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Big Data Analytics Capability and Decision-Making: The Role of Data-Driven Insight on Circular Economy Performance

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Abstract

Big data analytics (BDA) is a revolutionary approach for sound decision-making in organizations that can lead to remarkable changes in transforming and supporting the circular economy (CE). However, extant literature on BDA capability has paid limited attention to understanding the enabling role of data-driven insights for supporting decision-making and, consequently, enhancing CE performance. We argue that firms drive decision-making quality through data-driven insights, business intelligence and analytics (BI&A), and BDA capability. In this study, we empirically investigated the association of BDA capability with CE performance and examined the mediating role of data-driven insights in the relationship between BDA capability and decision-making. Data were collected from 109 Czech manufacturing firms, and partial least squares structural equation modelling was applied to analyze the data. The results reveal that BDA capability and BI&A are positively associated with decision-making quality. This effect is stronger when the manufacturer utilizes data-driven insights. The results demonstrate that BDA capability drives decision-making quality in organizations, and data-driven insights do not mediate this relationship. BI&A is associated with decision-making quality through data-driven insights. These findings offer important insights to managers, as they can act as a reference point for developing data-driven insights with the CE paradigm in organizations.

Keywords: Big data analytics, data-driven insights, big data analytics capabilities, decision-making, circular economy, manufacturing firms

1. Introduction

Recently, big data analytics (BDA) has emerged as one of the most important factors for generating meaningful insights for decision-making (Dubey, Gunasekaran, Childe, Blome, & Papadopoulos, 2019). It is in such a context that there is a growing interest in linking BDA and the circular economy (CE; Gupta, Chen, Hazen, Kaur, & Santibañez Gonzalez, 2019). The power of BDA in the pursuit of more regenerative and restorative business operations has led to emerging literature on the CE. The CE refers to closing loops in production and consumption and increasing resource utilization (Murray, Skene, & Haynes, 2017). Due to the important role of BDA in organizations, scholarly attention has focused on exploring the links between BDA and decision-making performance in emerging market firms (Shamim, Zeng, Khan, & Zia, 2020). Despite BDA potential, however, there is relatively limited research that has empirically explored the antecedents of data-driven insights for enhancing decision-making quality (Rialti, Zollo, Ferraris, & Alon, 2019), and its impact on CE performance (Gupta et al., 2019).

BDA capabilities are increasingly becoming important for broader decision-making in the CE and are gaining significant attention from academicians and practitioners (Gupta et al., 2019). BDA refers to the data sets and analytical techniques in applications that are so large and complex that they require advanced and unique storage, management, analysis, and visualization technologies (Chen, Chiang, & Storey, 2012). The existing literature on the role of BDA in facilitating and making informed decisions has largely focused on organizational performance (Ghasemaghaei & Calic, 2019; Gunasekaran et al., 2017; Wamba et al., 2017) and innovation competency (Ghasemaghaei & Calic, 2019). Although BDA extracts meaningful information on production activities at different stages of the production cycle for achieving the maximization of resource utilization (Gupta et al., 2019), what is not yet clear is how manufacturers could improve their existing product and process knowledge to renew it through data-driven insights (Ghasemaghaei & Calic, 2019). There is a growing recognition of BDA for effective decision-making; however, scant attention has been focused on how BDA shapes firm decision-making quality (Janssen, van der Voort, & Wahyudi, 2017).

There are growing concerns across developed and developing markets about productivity improvements and design products and processes that incorporate regenerative and reusable design (Sauvé, Bernard, & Sloan, 2016). In this situation, a fundamental issue is how BDA assists decision-making in today's complex CE activities (Gupta et al., 2019b). There has been no detailed investigation of how BDA capability matters in terms of helping firms to gain insights that lead to improving decision-making (Acharya, Singh, Pereira, & Singh, 2018a; Kowalczyk & Buxmann, 2014) and, consequently, firm outcomes (Ghasemaghaei & Calic, 2019). However, some researchers have proposed that increased BDA is likely to improve decision-making ability (Dubey, Gunasekaran, Childe, Bryde, et al., 2019). In contrast, others have suggested that increased BDA is likely to generate more data insights (Ghasemaghaei & Calic, 2019). While a potential link between BDA and an improved decision-making process has been identified (Božič & Dimovski, 2019a), extant research has ignored the specific role of data-driven insights in decision-making. There is still little understanding regarding whether BDA drives CE performance (Gupta et al., 2019). Specifically, the underlying mechanisms are not well known in the extant literature. One such mechanism is data-driven insights that can facilitate the relationship between BDA and decision-making quality—which, in turn, improves CE performance.

This study contributes to the emerging literature on BDA capability and the CE (Gupta et al., 2019) by exploring how internal data analytics lead to data-driven insights and decision-making quality in organizations—which, in turn, affects CE performance. This study examines the relevance of BDA for achieving enhanced CE performance in manufacturing firms from an emerging country perspective. We specifically address the following research question: To what extent is BDA capability relevant for enhancing CE performance? Specifically, we seek to explore the roles of a manufacturer's BDA capability in enhancing their decision-making quality and CE performance. Our study differs from previous studies investigating the links between BDA capability and firm performance in important ways. First, prior research suggests that the dynamic capabilities perspective matters for performance outcomes (Dubey, Gunasekaran, Childe, Blome, & Papadopoulos, 2019; Mikalef, Boura, Lekakos, & Krogstie, 2019). Our study contributes to the literature by demonstrating that the knowledge-based view (KBV) also plays a key role in enhancing decision-making quality. Our results suggest that to enhance decision-making quality to gain CE outcomes in organizations, decision-makers need to rely on data analytics to keep pace with the dynamic needs of knowledge creation in organizations (Alavi & Leidner, 2001). Second, the study follows the call of Ghasemaghaei (2019) and extends prior research by examining data-driven insights as a mediator between BDA capability and decision-making quality. Previous research explicitly considers data-driven decision-making as a predictor of environmental performance (Dubey, Gunasekaran, Childe, Papadopoulos, et al., 2019). While Shamim, Zeng, Shariq, and Khan (2019) examined BDA capability as antecedents of decision-making quality. Limited studies have empirically examined the relationship between decision-making and CE outcomes. Third, the existing literature only has a limited understanding of how decision-making quality can be improved (Janssen et al., 2017). We suggest that firms, with better decision-making qualities, can transfer data-driven insights and knowledge for the creation of reusable and recyclable products. Therefore, this study complements previous research on the consequences of data-driven insights on decision-making outcomes (Ghasemaghaei & Calic, 2019). The rest of the paper is organized as follows: The next section reviews the literature on the CE and BDA. Next, we describe the hypothesis development. Then we introduce the methodology. The last section discusses the study contributions and closes the article with a discussion on limitations and future research directions.

2. A digital-enabled circular economy

A digital-enabled CE is an emerging concept for improving resource utilization, efficiency, and productivity in organizations. Increasing resource scarcity concerns are pushing manufacturing firms towards CE practices for achieving local and global sustainable development objectives through the efficient utilization of digital technologies (Alhawari, Awan, Bhutta, & Ülkü, 2021). There is a growing realization that companies must address the issues of resource scarcity and dematerialization in their products' physical life cycle. The CE is the understanding of how to improve production and consumption patterns to promote the resilience orientation of materials (Awan, Kanwal, & Bhutta, 2020). Hu et al. (2011) argue that the CE focuses on "resource-productivity and eco-efficiency improvement in a comprehensive way, especially on the industrial structure optimization of new technology development and application, equipment renewal and management renovation" (p. 221).

