1979; Recker and Rosemann, 2010) and construct measurement (MacKenzie et al., 2011) were employed. In addition, the recommendations and tactics (i.e., personalization, consent screening, and anonymity) by Cycyota and Harrison (2006) to improve response rates were followed. Relevant literature to identify suitable indicators for the constructs under investigation was reviewed, and previously published latent variables with psychometric properties to support their validity were sought. Where this was not possible, new indicators were created based on qualitative and conceptual studies. On the basis of this, a trial questionnaire was drafted and shared with a panel of experts for careful assessment and refinement of indicators, questions, and wording. All items were measured on a 7-point Likert scale due to its suitability for quantifying constructs such as organizational resources and capabilities (Kumar et al., 1993). Following the panel review, a pretest was conducted in a small sample of 11 firms (see Table 2 for details) to test the statistical properties of the constructs and assess the face and content validity of items to ensure respondents interpreted the questions as intended. After completing the pretest, the respondents were contacted by email and asked to comment on the quality of the questionnaire and to provide suggestions for improving the clarity of the questions. The

Table 2
Pretest characteristics.

Factors	Sample (N = 11)
Country	
Norway	3
Sweden	2
Other	6
Industry	
Manufacturing	2
Consultancy	2
Information technology	3
Other	4
Firm size (number of employees)	
1–9	3
10–49	1
50–249	2
250+	5
Age of company	
1–4 years	2
5–9 years	2
10–49 years	5
50+ years	2
Respondent position	
Head of digital strategy	2
Head of circular economy/sustainability strategy	2
Director	2
Manager	1
Other	4

aforementioned step satisfied the psychometric properties for suitability and validity of the questionnaire.

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

The responses in the sample represented a broad set of companies from a variety of countries (see Table 3 for details). The largest proportion of them operated from Norway (23.2%), Poland (9.6%), the United Kingdom (8.8%), Spain (8.8%), and Germany (8.8%). The majority of the companies were medium and large in size (33.6% and 38.4% respectively) from the industries of manufacturing (33.5%), retail and consumer goods (20.8%), information technology (13.6%), and energy, utilities, and resources (10.4%). The questionnaire was targeted at senior managers with knowledge of both the digital and the circular strategies of their organization. To ensure a collective response from the company, the survey participants were encouraged to confer with colleagues in areas outside of their expertise. Most companies had several years of experience using BA and were either somewhat or entirely targeting the CE in their strategy.

Given that each data point was collected from a single source at a single point in time, the possibility of bias exists. The risk of bias in the sample was investigated using a series of statistical tests. First, to reduce the risk of informant bias, the responses from the two data collection phases were divided into two groups, one for each phase. To compare the two groups a Mann-Whitney *U* test was run of the dependent variable measures using the SPSS software package. The test showed no significant difference between the groups, meaning response bias between the two data collection phases was not an issue (see Table 4 for the results). Second, to control for common method bias ex ante and post ante, the guidelines by Chang et al. (2010) and Podsakoff et al. (2003) were followed. With a view to encouraging the free flow of responses and reducing social desirability bias, the respondents were informed about the purpose of the survey and their data protection rights, receiving assurance that they would remain fully anonymous (Hossain et al., 2020). To test if common method bias was present, a collinearity assessment and Harman's single factor test were performed. For the collinearity assessment approach, VIF values were below 3.3 (at the factor-level), indicating that pathological collinearity was absent and the model was not contaminated by common method bias (Kock, 2015). Similarly, the results for Harman's single factor test indicated an absence of common method bias with a maximum variance by any factor

Table 3
Sample characteristics.

Factors	Sample (N = 125)	Percentage (%)
Country		
Norway	29	23.2%
Poland	12	9.6%
United Kingdom	11	8.8%
Spain	11	8.8%
Germany	11	8.8%
Italy	10	8%
France	9	7.2%
Netherlands	8	6.4%
Denmark	6	4.8%
Finland	6	4.8%
Sweden	5	4%
Other	7	5.6%
Industry		
Manufacturing	42	33.6%
Service provider	9	7.2%
Consultancy	7	5.6%
Energy, utilities, and resources	13	10.4%
Retail and consumer goods	26	20.8%
Information technology	17	13.6%
Other	11	8.8%
Firm size (number of employees)		
1–9	15	12%
10–49	20	16%
50–249	42	33.6%
250+	48	38.4%
Years of business analytics experience		
<1 year	16	12.8%
1–2 years	21	16.8%
3–4 years	36	28.8%
4+ years	52	41.6%
Extent to which firm strategy targets the circular economy		
Not at all	5	4%
A little	21	16.8%
Somewhat	50	40%
Entirely	49	39.2%
Age of company		
<1 year	1	0.8%
1–4 years	13	10.4%
5–9 years	24	19.2%
10–49 years	67	53.6%
50+ years	20	16%
Respondent position		
CEO/president	21	16.8%
CIO	10	8%
Head of digital strategy	5	4%
Head of circular economy/sustainability strategy	14	11.2%
Director	19	15.2%
Manager	49	39.2%
Other	7	5.6%

Table 4
Mann-Whitney *U* test.

Measure	Mann-Whitney U	Significance
PER-EN1	1952.5	0.800
PER-EN2	1832.0	0.707
PER-EN3	1920.0	0.934
PER-F1	1839.5	0.738
PER-F2	1657.5	0.203
PER-F3	1947.5	0.822
PER-CO1	1744.5	0.405
PER-CO2	1588.0	0.099
PER-CO3	1676.5	0.236
PER-CO4	1816.0	0.648
PER-CR1	1708.0	0.306
PER-CR2	1763.5	0.574
PER-CR3	1803.0	0.860
PER-CR4	1910.0	0.975

of 38.8%, meaning that not a single construct accounted for the majority of the variance (Fuller et al., 2016). This suggests that the research model and questionnaire were not contaminated by common method bias.

4.2. Measurements

The main constructs of the study were operationalized using a hierarchical component model with respective sub-constructs for each main construct (Sarstedt et al., 2019). *BAC* was put together as a third-order formative construct consisting of tangible, intangible, and human skills resources as second-order formative constructs, each incorporating three first-order constructs. First, the tangible BA-related resources – consisting of data, technology, and basic resources – were represented as formative first-order constructs. Second, the intangible resources of data-driven culture, circular-oriented innovation (COI) culture, and openness and co-creation were represented as reflective first-order constructs. Third, the human skills components of systems thinking and data science were represented as reflective first-order constructs (See Table 5 for the development and dimension structure of the BAC construct and Table 6 for definitions.). Respondents were asked to what degree they agreed with the listed questions (see Appendix A) on a 7-point Likert scale (1 – Totally disagree; 7 – Totally agree).

