Annals of Operations Research (2024) 333:1077–1101
https://doi.org/10.1007/s10479-022-05157-6

ORIGINAL RESEARCH

Big data analytics capability in healthcare operations and supply chain management: the role of green process innovation

Smail Benzidia[1] · Omar Bentahar[1] · Julien Husson[1] · Naouel Makaoui[2]

Accepted: 21 December 2022 / Published online: 18 January 2023

Abstract
Green approaches remain little disseminated in the healthcare sector despite growing interest in recent years from practitioners and researchers. Big Data Analytics Capability (BDAC) can play a critical role in the integration of environmental concerns into operations and supply chain management (OSCM) and further strengthen the environmental performance of healthcare facilities. According to the literature, the integration of the environment into operations process remains insufficient to achieve high levels of performance and requires efforts in green process innovation. However, this relationship between BDAC and green process innovation remains poorly justified empirically. To address this theoretical gap, we investigated the relationship between BDAC, environmental process integration, green process innovation in OSCM and environmental performance. The main contribution of this study is the valuable knowledge on how BDAC influences environmental process integration and green process innovation to enhance environmental performance. Moreover, the study highlights the mediating role of green process innovation on environmental performance, a finding that has not been mentioned in the extant literature. The paper provides valuable insight for managers and stakeholders that can assist them in supporting the application of BDAC in healthcare OSCM to create sustainable value.

Keywords Big data analytics capability · Green innovation · Operations · Supply chain · Healthcare · Environmental performance

✉ Smail Benzidia
smail.benzidia@univ-lorraine.fr

Omar Bentahar
omar.bentahar@univ-lorraine.fr

Julien Husson
julien.husson@univ-lorraine.fr

Naouel Makaoui
nmakaoui@groupe-igs.fr

1 IAE Metz, CEREFIGE, University of Lorraine, Nancy, France

2 ICD Business School, Paris, France

1 Introduction

Hospitals are known to consume considerable amounts of materials, energy, and water. They also generate voluminous waste, particularly toxic waste, compared with other sectors and have a high carbon footprint (Balan & Conlon, 2018). According to the French hospital federation (FHF), France produces approximately 700,000 tonnes of waste of all kinds per year or 3.5% of the national production, while England produces 538,600 tonnes, versus about 6600 tonnes of waste per day in the United States (Kaplan et al., 2012). This major contribution to environmental pollution generates numerous pathological, pharmaceutical, chemical, radioactive, and health risks because of the infectious and/or toxic characteristics of the waste (Tsakona et al., 2007). Numerous developed countries, including France, have consequently realised the urgency of taking an environmental approach and encouraging hospitals to rethink their entire model to move towards a green supply chain and sustainable operations management (Balabel & Alwetaishi, 2021). The literature has also identified other factors that have accelerated the urgency for hospitals to move towards green practices. These factors include patients who are constantly seeking quality care but who are also increasingly demanding green and sustainable services during their hospital stays (Bentahar et al., 2022; Fadda, 2020). Another factor is the regulatory constraints imposed on hospitals in a constant and evolving manner. Finally, a third factor is related to the COVID-19 pandemic that has created unprecedented environmental dynamism in industries, including hospitals, due to the strict measures taken by national governments to control the spread of the virus (de Haas et al., 2020; Dubey et al., 2021). This crisis has revealed hospitals' heavy carbon footprint, due in part to procurement policies that favour distant, low-cost countries such as China and India.