The CE is about managing and designing a linear-to-closed-loop industrial production and consumption system (Awan et al., 2020). While Stahel and Reday-Mulvey (1981) interpret the CE as a "spiral-loop system," Geng and Doberstein (2008) focus on the reuse of a material that is restorative or regenerative by intention and design (Ellen MacArthur Foundation, 2013). Stahel (2016) emphasizes the need to bring the material back for a new use. Recent literature highlights the business significance of circular business models, which enable firms to design operations such as a take-back system (Bocken, Short, Rana, & Evans, 2014), and product design aimed at closing and slowing resource loops (Bocken, de Pauw, Bakker, & van der

Grinten, 2016). Awan et al. (2020) defines the CE as a "set of processes for reducing the material used in production and consumption, promoting material resilience, closing loops and exchange sustainability offering in such a way that maximize the ecological system" (p. 30). For example, organizations can use the exo-system and the chrono system to examine how they can improve their CE practices over time. Conversely, the CE involves finding the best course of action to design improved reuse of material and improved utilization of material recovery. Hence, a digital-enabled CE enables an organization to uncover relationships from data and information in a novel way to produce useful insights involving a series of techniques and methods for data-driven decision-making.

The literature on the determinants of CE strategies is abundant (Bocken et al., 2016; Chiappetta Jabbour, Fiorini, Ndubisi, Queiroz, & Piato, 2020; Fatimah, Govindan, Murniningsih, & Setiawan, 2020). In contrast, little is known about the effect of BDA on CE performance (Gupta et al., 2019b). BDA serves as a tool for resource management, improving the waste to resource process (Bin et al., 2015), reducing production time and maximizing energy consumption (Lacy, Long, & Spindler, 2020), and contributing towards improving resource efficiency and productivity (Kristoffersen, Blomsma, Mikalef, & Li, 2020). The CE is a broad concept, and in this study, we particularly focused on the management of the product life cycle (Kristoffersen et al., 2020).

3. Theoretical background and hypothesis development

BDA plays a critical role in shaping organizations' decision-making and can be beneficial for CE performance. For example, BDA increases the likelihood of innovation performance (Lehrer, Wieneke, vom Brocke, Jung, & Seidel, 2018). Similarly, Wamba et al. (2017) found a positive relationship between BDA and organizational performance. A substantial amount of the literature on decision-making deals with organizational learning. In line with Alavi and Leidner's (2001) view, knowledge resources are complex and difficult to imitate. Researchers have laid the foundations for the application of organizational learning and KBV to understand the data-driven insights and decision-making within organizations (Ghasemaghaei, 2019; Ghasemaghaei & Calic, 2019).

This study draws key insights from the KBV perspective, suggesting that knowledge is the most important strategic resource of organizations (Grant, 1996) and valuable knowledge resources are embedded internally in information technologies and systems (such as the internet, data warehouses, data mining techniques, and software agents; Alavi & Leidner, 2001). Scholars have devoted considerable attention to examining how BDA leverages organizational performance (Rialti, Zollo et al., 2019), supply chain performance (Gunasekaran et al., 2017; Wamba, Dubey, Gunasekaran, & Akter, 2020), operations and supply chain management (Hazen, Skipper, Boone, & Hill, 2018), the optimization of resources (Zhao, Liu, Zhang, & Huang, 2017), environmental sustainability (Dubey, Gunasekaran, Childe, Papadopoulos, et al., 2019), manufacturing performance (Dubey, Gunasekaran, Childe, Blome, & Papadopoulos, 2019), decision-making performance (Nisar et al., 2020; Shamim et al., 2020), competitive advantage (Akter, Gunasekaran, Wamba, Babu, & Hani, 2020), and the improvement of CE performance (Gupta et al., 2019). Recently, attention has turned to examining the impacts of data-driven insights on decision-making (Ghasemaghaei & Calic, 2019).

This implies that BDA makes the application of knowledge more efficient by improving organizational learning. We contend that in knowledge management and its sharing across the boundaries of the firm, organizational learning plays an important role. BDA contributes to the generation of valuable and hard-to-imitate knowledge resources—which, in turn, leads to the development of sustainable competitive advantage. Organizational capacity to foster effective decision-making is deeply rooted in firms' learning abilities. More recently, learning theory has been examined as the basis of how organizations generate data insights (Ghasemaghaei & Calic, 2019). Organizational learning theory is central to taking advantage of emerging opportunities from external sources of knowledge, and it can create a competitive advantage for organizations (Argote & Hora, 2017). Although the previous literature seems to support the notion that BDA has improved resource utilization (Song et al., 2017), scholars have also suggested that organizational learning capability could quickly generate data-driven insights to improve decision-making efficiency (Ghasemaghaei & Calic, 2019). Studies have shown that organizational learning may have both immediate and distant consequences (Bingham & Davis, 2012). Firms have invested in BDA to generate different learning outcomes (Papadopoulos et al., 2017).

Big data can be particularly useful in the context of large-scale decision-making (LSDM), which is an emerging and rapidly developing research field and has become increasingly popular in practical decision situations (Ding et al., 2020). LSDM research provides appropriate insights to determine the best solution to solve practical problems and overcome the noncooperative behaviour of key decision-makers (Palomares, Martinez, & Herrera, 2013;). LSDM is usually a complex and challenging process (Ding et al., 2020). LSDM is defined as a situation in which more than 20 members are involved, and this number is not limited to personnel within the organization (Liu et al., 2014). In the study of operations management and electronic commerce, LSDM is commonly used to solve complex problems. Thus, in this study, LSDM captures the extent to which participants from the same industrial cluster are involved in solving complex problems of resource scarcity with the help of BDA. Recent efforts by Tang and Liao (2019) to increase the move from conventional decision-making to LSDM in the big data era illustrate this scenario. Big data has long been recognized as important in LSDM for addressing the problems of natural resource scarcity. As McAfee, Brynjolfsson, Davenport, Patil, and Barton (2012) observe, leading organizations can typically accept big data-driven decision-making. Research in operations and management science has begun to look at the potential benefits of using big data tools for decision-making (Tang & Liao, 2019). Previous studies have highlighted the importance of LSDM using adequate preference representations for the implementation of a data-driven large-group decision-support system (Ding et al., 2020). LSDM can contribute towards solving complex problems that modern organizations are facing; however, little research has been carried out on how big data tools and a decision-support system can be applied in LSDM situations to solve complex problems.