CE implementation was developed as a second-order formative construct with three first-order formative constructs. The second-order construct was based on the empirical study by Khan et al. (2020), whereas the first-order constructs and indicators were adapted from the *Circular strategies framework* by Blomsma et al. (2019). The framework presents seven categories of circular strategies (reinvent, rethink and reconfigure, restore, reduce and avoid, recirculate parts and products, recirculate materials, logistics, and energy), each with several sub-categories or areas of application. Informed by the *Smart CE framework* of Kristoffersen et al. (2020) of how BA relates to CE, the logistics and energy categories were omitted, and four of the remaining categories were combined into two. This was done for three reasons: to reduce the total number of survey questions for the sake of brevity, to maintain a formative structure with low indicator correlation, and to avoid first-order constructs with only one indicator. The outcome of the above was the three dimensions of circular strategies, namely reinvent and rethink (strategic activities), restore, reduce and avoid (operational activities), and recirculate (operational activities). Respondents were asked to indicate the level they had implemented or contributed to circular strategies on behalf of another stakeholder on a 7-point Likert scale (1 – Totally disagree; 7 – Totally agree).

ROC was established as a second-order formative construct with three first-order formative constructs: structuring, bundling, and leveraging. The measurements were adopted from prior conceptual research on resource orchestration (Sirmon et al., 2011) and empirical research on ROC (Choi et al., 2020; Wang et al., 2020). As the resource orchestration view is a generic theory, essentially all types of organizational resources all relevant. Therefore, to narrow the scope and ensure consistency with the BAC, respondents were asked to assess the current situation in their firm concerning IT resources and assets only. Questions were measured on a 7-point Likert scale (1 – Totally disagree; 7 – Totally agree).

Firm performance was devised as a second-order formative construct with four first-order formative constructs, specifically environmental performance, financial performance, competitiveness, and corporate reputation. The measurements were based on the scale of Khan et al. (2020) and build upon established indicators from previous studies (Bagur-Femenias et al., 2013; Eurostat, 2014; Zhu et al., 2010). Respondents were asked to assess the degree to which their firm had improved in different areas of organizational performance in the last five years. Questions were measured on a 7-point Likert scale (1 – Totally disagree; 7 – Totally agree). For *control variables,* descriptive information was collected on firm size and age, industry sector, country, ownership structure, experience levels with BA and CE, and the respondents' position within the firm.

5. Analysis

To conduct the analysis and assess the validity and reliability of the research model, partial least squares-based structural equation modeling (PLS-SEM) was employed using the SmartPLS 3 software package

Table 5
Latent constructs and sub-dimensions.

Third-order	Type	Second-order	Type	First-order	Type
BAC	Formative	Tangible resources	Formative	Data	Formative
				Technology	Formative
				Basic resources	Formative
		Intangible resources	Formative	Data-driven culture	Reflective
				COI culture	Reflective
				Openness and co-creation	Reflective
		Human skills	Formative	Systems thinking skills	Reflective
				Data science skills	Reflective
		CE implementation	Formative	Reinvent and rethink	Formative
				Restore, reduce and avoid	Formative
				Recirculate	Formative
		ROC	Formative	Structuring	Formative
				Bundling	Formative
				Leveraging	Formative
		Firm performance	Formative	Environmental	Formative
				Financial	Formative
				Competitiveness	Formative
				Corporate reputation	Formative

Table 6
Business analytics resources.

Second-order construct	First-order construct	Definition	Source(s)
Tangible	Data	Organizations utilizing BA for CE need to capture both internal and external data from multiple sources, independently of structures and on a continuous basis. Further, aspects concerning data (such as quality, sources, availability, and methods for curating) need handling.	(Arunachalam et al., 2018; Gupta and George, 2016; Hedberg et al., 2019; Janssen et al., 2017; Kwon et al., 2014; Mikalef et al., 2017)
	Technology	Novel digital technologies are necessary for handling the large volume, diversity, and speed of data accumulated throughout circular value chains. The complexity of these value chains increases the need for firms to deploy advanced data generation, integration, analysis, and sharing infrastructures.	(Arunachalam et al., 2018; Gupta and George, 2016; Gupta et al., 2019; Hedberg et al., 2019; Mikalef et al., 2017)
	Basic resources	This refers to an organization's investment of time and funds. It includes financial resources as direct investments in support of these technologies and working hours allocated to experimentation with utilizing the potential of BA.	(Gupta and George, 2016; Mikalef et al., 2017; Wamba et al., 2017)
Intangible	Data-driven culture	This describes the extent to which organizational members are committed to BA and make decisions based on insights derived from data.	(Arunachalam et al., 2018; Dubey et al., 2019; Gupta and George, 2016; Mikalef et al., 2020)
	COI culture	This describes the extent to which CE goals, principles, and strategies are integrated into technical and market-based innovations to create value by enabling the sustainable management of resources throughout the design of processes, products/services, and business models.	(Brown et al., 2019; Gupta et al., 2019; Munodawafa and Johl, 2019; Pauliuk, 2018; Prieto-Sandoval et al., 2019; The British Standards Institution, 2017)
	Openness and co-creation	This describes the extent to which organizational members are mutually open about decisions and activities that affect the society/economy/environment and willing to communicate these in a clear, accurate, timely, honest, and complete manner to enhance formal and/or informal arrangements internally and externally to create mutual value.	(Akter et al., 2021; Gupta et al., 2019; Hedberg et al., 2019; Pauliuk, 2018; The British Standards Institution, 2017)
Human skills	Systems thinking skills	This refers to the competencies of employees to take a holistic approach to understanding larger contexts over longer periods of time, looking at connections and patterns of how individual decisions and activities impact environmental, economic, and social issues beyond the immediate first-tier scope.	(Bocken et al., 2019; Gupta et al., 2019; Pauliuk, 2018; The British Standards Institution, 2017; Webster, 2013)
	Data science skills	This refers to the competencies of employees to formulate and solve machine learning problems, utilizing data analytics skills such as statistics, computing, and knowledge about correlation and causation.	(Dhar, 2013; Dubey et al., 2019; Gupta and George, 2016; Power, 2016)

(Ringle et al., 2015). The analysis followed the updated guidelines by Benitez et al. (2020) on how to perform and report on PLS analyses in IS research. Given that the proposed research model is targeted towards exploratory theory building as opposed to theory testing, PLS-SEM is seen as a better option than covariance-based SEM. Further, PLS-SEM allows the use of mixed model specification methods (i.e., simultaneous use of formative and reflective constructs in higher-order latent constructs), while covariance-based SEM methods do not (Akter et al., 2017). PLS-SEM is regarded as a robust and powerful statistical tool and has been applied across various disciplines (Joseph F. Joseph F. Hair et al., 2012a, 2012b), including BA and CE research (Akter et al., 2019; Khan et al., 2020a; Mikalef et al., 2020). Moreover, PLS-SEM is recommended when the research is exploratory, focusing on theory building and predicting target constructs for complex structural models, and allows for simultaneous estimation of multiple relationships between one or more independent and dependent variables (Henseler et al., 2016). Categorized as a variance-based soft modeling technique, PLS-SEM can be used to estimate both reflective and formative constructs and is a well-suited predictive tool for theory building in complex models using smaller samples (Nair et al., 2018). In terms of sample size requirements, the total of 125 respondents meant that the sample exceeded both requirements of *i)* ten times the largest number of formative indicators used to measure one construct and *ii)* ten times the largest number of structural paths directed at a particular latent construct in the model (Hair et al., 2011).

