Received 29 March 2022
Revised 27 July 2022
30 September 2022
25 November 2022
16 December 2022
Accepted 19 December 2022

Opening the black box of big data sustainable value creation: the mediating role of supply chain management capabilities and circular economy practices

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Abstract

Purpose – This article examines the mechanisms through which big data analytics capabilities (BDAC) contribute to creating sustainable value and analyzes the mediating roles that supply chain management capabilities (SCMC), as well as circular economy practices (CEP), play through their impact on sustainable performance.

Design/methodology/approach – Following a literature review, a serial mediation model is presented. Hypotheses regarding direct and mediating relationships are tested to determine their potential for sustainability impact and circularity. Partial least squares structural equation modeling (PLS-SEM) has been applied for causal and predictive purposes.

Findings – The results indicate that big data analytics capabilities do not have a direct positive impact on sustainable performance but influence indirectly through SCMC and CEP.

Originality/value – Although some authors have addressed the associations between IT business value, supply chain (SC), and sustainability, this paper provides empirical evidence related to these relationships. Additionally, this study performs novel predictive analyses.

Keywords Big data analytics capabilities, Supply chain management capabilities, Circular economy practices, Sustainable performance, PLS-SEM, Prediction, Mediation

Paper type Research paper

The authors acknowledge the financial support provided by “Fondo Europeo de Desarrollo Regional (FEDER)” and the “Consejería de Economía, Conocimiento, Empresas y Universidad de la Junta de Andalucía”, within the “Programa Operativo FEDER 2014–2020”, Research Project US-1264451.

The authors also express their gratitude to Nicholas Danks (Trinity College Dublin, the University of Dublin, Ireland) for his invaluable help in assessing the proposed mediators’ additive contribution to the model’s predictive accuracy.

Introduction

While the practice of big data analytics expands, so does academic research on their organizational implications. Big data analytics capabilities (BDAC) refer to managing, processing and analyzing massive data to gain a competitive advantage (Wang *et al.*, 2016). There is a broad consensus regarding the impact of BDAC on a firm's performance. However, a figurative black box conceals the complex mechanisms through which this influence occurs. This obscurity requires new theoretical approaches and additional empirical studies (Olabode *et al.*, 2022).

A current academic trend, regarding the effects of information technology (IT) on organizational performance, proposes that IT tools should be deployed together with other organizational capabilities to achieve superior performance (Benitez *et al.*, 2018; Rai *et al.*, 2006). In this line, our work proposes a model that explains the network of subjacent relationships by which BDAC contribute to value creation. This work recognizes two mediating variables: (1) supply chain management capabilities (SCMC), which allow a firm to identify, use and assimilate resources and information to enable supply chain (SC) activities (Wu *et al.*, 2006); and (2) circular economy practices (CEP), which are practices that turn traditional linear production into a cyclic model (Singh and Ordoñez, 2016). This theoretical framework connects IT business value, SC and sustainability. A few researchers have addressed this in its early development (Cheng *et al.*, 2021; Del Giudice *et al.*, 2021; Yu *et al.*, 2022). This article contributes to the literature by extending their research to the mechanisms which connect BDAC and sustainable value creation.

Academics in SC research call for expanding investigation into how exploiting BDAC can impact SCMC (Arunachalam *et al.*, 2018). Additionally, there is a need for a deeper understanding of the relationship between data-enabled SCs and the circular economy (CE) (Del Giudice *et al.*, 2021). IT has been identified as one of the critical enablers in adopting CEP (Kristoffersen *et al.*, 2021a). Some authors have advocated the development of data-driven CEP (Awan *et al.*, 2021) to better understand the relationship between BDAC and CEP in improving sustainability (Chiappetta Jabbour *et al.*, 2019). However, previous literature has failed to fully explain the BDAC value-creation mechanisms through CE models (Modgil *et al.*, 2021). Our article extends the research into this gap. More specifically, we address the following research questions:

RQ1. Do big data analytics capabilities directly contribute to enhancing the sustainable performance of firms?

RQ2. Do SCMC and CEP mediate the influence of big data analytics capabilities on sustainable performance?

This article provides empirical evidence regarding these relationships. A survey of Spanish companies demonstrates that BDAC do not impact SP directly but through the mediation of both SCMC and CEP. Therefore, this study provides academic and managerial insight into the different organizational capabilities, enabled by big data, which can form the basis for new sustainable business models.

This paper is structured as follows. The next section provides the theoretical background for BDAC, SCMC, CEP and SP and develops the hypotheses. Next, we present the methodology and report the results in their corresponding sections. Finally, we discuss the implications for theory and practitioners, closing with limitations and suggestions for future research.

Theory and hypotheses

Big data analytics capabilities

BDAC address the ability of organizations to "provide insights using data management, infrastructure, and talent to transform business into a competitive force" (Mikalef *et al.*, 2018,

p. 557). Thus, BDAC are identified as a set of tangible and intangible capabilities (AlNuaimi *et al.*, 2021). BDAC require IT capabilities to leverage the volumes of data from sources of structured data (such as enterprise information systems), as well as unstructured data from various field devices (e.g. sensors, RFID tags) (Arunachalam *et al.*, 2018). Additionally, BDAC encompass the IT infrastructure that supports analytics, connecting internal and external elements, such as that seen with customer relationship management data (Kim *et al.*, 2012). With this infrastructure, BDAC also require essential technical and managerial skills related to big data to create value (AlNuaimi *et al.*, 2021). Moreover, BDAC influence strategies such as pricing and inventory levels by exploiting data-driven predictive and optimization models (Barton and Court, 2012).

The relationship between big data analytics capabilities and sustainable performance

A 'three-pillar' concept of sustainable performance (SP) dominates the literature as described by the triple bottom line performance dimensions: economic, environmental and social (Purvis *et al.*, 2019). Economic performance refers to the maximization of the firm's economic value, as reflected in its profit or financial results (Andersson *et al.*, 2022). Environmental performance recognizes positive environmental achievements from the firm's operations, while minimizing negative impacts in terms of intakes and outflows (Nutsugah *et al.*, 2021). Finally, social performance refers to the firm's actions that benefit human capital and society in terms of, for example, community welfare or employee health (Nursimloo *et al.*, 2020).

Previous literature highlights a relevant gap regarding how BDAC affect companies' SP (Raut *et al.*, 2019). In a seminal work, Bharadwaj (2000) posited that firms could leverage organizational capabilities, such as those which fall within IT, to achieve superior firm performance. Some authors have extended this approach to BDAC, arguing that their deployment can lead to better performance (Akter *et al.*, 2016). In the present study, we examine how BDAC impact SP.

Economically, data-driven intelligence from both internal and external sources provides vital insight for management decisions and helps the firm meet customer needs, increase sales and revenue, create new offerings and expand into new markets. These actions result in increases in productivity and financial performance (Akter *et al.*, 2016).

Regarding environmental performance, AlNuaimi *et al.* (2021) highlight three fundamental forms of big data exploitation: (1) data processing to provide evidence of regulatory compliance; (2) big data analysis to address environmental challenges; and, (3) modeling and testing different production transformations and resource usage to improve environmental impact.

Finally, considering social performance, a data-skilled workforce can utilize advanced analytics tools with big data to manage social challenges, such as human safety, welfare and community development (Shafiq *et al.*, 2020).

Therefore, we propose the following (see Figure 1):

H1. BDAC positively impact sustainable performance.