Thus, given the importance of BDA in organizations, its role in the CE is becoming an important field of enquiry. According to Chen et al. (2012), BDA is an application of practices and methodologies “that analyze critical business data to help an enterprise better understand its business and market and make timely business decisions” (p. 1166). Raghunathan (1999) uses the term “decision-making quality” and refers to it as “the quality of the decision made by the decision-maker” (p. 280). Recently, Ghasemaghaei (2019) established a link between BDA and decision-making quality through knowledge-sharing practices. Prior research has indicated that knowledge sharing has important implications for decision-making outcomes (Ghasemaghaei, 2019). In this study, we especially focus on exploring how BDA affects CE performance through data-driven insights and decision-making performance. Although BDA has been recognized as the critical source for generating business value and firm performance, relatively limited research has examined the impact of BDA on decision-making quality. In the last few decades, knowledge focus in data analytics has become a topic of interest in several manufacturing firms (Alavi & Leidner, 2001; Ghasemaghaei, 2019), but research has yet to uncover whether and under what conditions a firm is able to apply the existing knowledge to create new knowledge and take effective actions (Alavi & Leidner, 2001).

3.1. Business intelligence and analytics and data-driven insights

Business intelligence and analytics (BI&A) and the field of BDA have become increasingly important within the academic and business communities over the past two decades. The concept of BI&A has been gaining attention from academicians and business practitioners over the last few years (Chen et al., 2012). The previous literature recognizes BI&A as an important resource for acquiring and assimilating intelligence on customer opinions and needs, leading to the identification of new business opportunities (Božič & Dimovski, 2019a). BI&A refers to "the techniques, technologies, systems, practices, methodologies, and applications that analyze critical business data to help an enterprise better understand its business and market and make timely business decisions" (Chen et al., 2012, p. 1166). The role of BI&A is well established in previous research; however, there is limited understanding of how BI&A may enhance CE performance through leveraging internal organizational capabilities. Business intelligence (BI) identifies the patterns whereby a firm is able to use different ways to scan and absorb information as a basis for predicting opportunities to reduce uncertainty (Gudfinnsson, Strand, & Berndtsson, 2015).

Recently, Dubey et al. (2019) explained that BI&A is positively associated with the ability to enhance innovation rather than firm performance. This implies that firms with better BI&A will have more knowledge-accumulation resources that they can use when making a decision. BI&A can enable firms to leverage a specific type of new knowledge to provide insights about the common base of organizational knowledge and process in order to understand how a particular task takes place (de Vasconcelos & Rocha, 2019). This implies that improved levels of BI&A enhance tasks and lead to improving the data-driven insights among decision-makers. To effectively collaborate and search for new knowledge from multiple points in time, firms rely on BI&A to realize value from the technology to generate diverse data insights. Conversely, although there exists some evidence that BI&A is evenly distributed across firms and encourages the pursuit of data insights, some firms might not benefit from such insights, given their weak data-related capabilities.

The concept of data-driven insights has recently gained attention by virtue of its potential to generate deep data insights. Moreover, the use of BDA reduces the complexity of generating insights from the data and increases the understanding of the optimal set of actions based on descriptive, prescriptive, and predictive data insights (Ghasemaghaei & Calic, 2019; Sheng, Amankwah-Amoah, Khan, & Wang, 2020). Data-driven insights are thus linked to three approaches: descriptive, predictive, and prescriptive insights. Descriptive insights focus on the importance of the relationship between historical (past data) and current tasks to gain insights into tasks, whereas predictive insights emphasize predicting possible future outcomes resulting from data and information originating from BI&A, and prescriptive insights emphasize the decision-making process carried out to improve future outcomes (Ghasemaghaei & Calic, 2019). In line with this, however, following the KBV, knowledge embedded in information technology requires that managers apply BI&A to deliver insights into what has happened in the past and how to integrate new insights into existing resources to improve future outcomes. This calls for managers and key workers to have greater learning capabilities and helps to foster more effective data-driven insights. We can thus hypothesize that BI&A can build capabilities, leading to building data-driven insights. Thus, we suggest the following:

H1: Business intelligence and analytics positively relates to a firm's data-driven insights.

Recently, Božič and Dimovski (2019b) highlighted the importance of BI&A for knowledge creation. Studies have increasingly emphasized that BDA plays an important role in shaping CE (Gupta & George, 2016). Data management insights shape analytics capabilities and encourage managers to make quick decisions in real time to solve problems and deliver innovative solutions. Kristoffersen et al. (2020) points out that digital technologies, such as BDA, might promote circular strategies. We argue that to enhance CE performance in a constantly changing environment, BI&A allows for faster decision-making based on past material use and collection trends; in turn, the manager uses it to design a system to support recycling, reuse, and remanufacturing activities. Hence, the use of BI&A allows an organization to enhance the existing stock of knowledge resources—which, in turn, promotes the design of new services—and products with better recyclability features. These arguments are consistent with the KBV, as BI&A is a knowledge-intensive activity and leads to knowledge-based capabilities such as CE performance. Therefore, we argue that BI&A is a prerequisite for CE performance in extracting new insights about the material recovery rate and generating value from end-of-life products. Based on the preceding discussion, we propose the following:

H2: Business intelligence and analytics positively relates to a firm's circular economy performance.

3.2. Big data analytics and data-driven insights

The literature recognizes that generating data-driven insights represents an important BDA capability (Ghasemaghaei & Calic, 2019). BDA capabilities are increasingly becoming an important component of the decision-making process in business (Hagel 2015; Shamim et al., 2020). BDA has frequently been discussed by scholars with a dynamic capability perspective to explore the relationship between BDA capabilities and organizational performance (Wamba et al., 2017). Wamba et al. (2017) argue that BDA leads to improved firm performance and BDA comes from BDA infrastructure flexibility, BDA management capabilities, and BDA personnel expertise. BDA infrastructure emphasizes the importance of the relationship between historical (past data) and current tasks to gain insights into tasks, BDA management capabilities emphasize predicting possible future outcomes resulting from data and information originating from BI&A, and BDA personnel expertise emphasizes the decision-making process carried out to improve future outcomes (Wamba et al., 2017). For example, Akter, Wamba, Gunasekaran, Dubey, and Childe (2016) show that BDA capabilities enable managers to quickly develop, deploy, and support firms' resources. Akter et al. (2016) propose that BDA personnel capabilities serve as catalysts to mobilize management to the understanding of different business functions to address changing needs in the big data environment. By fostering BDA management capabilities, firms can transform BDA for strategic use (Rialti et al., 2019). Considering this new reality, the analysis of the impact of big data has become a priority for executives who wonder how it can be used to generate insights from structured and unstructured data for better decision-making.

Research indicates that firms with a high level of BDA capabilities tend to have more focus on the generation of useful knowledge (Acharya, Singh, Pereira, & Singh, 2018b). By means of BDA, firms can improve internal processes, operations, and organizational efficiency, allowing them to identify opportunities from different kinds of data (Rialti et al., 2019) that could be used for decision-making (Ghasemaghaei, 2019). Previous research has established a positive association between BDA and organizational outcomes (Akter et al., 2016; Wamba et al., 2017). The effect of organizational BDA, often in the form of data-driven insights, has been debated in the information science literature (Ghasemaghaei & Calic, 2019). In data-driven insights, organizational BDA can be an explanatory factor to learn from past behaviours and understand their impact on future outcomes. In the literature, organizational BDA is considered an important capability (Akter et al., 2016) that impacts organizational performance. In the context of this study, BDA is a knowledge-based capability (Shamim et al., 2019b), and it is important for the effective utilization of business analytics to better plan and adapt to changing conditions (Wamba et al., 2017). Thus, we propose that enhancing the level of learning capabilities within organizations can help managers to improve their understanding of past and present trends and predict future trends. Based on this discussion, we suggest the following:

H3: Big data analytics capabilities positively relate to a firm's data-driven insights.