5.1. Measurement model

As the measurement model consisted of both formative and reflective constructs, several different assessment criteria were applied to examine their validity and reliability. The reflective measures, specifically first-order reflective constructs, were tested for discriminant validity, reliability, and convergent validity. Discriminant validity was assessed by calculating the Heterotrait-Monotrait ratio (HTMT). HTMT is seen as a more robust criterion for assessing discriminant validity compared to, for instance, the Fornell-Larcker criterion and assessment of cross-loadings between constructs (Benitez et al., 2020; Henseler et al., 2015). The test measures similarity between constructs by using the multitrait-multimethod matrix and calculating the average correlation of indicators across constructs, measuring different elements of the model relative to the average of the correlation of indicators within the same construct (Benitez et al., 2020). The HTMT should be below the 0.85 (stricter) or 0.9 (more tolerant) thresholds. In this case, all values were below the more stringent thresholds, indicating sufficient discriminant validity (see Table 7). Reliability was examined at the indicator and construct level. For indicator reliability, the construct-to-item loadings were confirmed to be above the threshold of 0.707 and significant (see Table 8). At the construct level, the Cronbach's alpha and composite reliability values were calculated, and it was confirmed that both values greatly exceeded the threshold of 0.70 (Nunnally, 1978). For composite reliability, Benitez et al. (2020) recommend using the Dikjstra-Henseler's indicator. Values over 0.70 indicate that more than 50% of the variance in the construct scores can be explained by the latent variable. For convergent validity, the average variance extracted (AVE) was calculated, and it was confirmed that all values were above the 0.50 threshold. The abovementioned results (see Table 9) suggest that the reflective measures are valid as all items are good indicators of their respective first-order constructs.

For formative measures, the weights and significance levels of each item were calculated first. Although most weights of the indicators were statistically significant, some were found to be non-significant at the first or second-order level (e.g., T2 to T5 of Technology, CE-INV1 to CE-INV3 of Reinvent and Rethink, and PER-CO2 to PER-CO4 of Competitiveness). However, Cenfetelli and Bassellier (2009) argue that formative constructs are likely to have indicators with non-significant weights. This is exasperated with the number indicators. Their recommendation is to keep non-significant indicators in the model provided that there is strong theoretical justification for their inclusion. This contrasts with the approach for reflective indicators, the reason being that reflective measures focus on maximizing the overlap between interchangeable indicators, whereas formative measures focus on minimizing the overlap between complementary indicators. Therefore, removing a formative measure would potentially remove a distinct and important characteristic from the phenomenon under investigation. As the non-significant dimensions and indicators developed to measure them are all based on rigorous theories and capture different critical factors, it is necessary to retain them in the model. Similar justifications can be found in related BAC studies by Gupta and George (2016) and Mikalef and Gupta (2021).

Next, the validity of the formative constructs was evaluated using Edwards' (2001) adequacy coefficient (R2a), following the guidelines of MacKenzie et al. (2011) Schmiedel et al. (2014). The R2a value is calculated by summing the squared correlation between indicators and their respective construct and dividing by the number of items. All values exceeded the threshold of 0.50, indicating that the items are a valid representation of the construct as most of the variance in the indicators is shared with the construct. The same approach was followed for the higher-order constructs, and all R2a values were above 0.50. Lastly, the presence of multicollinearity was examined using Variance Inflation Factor (VIF) values. While multicollinearity is encouraged for reflective constructs as they focus on maximizing overlap, it can be problematic for formative constructs. The threshold for VIF is typically set at values below 10 (MacKenzie et al., 2011), while Petter et al. (2007) recommend a more conservative cutoff at 3.3. Four items were observed to be above the conservative threshold, with the highest VIF value being 3.593. However, as these values are only slightly above the more strict cutoff, it is believed that multicollinearity is not a concern in this study (Cenfetelli and Bassellier, 2009). The above-mentioned results (see Table 10) suggest that the formative measures are valid as all items are good indicators of their respective constructs. Overall, both reflective and formative constructs demonstrated satisfactory psychometric properties.

Table 7
Discriminant validity (HTMT) of reflective constructs.

	COI culture	Data science skills	Data-driven culture	Openness and co-creation	Systems thinking
COI culture					
Data science skills	0.526				
Data-driven culture	0.692	0.700			
Openness and co-creation	0.809	0.628	0.602		
Systems thinking	0.847	0.595	0.607	0.775	

Table 8
Reflective constructs loadings.

Construct	Measure	Loading	Significance
COI culture			
	COI1	0.83	$p < 0.001$
	COI2	0.72	$p < 0.001$
	COI3	0.82	$p < 0.001$
	COI4	0.76	$p < 0.001$
Data science skills			
	DS1	0.86	$p < 0.001$
	DS2	0.91	$p < 0.001$
	DS3	0.85	$p < 0.001$
	DS4	0.81	$p < 0.001$
Data-driven culture			
	DD1	0.73	$p < 0.001$
	DD2	0.71	$p < 0.001$
	DD3	0.74	$p < 0.001$
	DD4	0.71	$p < 0.001$
Openness and co-creation			
	OCC1	0.81	$p < 0.001$
	OCC2	0.70	$p < 0.001$
	OCC3	0.79	$p < 0.001$
System thinking skills			
	ST1	0.71	$p < 0.001$
	ST2	0.80	$p < 0.001$
	ST3	0.84	$p < 0.001$

5.2. *Confirmatory composite analysis*

To assess the overall fit of the model, a confirmatory composite analysis of the saturated model was performed, following the recommendations of Gefen et al. (2011), Hair et al. (2020), and Henseler (2017). The saturated model allows all constructs to be freely correlated, while the concept's operationalization is as specified by the analyst. This is useful when assessing the model fit and the validity of the measurement and composite model because it helps determine potential misspecifications in the model (Benitez et al., 2020). This is done by comparing the empirical correlation matrix with the model-implied correlation matrix. Benitez et al. (2020) recommend using the standardized root means square residual (SRMR), unweighted least squares discrepancy (d_{ULS}), and geodesic discrepancy (d_g) for evaluating the goodness of fit for the saturated model. As a whole, the analysis provides empirical support to whether or not the indicators form a construct and if the latent variables exist. For SRMR, a value of 0.036 was observed, which is lower than the 0.080 threshold (Henseler et al., 2014; Hu et al., 1992). SRMR measures the average magnitude of the discrepancies between the observed and the expected correlations. The discrepancy indicators (d_{ULS} and d_G) were both below their corresponding 95% quantile reference distributions. Thus, empirical evidence for the latent variables was obtained (see Table 11).