The mediating role of supply chain management capabilities

SCMC identify the planning and management of activities involved in sourcing and procurement, including the coordination and collaboration with channel partners (Torasa and Mekhum, 2020). A construct of four dimensions conceptualizes these capabilities: (1) information exchange, which enables shared knowledge among SC partners; (2) coordination, allowing the firm to coordinate operations with partners; (3) integration, incorporating activities and technological tools; and, (4) responsiveness, acting on changes in the business environment (Wu *et al.*, 2006).

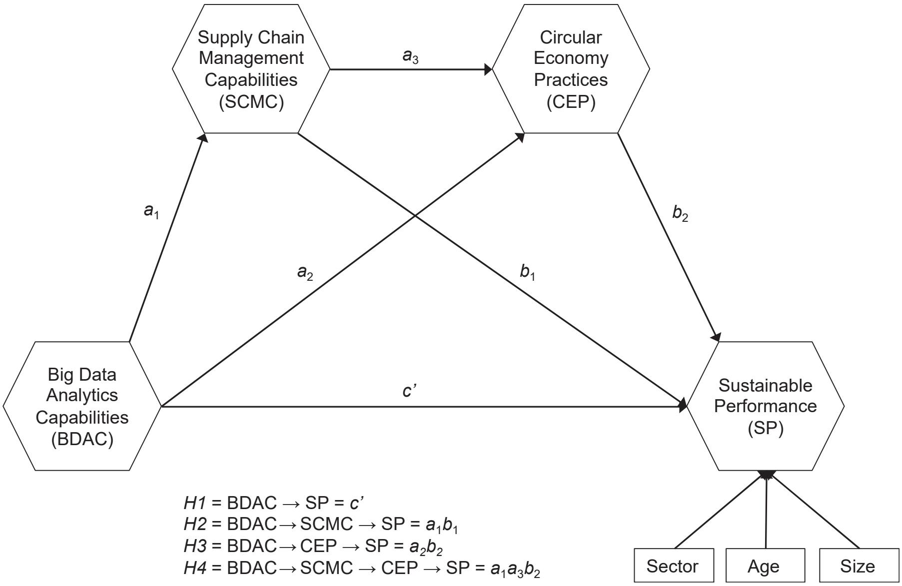


Figure 1.
Research model

Despite BDAC facilitation of SCMC being a contemporary topic, researchers have failed to reach a consensus on the specific mechanisms involved (Yu *et al.*, 2021). Therefore, our theoretical development addresses how BDAC enable the four SCMC dimensions. First, BDAC facilitate information exchange between SC partners, using systems that collect, manage and share voluminous data from a wide variety of sources, such as ERP systems, orders and shipment logistics, and other data-driven technologies (Govindan and Hasanagic, 2018). Second, data-driven information from internal and external sources enables SC coordination, as observed in inter-organizational SC processes, such as reverse logistics and manufacturing flows (Koot *et al.*, 2021). Third, the effect of BDAC on SCMC activity integration is illustrated by Yu *et al.* (2021). They show how hospitals gather, analyze and manage electronic health data through different healthcare information systems, increasing cross-functional, customer and supplier integration. Fourth, responsiveness is seen in Wang *et al.* (2016) in the deployment of data-based tools (e.g. statistical analysis, modeling and complex systems simulation), which uncover hidden data connections and turn them into critical insights related to product design and development, demand planning, sourcing and inventory. Additionally, these tools allow rapid reconfiguration of resources and capabilities in response to changing environments. From all the support mentioned above, sufficient evidence can be found regarding the impact of BDAC on SCMC.

The four dimensions of SCMC also contribute to SP (Lee *et al.*, 2016), which this paper represents using the triple bottom line. As an example, Philips Healthcare Refurbished Systems leverages information and knowledge exchange with its customers, to return reconditioned medical devices to the market, thus reducing manufacturing costs (economic impact), decreasing material consumption, extending the useful life of the products (environmental impact) and improving community access to medical devices (social impact) (Jensen *et al.*, 2019). SC coordination also significantly decreases SC vulnerabilities, which reduces costs and positively impacts economic performance (Munir *et al.*, 2020). Coordination, likewise, results in less waste generation, lower energy consumption and the development of environmental-friendly processes and products (Iranmanesh *et al.*, 2019). An example of how coordinated SC actions impact social performance can be seen in Apple's programs to improve working conditions with partners (Biswas *et al.*, 2018). In other instances, SC integration reduces supervision costs and produces more economical solutions through collective problem-solving (economic impact); partners optimize environmental results by sharing objectives and strategies (environmental impact); and, stakeholder needs are satisfied as a result of information sharing (social impact) (Han and Huo, 2020). SC responsiveness strengthens the market connection, enabling rapid responses and sales increases with a positive economic impact (Swafford *et al.*, 2008). Such responsiveness enables SC to detect environmental problems and adapt to legislative changes, positively affecting environmental performance (Ji *et al.*, 2020). It also facilitates awareness of potential SC disruptions, thus preventing negative social consequences, such as lower wages and unemployment (Cui *et al.*, 2022).

Therefore, and inferring from the support described, the deployment of BDAC in an organization enhances SCMC, and this advancement results in improved SP. Thus, the following hypothesis can be posited (see Figure 1):

H2. Supply chain management capabilities positively mediate the relationship between big data analytics capabilities and sustainable performance.

The mediating role of circular economy practices

CE, which aims to transform linear production and consumption systems into circular models, is operationalized through specific actions and practices (Schroeder *et al.*, 2019). These CEP are commonly conceptualized in "*R*" frameworks, such as 3R (reduce, reuse and recycle) (Cui *et al.*, 2021), 4R (reduce, reuse, recycle and recover) (Gebhardt *et al.*, 2022), or even, 9R (Potting *et al.*, 2017).

Govindan and Hasanagic (2018) provide a more holistic approach, which we subscribe to. They propose six clusters for internal CE practices (our CEP dimensions) based on similarities and context: (1) governance initiatives, such as CE policies and performance indicators; (2) economic initiatives that decouple economic growth from environmental impact; (3) cleaner production to increase eco-efficiency; (4) product development pursuing durable design or reuse; (5) management support or CE endorsement from top management; and, (6) knowledge, referred to as CE education, training and creativity.

There is a general call for a deeper understanding of how BDAC facilitate CE models (Modgil *et al.*, 2021). Specific mechanisms of this relationship can be seen in each of the CEP dimensions. (1) Governance initiatives: Big data sharing enables the development and monitoring of reliable CE indicators from all stakeholders, ensuring transparency across organizational boundaries (Kristoffersen *et al.*, 2021b). (2) Economic initiatives: this dimension considers CEP profitable business opportunities. For illustration, the Brazilian company, eStock, develops a profitable reverse logistics business of damaged electronic products, leveraging cloud applications and big data analytics to sort the products and decide their final use (recycle, resale, or repair) (Modgil *et al.*, 2021). (3) Cleaner production: Big data analytics enable real-time and predictive decision-making on clean practices, such as scheduled maintenance or optimizing material and energy consumption (Kristoffersen *et al.*, 2020). (4) Product development: the closed-loop model, advocated by CE, requires sharing massively traceable and trustworthy data on product life cycles among all stakeholders (Chiappetta Jabbour *et al.*, 2019). (5) Management support: data-driven insights on CEP outcomes provide top managers with tools to understand past and present trends and predict future ones (Awan *et al.*, 2021). (6) Knowledge: BDAC are critical enablers for implementing CE training and educational actions. For example, Alpha (a European household appliance retailer) exploits big data from sensors on their machines to offer tailored advice to their clients to improve resource efficiency (Bressanelli *et al.*, 2018). These examples provide sufficient theoretical and empirical evidence of the relationship between BDAC and CEP.