As highlighted in the literature, technological infrastructure such as sensors and RFIDs are increasingly being employed with electronics equipment that may enable a product to be traced for recycling, and effective utilization of new technologies can support remanufacturing, recycling, and reuse of parts or components at the end of the product's life (Okorie et al., 2018). The existing literature reveals that by integrating technological infrastructure, enhancing management capabilities to trace real-time material in the product life cycle, and integrating personal skills, several benefits can be generated in terms of reuse of the material—improving material efficiency and circularity of product design (reduction of waste from the production process and reuse of the material), among other sustainability-related benefits.

Anecdotal evidence suggests that BDA capability can improve tangible and intangible organizational productivity (Akter et al., 2016). Recently, Wamba et al. (2017) noted that BDA capability can assist organizations in aligning resources with long-term and short-term strategies; this is because BDA is acknowledged as an essential enabler of the CE (Awan, Sroufe, & Shahbaz, 2021; Kristoffersen et al., 2020). This follows the interpretation of Gupta et al. (2019), who argued that the effective utilization of BDA is important for the enhancement of the circulation of resources—increasing the effectiveness of the material and, thereby, increasing the effectiveness of business operations. We argue that BDA capabilities enable firms to successfully utilize infrastructure and manage personal expertise to develop processes and products compatible with reuse and recycling. Therefore, we propose the following:

H4: Big data analytics capabilities positively relate to a firm's circular economy process.

3.3. Data-driven insights and decision-making quality

The effective utilization of resources and effective decision-making among managers are sets of actions to be performed in relation to tasks (Ghasemaghaei, 2019). Decision-making quality ensures that managers understand what to do and what they are trying to achieve. Recently, Ghasemaghaei (2019) argued that decision-making in a digital environment is embedded in a better understanding of data or key information. Knowledge resources may lead to making better decisions inside organizations. The KBV also supports these arguments, given the vital role of knowledge in enhancing firms' competitive advantage (cf. Grant, 1996). Raghunathan (1999) defines decision-making quality as a decision-maker's ability to make the correct decision, referring to it as the quality of the decision made by the decision-maker. In contrast, decision-making effectiveness focuses on decision outcomes (Alavi & Leidner, 2001). However, there is little understanding of how the depth, breadth, and quality of organizational knowledge resources improve decision-making quality (Alavi & Leidner, 2001).

The acquisition of data resources sets the direction and action to be performed in relation to minimizing waste and recycling of the products. Based on the KBV, the acquisition of different types of data resources and knowledge could help a firm to extract the right insights on the design out of waste from process and products and enable products to be reused. The authentic and valuable insights generated from the data are important for the firm, as they can be chosen to formulate appropriate decisions to create new courses of action. Valuable insights generated from diverse data sources to understand past and present trends, as well as predict future trends, can positively influence decision-making quality.

H5: Data-driven insights positively relate to a firm's decision-making quality.

3.4. Big data decision-making and circular economy performance

Previous studies have increasingly highlighted the importance of effective decision-making for the management of the product life cycle (Kristoffersen et al., 2020). Data-driven insights create a good understanding of effective decision-making. For example, according to Ghasemaghaei (2019), an organization's learning capabilities integrate and leverage good insights into the best course of action to improve decision-making because a large amount of information is utilized to solve existing problems and generate innovative solutions. However, there is a lack of research that has explored how decision-making is affected by BI&A and its impact on value-added business activities (i.e., CE; Božič & Dimovski, 2019a). Selecting the best course of action involves learning about the optimal courses of action and may require the use of efficient technologies for the reuse and redesign of products and services to improve material recovery (Bocken et al., 2016). By effective decision-making, value is created for the organization by redesigning products, improving material efficiency and effectiveness for end-of-life products.

There is limited research on understanding the environmental performance outcomes of decision-making quality (Calza, Parmentola, & Tutore, 2020). The underlying mechanisms through which an organization improves CE initiatives have also received limited scholarly attention.

We propose that if CE-related decisions are based on correct and valid data insights, derived by discovering certain relationships, and rigorously implemented, firms will be in a better position to discover new patterns from using visualization tools to adapt to changing environmental challenges, thereby improving productivity and efficiency. Therefore, we propose the following:

H6: Big data decision-making effectiveness positively relates to circular economy performance.

3.5. The mediating role of data-driven insights

An organization's heightened concern to bolster its CE outcomes and, as a result, increase engagement in a decision is anchored in two dimensions: knowledge-based resources and organizational learning. According to learning theory (Puranam & Swamy, 2016), knowledge resources play a critical role in decision-making, as gathering information, processing, interpretation, and synthesis enable organizations to enhance their performance and competitive advantage. The organization's learning, therefore, is closely connected to the generation of data insights (Ghasemaghaei & Calic, 2019). Previous empirical studies have shown that improvisational learning is associated with real-time learning and can serve to solve emergent problems (Miner, Bassof, & Moorman, 2001). Scholars have long been interested in the effects of information processing and interpretation on decision-making (Joseph & Gaba, 2020). Firms may lack learning capabilities about information processing and therefore be unable to exploit the resources. Using theoretical reasoning that knowledge resources affect organizational learning, we argue that by using data-driven insights, decision-makers would be able to comply with the KBV to enhance CE performance. Decision-makers would be able to generate knowledge and insights from the computer-supported system to collect, interpret, and disseminate valuable knowledge and insights for better decision-making (Božič & Dimovski, 2019b). Following Grant (1996), we examined empirically whether and to what extent data-driven insights mediate the relationship between BDA capability and decision-making.

Firms are increasingly challenged by data-driven insights, which lead to effective decision-making (LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011). A more recent BI&A research by Božič and Dimovski (2019a) calls for a deep analysis to explore an organization's underlying mechanism that facilitates the knowledge-generation process for effective decision-making. A central issue in this area is whether BI&A and organizational BDA capabilities have a positive impact on firm decision-making. Previous studies have examined a mediating link of innovation between BI&A and firm performance (Božič & Dimovski, 2019b), and Ghasemaghaei (2019) established a mediating link of data analytics competency between data analytics and decision-making quality. Akter et al. (2016) examined a direct link between BDA capabilities and firm performance, and Rialti, Zollo, Ferraris, and Alon (2019) investigated a direct link between BDA capabilities and firm agility. By introducing data-driven insights, an organization can enhance decision-making—which, in turn, strengthens the value-added activities of the business. Recently, Ghasemaghaei and Calic (2019) established a mediating link of data-driven insights between big data characteristics and innovation competency. Acharya et al. (2018) show that BI&A helps to identify knowledge management practices and produce new insights for decision-making. In turn, these insights enable firms to make better decision advantages.