Table 9
Assessment of reliability and convergent validity of reflective constructs.

Construct	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1) Basic resources	n/a																	
(2) Bundling	0,636	n/a																
(3) Reinvent and rethink	0,651	0461	n/a															
(4) Recirculate	0,677	0438	0,575	n/a														
(5) Restore, reduce, and avoid	0,560	0419	0,549	0646	n/a													
(6) COI culture	0,750	0566	0,659	0731	0,521	0780												
(7) Competitiveness	0,437	0464	0,298	0452	0,348	0547	n/a											
(8) Corporate reputation	0,590	0650	0,435	0525	0,461	0656	0,728	n/a										
(9) Data	0,639	0656	0,462	0553	0,544	0479	0,356	0509	n/a									
(10) Data science skills	0,641	0668	0,374	0537	0,417	0524	0,346	0508	0,640	0858								
(11) Data-driven culture	0,739	0784	0,452	0531	0,452	0693	0,500	0700	0,636	0700	0,721							
(12) Environmental performance	0,532	0475	0,415	0501	0,532	0611	0,573	0661	0,434	0451	0,503	n/a						
(13) Financial performance	0,336	0433	0,212	0318	0,407	0369	0,648	0569	0,396	0300	0,313	0583	n/a					
(14) Leveraging	0,688	0798	0,448	0483	0,443	0604	0,474	0620	0,650	0684	0,747	0455	0,375	n/a				
(15) Openness and co-creation	0,711	0521	0,633	0740	0,551	0808	0,510	0625	0,493	0630	0,609	0522	0,303	0548	0,768			
(16) Structuring	0,642	0785	0,433	0428	0,482	0483	0,414	0591	0,678	0698	0,771	0517	0,401	0807	0,485	n/a		
(17) Systems thinking skills	0,760	0643	0,624	0694	0,566	0849	0,576	0697	0,594	0595	0,612	0541	0,368	0632	0,773	0522	0,786	
(18) Technology	0,643	0731	0,492	0478	0,524	0409	0,356	0492	0,749	0750	0,660	0416	0,384	0669	0,549	0716	0,538	n/a
Mean	5.00	5.03	4.84	5.39	5.44	5.16	5.56	5.46	5.10	5.27	4.99	5.49	5.29	5.06	5.27	4.98	5.38	5.23
Standard Deviation	1.32	1.27	1.00	1.24	1.00	1.27	0.99	0.98	1.23	1.26	1.11	1.12	1.11	1.16	1.17	1.18	1.17	1.19
AVE	n/a	n/a	n/a	n/a	n/a	0.608	n/a	n/a	n/a	0.735	0.520	n/a	n/a	n/a	0.589	n/a	0.618	n/a
Cronbach's Alpha	n/a	n/a	n/a	n/a	n/a	0.860	n/a	n/a	n/a	0.917	0.811	n/a	n/a	n/a	0.813	n/a	0.827	n/a
Composite Reliability	n/a	n/a	n/a	n/a	n/a	0.861	n/a	n/a	n/a	0.917	0.812	n/a	n/a	n/a	0.811	n/a	0.829	n/a

5.3. *Structural model*

The structural model from the PLS analysis is depicted in Fig. 3 and presents the results of the structural model explained by the variance of endogenous variables (R^2) and the standardized path coefficient (β). The model was verified by assessing the coefficient of determination (R^2) values, path coefficients, and effect size of the predictor variable (f^2). To obtain significance levels of the estimates (t-statistics), a bootstrap analysis using 5000 resamples was performed. Since PLS-SEM does not require the data to meet any particular assumptions about sample distribution, parametric significance tests cannot be applied. Instead, PLS-SEM relies on the non-parametric bootstrap resampling approach where randomly drawn sub-samples are used to derive standard errors, t-values, p-values, and confidence intervals (Hair et al., 2016; Preacher and Hayes, 2008). The structural model explained 59.3% of variance in CE implementation ($R^2 = 0.593$), 70.1% in ROC ($R^2 = 0.701$), and 52.2% of variance in firm performance ($R^2 = 0.522$). The expected magnitude of R^2 values is dependent on the phenomenon under investigation and should be judged relative to studies that investigate the same dependent variable (Benitez et al., 2020). In this case, all values exceeded the coefficient of determination in the Khan et al. (2020a) study on CE implementation and firm performance (reporting 0.180 and 0.409, respectively). Furthermore, as the R^2 values represent moderate to substantial predictive power (Henseler et al., 2009), all values are seen as satisfactory.

For the path coefficients, firms' BAC was found to have a significant direct impact on CE implementation ($\beta = 0.770$, $T = 17.738$, $p < 0.001$) and ROC ($\beta = 0.837$, $T = 29.497$, $p < 0.001$). The direct impact of BAC on firm performance was not significant ($\beta = 0.206$, $T = 1.178$, $p > 0.05$), as expected for mediation (see Subsection 5.4). Furthermore, both the impact of CE implementation on firm performance ($\beta = 0.253$, $T = 2.141$, $p < 0.05$) and ROC on firm performance ($\beta = 0.345$, $T = 2.561$, $p < 0.05$) were significant. In the model, the f^2 values from BAC to CE implementation (1.454) and ROC (2.349) indicated a strong effect size, while the effect from CE implementation (0.051) and ROC (0.070) on firm performance indicated a weak effect size (Cohen, 1988). The effect size is useful in measuring the practical relevance of relationships between constructs by indicating the extent to which the path coefficient exists in the population. The influence of control variables on the dependent variable, firm performance, was examined using dummy variables. All variables were found to have non-significant relationships to firm performance, with the exception of information technology companies ($\beta = 0.129$, $T = 2.204$, $p < 0.05$). Despite having a significant path coefficient, the change in explained variance ($\Delta R^2 = 0.015$) was small and the effect size ($f^2 = 0.034$, $T = 0.933$, $p = 0.351$) weak and non-significant. Furthermore, this is believed to have no practical relevance for the model due to when the data was collected (during the COVID-19 pandemic). Information technology companies might have been less affected, and this can be why they are more strongly correlated with firm performance.

5.4. *Test for mediation*

Mediation is the sequence in which a change in an exogenous variable causes a change in a mediator variable, which then affects the endogenous variable (Nitzl et al., 2016). In other words, it helps explain the underlying process, or mechanism, of the relationship between two constructs. Following the recommendations of Hair et al. (2016), the model was examined for mediation by comparing the direct and indirect effects between BAC and firm performance. As seen in Table 12, both indirect or mediated paths (BAC → CE implementation → firm performance and BAC → ROC → firm performance) were significant, and the direct path (BAC → firm performance) was non-significant. Thus, as the direct path from BAC to firm performance was non-significant while the indirect paths were significant, it is concluded that CE implementation and ROC fully mediate the effect of BAC on firm performance.

Table 10
Formative construct validation.