Meanwhile, adopting CEP can guide companies to a more sustainable business (Barros *et al.*, 2021). Conceptually, cleaner production and circular product development lead to economic benefits, by reducing costs and opening new revenue sources, thus improving competitive advantage (Rosa *et al.*, 2019). However, the environmental effects of CEP are most visible in practice. For example, recycling and remanufacturing activities involved in cleaner production and circular product development, result in more sustainable consumption of natural resources, while reducing pollutants and hazardous substances (Khan *et al.*, 2022). Focusing on social effects, CEP can promote new forms of business cooperation, between small and medium-sized enterprises, to exploit by-products, fostering knowledge co-creation and social welfare (Howard *et al.*, 2022).

Following this theoretical development, we posit that the deployment of BDAC to support CEP will increase SP (economic, environmental and social). Thus, we hypothesize the following (see Figure 1):

H3. CEP positively mediate the relationship between big data analytics capabilities and sustainable performance.

Sequential mediation of supply chain management capabilities and circular economy practices

Finally, SCMC can facilitate CEP in various forms. First, information exchange and coordination (reflected in training and collaborative work) allow firms and suppliers to produce shared knowledge, thus enhancing CEP (Stekelorum *et al.*, 2021). Other authors note that SC coordination, enabled by partner collaboration, contributes to CE governance initiatives, such as establishing CE standards within the SC (Dubey *et al.*, 2019). Likewise, SC coordination facilitates participation in cleaner production practices along the SC, such as using materials or products derived from recovered materials (Barros *et al.*, 2021). Focusing on SC integration, Calzolari *et al.* (2021) demonstrated that this integration directly contributes to successful CEP implementation among partners. Seuring and Müller (2008) also point to integration and coordination as means to create partnerships for developing new products with circular life cycles. In addressing SC responsiveness, Bag and Rahman, 2023 prove that SC flexibility enables firms to reconfigure their resources and processes to embrace CEP, resulting in significantly cleaner fabrication and product development.

According to this support, BDAC relate to SP first through SCMC and then via CEP. Thus, we hypothesize the following (see Figure 1):

H4. Supply chain management capabilities and CEP sequentially positively mediate the relationship between big data analytics capabilities and sustainable performance.

Methodology

Sample

Our study population comprises a selection of industries, identified by the European Commission in its new Circular Economy Action Plan, as critical sectors in their potential for environmental impact and circularity (European Commission, 2020). Considering companies within these sectors with at least fifty employees, we identified a population of 3,572 companies. Then, we used a random stratified sampling procedure to generate a representative sample of companies in terms of dimensional parameters and industry.

Since the analysis is performed at the organizational level, the questionnaire is completed by a single individual from each company. Therefore, data collection involved only top managers. Fieldwork was conducted between September 2021 and October 2021 using a questionnaire, following a previous contact by telephone. As a result, a total of 210 surveys were completed. The demographic data of the final sample can be consulted in Table 1.

Measures

Our study uses validated scales for most constructs, and all scales, except controls, were measured on a seven-point Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree). This work measured BDAC with eight indicators by applying the scale developed by Raut *et al.* (2021). SCMC were measured with the Wu *et al.* (2006) scale, in a second-order structure, consisting of four dimensions: information exchange, coordination, integration and responsiveness. Finally, all elements used to measure CEP, whose implementation depends on firm policies that correspond to internal application levels, originate in the research developed by Govindan and Hasanagic (2018). Thus, these practices were grouped into six dimensions that form a higher-order construct (i.e. CEP): governance initiatives; economic initiatives; cleaner production; product development; management support; and, knowledge. Finally, the SP scale has been adopted from Çankaya and Sezen (2019). SP is a multidimensional construct composed of three critical dimensions: economic,

	Frequency
Gender	
Male	130
Female	79
No Response	1
Total	*210*
Current Position	
Director of Environmental Sustainability/CSR	17
Quality Manager	127
Operations/Production Manager	28
Supply Chain Manager	1
General Manager	10
Other	27
Total	*210*
Firm Size	
50 to 249	179
250 to 1,000	28
Over 1,000	3
Total	*210*
Sector	
Batteries and Vehicles	20
Food, water, and nutrients	62
Electronics and ICT	6
Construction and Buildings	85
Packaging	15
Plastics	13
Textiles	9
Total	*210*

Table 1.
Respondent demographics

environmental and social performance. The questionnaire can be accessed in Table S1 of the Supplementary tables. Additionally, the study controls the industry sector (categorical variable), age (number of years since its founding) and firm size (number of employees).

Given that our primary variables correspond to capabilities, practices and indexes, they can be described as forged concepts (Henseler, 2021), conceptual variables resulting from theoretical thought and composed of a mixture of elements (Henseler, 2017). Consequently, we model our constructs as composites integrated with more specific elements, such as dimensions or facts (Henseler, 2021).

Data analysis

We have selected and applied partial least squares structural equation modeling (PLS-SEM) (Hair *et al.*, 2022; Ciavolino *et al.*, 2022) based on multiple factors. First, the primary constructs of our research model are consistent with a composite measurement model (Henseler, 2021). Second, we use component scores to model higher-order constructs (i.e. SCMC, CEP and SP) and apply the disjoint two-stage approach (Sarstedt *et al.*, 2019; Becker *et al.*, 2023). Finally, one of the purposes of the study is to evaluate the research model in terms of prediction, a task fundamentally incompatible with factor-based methods (Rigdon, 2012).

Thus, PLS-SEM enables us to address the causal-predictive goals of the study (Hair *et al.*, 2019). This study utilizes the Smart-PLS 3.3.9 software (Ringle *et al.*, 2015).

Common method bias

The potential bias introduced by common method bias (CMB) can jeopardize findings, due to systematic errors. We attempted to prevent CMB during the research design phase by adopting the procedural remedies of MacKenzie and Podsakoff (2012). Subsequently, we applied two statistical procedures developed for PLS-SEM to detect various sources of CMB. First, we performed a full collinearity test using variance inflation factors (VIFs) (Kock and Lynn, 2012). A VIF greater than 3.3 indicates pathological collinearity, implying that CMB contaminates the model. However, our model appears free of CMB as indicated by the highest VIF of 2.584 (Table S2–Supplementary tables). Second, we employed the measured latent marker variable (MLMV) technique (Chin *et al.*, 2014). The questionnaire included six items from the Chin *et al.* (2014) proposal of an observed latent marker variable (Table S1–Supplementary tables). The paths from the MLMV to the rest of the research model's constructs were nonsignificant. In addition, the hypothesized path coefficients were consistent with the initial estimates, with no essential variations (Table S3–Supplementary tables). This implies that CMB was not a significant concern, and hence we present the results of the original research model.

Results

Measurement model

Henseler (2017) argues that, because our primary constructs represent artifacts (forged concepts), indicators of the composites are likely to be correlated. As a result, we used correlation weights to estimate these components in Mode A (Rigdon, 2016).