BDA capability has become mainstream for organizations to create value (Wixom, Yen, & Relich, 2013); it leverages technology, management, and talent capabilities, which are likely to generate more business value (Akter et al., 2016) for better decision-making (LaValle et al., 2011). Hence, we expect that BI&A is more positively associated with data-driven insights than organizational BDA capabilities. Organizational concerns for the effective utilization of data-driven insights foster a farsighted approach to firm decision-making, with a focus on BI&A (Acharya et al., 2018a; Božič & Dimovski, 2019). The decision-making perspective is founded on the ideas formulated by March (1997). The fundamental assumption of this approach is that decisions are implemented in an organization based on reliable information. The decision-making process in an organization is thus influenced by information processing, gathering, and interpretations (March 1997). However, although the positive effects of data-driven insights on firm decision-making are widely acknowledged (Ghasemaghaei & Calic, 2019), there is still a lack of understanding of the process through which effective decision-making is implemented in an organization (Joseph & Gaba, 2020). We propose that BDA capability would enable a firm to choose the best possible plan of action and execute it through the utilization of data-driven insights. To summarize, the understanding of the effects of BDA capability remains mixed. We propose that BDA capability can revolutionize the decision-making process through data-driven insights. Therefore, we suggest the following:

H7: Data-driven insights mediate the relationship between business intelligence and analytics and decision-making quality.

H8: Data-driven insights mediate the relationship between big data analytics capabilities and decision-making quality.

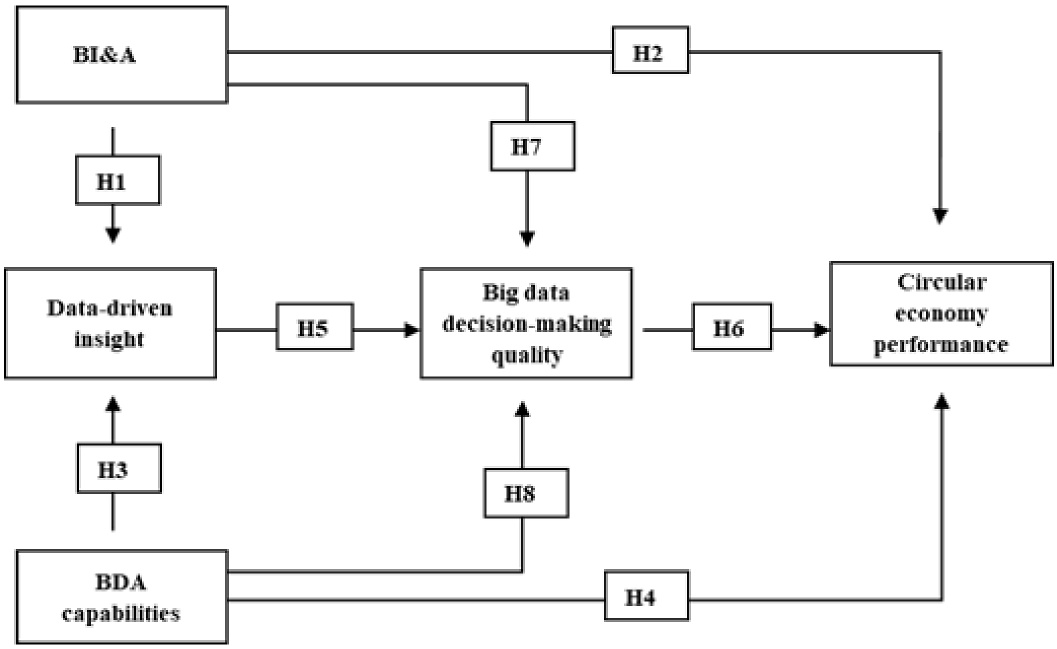

Figure 1. Research Model

4. Methodology

4.1. Sample and data collection

In this study, we used a survey method to collect data through a structured questionnaire. Data-driven manufacturing firms in the Czech Republic form the population of this study. The European Commission is introducing new measures regarding the Circular Economy Package, and the member states must implement its contents into their policies (Vilamová et al., 2019).

In response to the adoption of the Circular Economy Package, the Czech government approved the new Waste Management Plan for the period 2015–2024 (Vilamová et al., 2019). Europe is also developing a strategy for a digital economy and planning to shape the digital European society by 2030 (Georgiou, 2018; Misuraca et al., 2012). Being a part of the European Union, the government of the Czech Republic is also strongly working on the concept of a "Digital Czech Republic" by defining 15 major and 115 partial targets to support the digitization process in the country (Digital Czech Republic, 2019). The government is expending its best efforts to make the Digital Czech Republic the main policy concerning digitization, which will gradually replace the existing traditional policies (Digital Czech Republic, 2019). The mission of the Digital Czech Republic is to find out and eradicate all administrative and legislative barriers while aggressively encouraging the best environments for the success of individuals, Czech companies, and the whole country in this digital transformation period (Digital Czech Republic, 2019). This makes the Czech Republic a relevant context for this study.

We initially requested 914 firms to participate in the survey and shared the questionnaire with them. Google Forms was used to distribute the questionnaires. Each firm's contact details were collected using the Bisnode Albertina database. We shared the online questionnaire link with the contact persons in these firms and requested them to share it with employees involved in big-data–related activities and decision-making. We received a response from 109 firms and 358 employees, out of which 321 responses were usable. There were multiple respondents from each firm. The whole process of data collection took around 10 months—lasting from January to October 2020. Most of the firms that participated in the survey are 6- to 20-year-old manufacturing firms with approximately 20 to 200 employees. We collected data from key frontline employees and managers involved in big data–related activities, as well as from middle and top managers. In this study, we have controlled firm size, firm age, respondent experience, respondent age, education, and respondent managerial level to eliminate whatever effects these variables might have on decision-making. Several previous studies provide mixed findings on the effects of firm age and size on decision-making, while others provide evidence that firm size has no significant effect on decision-making.

4.2. Common method bias

To mitigate the effect of common method bias, we took several steps. For instance, we collected data in two waves. We ensured the anonymity of respondents. Furthermore, we randomized the items in the questionnaire so the respondents could not easily guess the antecedents and outcome variables. We ran exploratory factor analysis with an unrotated solution to ascertain the absence of common method bias. The statistical check was also satisfactory—that is, the Harman single-factor test suggested that a single factor explained only 32.03%, which provides support for the absence of common method bias. This approach is consistent with the existing literature (Yang et al., 2017).

4.3. Measures

A structured questionnaire was used to measure the variables. The questionnaire is a combination of adopted, adapted, and self-developed items. Decision-making quality was measured using eight items from Shamim et al. (2019a). We developed nine items to measure BI&A, and these items were inspired by Božič and Dimovski (2019) and Gold et al. (2001). BDA was measured by adopting eight items from Akhtar, Khan, Tarba, and Jayawickrama (2018). Data-driven insights were measured by adopting eight items from Ghasemaghaei and Calic (2019). The CE performance measurement scale was developed by authors using insights from the existing literature and adopted in the current study context. We asked respondents to indicate the extent to which they agreed with the following statements on a seven-point Likert scale: “1 – strongly disagree” to “7 – strongly agree.” The measurement scale of CE performance was developed from the existing literature and adopted in the current study context. We use a pilot test to refine the questionnaires. Based on the suggestions from the respondents, two measures of items were not included in the study. The items included are: (1) Improve the resource-productivity and eco-efficiency”,(2) “Decrease consumption of natural resources and materials,(3) “Improve the use of reprocessing material with energy recovery”,(4) “Improve reuse and recycling of material, parts, and components ”,(5) “Improve the refurbishment, redesign with different functions”,(6) “Improve utilization of energy and material recovery rate”,(7) “Increase of obtaining the high value of material and energy recovery”,(8) “Improve the extraction of materials for reuse and circular design ”

