Istanbul Business Research,
IBR 2026, 55 (2): 289–310

https://doi.org/10.26650/ibr.2026.55.1820019

Submitted: 08.11.2025
Revision Requested: 27.02.2026
Last Revision Received: 01.06.2026
Accepted: 02.07.2026
Published Online 04.09.2026

Istanbul Business Research

Research Article

Open Access

Mitigating operational costs for circular supply chain by leveraging big data analytics driven-dynamic capabilities: Insights and implications for the industry

Metin Uyar [1]

[1] Istanbul Gelişim University, Faculty of Economics, Administaritive and Social Sciences/Business Administration, İstanbul, Türkiye

Abstract The circular supply chain plays a critical role in minimizing operational costs and enhancing eco-efficiency by strategically aligning diverse organizational processes. To effectively generate these circular supply chains, it is vital to comprehend the dynamic capabilities shaped by big data analytics within a comprehensive framework. In this context, the capabilities driven by big data analytics are analyzed by using the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method, which assists in identifying intricate cause-and-effect relationships among the various factors affecting the supply chain. This method enables a nuanced understanding of how different elements interact and influence one another. Moreover, based on their level of influence, the Interpretive Structural Modeling (ISM) method is employed to organize these capabilities hierarchically. The resulting hierarchical model categorizes the factors into four distinct levels. The results reveal a four-level hierarchy in which the Sensing DC (BDDC3) and Seizing DC (BDDC13, BDDC11) at Level IV act as core capabilities for the entire system. The findings specifically demonstrate that prioritizing, sensing, and other capabilities are the primary drivers of operational cost optimization in successful resource reconfiguration and circular operations. Organizations can better navigate the complexities of circular supply chains by establishing this structured approach. It ultimately leads to improved sustainability outcomes and enhanced economic performance.

Keywords Circular supply chain · Dynamics capabilities theory · Big data analytics · Operational costs

Citation: Uyar, M. (2026). Mitigating operational costs for circular supply chain by leveraging big data analytics driven-dynamic capabilities: Insights and implications for the industry. *Istanbul Business Research*, *55*(2), 289-310. https://doi.org/10.26650/ibr.2026.55.1820019

Corresponding author: Metin Uyar meuyar@gelisim.edu.tr

1. Introduction

The current environmental sustainability landscape faces major challenges, such as global warming, toxic waste management, and ecosystem changes. Hannan and Freeman (1984) argued that organizations must respond to these pressures by developing dynamic capabilities and strategies. Additionally, Bocken and Geradts (2020) emphasized the potential of big data analytics-driven dynamic capabilities (BDA-driven DC) to support this transition toward a circular economy, enabling organizations to quickly adapt to environmental changes. BDA-driven DC improves supply chain management by identifying risks, boosting resource efficiency, and integrating technology within a circular business model.

The circular supply chain (CSC) model aims to reduce environmental impact through reuse, sharing, and recycling, which can also reduce operational costs and improve financial performance. However, a clearer understanding of how big data analytics (BDA), dynamic capabilities (DC), and CSC interact is needed. Current research provides a strong foundation for identifying capabilities that support the design of business models incorporating data analytics in a rapidly changing environment, and it points to a growing need for deeper investigation of the subject. Furthermore, additional analysis is needed to determine how various capabilities impact the hierarchical structure and sustainable design of CSC.

This study aims to identify and prioritize the BDA-driven dynamic capabilities that are necessary to enhance the cost performance, which is vital for such a redesign within the context of CSC. This research contributes to the existing literature by presenting a multilevel hierarchical structure that discusses the relationships between BDA-driven DC and operational cost efficiency in circular systems. The methodology allows for the examination of both pairwise and multiple interactions between dynamic capabilities. The primary research questions are as follows:

RQ1: What is the role of BDA-driven DC in mitigating operational costs in CSC development and improvement?

RQ2: Do each DC influence the development and improvement of CSC to the same degree?

RQ3: Does BDA-driven DC have a hierarchical structure in terms of influence degree?

The proposed model offers both theoretical and managerial insights by emphasizing the importance of BDA-driven DC in designing and enhancing CSC to reduce operational costs. It also provides micro-foundations to help practitioners develop more effective supply chain management strategies, thereby making other organizational capabilities and their relationships clearer.

2. Theoretical framework

2.1. Dynamic capabilities and cost mitigation in the circular supply chain

Capabilities are an organization's capacity to use processes and resources together to achieve a desired goal. (Ye & Lau, 2022). This study discusses BDA-driven DC within the context of the dynamic capabilities theory specified by Teece (2007). Temporary problem solutions and disjointed managerial efforts are not feasible and cannot be considered capabilities because they do not exhibit continuity over time or do not provide a pattern of emergence (Sjödin et al., 2023). Kazancıoglu et al. (2021) stated that the effective use of system dynamics plays an important role in increasing supply chain resilience in Türkiye. DC, which is concerned with how organizations can integrate, design, and reconfigure sustainable resources under uncertainty and risk, differs from ordinary capabilities and enables an expansion of the resource-based view. DC refers to the “sensing,” “seizing,” and “reconfiguration” of internal and external skills, competencies, and resources to adapt to varying economic, social, and environmental conditions (Brewis et al., 2023). Sensing DC is the organizational capability that enables the organization to identify, develop, and transform technological opportunities into strategic elements related to customer needs (Irfan et al., 2022). Seizing DC refers to the capabilities that enable organizational resources to be mobilized to meet the needs of consumers, producers, distributors, and other supply chain elements. Reconfiguration DC refers to capabilities that enable business model development and organizational resource optimization by restructuring internal and external capabilities to adapt to changes in market conditions (Sandberg & Hultberg, 2021).

Fawcett et al. (2011) stated that developing dynamic capabilities that include sequential processes, such as perception, capture, and restructuring, allows organizations to balance risk in a competitive environment and reorganize their resources. In this context, BDA-driven DC serves as the theoretical foundation for organizations seeking to amplify cost performance while implementing the CSC model. Table 1 summarizes the theoretical foundation, and Figure 4 illustrates the implementation steps. DC encourages organizations to circularly redesign and configure their processes and unlock their capabilities.

2.2. Significance of big data analytics for circular supply chains

BDA refers to the analysis and decision-making processes used to develop strategies and predictions from large-volume, volatile datasets generated by the internet ecosystem and market dynamics, which cannot be effectively analyzed with traditional analytical techniques. In addition, BDA is an integral component of modern circular supply chains (CSCs), as conventional SC technologies often fail to address the complexities of emerging uncertainties and market trends. Perçin (2023) stated that the adoption of big data analytics in CSC improves overall performance, thereby increasing resource efficiency and enhancing cost performance in Türkiye. When BDA is integrated with advanced technologies, such as the Internet of Things and artificial intelligence, significantly enhances the processing of real-time information. This integration facilitates more efficient data management practices and optimizes recycling processes, which are essential for cost mitigation.

Gilanlı and Çetin (2023) stated that the effectiveness of supply chain practices is associated with operational performance. BDA tools and applications play a fostering role in enhancing the effectiveness of SC processes and, thus, operational performance. Research has demonstrated that traditional resource-based theories do not adequately support the development of sustainable SC within rapidly evolving technological contexts (Meier et al., 2023).

Static viewpoints on resource management can restrict effective decision-making, highlighting the urgent need for more dynamic and integrated strategies that enable organizations to effectively leverage their capabilities and resources. This transformation is illustrated in Table 1, which outlines the methodologies and benefits derived from implementing BDA within the CSC ecosystem.

Table 1

Big Data Analytics-Driven Dynamic Capabilities Influencing Circular Supply Chain Operational Cost Mitigation

Factors	Description	Dimension	Sources
BDDC-1-Real-time market monitoring capability to understand the needs of consumers and other supply chain members	Understanding the needs of customers and other supply chain members through BDA-driven DC enables the organization to adapt to dynamic market conditions.	Sensing DC	(Shan et al., 2019; Horng et al., 2022)
BDDC2-Capability to access the information of supply chain members	Access to supply chain members' information through BDA is a key driver for CSC.	Sensing DC	(Shokoohyar et al., 2022); (Saleem et al., 2021); Williams and Moore (2007)
BDDC3: Systematic data-sharing capability for SC members	Information sharing supports collaboration with various partners, enabling improved secure data flow and building micro-foundations for CSC model development and improvement	Sensing DC	(Stekelorum et al., 2021)
BDDC4: Capability to understand data-sharing needs and data from external sources	Through BDA, DC ensures that information-sharing	Sensing DC	(Kache & Seuring, 2017) (Feroz et al., 2023); (Kache & Seuring, 2017); (Saleem et al., 2021)
BDDC5-Capability to measure the environmental impacts of products	Measuring the environmental impacts of products supports organizations in implementing the CSC model.	Sensing DC	(Teng et al., 2020)
BDDC6-Capability: Data collection to forecast supply chain trends	Collecting data and forecasting demand to ensure that production is aligned with market needs is achievable with BDA-driven DC.	Sensing DC	(Roh et al., 2019)
BDDC7: capacity for efficient waste management	The use of BDA reduces environmental concerns by increasing waste management capacity.	Sensing DC	(Straka et al., 2020; Ciccullo et al., 2022)
BDDC8-Capability to access key information of competitors	Using BDA enables tracking key information of competitors in a timely and accurate manner.	Seizing DC	(Aljumah et al., 2021);
BDDC9: Capability to develop green marketing strategies	Through BDA, DC drives the development of green marketing strategies using knowledge generated autonomously by the business or acquired externally.	Seizing DC	(Lu et al., 2024) (Ranjan & Foropon, 2021)
BDDC 10- Capability to scan new technologies	The use of BDA tools supports businesses in scanning and adapting new technologies, enabling the organization to acquire more sustainable technologies.	Seizing DC	(Köhler et al., 2022)
BDDC-11 Capability for sustainability strategy development	Through BDA, DC facilitates the development of sustainable strategies by ensuring that the organization efficiently collects and uses valuable information.	Seizing DC	(Wilden et al., 2013; Wang et al., 2023);
BDDC12- Collaboration with supply chain	BDA-driven DC influences the collaboration required for the circular economy's sustainability.	Seizing DC	(Straka et al., 2020); (Nilashi et al., 2023)