Following Hair *et al.* (2022), we observed that both indicators and dimensions (lower-order components) generally had loadings greater than 0.7 (Table 2). Then, we evaluated the internal consistency reliability of the constructs using composite reliability (CR). Since lower- and higher-order constructs showed CR values greater than 0.7, they had good reliability levels (Table 2). The average variance extracted (AVE) was then used to determine the convergent validity (Table 2), and all constructs achieved convergent validity with AVE values greater than 0.5. Similarly, discriminant validity was achieved for all primary

Construct/*Dimension*/Indicator	Loadings	Weights	CR	AVE
Big data analytics capabilities (composite Mode A)			0.957	0.736
bdac1	0.881	0.140		
bdac2	0.896	0.154		
bdac3	0.886	0.145		
bdac4	0.836	0.146		
bdac5	0.911	0.162		
bdac6	0.856	0.138		
bdac7	0.757	0.130		
bdac8	0.831	0.148		
Supply chain management capabilities (HOC Mode A)			0.886	0.661
Information exchange (composite Mode A)	0.778	0.267	*0.977*	*0.915*
ie1	0.934	0.265		
ie2	0.964	0.267		
ie3	0.963	0.258		
ie4	0.965	0.256		
Coordination (composite Mode A)	0.840	0.299	*0.926*	*0.714*
c1	0.818	0.222		
c2	0.872	0.256		
c3	0.853	0.227		
c4	0.860	0.248		
c5	0.820	0.230		
Integration (composite Mode A)	0.808	0.348	*0.950*	*0.792*
i1	0.857	0.238		
i2	0.884	0.211		
i3	0.899	0.225		
i4	0.903	0.221		
i5	0.905	0.229		
Responsiveness (composite Mode A)	0.824	0.315	*0.934*	*0.738*
r1	0.857	0.186		
r2	0.879	0.228		
r3	0.833	0.206		
r4	0.849	0.264		
r5	0.875	0.280		
Circular economy practices (HOC Mode A)			0.936	0.712
Governance initiatives (composite Mode A)	0.839	0.199	*0.873*	*0.775*
gi1	0.874	0.554		
gi2	0.887	0.581		
Economic initiatives (composite Mode A)	0.842	0.199	*0.835*	*0.718*
ei1	0.916	0.713		
ei2	0.772	0.449		
Cleaner production (composite Mode A)	0.922	0.225	*0.929*	*0.620*
cp1	0.794	0.172		
cp2	0.827	0.167		
cp3	0.869	0.183		
cp4	0.696	0.142		
cp5	0.750	0.147		
cp6	0.812	0.165		
cp7	0.769	0.140		
cp8	0.770	0.151		
Product development	0.674	0.142	*1*	*1*
pd1	1	1		
Management support	0.862	0.198	*1*	*1*
ms1	1	1		
Knowledge (composite Mode A)	0.901	0.212	*0.934*	*0.824*

Table 2. Measurement model results

(*continued*)

Construct/*Dimension*/Indicator	Loadings	Weights	CR	AVE
k1	0.893	0.363		
k2	0.910	0.350		
k3	0.920	0.388		
Sustainable performance (HOC Mode A)			0.901	0.752
Economic performance (composite Mode A)	0.798	0.292	*0.895*	*0.553*
ep1	0.595	0.128		
ep2	0.678	0.155		
ep3	0.705	0.192		
ep4	0.871	0.242		
ep5	0.833	0.217		
ep6	0.708	0.201		
ep7	0.777	0.192		
Social performance (composite Mode A)	0.908	0.431	*0.918*	*0.585*
sp1	0.736	0.148		
sp2	0.759	0.171		
sp3	0.716	0.157		
sp4	0.754	0.147		
sp5	0.808	0.191		
sp6	0.760	0.155		
sp7	0.765	0.160		
sp8	0.814	0.177		
Environmental performance (composite Mode A)	0.892	0.421	*0.935*	*0.743*
ep1	0.854	0.289		
ep2	0.870	0.226		
ep3	0.909	0.229		
ep4	0.857	0.202		
ep5	0.817	0.215		

Note(s): CR: Composite reliability. AVE: Average variance extracted. HOC: Higher-order construct. All loadings and weights with *p*-value <0.05, two-tailed test

Table 2.

constructs. This condition was achieved by adopting both the Fornell–Larcker criterion and the toughest Heterotrait–Monotrait ratio (HTMT) standard of 0.85 (Table 3).

In the end, we performed a confirmatory composite analysis applying bootstrap-based saturated model fit tests (SRMR, d_{ULS} and d_G), which assessed the external validity of primary constructs (Henseler, 2021). The three measures of the discrepancy between the empirical correlation matrix and the model-implied were all less than the corresponding values of HI95 or HI99 of their saturated model (Table 4), indicating that the discrepancy was not significant. As a result, we found support for the proposed composite model.

	BDAC	SCMC	CEP	SP	Sector	Age	Size
BDAC	0.858	*0.651*	*0.650*	*0.540*		*0.158*	*0.056*
SCMC	0.582	0.813	*0.670*	*0.643*		*0.142*	*0.035*
CEP	0.609	0.595	0.844	*0.822*		*0.105*	*0.131*
SP	0.495	0.545	0.743	0.867		*0.211*	*0.126*
Sector	0.088	−0.018	0.035	−0.050	n.a		
Age	−0.154	−0.133	−0.101	−0.184	0.084	n.a	*0.084*
Size	0.050	0.013	0.125	0.116	0.100	0.084	n.a

Note(s): The diagonal elements (underline) are the square roots of the AVEs. The Fornell–Larcker criterion in the lower-left corner, and the heterotrait–monotrait ratio (HTMT; italics) in the upper-right corner. Off-diagonal lower elements are the correlations between constructs. n.a.: non-applicable

Table 3.
Discriminant validity

Structural model

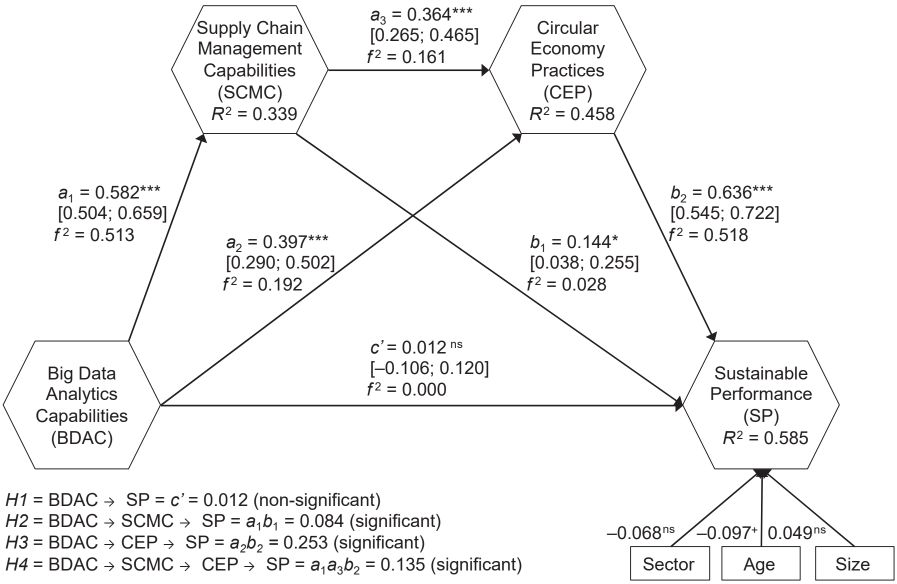
First, the VIF values for the antecedent variables of the endogenous constructs ranged from 1.032 to 1.880, indicating that multicollinearity was not a concern in our structural model (Hair *et al.*, 2022). Next, we examined the structural model for potential nonlinearities. Interaction terms were included to represent the quadratic effects of each antecedent variable on each dependent construct (Sarstedt *et al.*, 2020). According to the bootstrapping results (10,000 samples), neither of the quadratic effects was significant. As a result, we concluded that the linear effects model was robust.