5. Results

5.1. Reliability and validity

All the constructs were tested for reliability and validity. The results indicate that Cronbach’s alpha for all the constructs was more than 0.7, which indicates construct reliability. To examine the discriminant validity, Fornell and Larcker’s (1981) approach was followed. To establish convergent validity, factor loadings of the construct should be greater than 0.65, average variance extracted (AVE) and composite reliability (CR) should be more than 0.5, and AVE should be less than the CR of the construct (Fornell & Larcker, 1981). The results in Table 1 indicate that all the constructs meet these requirements. Factor loadings for all the constructs are greater than 0.65. The values in italics are the items that were excluded because the loadings were less than 0.65. Factor loadings for BI&A ranged from 0.74 to 0.81. BDA factor loadings were 0.72 to 0.82. Data-driven insights showed loadings ranging from 0.70 to 0.82. Decision-making quality showed factor loadings from 0.75 to 0.85, and loadings for the CE process ranged from 0.84 to 0.89. The AVE and CR of all the constructs were greater than 0.5, and the AVE of each construct was higher than the CR. These results meet the Fornell and Larcker (1981) criterion for the evaluation of convergent validity. On the basis of these findings, convergent validity is established. The results of the convergent validity are summarized in Table 1.

Table 1. Reliability and Convergent Validity

Variable	Items	Factor loadings	AVE	CR	Cronbach's alpha
BI&A	*BI&A1*	*0.65*	0.61	0.88	0.84
	BI&A2	*0.59*			
	BI&A3	*0.61*			
	BI&A4	*0.51*			
	BI&A5	0.74			
	BI&A6	0.77			
	BI&A7	0.80			
	BI&A8	0.81			
	BI&A9	0.77			
BDA capabilities	BDA1	0.78	0.61	0.90	0.87
	BDA2	0.76			
	BDA3	0.79			
	BDA4	0.75			
	BDA5	0.82			
	BDA6	0.72			
	BDA7	*0.68*			
	BDA8	*0.61*			
Data-driven insights	DDI1	0.70	0.60	0.93	0.91
	DDI2	0.78			
	DDI3	0.76			
	DDI4	0.81			
	DDI5	0.80			
	DDI6	0.82			
	DDI7	0.78			
	DDI8	0.74			
	DDI9	0.71			

Decision-making quality	DDMQ1	0.82	0.65	0.92	0.91
	DDMQ2	0.85			
	DDMQ3	0.82			
	DDMQ4	0.79			
	DDMQ5	0.75			
	DDMQ6	0.78			
	DDMQ7	0.79			
	DDMQ8	*0.62*			
Circular economy performance	CE1	0.87	0.76	0.94	0.92
	CE2	0.89			
	CE3	0.87			
	CE4	0.87			
	CE5	0.84			

To establish discriminant validity, the AVE of each construct should be more than the squared correlation among the constructs (Fornell & Larcker, 1981). The results in Table 2 show that the AVE of each construct was higher than the squared correlation, which indicates discriminant validity.

Another criterion for evaluating discriminant validity is the heterotrait–monotrait (HTMT) ratio, a newly proposed approach based on the multithread–multimethod matrix. This approach is superior to cross-loading and the Fornell and Larcker (1981) approach (Henseler, Ringle, & Sarstedt, 2015). The HTMT criterion involves comparing the ratio to a predefined threshold; this is the first approach. If the level of HTMT exceeds the threshold, then there is a lack of discriminant validity. The criterion suggests that to establish convergent validity, the HTMT ratio for each construct should be less than 0.85. Table 3 shows that all the constructs meet the criterion; therefore, discriminant validity is established. The chi square of the model is 2035.4, the R-square of the dependent variable is 0.57, and the NFI is 0.91, which indicates a good model fit. Table 3 shows the mean, standard deviation, and correlation among the constructs.

Table 2. Mean, Standard Deviation and Correlation

		Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12
1	**BDA capabilities**	4.14	1.44	**0.61**											
2	**CE performance**	3.83	1.90	0.73**	**0.76**										
3	**Decision-making quality**	4.09	1.47	0.52**	0.54**	**0.65**									
4	**Data-driven insight**	4.04	1.71	0.53**	0.46**	0.61**	**0.60**								
5	**BI&A**	4.26	1.36	0.68**	0.59**	0.54**	0.67**	**0.61**							
6	**Managerial level**	2.72	1.14	0.02	0.10**	0.10*	0.00	0.04	1						
7	**Highest education**	2.95	0.72	0.00	0.03	0.05	0.03	0.07	0.08	1					
8	**Age of respondent**	2.3	1.15	0.02	0.11*	0.11**	0.00	0.04	0.98**	0.03	1				
9	**Experience**	2.32	1.15	0.02	0.12*	0.10*	-0.01	0.02	0.94**	0.02	0.96**	1			
10	**Age of firm**	3.01	1.25	-0.1*	-0.10*	-0.15*	-0.07	-0.05	-0.21**	-0.04	-0.20**	-0.18**	1		
11	**Number of employees**	2.11	0.55	-0.09*	-0.04	-0.0	-0.12*	-0.07	0.10**	0.11	0.10*	0.11*	0.37**	1	
12	**Annual sales**	1.74	0.64	-0.085	-0.09*	-0.07	-0.04	0.08	0.08	0.16	0.04	0.01	0.12**	0.38**	1

Note. *Bold values are AVE; * Correlation significant at 0.05; ** Correlation significant at 0.01*

Table 3. Heterotrait–Monotrait Ratio, Skewness, and Kurtosis

	Factors	**Skewness**	**Kurtosis**	**1**	**2**	**3**	**4**
1	BDA capabilities	-0.25	-1.23				
2	BI&A	-0.24	-0.81	0.74			
3	Circular economy process	-0.24	-1.46	0.78	0.61		
4	Data-driven decision-making quality	-0.08	-1.52	0.50	0.60	0.60	
5	Data-driven insights	-0.43	-1.16	0.53	0.77	0.50	0.65

5.2. Hypotheses testing

We used partial least squares (PLS) structural equation modelling to test the hypotheses. There are several reasons to use PLS: (1) PLS is a structural equation modelling method designed to estimate composite factor models, and its construct scores are more reliable than sum scores. (2) PLS has sufficient information to estimate different weights, and it can also help to detect a wide spectrum of measurement model misspecifications. (3) PLS can be applied in many instances of small samples when other models fail (Henseler et al., 2014). (4) PLS can be a valuable tool for exploratory research (Henseler et al., 2014). Moreover, it simultaneously considers the measurement model and the theoretical structural model (Chin, Marcolin, & Newsted, 2003).

First, we tested direct associations. The results revealed that BI&A is positively and significantly associated with data-driven insight ($\beta = 0.65$, $p < 0.001$) and CE performance ($\beta = 0.15$, $p < 0.01$). These findings support H1 and H2. A direct association of BDA with data-driven insights ($\beta = 0.60$, $p < 0.001$) and CE performance ($\beta = 0.54$, $p < 0.001$) is also supported by the results, so H3 and H4 are also accepted. Data-driven insights are positively related to decision-making quality ($\beta = 0.45$, $p < 0.001$), and decision-making quality is positively related to CE performance ($\beta = 0.28$, $p < 0.001$). These findings support H5 and H6.