The green hospital literature has often highlighted the lack of techniques to exploit quantitative data from diverse OSCM and measure the environmental impact of hospitals (Campion et al., 2015). Balan and Conlon (2018) argue that hospitals need to adopt a computerised approach using more practical data exploration technologies to give their green supply chains greater visibility. To this end, BDAC is one of the technologies that could solve data processing problems that hospitals face. Big data has been quickly adopted and widely implemented in the health industry in recent years. This diffusion can generate savings and improve the quality and efficiency of health services. Beyond these objectives, BDAC also facilitates the decision-making process regarding the integration of environmental approaches in hospital OSCM (Papadopoulos et al., 2017). Such initiatives pertain to procurement, forecasting and demand, transportation and production, optimising waste management, and reverse logistics. Nonetheless, this integration of the environment into hospital processes appears to be insufficient to achieve high environmental performance (Seman et al., 2019; Wu, 2013). Thus, hospitals need to go beyond prescriptive approaches and support environmental innovations in processes by adopting a proactive strategy. BDAC can support this strategy in that it grants a capability to organisations promoting green innovation (El-Kassar & Singh, 2019). A literature review highlights the key role of big data in innovation at organisations through the sharing of information and knowledge useful for operating processes and customers (Babu et al., 2021). However, little is known about the role of big data in innovation in the healthcare context. Further, regardless of the industry, the relationship between big data and green process innovation remains poorly justified empirically. El-Kassar and Singh (2019) found only a weak direct influence of big data on green process innovation.

To address this gap, this study aims to examine the connection between BDAC, environmental process integration, and green process innovation in OSCM. We also investigate how this relationship contributes to environmental performance in a dynamic context. Given the complexity of hospitals that are characterized by heterogeneous internal activities and actor diversity, this article presents valuable information that will help academics and practitioners in the OSCM community better understand the value of internal environmental integration allowing hospitals to operate in an integrated process to support green process innovation and hospital performance.

The study also highlights the significant influence of green process innovation between environmental process integration and performance, a finding that has not been identified in the literature.

These results suggest that managers of OSCM should fully seize the value of BDAC for environmental approaches and green process innovation to improve the environmental performance of the healthcare system.

The paper is organised as follows. Section 2 reviews previous studies related to the main constructs of the study, and Sect. 3 presents the conceptual model and the research hypotheses. Further, Sect. 4 covers the research methodology, data collection, and data analysis, while Sect. 5 specifies and discusses the results. Finally, Sect. 6 contains the discussion, implications, limitations, and future research directions.

2 Literature review

2.1 Green healthcare operations and supply chain management

Green OSCM has recently drawn growing interest among researchers and practitioners (Rezaee et al., 2017; Shen et al., 2019). This trend is motivated by escalating pollution (waste, air), along with state regulation and consumer sensitivity. Several companies have incorporated environmental approaches into their OSCM: waste and greenhouse gas emission reduction, green procurement, green packaging, and reverse logistics. For example, research on production systems focuses on reducing solid waste and air pollutant emissions, recycling, and reuse (Li et al., 2020). To achieve these goals, organisations must integrate clean technologies into their production systems.

These environmental practices are considered to be a source of performance and competitive advantage for companies (Dubey et al., 2015; Giannakis & Papadopoulos, 2016; Homayouni et al., 2021). Nonetheless, the implementation of green approaches in OSCM is hindered by a lack of skills and institutional as well as technological barriers.

The challenge of introducing green approaches in OSCM is a concern not only for the industrial sector but also for the health sector a large consumer of energy and a major polluter in particular through its infectious waste.

Compared with the industrial supply chain, the hospital supply chain is in its early stages of development. This lag is due to the lack of expertise and logistics skills, organisational inertia, and slow digital transformation (Ageron et al., 2018; Beaulieu & Bentahar, 2021). Despite the delay in the development of hospital OSCM, in the past decade, sector actors have recognised the merits of environmental approaches and have decided to commit to their implementation. Health organisations are moving from the traditional cost-focused vision to a philosophy based on eco-efficiency, a transition further justified by the COVID-19 crisis.

Overall, the implementation of environmental approaches in the hospital sector remains limited and concentrated on a few operations (e.g. waste reduction). Empirical studies of the implementation of green approaches in hospital OSCM have mainly examined waste management or green procurement. However, a few hospitals are rejecting this reactive approach in favour of a proactive approach that entails integrating environmental practices throughout their OSCM process (Benzidia et al., 2021). Notably, this proactive approach includes the adoption of European certification projects such as the *Eco-Management and Audit Scheme* (EMAS) and the implementation of innovative technologies (AGV, BDAC, RFID, cloud) that serve as internal levers for environmental practices.