Construct	Measures	Weight	Significance	VIF	R^2_a
Data	D1	0.221	*Ns*	1.781	0.64
	D2	0.158	*Ns*	1.856	
	D3	0.480	$p < 0.01$	2.013	
	D4	0.351	$p < 0.01$	1.896	
Basic resources	BR1	0.330	$p < 0.01$	1.637	0.73
	BR2	0.551	$p < 0.001$	1.974	
	BR3	0.275	$p < 0.05$	2.145	
Technology	T1	0.434	$p < 0.001$	1.895	0.66
	T2	0.125	*Ns*	2.565	
	T3	0.219	*Ns*	2.454	
	T4	0.197	*ns*	2.542	
	T5	0.239	*ns*	2.086	
Tangible	Data	0.187	$p < 0.05$	2.629	0.76
	Basic resources	0.663	$p < 0.001$	2.012	
	Technology	0.255	$p < 0.01$	2.557	
Intangible	Data-driven culture	0.487	$p < 0.001$	1.557	0.72
	COI culture	0.327	$p < 0.01$	2.173	
	Openness and co-creation	0.365	$p < 0.001$	1.907	
Human skills	Systems thinking skills	0.625	$p < 0.001$	1.374	0.76
	Data science skills	0.520	$p < 0.001$	1.374	
BAC	Tangible	0.407	$p < 0.001$	3.171	0.85
	Intangible	0.476	$p < 0.001$	2.940	
	Human skills	0.198	$p < 0.05$	3.461	
Structuring	ROS1	0.290	$p < 0.05$	1.905	0.74
	ROS2	0.420	$p < 0.01$	2.027	
	ROS3	0.434	$p < 0.001$	1.830	
Bundling	ROB1	0.531	$p < 0.001$	2.465	0.79
	ROB2	0.378	$p < 0.01$	2.578	
	ROB3	0.194	$p < 0.05$	2.171	
Leveraging	ROL1	0.471	$p < 0.001$	2.246	0.78
	ROL2	0.229	$p < 0.05$	2.177	
	ROL3	0.416	$p < 0.001$	2.472	
ROC	Structuring	0.249	*ns*	3.473	0.86
	Bundling	0.430	$p < 0.05$	3.351	
	Leveraging	0.393	$p < 0.01$	3.593	
Reinvent and rethink	CE-INV1	0.317	*ns*	2.133	0.63
	CE-INV2	0.260	*ns*	1.360	
	CE-INV3	0.157	*ns*	2.430	
	CE-INV4	0.507	$p < 0.01$	1.963	
Restore, reduce, and avoid	CE-RRA1	0.437	$p < 0.01$	1.218	0.57
	CE-RRA2	0.364	$p < 0.05$	1.227	
	CE-RRA3	0.513	$p < 0.001$	1.269	
Recirculate	CE-REC1	0.524	$p < 0.001$	1.352	0.66
	CE-REC2	0.344	$p < 0.05$	1.615	
	CE-REC3	0.361	$p < 0.01$	1.592	
CE implementation	Reinvent and rethink	0.334	$p < 0.01$	1.755	0.73
	Restore, reduce, and avoid	0.199	*ns*	2.041	
	Recirculate	0.608	$p < 0.001$	1.991	
Environmental	PER-EN1	0.314	$p < 0.05$	2.247	0.73
	PER-EN2	0.473	$p < 0.01$	2.351	
	PER-EN3	0.380	$p < 0.05$	1.476	
Financial	PER-F1	0.475	$p < 0.01$	1.305	0.63
	PER-F2	−0.038	*ns*	2.045	
	PER-F3	0.724	$p < 0.01$	2.029	
Competitiveness	PER-CO1	0.577	$p < 0.01$	1.733	0.67
	PER-CO2	0.354	*ns*	2.199	
	PER-CO3	0.141	*ns*	2.338	
	PER-CO4	0.097	*ns*	2.180	
Corporate reputation	PER-CR1	0.161	*ns*	2.706	0.65
	PER-CR2	0.388	$p < 0.01$	2.097	
	PER-CR3	−0.002	*ns*	2.258	
	PER-CR4	0.603	$p < 0.001$	1.833	
Firm performance	Environmental	0.360	$p < 0.01$	2.028	0.62
	Financial	−0.085	*ns*	1.992	
	Competitiveness	0.002	*ns*	2.724	
	Corporate reputation	0.777	$p < 0.001$	2.827	

5.5. *Predictive validity*

Lastly, the predictive validity of the model was examined. Predictive validity can be assessed through sample re-use by computing the predictive relevance of constructs and evaluating how well values are reproduced by the model and its parameter estimates (Chin, 1998; Woodside, 2013). Known as the Stone-Geisser (Q^2) indicator, the method is a combination of function fitting and cross-validation, which omits certain inner model relationships and examines each construct's predictive relevance by changes in the criterion estimates (Joe F. Joe F. Hair et al., 2012a, 2012b). Values above 0 indicate predictive relevance, with values above 0.35 indicating a high effect, and contrary values

Table 11
Results of the confirmatory composite analysis.

Discrepancy	Saturated model fit		
	Value	HI_{95}	Conclusion
SRMR	0.036	0.042	Supported
d_{ULS}	0.117	0.163	Supported
d_G	0.129	0.167	Supported

below 0 indicate insufficient predictive relevance (Hair et al., 2016). It was found from the analysis that ROC ($Q^2 = 0.697$), CE implementation ($Q^2 = 0.573$), and firm performance ($Q^2 = 0.502$) all had satisfactory and high predictive relevance. Overall, the proposed nomological network fits the data quite well based on consistency in the analysis results, and all five hypotheses were empirically supported, reinforcing the validity of the findings.

6. Discussion

While real examples of information flows enabling circularity exist, and researchers' theoretical understanding of the relationship between BA and CE has been improving (Nobre and Tavares, 2019; Rosa et al., 2020), the mechanisms and conditions under which BA can accelerate firms' CE implementation remain largely unexplored in empirical research. Notwithstanding the number of empirical studies on BA for general business operation and supply chain management (Akter et al., 2016; Wamba et al., 2020), these are all rooted in the linear economic model and way of thinking. In other words, they lack alignment with more holistic information management and sustainable principles core to the CE (Gupta et al., 2019). Furthermore, little is known about the orchestration process required to leverage these BA investments towards firm performance (Mikalef et al., 2018).

6.1. Research implications

This study addresses the issue in an attempt to understand if BA can aid in firms' CE implementation and resource orchestration and how their effects on several facets of organizational performance can be measured. To this end, four main contributions are made in terms of research implications: (1) a construct for capturing CE-specific BAC is developed, (2) the importance of having this capability is demonstrated, not just circular strategies to operationalize it (H1), thus differentiating between strategy and its enactment, (3) the effect BAC has on ROC is highlighted (H2), which is an assumption many studies carry but has not been empirically validated, and (4) it is demonstrated how this affects different mechanisms of firm performance (H3-H5).