Second, we tested the mediation effect using SmartPLS (Ringle, Wende, & Becker, 2015) with a bootstrapping procedure, setting the bootstrap at 5,000 runs. To assess the mediation effect, we used a bootstrap confidence interval for the indirect effect. An SRMR value less than 0.08 in the PLS path model provides support for the model fit of the empirical data. Our results show that the SRMR value was less than the desired value, excluding the direct effect. We then identified partial mediation to assess the variance accounted for (VAF) value in explaining the extent to which mediation variables account for the variance of the dependent variable. A VAF value between 20 percent and 80 percent indicates that a partial mediation exists. A VAF value greater than or equal to 1 is described as a full mediation (Hair & Hult, 2016).

We followed the Baron and Kenny (1986) and MacKinnon, Fairchild, and Fritz (2007) approach to examine whether the mediation had occurred or not since it is widely employed in examining the role of mediating variables. The mediation is said to occur if the indirect effect is significant. We further tested whether there was a full mediation relationship or a partial mediation relationship, following the guidelines of MacKinnon et al. (2007). Significance level was measured by bootstrapping. Then we examined the mediating role of data-driven insights in the association of decision-making quality with BI&A and BDA. The results suggest full mediation of data-driven insights in the relationship of BI&A and decision-making quality; after entering data-driven insights as a mediator in this relationship, the direct association of BI&A and decision-making quality became insignificant ($\beta = 0.11$, $p > 0.1$). The indirect relationship between BI&A and decision-making quality was positive and significant ($\beta = 0.30$, $p < 0.001$). These findings support H7. However, the results do not suggest that data-driven insights mediate the relationship between BDA and decision-making quality ($\beta = 0.03$, $p > 0.1$).

Table 5. Path Analysis and Hypothesis Testing

Path	Direct effects β/t-value	Indirect effects β/t-value	Total effects β/t-value	Hypothesis	Result
BI&A → Data-driven insights	0.65***/10.55			H1	Accepted
BI&A → CE performance	0.15**/2.72			H2	Accepted
BDA capability → Data-driven insights	0.60***/12.10			H3	Accepted
BDA capability → CE performance	0.54***/10.47			H4	Accepted
Data-driven insights → Decision-making quality	0.45***/7.09			H5	Accepted
Decision-making quality → CE performance	0.28***/4.68			H6	Accepted
BI&A → Data-driven insights → Decision-making quality	0.11/1.61	0.30***/5.61	0.41***/6.59	H7	Accepted
BDA → Data-driven insights → Decision-making quality	0.18**/3.01	0.03/1.08	0.21**/3.23	H8	Rejected

6. Discussion

This study examined how BI&A and BDA influence CE performance by enhancing data-driven insights and decision-making quality by drawing data from 109 Czech manufacturing firms. The findings suggest that both BI&A and BDA capabilities are positively related to CE performance. These findings are consistent with those of Kristoffersen et al. (2020). Furthermore, BDA capabilities constitute a stronger predictor of CE performance. BI&A fully relies on data-driven insights to enhance CE performance; however, BDA capabilities are directly related to CE performance. Our results are also consistent with suggestions made by Ghasemaghaei and Calic (2019)—that is, BI&A and BDA capabilities are positively associated with data-driven insights, which enhances decision-making quality. Our findings suggest that BI&A influences decision-making quality through the mediating role of data-driven insights, which means it relies on data-driven insights to connect with decision-making quality. In the absence of data-driven insights, the relationship between BI&A and decision-making quality is insignificant. However, BDA does not rely on data-driven insights to influence decision-making quality, as the results show that there is no indirect relationship between BDA capability and decision-making quality. However, the direct relationship between BDA capability and decision-making quality is significant, which is consistent with Shamim et al. (2020). This may be because companies are now moving towards autonomous decision-making, and BDA capability is a broader construct that involves human talent, technological infrastructure, and management capability (Wamba et al., 2017). The multidimensional nature of the BDA construct does not depend on mediators such as data-driven insights to influence decision-making quality. However, this issue needs further investigation. Finally, the results suggest that decision-making quality achieved using BI&A, BDA capabilities, and data-driven insights enhances CE performance of firms and that BI&A can have a stronger impact on data-driven insights than BDA capability can. We also found that BDA is more strongly related to decision-making quality than BI&A is. Previous studies have highlighted the importance of LSDM using adequate preference representations for the implementation of a data-driven large-group decision-support system (Ding et al., 2020). Thus, in this study, LSDM captures the extent to which participants from the same industrial cluster are involved in solving complex problems of resource scarcity with the help of BDA. Our findings reveal that data-driven insights act as a mediating factor between BI&A and big data decision-making quality.

Given the importance of BDA capability, there remains a paucity of evidence of BDA capability on CE performance—although there are a few exceptions to this, such as Gupta et al. (2019) and Popovič, Hackney, Tassabehji, and Castelli (2018). We conclude that CE performance can be improved through robust BI and the use of BDA, as well as through recognizing the value of good decision-making in organizations. Our results suggest that an organization's BDA capabilities are an important resource to realize the value of knowledge and information and that data-driven insights need to encompass the importance of BI&A for effective big data decision-making for CE performance. These findings are particularly useful because the emergence of a digital economy and new forms of digital business models for firms and markets has raised the demand for strategic decision-making processes to an unprecedented scale. Decision-making in this situation relies heavily on artificial intelligence and data-driven technologies such as big data (Ding et al., 2020). Our proposed framework can enable better decision-making in this context.

6.1. Theoretical contributions

Our research contributes to the literature in several ways. The main contribution of our study is proposing and testing a conceptual model that identifies the mechanism that enables a firm to enhance the CE. First, this study seeks to advance the current decision-making literature by explicitly exploring if and how BDA capabilities affect data generation and CE performance in manufacturing firms. Prior research has suggested that the dynamic capabilities perspective matters for performance outcomes (Dubey, Gunasekaran, Childe, Blome, & Papadopoulos, 2019; Mikalef et al., 2019). Our study contributes to the literature by demonstrating that the KBV also plays a key role in enhancing decision-making quality. This study contributes to the decision-making literature by linking it to the KBV to show that data generation insights affect decision-making quality. Our conceptual model can be interpreted through the KBV lens. We build on the KBV to suggest that learning is a key characteristic that provides a new source of information and generates new knowledge that enables organizations to capture value from key knowledge sources. Our results suggest that to enhance decision-making quality and gain CE outcomes, decision-makers need to rely on data analytics to keep pace with the dynamic needs of knowledge creation (Alavi & Leidner, 2001).

Second, this study proposes that enhanced CE performance requires a specific set of internal organization processes (data-driven insights and decision-making) and BDA (Ghasemaghaei & Calic, 2019) and responds to the call for a better understanding of the relationship between BDA and CE (Gupta et al., 2019b). However, our results suggest that an organization's ability to shift data-driven insights to decision-making is based on organizational learning capabilities.

Third, we maintain that decision-making can be realized by generating data-driven insights, which are accumulated within an organization through BDA. There is a growing recognition of the importance of BDA capability for effective decision-making; however, scant attention has been focused on how BDA capability shapes firm decision-making (Janssen et al., 2017). There remains a limited understanding in the existing literature on how decision quality can be improved (Janssen et al., 2017). We suggest that firms with better decision-making qualities can transfer and internalize knowledge for the creation of recycling products.