Factors	Description	Dimension	Sources
members for recyclable materials			
BDDC13-Idea generation and knowledge creation capacity	The ideas and knowledge generated by BDA in the organization are important drivers for the development and improvement of CBMs.	Seizing DC	(Härting & Sprengel, 2019)
BDDC14: Capability to acquire recyclable materials	BDA-driven DC facilitates the supply of recyclable materials, enabling the production of eco-friendly products and reducing water pollution and carbon emissions.	Seizing DC	(Stekelorum et al., 2021) and (Yu et al., 2021)
BAC15-Capacity to use smart maintenance tools	The use of BDA reduces post-consumer costs and supports the sustainability of circular business models by improving the performance of smart maintenance tools.	Seizing DC	(Zhang et al., 2017; O'Donovan et al., 2015);
BDDC16-Capacity to reconfigure CSC business models	Capacity to strategically restructure the overall business model to create value in the circular economy and build resilience to challenges.	Reconfiguration DC	(Saleem et al., 2021; Pieorini et al., 2019; Awan & Sroufe, 2022).
BDDC17-Capability to change, redesign, and develop CSC work models	BDA facilitates the managerial ability for the operational redesign of specific business processes, daily routines, digital workflows, and data-driven processes.	Reconfiguration DC	(Ciccullo et al., 2022); (Nilashi et al., 2023)
BDDC18-Capability for new CSC-oriented work methods	BDA-driven-DC enables organizations to design their production, logistics, distribution, supply, and recycling processes around CSC-focused new work models.	Reconfiguration DC	(Chen et al., 2024)
BDDC19: Capability to develop CSC-oriented new relationships with consumers	BDA-driven DC supports the development of new communication methods that enable the generation of timely and sustainable solutions by instantly monitoring customer needs.	Reconfiguration DC	(Li et al., 2018)
BDDC20-Opportunities for employee training for CSC adoption	Providing employees with BDA-focused training opportunities significantly impacts the implementation of CBMs, as employee engagement affects managerial decisions and firm-level sustainability practices.	Reconfiguration DC	(Shafique et al., 2024)
BDDC21: Capability to merge with other organizations for CSC	BDA-driven DC enables the transition to a sustainable economy by providing accurate, volume, velocity, and valuable data flow for mergers that enable organizations to create additional blocks to gain competitive power in dynamic market conditions.	Reconfiguration DC	(Alkaraan, 2022)
BDDC22: Capability to transform logistics processes	DC, supported by BDA tools, builds micro-foundations for logistics processes to adapt to environmental conditions.	Reconfiguration DC	(von Stietencron et al., 2022; Jeble et al., 2018)

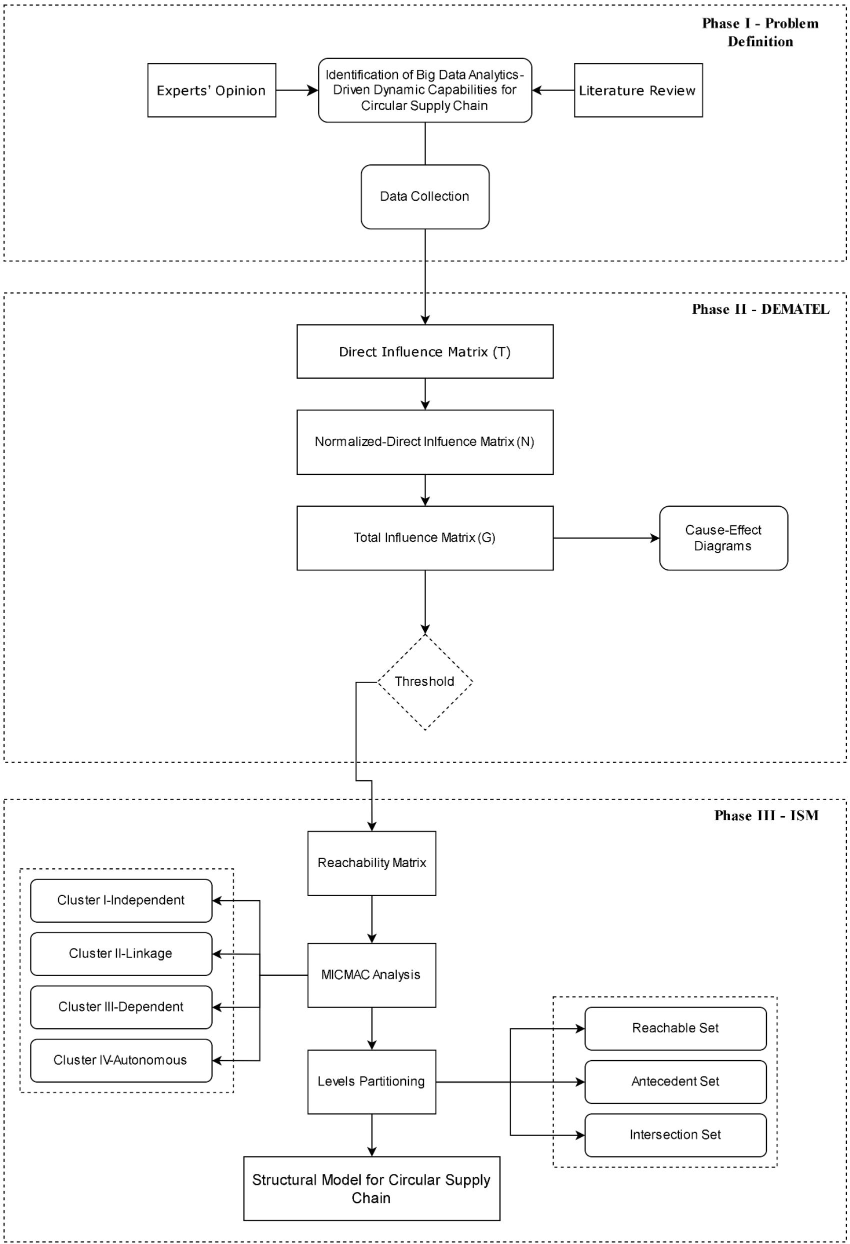
3. Solution methodology

3.1. Data collection

This study employs a multi-phase approach to examine the impact of Big BDA on CSC implementation. Key factors that influence CSC were identified through literature review and expert consultations, enabling a detailed analysis of interaction mechanisms across three phases. In Phase I, we conducted an extensive literature review that focused on the relationship between BDA, DC, and CSC. Insights were gathered from a panel of 15 professionals from various supply chain sectors in Türkiye, ensuring a broad understanding of the critical .

Figure 1

Proposed model, Source: Generated by the authors



Second, Phase II used the DEMATEL method to analyze the weights and interactions among the identified factors. This analysis provided valuable insights into their driving power and influence on CSC. Lastly, the ISM technique was employed in Phase III to further explore the hierarchical relationships among factors and their causal effects. It created a comprehensive framework for understanding these dynamics.

A combination of these two methods can be used to solve complex hierarchical structures and problems in supply chain management. Wang et al. (2024) presented a blockchain adaptation model in CSS using a combined ISM-DEMATEL approach. Öztürk (2025) states that the design and management of the digitalization process in a sustainable supply chain throughout ISM-DEMATEL in the context of Türkiye. This study addresses BDA-driven DC in the context of operational costs, contributing to and expanding the existing literature.

3.2. Results

3.2.1. Phase I: Definition of the problem

During this phase of the research, the weights of the critical factors within the Sensing, Seizing, and Reconfiguration dimensions are defined in Table 1, and the expert group opinion was used to determine the influencing CSC. This expert group comprised 15 participants who provided insights into 22 factors affecting CSC (Table 1). The respondents completed a questionnaire that employed a linguistic scale ranging from 0 (no impact) to 4 (very high impact). This questionnaire is used to identify key factors based on expert opinions.