Figure 2 shows the path coefficients' signs, magnitude, significance and R^2 values for the dependent variables. We used bootstrapping (10,000 samples) to generate t-statistics and confidence intervals. While five of the six direct effects were significant (Figure 2) (Table S4– Supplementary tables), we did not find a significant relationship in the direct effect (c') of BDAC on SP (H1). In terms of in-sample predictive power, the dependent variables achieved a

	Value	HI95	HI99
Saturated model			
SRMR	0.050	0.050	0.055
d_{ULS}	0.865	0.893	1.065
d_G	0.416	0.375	0.416
Estimated model			
SRMR	0.052	0.053	0.058
d_{ULS}	0.939	0.990	1.183
d_G	0.421	0.378	0.427

Note(s): SRMR: Standardized root mean squared residual. d_{ULS}: Unweighted least squares discrepancy. d_G: geodesic discrepancy. HI95: bootstrap-based 95% percentile. HI99: bootstrap-based 99% percentile

Table 4.
Tests of model fit



Note(s): *$p < 0.05$, ***$p < 0.001$, ns: non-significant (based on t(9999), one-tailed test) +$p < 0.05$, ns: non-significant (based on t(9999), two-tailed test)

Figure 2.
Structural model results

satisfactory level as the lowest coefficient of determination (R^2) achieved is 0.339 for SCMC (Figure 2). At the same time, SP reached an R-square of 0.585, which can be considered a moderate degree of explanatory power.

From a confirmatory perspective (Hair *et al.*, 2019), we first evaluated the existence of a potential endogeneity problem by applying the Gaussian copula approach (Hult *et al.*, 2018). We focused on the most complex regression of the hypothesized model, SP regressed to BDAC, SCMC and CEP. As a first step, the Gaussian copula technique demands that the antecedent variables, which may be affected by endogeneity issues, have a nonnormal distribution. Both the Shapiro–Wilk test and the Anderson–Darling test (Becker *et al.*, 2022) showed that the distributions of BDAC, SCMC and CEP were not normal ($p < 0.05$; Table 5). Next, we performed a Gaussian copula analysis in PLS-SEM using the REndo package of the statistical software R (Gui *et al.*, 2017). None of the copula terms was statistically significant at the 5% probability of error level. Table 5 shows the results for the most complex model with the three copulas. As a result, we conclude that the PLS-SEM results are robust and significantly unaffected by possible endogeneity issues, mainly due to omitted constructs that could correlate with one or more predictor constructs and SP.

Subsequently, we also evaluated the overall fit of the estimated model, through several measures of the overall goodness of fit available for PLS-SEM (Henseler, 2021), to obtain empirical evidence for the research model. First, the standardized root mean square residual (SRMR) evaluation offered a fair value of 0.052 (Table 4), below the usual cut-off of 0.08. Next, we conducted several bootstrap-based tests of the overall model fit (SRMR, d_{ULS}, d_G). Our results showed that all discrepancy values were less than the 95th percentile of their corresponding reference distribution (HI95). This suggests that the estimated model was not rejected at the 5% significance level (Henseler, 2021). Consequently, the postulated model cannot be rejected, as it is likely true.

Once we obtained evidence on the causality of the model, we tested the mediation hypotheses (H2–H4), following Nitzl *et al.* (2016). We examined the total, direct and indirect effects of BDAC on SP, the latter being controlled by sector, age and size variables. We executed a bootstrapping routine (10,000 samples) using percentile confidence intervals to test the indirect effects. As Table 6 shows, BDAC had a significant total effect on SP.

Table 5. Results of the Gaussian copula approach

Results of nonnormality tests	BDAC	SCMC	CEP
Shapiro–Wilk	0.947	0.987	0.970
Shapiro–Wilk p-value	<0.001	0.045	<0.001
Anderson–Darling test			
A	3.396	0.982	1.570
p-value	0.000	0.013	0.000

Gaussian copula results	β	p-value
BDAC	−0.105	0.348
SCMC	0.073	0.752
CEP	0.723	0.000
c_{BDAC}	0.115	0.170
c_{SCMC}	0.071	0.734
c_{CEP}	−0.072	0.679

Note(s): c_{BDAC}: Gaussian copula term for BDAC. c_{SCMC}: Gaussian copula term for SCMC. c_{CEP}: Gaussian copula term for CEP

Table 6.
Summary of mediating effect tests

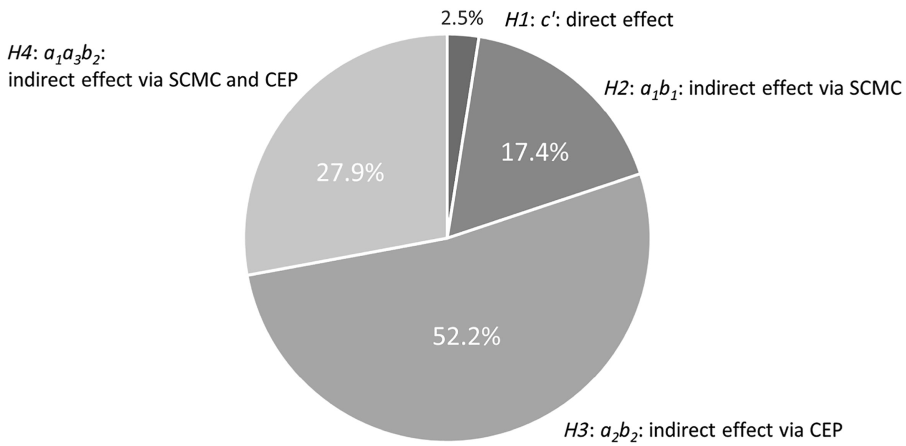
	Coefficient	t-value	p-value		
Total effect of BDAC on SP	0.484	8.194	0.000		
Direct effect of BDAC on SP	Coefficient	t-value	p-value	Support	VAF
H1: c'	0.012	0.177	0.430	No	2.5%
Indirect effects of BDAC on SP	Point estimate	5% PBCI	95% PBCI	Support	VAF
H2: a_1b_1 (via SCMC)	0.084	0.022	0.151	Yes	17.4%
H3: a_2b_2 (via CEP)	0.253	0.175	0.334	Yes	52.2%
H4: $a_1a_3b_2$ (via SCMC + CEP)	0.135	0.091	0.186	Yes	27.9%
Total	0.472	0.380	0.567	Yes	97.5%

Note(s): Total, direct, and indirect effects are estimated considering Sector, Age, and Size as control variables on SP. PBCI: Percentile bootstrap confidence interval. Bootstrapping based on n = 10,000 subsamples. Mediating effects are assessed by applying a one-tailed test. VAF: Variance accounted for

However, after introducing both mediating variables, BDAC no longer had a substantial direct influence on SP (H1: c') (Figure 2). Consequently, H1 was not supported.

Furthermore, all indirect impacts of BDAC on SP were significant. This indicated that H2 through H4 were supported. Therefore, we found evidence that SCMC positively mediated the relationship between BDAC and SP (H2: a_1b_1). The results also indicated that CEP mediated the relationship between BDAC and SP (H3: a_2b_2). Lastly, we found that BDAC were positively associated with greater SCMC and CEP, which were related to a higher level of SP (H4: $a_1a_3b_2$). Considering that the direct effect (c') between BDAC and SP was not significant, we identified a full mediation model, meaning that the effect of BDAC on SP was transmitted entirely with the help of SCMC and CEP. This scenario was also supported by analyzing the variance accounted for (VAF) (Henseler, 2021) (Table 6, Figure 3) for the total indirect effect. As we could observe, 97.5% of the total effect of BDAC on SP was attributable to the sum of indirect effects.

Next, we performed a novel analysis that allowed us to know the additive contribution of the proposed mediators to the model's predictive accuracy. For this purpose, we used the predictive contribution of the mediator (PCM) metric proposed by Danks (2021). We generated three models, according to the mediating hypotheses, that allow us to assess the predictive contribution of SCMC, CEP and SCMC combined with CEP (as sequential mediators), respectively (Figure 4). The SEMinR package (Ray *et al.*, 2022) was used to estimate the PCM metrics for each indicator representing the three dimensions of SP.