Fourth, most previous studies have analyzed the impact of BDA in combination with the dynamic capability perspective on firm performance and innovation performance (Lehrer et al., 2018; Wamba et al., 2017), but comparatively, few empirical studies have examined the influence of BDA capability on decision-making outcomes (Ghasemaghaei, 2019; Shamim et al., 2020). The qualitative study of Gupta et al. (2019) highlights the need to establish the relationship between BDA and CE outcomes. Mikalef et al. (2019) and Zhang and Xiao (2020) show that from the capabilities perspective, firms with strong BDA may enhance innovation. Our results suggest that big data decision-making embedded in data-driven insights is important for enhanced CE performance. These findings provide a deeper understanding of the importance of data-driven insights and their vital role in big data decision-making.

Furthermore, the literature suggests that for large-group decision-making, groups should not overrely on experts (Emmerling & Rooder, 2020). This study suggests an important mechanism to reduce dependency on experts for LSDM—that is, with the help of BI&A, BDA, and data-driven insights. Ding et al. (2020) argue that large-scale group decision-making requires the application of artificial intelligence for quality decisions. This study offers a mechanism of incorporating artificial intelligence into the decision-making process through BDA, BI&A, and data-driven insights leading to CE performance.

6.2. Managerial relevance

This research attempts to provide important managerial guidelines to managers and firms on managing data-driven insights for effective decision-making. Our study investigated the impact of BI&A and organizational BDA capability on data-driven insights and big data decision-making and, consequently, on enhancing CE performance. Gupta et al. (2019) highlight the need to establish a relationship between BDA and CE outcomes. There is a growing recognition of the need for BDA in effective decision-making; however, scant attention has been focused on how BDA capability shapes firm decision-making (Janssen et al., 2017). First, managers in the manufacturing industry can develop a set of viable data-driven strategies in order to transform linear production activities into a closed-loop production system; having strong BDA capabilities appears to be critical to making better decisions to use efficient technologies for the reuse and recovery of material from end-of-life products. In contrast, an organization with strong BI&A is required to focus on the effective utilization of data-driven insights for decision-making. Our results suggest that the insights delivered through the application of predictive, perspective, and descriptive analytics illuminate the gaps in CE performance.

Second, although previous research has established a positive association between BDA and data-driven culture (Duan, Cao, & Edwards, 2020), there have been few or no previous research attempts to theorize and empirically investigate the link between BI&A and data-driven insights. The findings of this study offer important insights into big data decision-making enhanced through data-driven insights. Our results suggest that top management may follow data-driven-based insights more than simply relying on BDA capabilities. The overreliance on BDA capabilities may lead to less effective decision-making, and this may have strong implications for the firms, as well as for the impact of decision-making on CE performance. One important implication for managers is that decision-making entails an increasing level of dependence on data-driven insights affected by BI&A.

Third, data-driven insights have attracted attention from researchers and practitioners in recent years due to the increasing awareness and importance of BDA and business analytics capabilities. Previous research has emphasized the importance of big data to make better and high-quality decisions (Tang & Liao, 2019). However, there have been no research attempts to empirically test if organizational BDA capability enhances data-driven insights and determine what role data-driven insights play in effective big data decision-making. As McAfee et al. (2012) observe, leading organizations can typically accept big-data-driven decision-making. CE performance can be well implemented and sustained with the effective utilization of BI&A. Our results also identify that BI&A helps in aligning CE performance goals through data-driven insights to support decision-making as an organization transitions towards more circularity-oriented business practices. Thus, we inform managers that a digital-enabled CE resides in the firm's ability to effectively utilize data-driven insights to arrive at decisions. Thus, it is important to select the best data-driven insights to design strategies that enable firms to enhance their CE performance. The implications for the top management of firms are that BI&A and data-driven insights may be useful when they have a greater chance of implementing CE performance. Firms that wish to improve their social impact may consider the data-driven insights in analyzing and understanding the different views of the CE implementation–related problems.

The literature suggests that for large-group decision-making, groups should not overrely on experts (Emmerling & Rooders, 2020). This study suggests a mechanism to reduce dependency on experts for large-group decision-making—that is, with the help of BI&A, BDA capability, and data-driven insights. Ding et al. (2020) argue that large-scale group decision-making requires the application of artificial intelligence for quality decisions. Although previous studies have highlighted the importance of LSDM using adequate preference representations for the implementation of a data-driven large-group decision-support system (Ding et al., 2020), little or no research has directly examined the influence of big data tools on decision-making quality (Tang & Liao, 2019). We suggest that superior CE performance is more likely when BDA capabilities are aligned and nurtured in a way that fits the nature of the firm's data-driven insights. Because effective decision-making is complex, firms with greater data-driven insights may expand the base of knowledge, expertise, and resources, and this enhances CE performance.

7. Conclusion

This study focused on the impact of BDA capability on CE performance and examined the decision-making quality of manufacturing firms in the Czech Republic, a country where firms are very active in using big data. Our findings highlight the positive influence of BDA and BI&A on data-driven insights and decision-making, which leads to enhanced CE performance. BI&A is a stronger predictor of data-driven insights, and BDA is a stronger predictor of decision-making quality. Our findings on the mediating relationship of data-driven insights show a more direct and indirect relationship between BDA capabilities and decision-making than BI&A. BI&A fully relies on data-driven insights to connect with decision-making quality, and BDA has a direct relationship with decision-making quality. Overall, we conclude that the important and effective use of BDA capabilities in the generation of data-driven insights may shape the relationship between decision-making and CE. In summary, this line of research suggests that CE performance can often be understood from an organizational learning perspective. This study contributes to the extant literature on decision-making as an important source of CE performance. Our findings provide a better understanding of how BI&A applications may enhance data-driven insights focused on big data decision-making for CE performance. The study also lends support to the notion that a firm's CE performance stems from its data-driven insights and decision-making quality.

7.1. Limitations and future research

This study has a few limitations, which provides important avenues for future research. The first limitation is that the data collection was limited to the Czech Republic, which provides the context of an emerging economy. Value creation through big data in an emerging economy context can be different from that of developed and less developed countries. However, being in a single economic zone, these findings can be generalized for other similar European countries, but future research is needed to enhance the generalizability of the findings in other regions, including Asia, Latin America, and Africa. Another limitation is the cross-sectional design of this study; however, we responded appropriately by reducing the common method bias: the data were collected in two waves, we randomized the items, and we ensured the anonymity of respondents. Future studies may examine the relationship between CE and environmental performance and could use a longitudinal experimental design. Furthermore, future studies may investigate the mediating effect of CE performance in the relationship between BDA capability and environmental and innovation performance.

In addition, we suggest that scholars should test data integration management capability as a mediating variable between BDA capabilities and decision-making and investigate how such capabilities enhance CE performance across different types of firms. Such studies could also examine sustainable digital business models and the role of supply chain firms in enhancing end-of-life product performance and sustainability. Lastly, the role of diverse stakeholders is important in a CE; thus, future studies need to pay greater attention to the role of stakeholders in enhancing CE performance.

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