Table 2

Descriptive statistics of the BDA-driven DC

	Ex1″	Ex2.	Ex3.	Ex4.	Ex5.	Ex6.	Ex7.	Ex8.	Ex9.	Ex10.	Ex11.	Ex12.	Ex13.	Ex14.	Ex15.	Mean	St. D.
BDDC-1	2	3	3	3	3	2	2	3	2	3	3	3	2	2	3	2,6000	0,5071
BDDC2	3	3	3	2	3	2	3	2	4	2	3	3	3	3	2	2,7333	0,5936
BDDC3	4	4	4	3	3	3	3	3	4	3	3	3	3	3	3	3,2667	0,4577
BDDC4	3	3	2	3	3	3	4	3	4	3	3	3	3	4	4	3,2000	0,5606
BDDC5	2	2	2	3	2	3	2	3	3	3	3	3	4	3	2	2,6667	0,6172
BDDC6	4	4	4	3	3	4	4	4	3	4	4	4	3	3	3	3,6000	0,5071
BDDC7	2	3	3	4	4	2	3	3	2	3	3	3	1	3	3	2,8000	0,7746
BDDC8	2	3	3	4	2	2	3	3	2	3	3	3	1	3	3	2,6667	0,7237
BDDC9	4	3	4	3	4	4	4	3	4	4	3	3	3	2	3	3,4000	0,6325
BDDC10	3	3	4	3	3	3	3	3	3	3	3	3	3	3	3	3,0667	0,2582
BDDC11	3	3	2	3	3	3	4	3	4	3	4	3	4	4	4	3,3333	0,6172
BDDC12	2	2	3	3	3	2	3	3	3	3	2	3	3	4	3	2,8000	0,5606
BDDC13	4	4	4	4	3	3	4	4	4	3	4	4	4	3	3	3,6667	0,4880
BDDC14	2	2	2	2	2	3	2	2	3	2	2	3	2	3	2	2,2667	0,4577
BDDC15	3	2	3	3	3	3	3	2	2	2	2	2	2	2	3	2,4667	0,5164
BDDC16	3	3	3	3	3	3	3	4	4	3	3	4	4	2	3	3,2000	0,5606
BDDC17	3	3	3	2	3	2	3	2	4	2	3	3	3	3	2	2,7333	0,5936
BDDC18	3	3	2	3	4	3	4	3	4	3	4	4	4	4	4	3,4667	0,6399
BDDC19	3	3	3	3	3	3	4	3	3	3	3	3	3	3	4	3,1333	0,3519

	Ex1˝	Ex2.	Ex3.	Ex4.	Ex5.	Ex6.	Ex7.	Ex8.	Ex9.	Ex10.	Ex11.	Ex12.	Ex13.	Ex14.	Ex15.	Mean	St. D.
BDDC20	4	3	3	3	3	4	4	4	4	3	3	4	4	4	3	3,5333	0,5164
BDDC21	3	2	3	4	3	4	4	3	4	3	2	3	2	2	3	3,0000	0,7559
BDDC22	2	2	2	3	3	3	3	2	3	3	2	3	3	3	3	2,6667	0,4880

3.2.2. Phase II: Demographic results

Visualizing the causal relationships among factors within advanced complex structures through a diagram increases the DEMATEL method's appeal. DEMATEL is a sophisticated technique that provides decision-makers with the environment necessary to identify issues and find suitable solutions (Hajiagha et al., 2022). A three-way feedback process was used to improve the reliability of the results and minimize bias in the data, incorporating insights from experts and academics across the supply chain's manufacturing, distribution, and retail sectors. The factors were determined based on the literature review summarized in Table 1. As is frequently preferred in MCDM methods, factors with a mean above a certain threshold were advanced to the next stage. By the consensus of the experts, factors with a mean above 2.00 were included in the analysis. Based on the consensus among experts, the factors listed in Table 2 were deemed appropriate for the next steps in the DEMATEL analysis. Individual scores for each expert were first collected to ensure consensus and robustness in the expert group, and then the individual pairwise comparison matrices were combined with the mean value approach. This eliminated the effects of extreme values and unified subjective evaluations. The proposed DEMATEL procedure includes the following steps:

$$T = [0 \cdots f_{1u} \vdots \ddots \vdots f_{u1} \cdots 0] \tag{1}$$

Step 2–Normalized Direct-Influence Matrix (N): The direct influence matrix is normalized using Equations 2 and 3. To normalize, the sum of the rows and columns in the direct impact matrix is computed, and then the largest value (z) in the sums is determined. All values in the normalized direct-influence matrix range from 0 to 1 after the normalization of matrix T.

$$z = \max\left(\max \sum_{j=1}^{f} x_{ij}, \sum_{i=1}^{f} x_{ij}\right) \tag{2}$$

$$N = \frac{1}{Z} T \tag{3}$$

Step 3-Total influence matrix (G): After establishing matrix N, the total influence matrix (G) can be calculated as equation 4.

Table 3

Direct influence matrix (T)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
BDDC-1	0,00	1,93	1,67	2,13	1,60	1,87	1,93	2,13	2,13	2,53	1,87	2,00	2,47	2,67	1,47	1,40	2,20	1,47	1,67	1,73	1,73	1,67
BDDC-2	2,20	0,00	2,00	2,13	1,60	2,40	2,40	2,07	2,40	1,73	2,40	2,00	1,53	1,87	2,13	1,87	1,40	1,93	1,87	1,67	2,07	2,00
BDDC-3	2,00	2,40	0,00	1,73	2,33	1,67	1,67	2,13	2,13	2,20	2,40	2,40	2,20	2,07	1,80	2,33	2,00	2,13	2,27	2,13	2,20	2,07
BDDC-4	1,53	1,40	1,60	0,00	1,60	1,67	1,47	1,47	1,53	1,80	2,47	1,33	1,87	2,20	1,53	1,80	2,00	1,93	1,87	2,27	2,13	1,80
BDDC-5	2,47	1,47	2,00	1,33	0,00	1,53	2,07	1,87	1,80	2,33	1,47	1,87	2,00	1,67	1,53	1,47	1,40	1,40	1,93	1,33	2,07	1,80
BDDC-6	1,80	1,87	3,00	2,47	1,73	0,00	1,60	1,00	2,20	2,00	1,93	2,13	1,73	1,60	1,53	1,53	1,20	1,47	1,40	1,93	1,73	1,73
BDDC-7	1,93	2,13	1,87	2,07	2,07	1,93	0,00	2,53	1,53	1,73	1,47	1,13	0,93	1,60	1,47	1,47	1,60	1,33	1,67	1,40	1,33	1,87
BDDC-8	1,80	2,07	2,27	1,53	1,27	1,47	1,73	0,00	1,53	1,80	2,00	1,47	2,13	1,60	1,67	1,53	1,60	1,60	1,53	1,33	2,07	1,67

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
BDDC-9	1,53	2,40	2,13	2,07	1,93	2,07	1,60	2,33	0,00	1,27	1,73	1,60	1,73	1,73	1,93	1,67	2,13	1,80	1,47	1,47	1,67	2,13
BDDC-10	2,07	2,33	2,13	1,80	1,80	1,27	1,87	1,60	1,73	0,00	1,60	1,53	1,87	2,00	1,80	1,87	2,07	1,53	1,93	1,40	1,00	1,53
BDDC-11	2,07	2,27	2,40	1,93	2,33	1,87	1,80	1,33	2,47	1,67	0,00	1,60	1,20	2,07	1,93	2,07	2,07	1,47	1,33	1,87	1,40	1,40
BDDC-12	2,13	1,93	2,20	2,07	2,07	1,60	1,33	2,07	1,60	2,07	1,53	0,00	1,27	1,53	2,00	1,47	1,53	1,80	1,40	1,67	1,67	1,53
BDDC-13	1,13	1,93	2,00	3,00	1,80	2,00	3,20	1,93	0,13	1,13	1,93	2,80	0,00	2,07	3,13	0,13	3,20	1,07	1,73	1,20	1,87	2,67
BDDC-14	2,67	1,93	1,60	1,53	1,80	1,47	1,20	1,93	1,93	1,33	1,47	1,80	1,27	0,00	1,53	1,73	1,40	1,73	1,73	1,27	1,47	1,60
BDDC-15	1,53	2,20	2,33	1,60	2,13	1,27	1,20	1,80	1,40	1,60	1,53	1,47	1,93	1,47	0,00	1,53	1,67	1,47	1,47	1,67	1,60	2,00
BDDC-16	2,07	2,27	1,80	1,27	1,27	1,40	1,60	1,60	1,60	1,47	1,40	1,60	1,07	2,00	1,60	0,00	2,27	1,67	1,67	1,87	1,60	1,47
BDDC-17	1,87	2,00	2,07	2,20	2,27	1,73	1,47	1,47	1,53	1,80	1,40	1,93	1,33	1,67	1,27	1,40	0,00	1,53	1,80	1,13	1,60	2,00
BDDC-18	1,87	2,33	2,13	2,13	1,53	1,60	1,47	1,67	1,73	1,47	1,80	1,73	1,00	2,07	2,20	1,80	1,73	0,00	1,20	1,67	1,27	1,67
BDDC-19	2,13	1,87	2,47	1,80	1,80	1,40	1,53	1,73	1,93	1,73	1,27	1,33	1,73	1,67	1,40	1,60	1,60	1,67	0,00	1,40	1,53	1,67
BDDC-20	2,00	1,87	1,60	1,73	2,33	1,73	1,60	1,73	1,60	1,60	1,33	1,47	2,13	1,73	1,80	2,13	1,87	1,67	1,53	0,00	1,47	1,53
BDDC-21	2,13	2,13	1,60	1,60	1,40	1,27	1,53	1,47	1,47	1,87	1,73	1,27	1,73	1,73	1,80	1,60	1,60	1,80	1,53	1,80	0,00	2,27
BDDC-22	1,87	2,27	1,73	1,73	1,73	1,60	1,60	1,13	1,80	1,53	1,87	1,73	1,60	1,67	2,07	1,27	2,07	1,47	1,87	1,40	1,73	0,00

$$G = N(I - N)^{-1} \tag{4}$$

Step 4- Developing Cause-Effect Diagrams: The sum of the rows (r) and the sum of columns (r) are calculated from Matrix G to develop the cause-effect diagram.