The measurement model was established with a BAC construct adapted explicitly for the CE context alongside operationalization of the resource orchestration theory and circular strategies as higher-order constructs. The model was grounded in both established (the resource-based and resource orchestration views) and emergent (the Smart CE framework of Kristoffersen et al. (2020)) theories and enacted through a questionnaire-based survey for empirical investigation with PLS-SEM for analysis. By analyzing survey data from 125 European companies, important contributions are made to both the IS and organizational sustainability research fields by exploring the inner mechanisms of how BA improves CE implementation, along with their combined effect on firm performance. For research on how firms transition towards the CE,

Table 12
Summary of hypotheses and results.

Structural path	Effect	t-value[a]	Bias corrected 95% confidence interval	Conclusion
BAC → CE impl.	0.770	17.738***	[0.670–0.840]	H1 supported
CE impl. → firm performance	0.253	2.141*	[0.021–0.476]	H3 supported
BAC → ROC	0.837	29.497***	[0.772–0.888]	H2 supported
ROC → firm performance	0.345	2.561*	[0.057–0.586]	H4 supported
BAC → firm performance	0.206	1.178	[-0.111 – 0.581]	(Full mediation)
BAC → CE impl. → firm performance	0.195	2.114*	[0.026–0.389]	H5 supported
BAC → ROC → firm performance	0.289	2.529*	[0.064–0.499]	H5 supported
Total indirect effect	0.483	3.164**	[0.172–0.766]	

[a] * significant at $p < 0.05$; ** significant at $p < 0.01$; *** significant at $p < 0.001$ (two-tailed test).

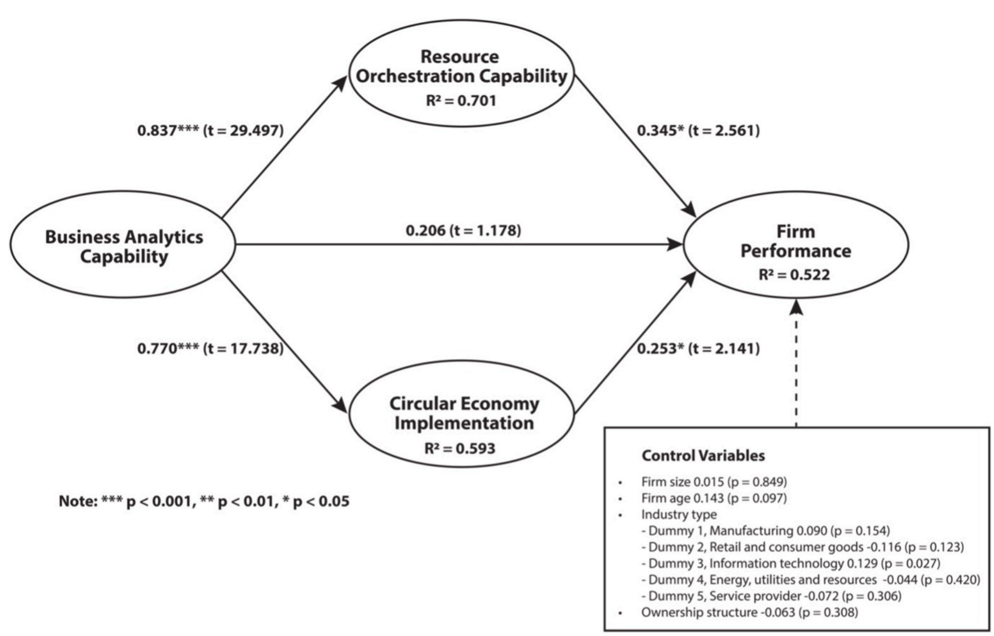

Fig. 3. Results and estimated relationships of the structural model.

the importance of developing a strong BAC is demonstrated by showing it to *i)* enable the operationalization of circular strategies and *ii)* promote better leveraging of such strategies for improved value generation and firm performance. Furthermore, this study contributes to the strategic management theory on the resource-based and resource orchestration views by developing and empirically validating an instrument to measure the IT-based ROC of firms. This builds on previous literature showcasing the importance of BACs for developing dynamic capabilities and supporting decision-making across different stages of the industrial life cycle of assets (Mikalef et al., 2018; Wamba et al., 2017; Wang et al., 2016). The latter put forward interesting propositions on the role of ROC and CE implementation in mediating the effect of BAC on firm performance.

The results are consistent with related BA and CE studies. For instance, the findings of Gupta et al. (2019) and Kristoffersen et al. (2021) on the importance of BA for CE, the effect of CE implementation on firm performance in Khan et al. (2020a), and Mikalef et al. (2020) result in the contingent role of dynamic and operational capabilities in the effect of BAC on firm performance. The present study has several implications for research. Specifically, it highlights the role of digital transformation in sustainable development, explained through the role of BA in accelerating firms' CE adoption and realizing business value. While the development of a BAC is not a prerequisite for CE implementation, it can help organizations generate faster returns and make a more significant impact on their CE investments. Notwithstanding the direct effects of BAC on firm performance for general business operation (Akter et al., 2016), emphasis is placed on the importance of IS research to examine the impact of IT beyond firm performance and strengthen research in the areas of CE and sustainability.

6.2. Practical implications

In terms of practical relevance, firms may find this research useful in three main areas. First, it can provide motivation for transitioning towards the Smart CE. It was found that BA strengthened firms' implementation of circular strategies and organizational performance in terms of competitiveness, corporate reputation, financial results, and environmental efforts. These are valuable findings for companies as they provide a business rationale for implementing circular strategies and ways of capitalizing on BA investments. Furthermore, this research offers strategic justifications for transitioning to a more sustainable mode of business operation. This may be particularly useful for forward-thinking managers and early CE adopters lacking arguments or proof to support a corporate strategy change. Second, it can help companies understand which organizational resources and capabilities are important for leveraging BA for CE. As firms reposition their business to meet new customer needs and sustainability requirements, the investments they make will be crucial for their survival and lasting competitiveness. Therefore, correctly identifying which resources to invest in and which capabilities to develop will be critical. The study also shows that leveraging BA for CE requires investments across talent, culture, and technology. As evident from the eight distinct factors comprising the BAC for CE, companies should be wary of focusing only on tangible assets like data and IT infrastructure, making sure to target investment in their human capital as well, for instance, by improving managers' systems thinking skills and commitment to establishing a data-driven culture. By untangling the relationship between BA and CE, this study advocates for more holistic information management, encouraging a greater focus on 'green digital transformation' within companies. These findings can support the development of more constructive guidelines for implementing circular strategies and aid organizations in making more cost-effective BA investments, for example, by developing the BAC into a benchmarking tool to map a firm's maturity and guide its investments through customized roadmaps. Third, by establishing the ROC, the study demonstrates the importance of managing BA resources to seize business value and the performance returns of BACs. For instance, the ROC can be integrated in the BAC benchmarking tool and roadmap to facilitate SWOT (strengths, weaknesses, opportunities, and threats) analyses and help companies understand where and how to target development activities. The ROC is confluent with previous strategic management theory, arguing that merely procuring and holding valuable resources does not translate into business value or performance gains. Instead, organizations should focus on developing internal capabilities to orchestrate such resources better. Thus, they may find this study useful as a guide to better managing their employees at various levels around the structuring, bundling, and leveraging processes of resource orchestration. Through improved understanding of the relationship between BAC, firm performance, and the mechanisms in-between, companies become better equipped to facilitate change.