Note(s): SCMC: Supply chain management capabilities. CEP: Circular economy practices

Figure 3.
Partitioning the total effect of big data analytics capabilities on sustainable performance using VAF

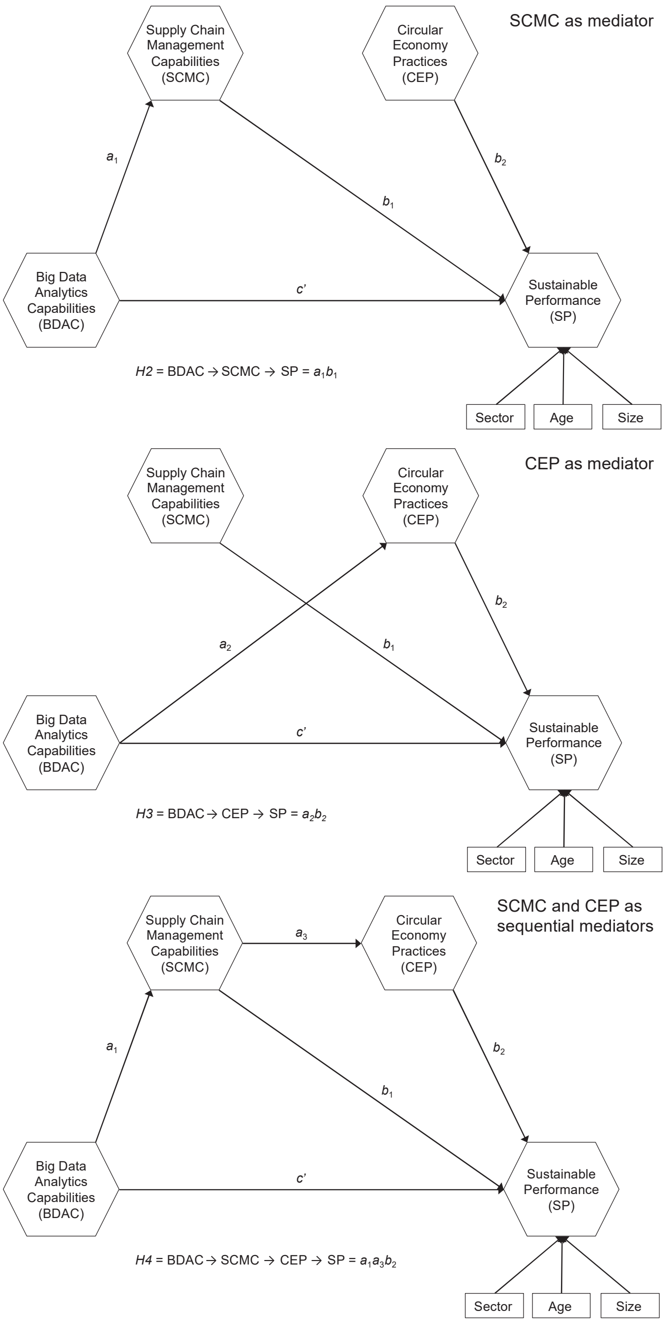


Figure 4.
Models for the estimation of the predictive contribution of the mediator (PCM)

We analyzed the mediated effect of BDAC through SCMC on SP (Table 7). PCM estimates were above zero but below 0.05 for the three indicators. This result provided weak but confirmatory predictive evidence for the mediation effect of SCMC. However, in the context of the mediated path of BDAC through CEP on SP, the three PCM values for each dimension ranged from close to moderate (0.05), to strong (above 0.10) (Table 7). Therefore, CEP contributed substantially and provided strong confirmatory predictive evidence for the mediation effect. Ultimately, the sequential indirect effect through SCMC and CEP obtained moderate to very high PCM values (Table 7). This result represented a solid contribution to the predictive power of the two mediators.

In conclusion, the results of the PCM metric attained for the three mediated effects provided additional *post hoc* evidence to support the generalizability of the proposed mediators. Furthermore, our findings justified the added complexity of the inclusion of SCMC and CEP as mediators in our research model, as both constructs yielded an improved predictive accuracy of SP (Danks, 2021).

Evaluation of the predictive power of the model

We performed the $PLS_{predict}$ procedure (Shmueli *et al.*, 2019) to assess the out-of-sample predictive power of the model. We began by selecting SP as the target construct. Next, we performed k-fold cross-validation, setting $k = 7$ subgroups to meet the requirement of reaching a minimum sample of 30 cases in each holdout sample. Then we selected to repeat the algorithm ten times. Afterward, we interpreted the results (Table 8) by completing the following stages (Shmueli *et al.*, 2019):

(1) The indicators representing each dimension of SP showed $Q^2_{predict} > 0$.

(2) Since prediction errors are symmetrically distributed, we have used the root mean squared error (RMSE) to assess the degree of prediction error (Table 8). Subsequently, the RMSE statistics from the PLS-SEM analysis were compared with the naive values provided by a linear regression model (LM). Indicators representing economic, social and environmental performance produced smaller prediction errors in the PLS-SEM analysis than LM, showing a high predictive power. In conclusion, these results indicate that the research model could provide generalizable findings for other datasets and potentially equivalent contexts.

Table 7. Predictive contribution of the mediator (PCM) results

Dimension	SCMC PCM	Conclusion	CEP PCM	Conclusion	SCMC + CEP PCM	Conclusion
Economic performance	0.009	Weak	0.048	Weak	0.068	Moderate
Social performance	0.010	Weak	0.158	Strong	0.209	Strong
Environmental performance	0.0003	Weak	0.191	Strong	0.220	Strong

Table 8. $PLS_{predict}$ assessment of the dimensions of sustainable performance

	PLS RMSE	PLS $Q^2_{predict}$	LM RMSE	PLS-LM RMSE
Economic performance	0.964	0.080	0.989	−0.025
Social performance	0.870	0.253	0.893	−0.023
Environmental performance	0.919	0.165	0.959	−0.040

Note(s): PLS: Partial least squares. LM: Linear regression model. RMSE: Root mean squared error

Discussion

This study analyzes how BDAC contribute to improving firm SP and how SCMC and CEP mediate the influence of BDAC on SP. Our results illustrate how BDAC do not directly influence SP. Instead, their influence is fundamentally indirect through SCMC and CEP (97.5% of their impact on SP is indirect). In this result, our findings coincide with previous studies. For example, Cheng *et al.* (2021) found that the level of CEP, and the flexibility of sustainable SC, mediated the influence of BDAC. Moreover, Kristoffersen *et al.* (2021a) concluded that the relationship between BDAC and company performance was not significant, and that the implementation of CEP fully mediated the effect of BDAC on performance.

The results also show that SCMC mediate the relationship between BDAC and SP. Applications that take advantage of big data provide greater insight, leading to better SC management and, as a result, better business performance (Bamel and Bamel, 2021) and according to Chiappetta Jabbour *et al.* (2020), acquiring BDAC can create competitive and sustainable SCs. To this end, Industry 4.0 technology has helped companies by allowing more efficient planning, execution and forecasting in SC processes (Yu *et al.*, 2022).

CEP mediate the relationship between BDAC and SP. Scholars agree that CEP increase a company's environmental and financial performance (Kristoffersen *et al.*, 2021a). However, few studies still consider the impact of CEP on the three dimensions of sustainability as an integrated whole (Cheng *et al.*, 2021). Our findings are consistent with recent studies (Dey *et al.*, 2022; Le *et al.*, 2022) which confirm that CEP impact SP. Even further, our study demonstrates that the CEP variable is the most critical mediator in the effect of BDAC on SP (VAF = 52.2%) and plays a decisive role in achieving sustainability. This aligns with Rodríguez-Espíndola *et al.* (2022) by recognizing the mediating role of CEP in the relationship between technology adoption and SP.