$$r = \sum_{j=1}^{f} G_{ij} \tag{5}$$

$$s = \sum_{i=1}^{f} G_{ij} \tag{6}$$

In this study, we evaluated the interactions among various factors by calculating the degree of influence (r-s) and causal dependency (r+s), as defined in Table 1. A positive r-s value indicates that a factor is part of the causal group, significantly impacting CSC development. Conversely, a negative r-s value signifies an effect group factor that is influenced by other elements in the CSC model. Figure 3 illustrates the combined effects of the dimensions along two axes: (r_i+s_i) represents the centrality of each factor, and (r_i-s_i) denotes the net contribution (causality). Causality reveals the relationships among DCs driven by the BDA. Eleven dynamic capabilities show positive causality, categorized as cause factors, with BDDC3-Sensing, BDDC13-Seizing, BDDC20-Reconfiguration, and BDDC6-Sensing being the most influential. These factors should be prioritized in the development of the CSC model. The importance of information sharing and idea generation further highlights these causal factors' role. In contrast, factors such as BDDC14-seizing, BDDC17-reconfiguration, BDDC22-reconfiguration, and BDDC4-sensing exhibit negative causality; indicating that they are influenced by multiple causes and require long-term balanced strategies for effective CSC practice. Given their nature as operational-level capabilities, these factors are shaped by the strategic hierarchy established in Table 1.

3.2.3. Phase III: Results of ISM

The total influence matrix (G) shows the interactions among the factors; however, it does not indicate the extent of the influence of the individual elements. To address this, the ISM method was used in Phase III, which confirmed the DEMATEL results. While DEMATEL captures pairwise relationships in detail, ISM hierarchically arranges these factors, allowing for multidimensional relationship simulations at a broader level. This ISM-based model offers a comprehensive framework for developing and mitigating CSC costs.

Step 1-Reachability Matrix (K): The ISM approach uses binary encoding to convert DEMATEL data into a reachability matrix. Establishing this matrix involves calculating a threshold that simplifies the structure and clarifies hierarchies by eliminating weak interactions among factors. Care must be taken not to miss nonlinear relationships, with the threshold determined based on the normal data distribution, as shown in Equation 7.

$$\theta = \mu + \sigma \tag{7}$$

Where μ is the mean of all elements, and σ is the standard deviation of all elements in matrix G. μ is 0.249, and σ is 0.025. Therefore, θ=μ+σ=0.274. We developed the reachability matrix with 0s and 1s based on Equations 8 and 9 using this. In the CSC model, if a factor's influence on another factor exceeds the threshold, it is marked as 1 in the matrix, indicating a direct effect; if it is less, it is marked 0, indicating an indirect or negligible influence. Here, k_{ij} is an element in Matrix K, and f_{ij} is an element in Matrix G. Driving power is the sum of factors that an X factor influences, including itself. Dependence is the total sum of factors, including itself, that influence the development of a Y factor.

$$if\ f_{ij} > \theta(i, j = 1, 2, 3, ..., n), k_{ij} = 1 \tag{8}$$

$$if\ f_{ij} < \theta(i, j = 1, 2, 3, ..., n), k_{ij} = 0 \tag{9}$$

Step 2: MICMAC analysis

MICMAC can be used to prioritize factors by categorizing the cause-and-effect relationships between factor clusters in complex supply chain decision-making processes (Primadasa et al., 2025). The matrix impact-multiplication appliquée et classification (MICMAC) method was used to analyze the driving power and dependency among the factors identified earlier in the ISM process. This analysis groups factors into four clusters: autonomous (Cluster IV), dependent (Cluster III), linkage (Cluster II), and independent (Cluster I) (Figure 4).

The clustering threshold was calculated by dividing the sum of the matrix's column and row powers (91) by the total number of factors (22), resulting in a threshold of 4.136. Factors with a power of 5 or higher have high driving power, whereas those below are considered to have low driving power. Cluster I (upper left of the diagram, contains independent factors with high driving power but low dependency. These are the key factors that impact the development of the CSC model. Cluster II (upper right) contains linkage factors with high driving and dependency powers (e.g., BDDC3-Sensing, BDDC2-Sensing, and BDDC1-Sensing). These linkages play a fundamental role in mediating the effects of independent and dependent factors.

Cluster III (lower right) includes dependent factors characterized by high dependency but low driving power (e.g., BDDC14-Seizing, BDDC4-Sensing). Their influence on CSC depends on the effects of other factors earlier in the chain. Finally, Cluster IV, in the lower left, contains autonomous factors with low driving and dependency powers (e.g., BDDC6-Sensing, BDDC9-Seizing, BDDC12-Seizing, BDDC5-Sensing, BDDC18-Reconfiguration, BDDC8-Seizing, BDDC15-Seizing, BDDC17-Reconfiguration, BDDC16-Reconfiguration, BDDC19-Reconfiguration, BDDC20-Reconfiguration, BDDC21-Reconfiguration, BDDC7-Sensing, BDDC22-Reconfiguration). Their impact on CSC is less significant than that of other clusters, and their influence depends on the effective management of factors within the other clusters.

Table 4

Sum of the Rows and Columns for the Factors

Dimension	Criteria	r (degree of influence)	s (degree of influence)	r+s (centrality)	r-s (causality)	Factor Rank	Influence Group
BDA-driven sensing DC	BDDC-1	5,919	6,002	11,921	−0,082	XIII	Effect
	BDDC2	6,119	6,295	12,414	−0,177	XV	Effect
	BDDC3	6,483	6,232	12,715	0,251	VII	Cause
	BDDC4	5,481	5,856	11,337	−0,375	XX	Effect
	BDDC5	5,437	5,659	11,096	−0,222	XVII	Effect
	BDDC6	5,585	5,159	10,743	0,426	II	Cause
	BDDC7	5,190	5,301	10,491	−0,111	XIV	Effect
BDA-driven seizing DC	BDDC8	5,291	5,471	10,762	−0,179	XVI	Effect
	BDDC9	5,667	5,374	11,041	0,292	V	Cause
	BDDC-10	5,436	5,433	10,870	0,003	XI	Cause
	BDDC-11	5,694	5,434	11,128	0,260	VI	Cause
	BDDC12	5,397	5,360	10,757	0,036	X	Cause
	BDDC13	5,868	5,158	11,026	0,709	I	Cause
	BDDC14	5,099	5,706	10,804	−0,607	XXII	Effect
	BDDC15	5,178	5,530	10,708	−0,352	XIX	Effect
BDA-driven reconfiguration DC	BDDC16	5,109	4,998	10,107	0,111	VIII	Cause
	BDDC17	5,253	5,673	10,926	−0,419	XXI	Effect
	BDDC18	5,337	5,035	10,372	0,301	IV	Cause
	BDDC19	5,237	5,179	10,416	0,059	IX	Cause
	BDDC20	5,382	4,981	10,363	0,401	III	Cause
	BDDC21	5,226	5,228	10,454	−0,002	XII	Effect
	BDDC22	5,288	5,613	10,901	−0,325	XVIII	Effect

Step 3 - Level Partitioning: The reachability matrix is partitioned into levels based on the factors' dependencies and driving power. We created a canonical matrix that includes this level partitioning to assess the factors' importance levels, as indicated in the reachability matrix for the CSM. Following the previous steps, the reachability matrix of each factor was systematically divided into levels and organized through iterations, as defined by Equations 10-11-12. Here, R_i denotes the reachability set, S_i denotes the antecedent set, and C_i denotes the intersection set.

$$R_i = \{x_j \,| x_j \in X, k_{ij} = 1\}, (i = 1, 2, ..., n) \tag{10}$$

$$S_i = \{x_j \,| x_j \in X, k_{ij} = 1\}, (i = 1, 2, ..., n) \tag{11}$$

$$C_i = R_i \bigcap S_i \tag{12}$$

The reachability set consists of the variable itself and the sum of the variables that it affects, whereas the antecedent set consists of the sum of the variables that affect it, including itself. Intersection sets contain factors that are common to both antecedents and reachability sets. A variable that includes the same set of reachability and intersection sets takes part in the ISM hierarchy's first level. This leveling process continues until all factors have been assigned a certain level on the ISM hierarchy.