6.3. Policy implications

Notwithstanding the growing interest from industry and academia alike, CE as a concept is still in its infancy. As a result, multiple frameworks and definitions co-exist (Blomsma et al., 2019; Kirchherr et al., 2017), and international standardization efforts have recently been initiated (ISO, 2021). Despite the barriers of conflicting definitions and lack of standardization, this also presents an array of opportunities for developed and developing economies to establish unique positions. Studies have suggested a total annual benefit of €1.8 trillion from a complete CE transition for Europe by 2030 (EMF, 2015b). Additionally, with the unprecedented amount of data available in the modern age (McAfee et al., 2012), data itself is becoming a key source of value generation for countries and may even emerge as the most prominent commodity traded in the future (Xiao et al., 2014). For example, the Confederation of Norwegian Enterprise recently estimated the value creation potential of data for Norway to surpass that of oil and gas by 2030 for a total of €30 billion annually (Skogli et al., 2019).

Despite the significant economic benefits to be found in a complete transition to the nexus of these developments, the Smart CE, the challenges facing businesses and policymakers are diverse. This study focused on the perspective of a single company's transition and performance gains; hence, it did not consider issues typical of policy development, such as dealing with a multitude of stakeholders and their joint competitiveness for a fair value distribution in the CE. However, based on the factors identified in the research model, the authors believe that maintaining an open and transparent digital ecosystem where data and services can be made available and shared in an environment of trust will be more important than ever before with the CE. The core success criteria of the Smart CE being its ability to connect material flow with information flow, a framework and data governance model is needed for the free flow of non-personal data. For instance, data on the location, availability, and condition of assets alongside guidelines for tracking products, parts, and materials across value chains should be made available. In this respect, a set of criteria for the minimum amount of data to be shared for circular activities should be established. A balance between data sharing and protection of commercial and strategic information could support collaborative efforts and trust between companies, improving their ability to adopt circular strategies.

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

6.4. Limitations and future research

As with any research, the present study is constrained by certain limitations. To structure the reflection, this is discussed in terms of threats to construct validity and external validity.

6.4.1. Threats to construct validity

Construct validity refers to the adherence of inference made based on the measurements in the study, in other words, whether the study measures what it claims to be measuring. Firstly, the survey relies on self-reported data. Despite this being a common approach to collecting data in several disciplines, people are often biased when reporting on their own experience, meaning factual data may not coincide with respondents' perceptions (Devaux and Sassi, 2016). Reasons can include the interpretation of questions, honesty, introspective ability, and knowledge. To remedy this, the respondents were informed about data protection and anonymity and encouraged to consult with colleagues when answering questions. Despite the researchers' considerable efforts to reduce the potential of bias and ensure good data quality, the occurrence of bias cannot be excluded. Future studies could explore the topic for variance in levels of hierarchy and discrepancies between BA and CE expertise, for instance, by interviewing multiple levels and types of managers from the same firm, checking for interrater validity, and improving internal validity. Secondly, since a different and objective data source (i.e., for firm performance) was not included, there is a risk of mono-method bias in the study. Given its operational scope, with companies from multiple countries and alternatives for complete anonymity (meaning the submission of company name and/or contact details were optional), the authors were unable to collect adequate data on objective firm performance. Establishing firm performance as a higher-order construct addresses this issue to some extent as it provides multiple measures of performance. However, future studies should include an objective measure of both firm performance and CE implementation (e.g., using the circular transition indicators (WBCSD, 2021)).

6.5. Threats to external validity

External validity refers to the extent to which the results of the study can be applied or generalized to other situations or population groups. Despite efforts to develop an inclusive model and generic constructs, the model cannot be considered universal and fully applicable to all companies and applications. Some firms may likely need to develop different BA resources and/or resource orchestration processes to improve their performance and effectively leverage their circular strategies. In particular, CE research has established that firms require many different circular strategies and business model configurations, highly contingent on their size, industry setting, and individual value chain (Bocken et al., 2014). Additionally, paradigm shifts such as those the CE introduces require a change in people's mindset as well as system changes and take decades to unfold (Koschmann, 1996). The concept of CE is still in its early stages, and adoption by industry is modest (Circle Economy, 2020). As this study is only a snapshot in time, longitudinal studies (e.g., a panel survey) could help alleviate endogeneity concerns and provide interesting findings on firms' development and stage-wise adoption of circular strategies. Nevertheless, this is an important and much-needed first step towards a BA construct for CE. By crystallizing related IS theories, the study lays a solid foundation for future studies to extend the application of the model.

7. Conclusion

Now more than ever, implementing circular strategies is dependent on the use of digital technologies like BA. Thus, firms must develop a capability to utilize BA for CE purposes, which can improve their ability to pursue circular strategies, boost value creation, and achieve higher performance returns. Motivated by this prolific BA-CE relationship, the present study utilized PLS-SEM to analyze survey data from 125 European companies. It developed and empirically validated several higher-order constructs alongside a conceptual model for the relationship between a CE-specific BAC, IT ROC, CE implementation, and firm performance. The study was built on the resource-based and resource orchestration views and emergent theory on the Smart CE. The empirical results highlight the importance of taking a more holistic view of BA development. By doing so, firms can better manage their CE implementation and ROC of their IT portfolio, which, in turn, results in improved organizational performance, yielding higher returns on BA investments.