SCMC and CEP sequentially mediate the relationship between BDAC and SP. SCMC impact SP, both directly and indirectly, although their indirect effect through CEP is more relevant. As a result, SCMC play an essential role as facilitators of CEP in transitioning to sustainable consumption and production patterns (Schroeder *et al.*, 2019). These results are supported by the findings of Yu *et al.* (2022), which examine the impact of Industry 4.0 technologies on the ability of CE and SCMC to improve economic and operational performance.

Theoretical implications

Considering the results obtained, the first contribution of this research is that BDAC do not directly influence SP. This finding deviates from previous studies which establish that BDAC positively influence SP (Kamble *et al.*, 2020). Still, little is known about the process that leverages big data analytics investments toward firm performance, either directly or indirectly – for example, how a company using IT infrastructure to develop higher-order capabilities of SC processes generates significant and sustainable gains (Rai *et al.*, 2006). Our results demonstrate that SCMC and CEP play a central role in mediating this relationship. Adopting BDAC to achieve SP is complex and requires complementary resources to help organizations realize their full potential. In the hierarchy of capabilities and from the perspective of IT-enabled organizational capabilities (Benitez *et al.*, 2018), lower-order capabilities require higher-order capabilities to affect business outcomes. This research contributes to the literature on IT business value by demonstrating how one IT capability develops other capabilities that influence SP.

The second contribution of this research highlights the mediating role of SCMC. The IT infrastructure for big data analytics can assist in SC functions, such as procurement, warehousing, manufacturing, demand management and logistics (Govindan *et al.*, 2018). To achieve SC innovation and sustainable SC performance, BDAC are considered essential (Akter *et al.*, 2016). Therefore, BDAC and SCMC are fundamental capabilities which provide vital theoretical insights for big data and SC management. SCMC include information exchange, integration, coordination and responsiveness which help firms at distinct stages of SC operations and are key performance indicators for businesses (Shen *et al.*, 2019). The results of previous studies on the impact of SCMC on financial performance show that the result is inconclusive (Yu *et al.*, 2022). However, our results have revealed a significant impact of SCMC on SP. Given this, we attempt to clarify the elements which contribute to determining SCMC and how these capabilities are related to influence SP (Gani *et al.*, 2022).

A third contribution points to the mediating role of CEP in the impact of BDAC on SP. Therefore, adopting digital technologies is consistent with the concepts of CE (Khan *et al.*, 2022). Our contribution underscores the importance of CEP in performance sustainability. The successful implementation of a CE model facilitates the growth of all three aspects of SP, and CEP help to achieve sustainability goals (Schroeder *et al.*, 2019).

Our fourth theoretical insight reveals that SCMC are associated with CEP, and both constructs sequentially mediate the relationship between BDAC and SP. The demonstrated relationship between SCMC and CEP confirms the argument that embracing complex environmental or social initiatives, such as CE models, will inevitably fail without the commitment of SC partners (Silvestre *et al.*, 2018). CE is an innovation in closed-loop SC, since it affects design, implementation and managing activities that combine the upstream and downstream stages of the SC, increasing value generation throughout the entire life cycle of a product (Chowdhury *et al.*, 2022). Finally, the entire mediation sequence emphasizes the importance of digitally transforming key organizational capabilities to achieve sustainable development, as evidenced by BDAC enhancing SCMC, accelerating the adoption of CEP, and thus increasing SP.

Implications for practitioners and policymakers

The positive results achieved in our predictive analyses imply the model's generalizability to potentially similar contexts. Therefore, if companies follow the recommendations based on our model, they could achieve equivalent results, attaining benefits in four primary areas.

First, an organization with appropriate BDAC can develop SCMC to exchange and coordinate information with SC partners, leading to improved integration and responsiveness. The current competitive environment encourages companies to adopt big data analytics techniques. The framework provided can help implement these capabilities to enhance SP.

The knowledge provided by big data analytics and SC capabilities is based on tacit resources. These resources are not visible but can be achieved through learning and practice. From them, it is possible to develop CEP, which can establish a competitive advantage for the company. Additionally, top managers and executives can see how CEP can help them improve their company's performance and what role BDAC and SCMC play as CEP enablers.

Production and SC managers should know that implementing BDAC does not directly improve sustainability, especially at the firm level. However, from a managerial perspective, BDAC have emerged as a critical component that can help companies implement CE models, optimize operations and generate long-term solutions.

Therefore, managers must pay close attention to the various CEP to reap benefits from a sustainability performance perspective. Government policymakers can also justify increasing incentives for CE projects that lead to sustainable community benefits.

Limitations and future research

This study has some limitations. First, the authors evaluated the model in a single country under unique conditions; therefore, the findings should be replicated in different situations. Second, the study relied on measurements based on the participants' perceptions. As such, it must account for the risk that the respondents' impressions do not accurately reflect reality. Finally, the research was carried out cross-sectionally rather than longitudinally.

Future studies could focus on including additional variables into the model proposed in our research, thus increasing the understanding of the mechanisms which drive the creation of sustainable value from BDAC. First, we could focus on establishing interdependence relationships between the different SCMC and the different CEP, determining a sequence of implementation, thus identifying those practices that constitute the base on which the other activities can be successfully implemented. Second, we could analyze certain contingent elements that could affect the contribution of the variables in the model to SP (e.g. environmental uncertainty, industrial sector), facilitating the generation of conditional mediation analyses (Cheah *et al.*, 2021). Third, some variables may affect firm behavior and could increase our understanding of the phenomenon. Examples include the company's strategic orientation driven by big data, environmental self-awareness and stakeholder pressure. Finally, to improve the robustness of the findings, future research might use longitudinal data to assess intertemporal impacts.

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Supplementary tables

Construct/*Dimension*/Indicator	
Big data analytics capabilities (composite Mode A)	
bdac1	Our organization is capable of parallel computing to address voluminous data
bdac2	Real-time assess of data and information has helped our organization in better decision making
bdac3	Our information systems are capable to handle semi-structured and unstructured data
bdac4	Truthfulness and accuracy of data has helped our organization
bdac5	Data driven intelligence has made decision making more effective
bdac6	Our organization has good infrastructure and facilities to support analytics
bdac7	Interchange ability of services (cloud, mobile, and analytics) plays key role
bdac8	Analytics personnel are proficient with programming, data management, new tools etc.
Supply chain management capabilities (HOC Mode A)	
Information exchange (composite Mode A)	
ie1	My firm exchanges more information with our partners than our competitors do with their partners
ie2	Information flows more freely between my firm and our partners than between our competitors and their partners
ie3	My firm benefits more from information exchange with our partners than do our competitors from their partners
ie4	Our information exchange with our partners is superior to the information exchanged by our competitors with their partners
Coordination (composite Mode A)	
c1	My firm is more efficient in coordination activities with our partners than are our competitors with theirs
c2	My firm conducts transaction follow-up activities more efficiently with our partners than do our competitors with theirs
c3	My firm spends less time coordinating transactions with our partners than our competitors with theirs
c4	My firm has reduced coordinating costs more than our competitors
c5	My firm can conduct the coordination activities at less cost than our competitors
Integration (composite Mode A)	
i1	My firm develops strategic plans in collaboration with our partners
i2	My firm collaborates actively in forecasting and planning with our partners
i3	My firm projects and plans future demand collaboratively with our partners
i4	Collaboration in demand forecasting and planning with our partners is something we always do in my firm
i5	My firm always forecasts and plans activities collaboratively with our partners
Responsiveness (composite Mode A)	
r1	Compared to our competitors, our supply chain responds more quickly and effectively to changing customer and supplier needs
r2	Compared to our competitors, our supply chain responds more quickly and effectively to changing competitor strategies
r3	Compared to our competitors, our supply chain develops and markets new products more quickly and effectively
r4	In most markets, our supply chain is competing effectively
r5	The relationship with our partners has increased our supply chain responsiveness to market changes through collaboration
Circular economy practices (HOC Mode A)	
Governance initiatives (composite Mode A)	
gi1	Our organization has developed a set of performance indicators in order to evaluate our recycling, reuse and remanufacture initiatives in supply chain
gi2	Our organization has increased the number of employees in circular economy positions
Economic initiatives (composite Mode A)	
ei1	Our organization favors economic growth opportunities that have minimal environmental impact
ei2	The price of our products includes costs associated with reuse, recycle and remanufacturing
Cleaner production (composite Mode A)	
cp1	Our organization has experienced increased eco-efficiency in production through the use of reduce, reuse, recycle, recover, redesign, and remanufacture