Figure 2

Cause/Effect Diagram for the BDA-driven DC. Source: Generated by the authors

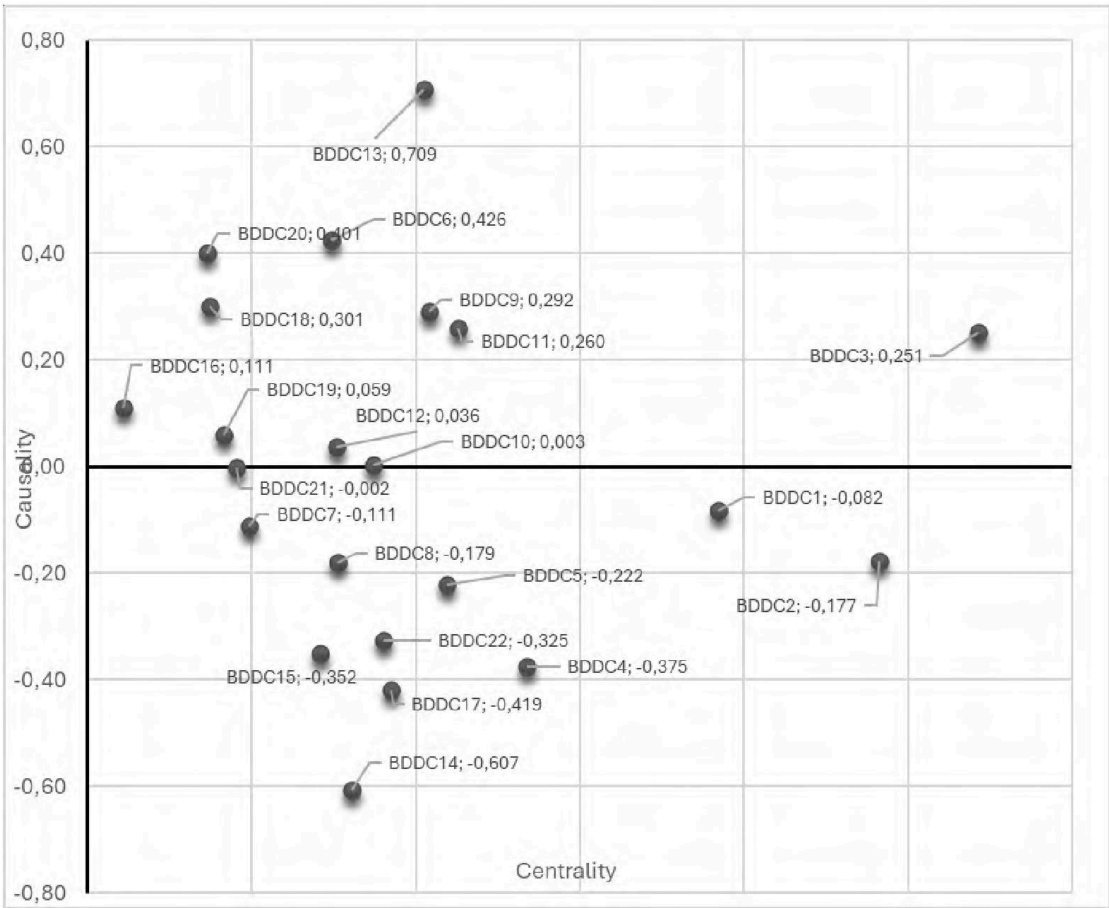


Table 5

Reachability matrix (K)

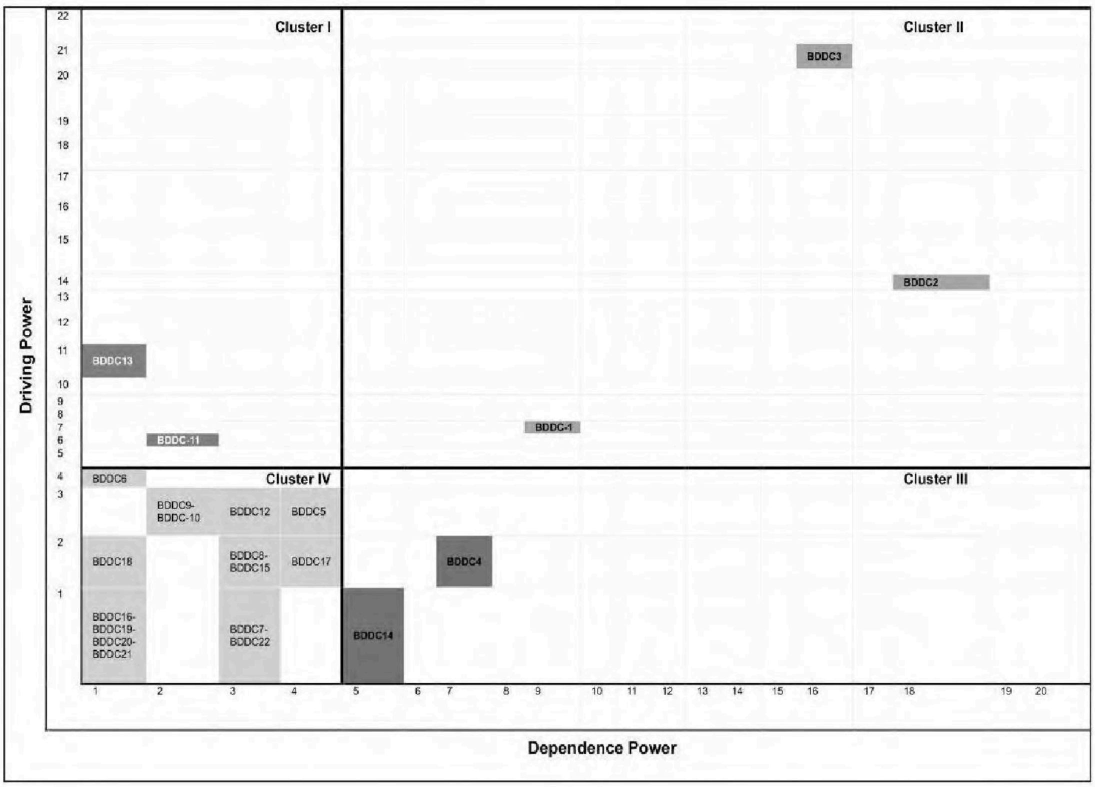
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	DRP*
BDDC-1	0	1	1	1	0	0	0	1	0	1	0	0	0	1	0	0	1	0	0	0	0	0	7
BDDC2	1	0	1	1	1	1	1	1	1	0	1	1	0	1	1	0	1	0	0	0	0	1	14
BDDC3	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	21
BDDC4	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
BDDC5	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3
BDDC6	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4
BDDC7	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
BDDC8	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
BDDC9	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3
BDC10	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3
BDC11	1	1	1	1	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	6
BDDC12	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3
BDDC13	1	1	1	1	1	0	1	0	0	0	0	1	0	1	1	0	1	0	0	0	0	1	11

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	DRP*
BDDC14	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
BDDC15	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
BDDC16	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
BDDC17	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
BDDC18	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
BDDC19	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
BDDC20	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
BDDC21	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
BDDC22	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
DPP*	9	18	16	7	4	1	3	3	2	2	2	3	1	5	3	1	4	1	1	1	1	3	91/91

Step 4-ISM-Based Model for Circular Supply Chain: The structural model was developed from level partitioning, as shown in Table 6. Figure 4 illustrates the ISM for the CSC. The main BDA-driven DC residing in level IV representing the prominent and most strategic priority of the proposed model are consistent with the definitions in Table 1: "BDDC3-Systematic data sharing capability for supply chain members (Sensing DC-Cause-Cluster II)," "BDDC13-Capacity for idea generation and knowledge creation (Seizing DC-Cause-Cluster I)," and "BDDC11-Capability to strategy development for sustainability (Seizing DC-Cause-Cluster I)."

Figure 3

MICMAC for the circular supply chain. Source: Generated by the authors



All Level IV DC are the main components with high driving power, positioned in the “cause” group in the DEMATEL and Cluster I in the MICMAC analysis, and have a significant influence on building CSC for organizations. The validation from the three DCs in Level I underscores the significant impact of management’s embrace of the use of BDA on CSC implementation within the organization. This unequivocally highlights the pivotal role of data analytics. Data analytics not only amplifies dynamic capabilities but also facilitates the seamless and velocity flow of data in SCM, fostering idea generation and enabling the development of sustainable strategies. Level IV DC influences Level III DC, serving as the cornerstone for organizations to cultivate circular and sustainable business models.

Table 6

Iterations for partitioning levels

Iteration 1	**Reachability/BDDC**	**Antecedents/BDDC**	**Intersection/BDDC**	**Level**
BDDC1	2/3/4/8/10/14/17	2/3/5/6/10/11/12/13/14	2/3/10/14	
BDDC2	1/3/4/5/6/7/8/9/11/12/14/15/17/22	1/3/4/5/6/7/8/9/10/11/12/13/15/16/17/18/20/21/22	1/3/4/5/6/7/8/9/11/12/15/17/22	
BDDC3	1/2/3/4/5/7/8/9/10/11/12/13/14/15/16/17/18/19/20/21/22	1/2/3/4/5/6/8/9/10/11 /12/13/15/17/18	1/2/3/4/5/8/9/10/11/12/13/15/17/18	
BDDC4	2/3	1/2/3/6/9/11/13	2/3	I
BDDC5	1/2/3	2/3/11/13/	2/3	
BDDC6	1/2/3/4	2/	2	
BDDC7	2	2/3/13	2	I
BDDC8	2/3	1/2/3	2/3	I
BDDC9	2/3/4	2/3	2/3	
BDDC10	1/2/3	1/3	1/3	
BDDC11	1/2/3/4/5/14	2/3	2/3	
BDDC12	1/2/3	2/3/13	2/3	
BDDC13	1/2/3/4/5/7/12/14/15/17/22	3	3	
BDDC14	1	1/2/3/11/13	1	I
BDDC15	2/3	2/3/13	2/3	I
BDDC16	2	3	∅	
BDDC17	2/3	1/2/3/13	2/3	I
BDDC18	2/3	3	3	
BDDC19	3	3	3	I
BDDC20	2	3	∅	
BDDC21	2	3	∅	
BDDC22	2	2/3/13	2	I
Iteration 2	Reachability/BDDC	Antecedents/BDDC	Intersection/BDDC	Level
BDDC/1	2/3/10	2/3/5/6/10/11/12/13	2/3/10	II
BDDC2	1/3/5/6/9/11/12	1/3/5/6/9/10/11/12/13/16/18/20/21	1/3/5/6/9/11/12	II
BDDC3	1/2/3/5/9/10/11/12/13/16/18/20/21	1/2/3/5/6/9/10/11/12/13/18	1/2/3/5/9/10/11/12/13/18	
BDDC5	1/2/3	2/3/11/13	2/3	