A. Survey instrument.

Measure	Item
Control variables (C) (Mikalef et al., 2020)	
	C1. In which industry sector does your company operate in? (Manufacturing, Service provider, Consultancy, Financial services, Energy, utilities and resources, Retail and consumer goods, Information technology, Media and communication services, Transport, Other)
	C2. What is the approximate number of employees in your company? (1–9, 10–49, 50–249, 250+)
	C3. What is the approximate age of your company? (<1 year, 1–4 years, 5–9 years, 10–49 years, 50+ years)
	C4. What is your position within the company (CEO/President, CIO, Head of digital strategy, Head of circular economy/sustainability strategy, Director, Manager, Other)
	C5. For how many years, if any, has your company employed business analytics? (<1 year, 1–2 years, 3–4 years, 4+ years)
	C6. To what extent does your company's strategy involve circular economy? (Not at all, A little, Somewhat, Entirely)
	C7. For how many years has your company worked with circular economy? (<1 year, 1–2 years, 3–4 years, 4+ years)
	C8. In which country is your company registered?
	C9. What is the ownership structure of your firm? (Public, Private)
Business analytics capability (Gupta and George, 2016; Kristoffersen et al., 2021; Mikalef et al., 2020; Wamba et al., 2017)	
In connection to your circular economy strategies, to what extent do the following statements reflect the situation in your firm? On a scale of (1. Strongly disagree, 2. Disagree, 3. Somewhat disagree, 4. Neither agree or disagree, 5. Somewhat agree, 6. Agree, 7. Strongly agree)	
Tangible	
Data (D)	D1. We have access to high quality data on products/services such as location, availability, and condition data
	D2. We have access to data throughout the life cycle of products/services
	D3. We integrate data from multiple sources into a data warehouse for easy access
	D4. We integrate external data with internal to facilitate analysis of business environment
Basic resources (BR)	BR1. Our 'business analytics' projects are adequately staffed
	BR2. Our 'circular economy' projects are adequately staffed
	BR3. Our joint 'business analytics and circular economy' projects are adequately staffed
Technology (T)	T1. We have implemented different data visualization tools
	T2. We have implemented cloud-based services for processing data and performing analytics
	T3. We have implemented software for business analytics
	T4. We have implemented different data integration technologies
	T5. We have implemented automated data collection technologies (e.g. IoT)
Human Skills	
Systems Thinking skills (ST)	

(continued on next page)

(*continued*)

Measure	Item
	ST1. Our managers take a holistic view of the firm and its value chain, understanding both upstream and downstream impacts over longer periods of time
	ST2. Our managers understand how individual decisions and activities impact economic, environmental as well as social issues
	ST3. Our managers view the firm as a collection of parts and relationships within a wider environment
Data science skills (DS)	DS1. Our 'data scientist' staff have the necessary skills to accomplish their jobs successfully (e.g., statistics and computing)
	DS2. Our 'data scientist' staff are well trained
	DS3. Our 'data scientist' staff effectively process complex data sets (e.g. through machine learning, data mining, or statistical analyses)
	DS4. Our 'data scientist' staff are able to understand the business needs and impact of business analytics
<u>Intangible</u>	
Data-driven Culture (DD)	DD1. We base our decisions on data rather than on instinct
	DD2. We are willing to override our own intuition when data contradict our viewpoints
	DD3. We continuously coach our employees to make decisions based on data
	DD4. We offer training on analytics and data-driven decision making to our employees
Circular-oriented innovation culture (COI)	COI1. We have a clear vision of the circular economy and have aligned our corporate strategy accordingly
	COI2. We integrate circular economy objectives into our innovation process
	COI3. We continuously coach our employees to make decisions based on circular economy principles
	COI4. We offer training on circular economy and/or sustainability to our employees
Openness and co-creation (OCC)	OCC1. We actively share data
	OCC2. We actively promote working across departments and in multi-skilled teams
	OCC3. We continuously look for ways to support co-creation by developing, experimenting with, and demonstrating, new business models together with end-users, suppliers, and partners
Resource orchestration capability (Choi et al., 2020; Sirmon et al., 2011; Wang et al., 2020)	
Please indicate to what extent the following statements reflect the current situation in your firm related to IT resources or assets on a scale of (1. Strongly disagree, 2. Disagree, 3. Somewhat disagree, 4. Neither agree or disagree, 5. Somewhat agree, 6. Agree, 7. Strongly agree)	
Structuring (ROS)	ROS1. We are effective at purchasing valuable IT resources/assets from suppliers
	ROS2. We are effective at developing valuable IT resources/assets internally
	ROS3. We are effective at decommission less-valuable IT resources/assets
Bundling (ROB)	ROB1. We are effective at integrating IT resources/assets to build IT capabilities
	ROB2. We are effective at enriching, or extending, existing IT capabilities with new IT resources/assets
	ROB3. We are effective at pioneering, or creating, new IT capabilities
Leveraging (ROL)	ROL1. We are effective at mobilizing our IT capabilities towards a common vision
	ROL2. We are effective at coordinating, or integrating, our IT capabilities
	ROL3. We are effective at deploying our joint IT capabilities to take advantage of specific market opportunities
Circular Economy implementation (Blomsma et al., 2019)	
Please indicate whether you have implemented the listed circular economy strategies in your company, or contributed to its implementation for another stakeholder (e.g. if you are a service provider, consultancy or similar), on a scale of (1. Strongly disagree, 2. Disagree, 3. Somewhat disagree, 4. Neither agree or disagree, 5. Somewhat agree, 6. Agree, 7. Strongly agree)	
Reinvent and rethink (CE-INV)	CE-INV1. We provide value offerings that are decoupled from material use (e.g. abandoning

(*continued on next column*)

(*continued*)

Measure	Item
	physical product for digital service)
	CE-INV2. We support products during their lifetime through providing spare parts and/or repair services as separate sales offerings
	CE-INV3. We provide the result or performance of a product as a service instead of selling the physical product (e.g. performance-based business models)
	CE-INV4. We provide the access or usage of a product as a service instead of selling the physical product (e.g. usage-based business models)
Restore, reduce and avoid (CE-RRA)	CE-RRA1. We source secondary, recycled and/or renewable materials (e.g. industrial symbiosis, using ocean plastics or non-toxic materials)
	CE-RRA2. We run a lean and clean production (e.g. use less energy and materials, treat wastes, rework)
	CE-RRA3. We optimize product use and operation to extend the product life, minimize energy use, and/or increase product utilization.
Recirculate (CE-REC)	CE-REC1. We provide activities for extending the existing use-cycles of products and parts (e.g. upgrade, repair, maintenance)
	CE-REC2. We provide activities for extending products and parts to new use-cycles (e.g. reuse, refurbish, remanufacture)
	CE-REC3. We provide activities for extending the lifespan of materials (e.g. recycle, cascade, energy recovery)
Firm Performance (Khan et al., 2020a)	
In comparison to your firm's overall performance 5 years ago, please indicate your level of agreement to the following statements, on a scale of (1. Strongly disagree, 2. Disagree, 3. Somewhat disagree, 4. Neither agree or disagree, 5. Somewhat agree, 6. Agree, 7. Strongly agree)	
Environmental (PER-EN)	PER-EN1. We reduced energy consumption
	PER-EN2. We reduced waste generation
	PER-EN3. We reduced atmospheric pollution
Financial (PER-F)	PER-F1. We decreased manufacturing/operational costs
	PER-F2. We increased annual turnover
	PER-F3. We increased market share
Competitiveness (PER-CO)	PER-CO1. We increased capability to introduce innovative products/services
	PER-CO2. We improved quality of products/services
	PER-CO3. We improved brand value of products/services
	PER-CO4. We increased accessibility to new markets
Corporate reputation (PER-CR)	PER-CR1. We improved corporate image among customers
	PER-CR2. We improved relationship with suppliers/local community/regulatory organization
	PER-CR3. We increased satisfaction and support from investors/partners
	PER-CR4. We increased satisfaction and loyalty of employees

Declaration of competing interest

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