(*continued*)

Table S1.
Questionnaire

Construct/*Dimension*/Indicator	
cp2	Our organizational purchasing processes consider sustainability factors in addition to price
cp3	Our organization experiments with new strategies in supply chain to constantly improve our circular economy efforts
cp4	Our firm collaborates with other organizations in order to make it possible to reuse/recycle/remanufacture
cp5	Our organization classifies the materials as either those candidates for reuse/recycle/remanufacture, or those that can be safely returned to the environment
cp6	Our organization reviews logistical routes and modes for constant improvement in terms of sustainability
cp7	Our organization utilizes equipment specifically designed to produce output that can be remanufactured
cp8	Our organization has implemented measurable data gathering systems to measure the environment performance in regards of the initiatives by implementing circular economy in supply chain
Product development	
pd1	Our organization's products are designed as durable products for multiple cycles of use and for disassembly and reuse
Management support	
ms1	Top managers of our organization actively endorse the circular economy efforts in supply chain
Knowledge (composite Mode A)	
k1	Our organization supports education and awareness programs that support recycling, remanufacturing and reuse among actors in our supply chain
k2	Our organization implements formal training programs that educate our workforce about circular economy concepts and benefits in the supply chain
k3	Our organization demonstrates visionary thinking and technical creativity to implement circular economy in supply chain
Sustainable performance (HOC Mode A)	
Economic performance (composite Mode A)	
ep1	Decrease in cost of materials purchased
ep2	Decrease in cost of energy consumption
ep3	Decrease in fee for waste discharge
ep4	Improvement in earnings per share
ep5	Improvement in return on investment
ep6	Sales growth
ep7	Profits growth
Social performance (composite Mode A)	
sp1	Improvement in customer satisfaction
sp2	Improvement in its image in the eyes of its customers
sp3	Improvement in investments on social projects (education, culture, sports)
sp4	Improvement in relations with community stakeholders, e.g. nongovernmental organizations (NGOs) and community activists
sp5	Improved awareness and protection of the claims and rights of people in community served
sp6	Improvement in employee training and education
sp7	Improvement in occupational health and safety of employees
sp8	Improvement in overall stakeholder welfare or betterment
Environmental performance (composite Mode A)	
ep1	Improvement of an enterprise's environmental situation
ep2	Reduction in waste (water and/or solid)
ep3	Reduction in air emission
ep4	Decrease of consumption for hazardous/harmful/toxic materials
ep5	Decrease of frequency for environmental accidents
Measured latent marker variable (composite Mode B)	
mlmv1	Air travel is a better mode of transportation than by car
mlmv2	It is important to spend time with your immediate family
mlmv3	Mountains make a great destination for a vacation
mlmv4	Music is important in my life
mlmv5	I find rugby interesting
mlmv6	I would rather read a book than go see a movie

Note(s): HOC: Higher-order construct

Table S1.

Variables	BDAC	SCMC	CEP	SP	Sector	Age	Size
VIF	1.825	1.794	2.584	2.240	1.028	1.058	1.030

Note(s): BDAC: Big data analytics capabilities. SCMC: Supply chain management capabilities. CEP: Circular economy practices. SP: Sustainable performance. VIF: Variance inflation factor

Table S2. Common method bias test. Full collinearity VIFs

	Research model			Model with MLMV		
	Direct effect	*t*-value	*p*-value	Direct effect	*t*-value	*p*-value
SCMC						
BDAC	0.582	12.360	0.000	0.549	10.191	0.000
MLMV				0.137^{ns}	1.895	0.058
CEP						
BDAC	0.397	6.161	0.000	0.395	6.195	0.000
SCMC	0.364	5.971	0.000	0.361	5.682	0.000
MLMV				0.013^{ns}	0.208	0.835
SP						
BDAC H1(+): (*c*')	0.012^{ns}	0.177	0.430	-0.003^{ns}	0.046	0.482
SCMC	0.144	2.197	0.014	0.138	2.117	0.017
CEP	0.636	11.811	0.000	0.633	11.718	0.000
Sector	-0.068^{ns}	0.924	0.356	0.027^{ns}	0.38	0.700
Age	-0.097^{ns}	2.216	0.027	−0.091	1.956	0.050
Size	0.049^{ns}	1.244	0.213	0.051^{ns}	1.283	0.200
MLMV				0.070^{ns}	1.040	0.298

Note(s): BDAC: Big data analytics capabilities. SCMC: Supply chain management capabilities. CEP: Circular economy practices. SP: Sustainable performance. MLMV: Measured latent marker variable. Hypothesized effects are assessed by applying a one-sided test. The effects of the control variables and MLMV are evaluated applying a two-tailed test for a Student *t* distribution. Bootstrapping based on $n = 10{,}000$ subsamples. *ns*: non-significant

Table S3. Common method bias test. Measured latent marker variable analysis

	Direct effect	*t*-value	*p*-value	PBCI	Support	Explained variance	f^2	VIF
SCMC ($R^2 = 0.339$)								
BDAC	0.582	12.360	0.000	[0.504; 0.659]	Yes	33.9%	0.513	
CEP ($R^2 = 0.458$)								
BDAC	0.397	6.161	0.000	[0.290; 0.502]	Yes	24.2%	0.192	1.513
SCMC	0.364	5.971	0.000	[0.265; 0.465]	Yes	21.6%	0.161	1.513
SP ($R^2 = 0.585$)								
BDAC H1(+): (*c'*)	0.012	0.177	0.430	[−0.106; 0.120]	No	0.6%	0.000	1.845
SCMC	0.144	2.197	0.014	[0.038; 0.255]	Yes	7.9%	0.028	1.780
CEP	0.636	11.811	0.000	[0.545; 0.722]	Yes	47.3%	0.518	1.880
Sector	−0.068	0.924	0.356	[−0.184; 0.091]		0.3%	0.011	1.032
Age	−0.097	2.216	0.027	[−0.186; −0.014]		1.8%	0.022	1.044
Size	0.049	1.244	0.213	[−0.032; 0.123]		0.6%	0.006	1.038

Note(s): BDAC: Big data analytics capabilities. SCMC: Supply chain management capabilities. CEP: Circular economy practices. SP: Sustainable performance. VIF: Variance inflation factor. PBCI: Percentile bootstrap confidence interval. Bootstrapping based on $n = 10{,}000$ subsamples. The hypothesized effects are evaluated using a one-tailed test for a Student *t* distribution (CI 90%). The effects of the control variables are assessed by applying a two-tailed test (CI 95%)

Table S4.
Direct effects on endogenous variables

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