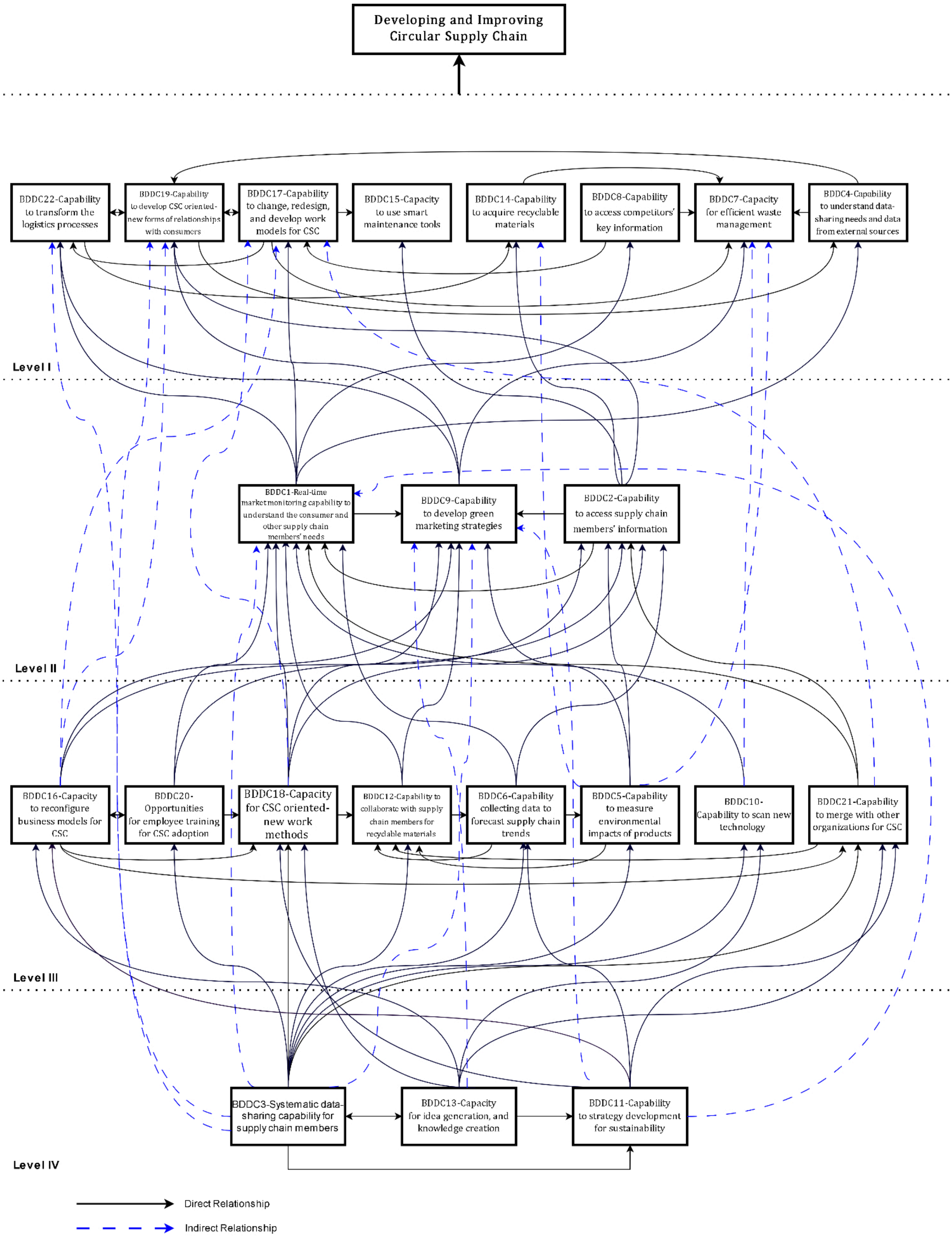
Iteration 1	Reachability/BDDC	Antecedents/BDDC	Intersection/BDDC	Level
BDDC6	1/2/3	2	2	
BDDC9	2/3	2/3	2/3	II
BDDC10	1/2/3	1/3	1/3	
BDDC11	1/2/3/5	2/3	2/3	
BDDC12	1/2/3	2/3/13	2/3	
BDDC13	1/2/3/5/12	3	3	
BDDC16	2	3	∅	
BDDC18	2/3	3	3	
BDDC20	2	3	∅	
BDDC21	2	3	∅	
Iteration 3	Reachability/BDDC	Antecedents/BDDC	Intersection/BDDC	Level
BDDC3	3/5/10/11/12/13/16/18/20/21	3/5/6/10/11/12/13/18	3/5/10/11/12/13/18	
BDDC5	3	3/11/13	3	III
BDDC6	3	∅	∅	III
BDDC10	3	3	3	III
BDDC11	3/5	3	3	
BDDC12	3	3/13	3	III
BDDC13	3/5/12	3	3	
BDDC16	∅	3	∅	III
BDDC18	3	3	3	III
BDDC20	∅	3	∅	III
BDDC21	∅	3	∅	III
Iteration 4	Reachability/BDDC	Antecedents/BDDC	Intersection/BDDC	Level
BDDC3	3/11/13	3/11/13	3/11/13	IV
BDDC11	3	3	3	IV
BDDC13	3	3	3	IV

The BDA-driven DC set at level III includes the following: "BDDC16-Capacity to reconfigure business models for CSC (Reconfiguration DC-Effect-Cluster IV)," "BDDC20-Opportunities for employee training for CSC adoption (Reconfiguration DC-Cause-Cluster IV)," "BDDC18-Capacity to CSC-oriented new work methods (Reconfiguration DC-Cause-Cluster IV)," "BDDC12-Capability to collaborate with supply chain members for recyclable materials (Seizing DC-Cause-Cluster IV)," "BDDC6-Capability to collect data to forecast supply chain trends (Sensing DC-Cause-Cluster IV)," "BDDC5-Capability to measure the environmental impacts of products (Sensing DC-Effect-Cluster IV)," "BDDC10-Capability to scan new technology (Seizing DC-Cause-Cluster IV)," and "BDDC21-Capability to merge with other organizations for CSC (Reconfiguration DC-Effect-Cluster IV)," The integration of data analytics transforms information sharing, idea creation, and strategy development by significantly increasing the speed, volume, and accuracy of data within the organization." Increased effectiveness in information sharing enables smooth strategy implementation and supports the shift toward circular business models. Leveraging dynamic capabilities through data analytics allows organizations to reconfigure their current business models (BDDC16-Reconfiguration), enhance their ability to develop CSC-oriented models (BDDC18-Reconfiguration), and build a strong framework for predicting market trends (BDDC6-Reconfiguration). Improving organizational capabilities through data analytics also offers opportunities for CSC employees to be trained, keeping the organization updated with new technologies. This enhancement in learning opportunities and technological infrastructure further elevates the ability to collaborate with other organizations for CSC (BDDC21-Reconfiguration), work with supply chain partners (BDDC12-Seizing), and track environmental impacts (BDDC5-Sensing). In the hierarchical model, Level II comprises the following factors: "BDDC-1 Real-time market monitoring capability to understand customer and supply chain needs (Sensing DC-Effect-Cluster II)," "BDDC9-Capability to develop green marketing strategies (Seizing DC-Cause-Cluster I)," and "BDDC2-Capability to access supply chain information (Sensing DC-Effect-Cluster II)." These dynamic capabilities impact organizational performance based on factors from earlier levels and support the development of CBMs." Monitoring market data in real-time using data analytics enables the organization to stay aligned with rapid market changes and consumer needs. This crucial capacity not only helps develop impactful green marketing strategies (BDDC9-Seizing) but also facilitates the implementation of CSC by providing access to necessary information on manufacturers, distributors, and retailers (BDDC2-Sensing).

The reconfiguration of business processes and assets to optimize resources and capabilities for effective CSC implementation is driven by Level I factors, which are influenced by earlier levels. Level I factors include: "BDDC22-Capability to transform logistics (Reconfiguration DC-Effect-Cluster IV)," "BDDC19-Capability to develop new CSC-oriented relationships with consumers (Reconfiguration DC-Cause-Cluster IV)," "BDDC17-Capability to redesign and develop work models for CSC (Reconfiguration DC-Effect-Cluster IV)," "BDDC15-Capacity to use smart maintenance tools (Seizing DC-Effect-Cluster IV)," "BDDC14-Capability to acquire recyclable materials (Seizing DC-Effect-Cluster III)," "BDDC8-Capability to access competitors' key information (Seizing DC-Effect-Cluster IV)," "BDDC7-Capacity for efficient waste management (Sensing DC-Effect-Cluster IV)," and "BDDC4-Capability to understand data-sharing needs and data from external sources (Sensing DC-Effect-Cluster III)." Incorporating data analytics into organizational processes reinforces the ability to effectively manage change, redesign existing business models (BDDC17-Reconfiguration), and maintain CSC-oriented customer relationships (BDDC19-Reconfiguration)." By developing these relationships, organizations can better understand societal environmental concerns and develop dynamic capabilities, such as efficient waste management (BDDC7-Sensing), smart maintenance (BDDC15-Seizing), and the acquisition of recyclable materials (BDDC14-Seizing).

Figure 4

Hierarchical Model for Circular Supply Chain Development Through BDA-driven Dynamic Capabilities, Source: Generated by the authors



4. Conclusions and implications

4.1. Conclusions

This study used an integrated approach that combines a literature review and expert opinions to develop implications for a sustainable circular business model by analyzing how the BDA-driven DC defined in Table 1 influences cost performance. As natural resources become scarce and ecological concerns increase, CSC is becoming more vital for organizations (Khan et al., 2020).

During uncertain times, organizations face difficulties in identifying market trends, which can weaken supply chains (Meier et al., 2023). According to the model, Sensing DC (e.g., BDDC4, BDDC6, BDDC2, BDDC7) is required to improve CSC by reducing operational costs to monitor market trends and resource allocation. These BDA-driven capabilities allow businesses to respond quickly to market dynamics and cost changes, thereby facilitating SCM practices. This results in greater financial capacity for resource reuse and recycling. Sensing DC (e.g., BDDC14, BDDC8, BDDC11, BDDC12) should be used to mobilize the resources necessary for eco-innovation and reuse efficiency. Reconfiguration DC (e.g., BDDC16, BDDC19, BDDC20) is essential for redesigning CLBMs and reducing environmental costs through effective ecological management. As the findings underpinned, circular practices such as remanufacturing, reuse, and recycling cannot be reinforced without a strategic Sensing DC at Level IV. Without the use of Seizing DC and Reconfiguration capabilities at Levels III and II, organizations find it difficult to implement practices such as green production, ecological supply chain management (SC), and circular consumption, and cost performance management becomes more challenging.

4.2. Theoretical implications

This research offers valuable insights into the role of DC in developing CSC within the context of BDA by emphasizing operational cost mitigation. This study is one of the first to tightly integrate the hierarchical analysis capability of ISM and the analytical causality power of DEMATEL for CSC within the dynamic capabilities theory framework from a cost-oriented perspective. The findings indicate that BDA improves the performance of sensing, seizing, and reconfiguration capabilities, thereby helping organizations strengthen their CBMs. The findings empirically support Teece's (2007) dynamic capabilities theory by displaying the mechanism of how BDA-driven DC in CSC mitigates operational costs.

Additionally, the study introduces a multilevel hierarchical model that categorizes DC into high, transitional, and low levels, addressing a gap in prior research that overlooked this hierarchy. High-level DC, supported by BDA, presents significant opportunities for creating a sustainable CSC. Unlike Irfan et al. (2022), Sensing DC stands out at the higher levels (III-IV) of the hierarchical model, and it is indicated that in circular business models, market monitoring and resource creation for processes such as reuse and recycling are necessary to trigger reconfiguration and seizing dynamics. Moreover, the research also offers a methodological contribution through a three-phase integrated approach, combining expert opinions, DEMATEL, and ISM methods.

4.3. Managerial implications

This research significantly contributes to practitioners and provides managerial insights to mitigate operational costs to create CSC through BDA-driven DC. Organizations aiming to quickly and accurately adapt to competitive and dynamic market conditions must understand how to develop BDA-driven DC. Incorporating BDA into business models and strategies to address the challenges faced by organizations enables the development of sustainable solutions and applications (De Angelis et al., 2023). Instead of large-scale BDA investments, managers may adopt the ISM hierarchical model's roadmap. Prioritizing the core Sensing DC (BDDC3) and Seizing DC (BDDC13, BDDC11) at Level IV functions as primary cause factors for accurate cost planning and resource reconfiguration. These fundamental factors enable businesses to develop CSC strategies, allowing them to sustain reuse and recycling operations at efficient costs. The effective use of factors at Levels III and II fosters a transition to financial sustainability by reducing ecological production and supply operation costs. The impact of strategic capabilities such as Seizing DC (BDDC9, BDDC12, BDDC10) and Reconfiguration DC (BDDC16, BDDC20, BDDC18, BDDC21) at Levels III and II facilitates the measurement of the impact of production losses, reuse, and recycling practices on CSC. Level IV strategic alignment enhances the effectiveness of investments, enabling the DC defined at Level I to achieve cost optimization and improved circular performance. According to Nayal et al. (2022), organizations must support their dynamic capabilities with advancing technologies and BDA to develop strategies based on CBMs. In this regard, BDA tools should support the implementation of strategic and tactical factors from Level IV to I in the hierarchical model.

4.4. Limitations and future research

This study has several limitations that can form the basis for future research on CSC. The fact that all participants in the expert panel are from the Turkish market poses a limitation in terms of the research's generalizability. This situation may limit the generalizability of cultural and economic Future studies can expand their scope by considering macro-level dynamic capabilities and BDA-driven DC since the current study only considers the factors that are relevant at the organizational level. Empirical studies can be conducted to verify the findings in the DEMATEL-based cause-and-effect diagram and the ISM-based multi-level hierarchical model. Analysis can be conducted from perspectives that can compare the findings of this study with the results of cross-country studies. In this study, we used the hybridization of DEMATEL and ISM methods to identify the interrelationships among the 22 identified factors. The causal relationships revealed by the DEMATEL-ISM combination in this study can be empirically tested in local and international contexts using advanced analytical techniques such as SEM on larger datasets.

Peer Review	Externally peer-reviewed.
Conflict of Interest	The author have no conflict of interest to declare.
Grant Support	The author declared that this study has received no financial support.
Ethical Approval	This study was approved by İstanbul Gelişim University, Ethics Committee (29.08.2025/ 2025-16)

Author Details

Metin Uyar (Prof. Dr.)

[1] Istanbul Gelişim University, Faculty of Economics, Administaritive and Social Sciences/Business Administration, İstanbul, Türkiye

0000-0002-9773-9340 meuyar@gelisim.edu.tr

References

Aljumah, A. I., Nuseir, M. T., & Alam, M. M. (2021). Organizational performance and capabilities to analyze big data: do the ambidexterity and business value of big data analytics matter? *Business Process Management Journal*, *27*(4), 1088–1107.

Alkaraan, F. (2022). A new era of mergers and acquisitions: towards synergy between industry 4.0 and circular economy. In *Advances in mergers and acquisitions* (pp. 51–61). Emerald Publishing Limited.

Awan, U., & Sroufe, R. (2022). Sustainability in the circular economy: insights and dynamics of designing circular business models. Applied Sciences, 12(3), 1521.

Bocken, N.M., & Geradts, T. (2020). Barriers and drivers to sustainable business model innovation: Organization design and dynamic capabilities. Long Range Planning, 53, 101950.

Brewis, C., Dibb, S., & Meadows, M. (2023). Leveraging big data for strategic marketing: A dynamic capabilities model for incumbent firms. *Technological Forecasting and Social Change*, *190*, 122402.

Chen, C.-T., Chen, S.-C., Khan, A., Lim, M. K., & Tseng, M.-L. (2024). Big data analytics-artificial intelligence and supply chain ambidexterity impacts on corporate image and green communication. *Industrial Management & Data Systems*.

Ciccullo, F., Fabbri, M., Abdelkafi, N., & Pero, M. (2022). Exploring the potential of business models for sustainability and big data for food waste reduction. *Journal of Cleaner Production*, *340*, 130673.

De Angelis, R., Morgan, R., & De Luca, L. M. (2023). Open strategy and dynamic capabilities: A framework for circular economy business models research. *Business Strategy and the Environment*, *32*(7), 4861–4873.

Farris, D. R., & Sage, A. P. (1975). On the use of interpretive structural modeling for worth assessment. *Computers and Electrical Engineering*, *2*(2–3), 149–174. https://doi.org/10.1016/0045-7906(75)90004-X

Fawcett, S. E., Wallin, C., Allred, C., Fawcett, A. M., & Magnan, G. M. (2011). Information technology as an enabler of supply chain collaboration: a dynamic-capabilities perspective. *Journal of Supply Chain Management*, *47*(1), 38–59.

Feroz, A. K., Zo, H., Eom, J., & Chiravuri, A. (2023). Identifying organizations' dynamic capabilities for sustainable digital transformation: A mixed methods study. *Technology in Society*, *73*, 102257.

Hannan, M.T. and Freeman, J. (1984) Structural Inertia and Organizational Change. American Sociological Review, 49, 149-164.https://dx.doi.org/10.2307/2095567

Hajiagha, S. H. R., Dahooie, J. H., Kandi, N. A., Zavadskas, E. K., & Xu, Z. (2022). Sustainable Process Selection Using a Hybrid Fuzzy DEMATEL and Fuzzy Inference System. *International Journal of Fuzzy Systems*, *24*(2), 1232–1249. https://doi.org/10.1007/s40815-021-01221-8

Gilanlı, E., & Çetin, O. (2023). The Mediation Role of Supply Chain Practices and Logistics Integration on the Effect of Lean Supply Chain Strategy on Operational Performance. Istanbul Business Research, 52(1), 87-106.https://izlik.org/JA49LH73GZ

Härting, R.-C., & Sprengel, A. (2019). Cost-benefit considerations for data analytics-an SME-oriented framework enhanced by a management perspective and the process of idea generation. *Procedia Computer Science*, *159*, 1537–1546.

Horng, J.-S., Liu, C.-H., Chou, S.-F., Yu, T.-Y., & Hu, D.-C. (2022). Role of big data capabilities in enhancing competitive advantage and performance in the hospitality sector: Knowledge-based dynamic capabilities view. *Journal of Hospitality and Tourism Management*, *51*, 22–38.

Irfan, I., Sumbal, M. S. U. K., Khurshid, F., & Chan, F. T. S. (2022). Toward a resilient supply chain model: critical role of knowledge management and dynamic capabilities. *Industrial Management & Data Systems*, *122*(5), 1153–1182.

Jeble, S., Dubey, R., Childe, S. J., Papadopoulos, T., Roubaud, D., & Prakash, A. (2018). Impact of big data and predictive analytics capability on supply chain sustainability. *The International Journal of Logistics Management*, *29*(2), 513–538.

Kache, F., & Seuring, S. (2017). Challenges and opportunities of digital information at the intersection of Big Data Analytics and supply chain management. *International Journal of Operations & Production Management*, *37*(1), 10–36.

Kazancıoglu, Y., Ekinci, E., Mangla, S. K., Sezer, M. D., & Kayikci, Y. (2021). Performance evaluation of reverse logistics in food supply chains in a circular economy using system dynamics. *Business Strategy and the Environment*, 30(1), 71-91.

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

Köhler, J., Sönnichsen, S. D., & Beske-Jansen, P. (2022). Towards a collaboration framework for circular economy: The role of dynamic capabilities and open innovation. *Business Strategy and the Environment*, *31*(6), 2700–2713.

Li, L., Chi, T., Hao, T., & Yu, T. (2018). Customer demand analysis of the electronic commerce supply chain using Big Data. *Annals of Operations Research*, *268*, 113–128.

Lu, H., Zhao, G., & Liu, S. (2024). Integrating circular economy and Industry 4.0 for sustainable supply chain management: A dynamic capability view. *Production Planning & Control*, *35*(2), 170–186.

Meier, O., Gruchmann, T., & Ivanov, D. (2023). Circular supply chain management with blockchain technology: A dynamic capabilities view. TransportationResearch Part E: Logistics and Transportation Review, 176, 103177.

Nayal, K., Kumar, S., Raut, R. D., Queiroz, M. M., Priyadarshinee, P., & Narkhede, B. E. (2022). Supply chain firm performance in circular economy and digital era to achieve sustainable development goals. *Business Strategy and the Environment*, *31*(3), 1058–1073.

Ni, G., Li, H., Jin, T., Hu, H., & Zhang, Z. (2022). Analysis of Factors Influencing the Job Satisfaction of New Generation of Construction Workers in China: A Study Based on DEMATEL and ISM. *Buildings*, *12*(5). https://doi.org/10.3390/buildings12050609

Nilashi, M., Baabdullah, A. M., Abumalloh, R. A., Ooi, K.-B., Tan, G. W.-H., Giannakis, M., & Dwivedi, Y. K. (2023). How can big data and predictive analytics impact the performance and competitive advantage of the food waste and recycling industry? *Annals of Operations Research*, 1–42.

O'Donovan, P., Leahy, K., Bruton, K., & O'Sullivan, D. T. J. (2015). An industrial big data pipeline for data-driven analytics maintenance applications in large-scale smart manufacturing facilities. *Journal of Big Data*, *2*, 1–26.

Öztürk, C. (2025). Digitalization as a catalyst for social sustainability in supply chains: an ISM-fuzzy MICMAC and DEMATEL approach. Environment, Development and Sustainability, 1-61.

Perçin, S. (2023). Identifying barriers to big data analytics adoption in circular agri-food supply chains: a case study in Turkey. *Environmental Science and Pollution Research*, *30*(18), 52304-52320.

P. P. Pieroni, M., C. McAloone, T., & C. A. Pigosso, D. (2019). Configuring New Business Models for Circular Economy through Product–Service Systems. *Sustainability*, *11*(13), 3727. https://doi.org/10.3390/su11133727

Primadasa, R., Azzat, N. N., Kusrini, E., Mansur, A., & Masudin, I. (2025). Enhancing circular supply chain management (CSCM) in manufacturing SMEs: an integrated CODAS-ISM-MICMAC approach to big data analytics capability. Process Integration and Optimization for Sustainability, 9(2), 695-715.

Ranjan, J., & Foropon, C. (2021). Big data analytics in building the competitive intelligence of organizations. *International Journal of Information Management*, *56*, 102231.

Roh, Y., Heo, G., & Whang, S. E. (2019). A survey on data collection for machine learning: a big data-ai integration perspective. *IEEE Transactions on Knowledge and Data Engineering*, *33*(4), 1328–1347.

Saleem, H., Li, Y., Ali, Z., Ayyoub, M., Wang, Y., & Mehreen, A. (2021). Big data use and its outcomes in supply chain context: the roles of information sharing and technological innovation. *Journal of Enterprise Information Management*, *34*(4), 1121–1143.

Sandberg, E., & Hultberg, E. (2021). Dynamic capabilities for the scaling of circular business model initiatives in the fashion industry. *Journal of Cleaner Production*, *320*, 128831.

Shafique, M. N., Yeo, S. F., & Tan, C. L. (2024). Roles of top management support and compatibility in big data predictive analytics for supply chain collaboration and supply chain performance. *Technological Forecasting and Social Change*, *199*, 123074.

Shan, S., Luo, Y., Zhou, Y., & Wei, Y. (2019). Big data analysis adaptation and enterprises' competitive advantages: the perspective of dynamic capability and resource-based theories. *Technology Analysis & Strategic Management*, *31*(4), 406–420.

Shokoohyar, S., Shokouhyar, S., & Hakimioun, S. (2022). Explicating the effects of big data analytics capabilities on supply chain resilience dimensions: dynamic capabilities approach and complex adaptive system perspective. *International Journal of Logistics Systems and Management*, *43*(4), 451–483.

Sjödin, D., Parida, V., & Kohtamäki, M. (2023). Artificial intelligence enabling circular business model innovation in digital servitization: Conceptualizing dynamic capabilities, AI capacities, business models and effects. *Technological Forecasting and Social Change*, *197*, 122903.

Stekelorum, R., Laguir, I., Lai, K., Gupta, S., & Kumar, A. (2021). Responsible governance mechanisms and the role of suppliers' ambidexterity and big data predictive analytics capabilities in circular economy practices improvements. *Transportation Research Part E: Logistics and Transportation Review*, *155*, 102510.

Straka, M., Taušová, M., Rosová, A., Cehlár, M., Kačmáry, P., Sisol, M., Ignácz, P., & Farkas, C. (2020). Big data analytics of a waste recycling simulation logistics system. *Polish Journal of Environmental Studies*, *29*(3), 2355–2364.

Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. Strategic Management Journal, 28(13), 1319-1350. https:/\/doi.org/10.1002/smj.640

Teng, S., Khong, K. W., & Ha, N. C. (2020). Palm oil and its environmental impacts: A big data analytics study. *Journal of Cleaner Production*, *274*, 122901.

von Stietencron, M., Hribernik, K., Lepenioti, K., Bousdekis, A., Lewandowski, M., Apostolou, D., & Mentzas, G. (2022). Towards logistics 4.0: an edge-cloud software framework for big data analytics in logistics processes. *International Journal of Production Research*, *60*(19), 5994–6012.

Wang, Y., Ali, Z., Mehreen, A., & Hussain, K. (2023). The trickle-down effect of big data use to predict organization innovation: the roles of business strategy alignment and information sharing. *Journal of Enterprise Information Management*, *36*(1), 323–346.

Wang, L., Zhang, J., Li, J., Yu, H., & Li, J. (2024). An ISM-DEMATEL analysis of blockchain adoption decision in the circular supply chain finance context. *Management Decision*, *62*(9), 2814-2835.

Wilden, R., Gudergan, S. P., Nielsen, B. B., & Lings, I. (2013). Dynamic capabilities and performance: strategy, structure and environment. *Long Range Planning*, *46*(1–2), 72–96.

Williams, Z., & Moore, R. (2007). Supply chain relationships and information capabilities: the creation and use of information power. *International Journal of Physical Distribution & Logistics Management*, *37*(6), 469-483.

Ye, Y., & Lau, K. H. (2022). Competitive green supply chain transformation with dynamic capabilities—an exploratory case study of Chinese electronics industry. *Sustainability*, *14*(14), 8640.

Yu, W., Wong, C. Y., Chavez, R., & Jacobs, M. A. (2021). Integrating big data analytics into supply chain finance: The roles of information processing and data-driven culture. *International Journal of Production Economics*, *236*, 108135.

Zhang, Y., Ren, S., Liu, Y., & Si, S. (2017). A big data analytics architecture for cleaner manufacturing and maintenance processes of complex products. *Journal of Cleaner Production*, *142*, 626–641.