The different physical flows of the hospital, such as patient flow, pharmaceutical and medical supply flow, Andersenen flow, catering flow, and waste flow, are controlled by classical information systems (e.g. ERP) and increasingly by new advanced technologies (e.g. BDAC, AI, AGV). Therefore, we believe that health OSCM can reduce the gap with other sectors through the gradual and structured implementation of digitalisation technologies (Beaulieu & Bentahar, 2021). However, research studying the impact of digital technologies on health organisation OSCM and, more specifically, environmental performance is still in its infancy. Thus, empirical studies need to show how digitalisation technologies such as BDAC contribute to the integration of environmental approaches and innovation and how they can enhance the environmental performance of health OSCM.

2.2 Big data in health OSCM

Companies and, more specifically, operations and supply chain managers are facing strong growth in the amount of data. This increase in data access is linked to the development of information technologies such as ERP, RFID, wireless sensors, mobile devices, and social media. In the literature, there is no consensus on the definition of big data (Nguyen et al., 2018). However, researchers and practitioners agree that big data are datasets characterised by volume, velocity, and variety. The complexity of the data exceeds the capacity of traditional technological tools and processing applications (Wang et al., 2016). This context has given rise to BDAC, which constitutes the ability to handle and process massive amounts of data to gain value and insights and hence a competitive advantage (Akter et al., 2016; Gunasekaran et al., 2017; Wamba et al., 2017).

The growing interest in the application of big data to OSCM has been observed by both practitioners and researchers in connection with the development of digital technologies over the last decade. Various studies have been published in operation management, logistics, and supply chain management journals. The Annals of Operation Research is the journal with the highest number of publications on the topic of big data.

Beyond literature reviews and conceptual papers, researchers have conducted empirical studies that highlight the potential benefits of BDAC for OSCM in areas such as demand planning, forecasting, procurement, production, inventory, and logistics. These studies demonstrate the ability of BDAC to reduce waste in the food supply chain (Mishra & Singh, 2018), lower costs, and improve decisions related to demand forecasting and management (Schoenherr & Speier-Pero, 2015), efficiency in logistics and production planning (Zhong et al., 2015), and adaptation to the dynamics of the supply chain environment (Waller & Fawcett, 2013).

As in other sectors, interest in the use of BDAC in the health sector has been growing. However, the main focus is the application of BDAC to medical activities rather than to OSCM. Further, healthcare lags behind other sectors, such as distribution, not only in the adoption of new digital technologies (BDAC, AI, IoT, Cloud) but also in the development of traditional information technologies (ERP, RFID, DRP) used in information sharing and integration of organisational functions (Beaulieu & Bentahar, 2021). The lack of support for operations and supply chain managers from hospital top management partly explains the lack of technology investments and the poor organisational and environmental performance of healthcare facilities (Yoon et al., 2016).

Although BDAC in healthcare is in its nascent stage, the rapid development in recent years of digitalisation of processes via electronic applications and platforms (IoT, electronic health records, mobile devices) is rapidly generating data, which creates a challenge for managers. The analysis of a massive volume of data can provide opportunities, improve service quality and efficiency, and create value for healthcare stakeholders (physicians, patients, and managers). Researchers argue that BDAC could be used to improve treatments for patients and quality of care, support clinical operations, and reduce medical errors (Jee & Kim, 2013; Wang et al., 2018). Further, the adoption of big data by public and private healthcare organisations can enhance decision-making (Papadopoulos et al., 2017; Wang et al., 2018) and contribute to cost reduction. Dash et al. (2019) argue that healthcare organisations can lower their annual costs by 25% through the implementation of big data.

Beyond the medical domain, the application of BDAC within OSCM can offer healthcare institutions potential benefits. Indeed, BDAC can help optimise operational processes, reduce costs, and improve decision-making processes and service quality (Guha & Kumar, 2018). Further, BDAC can help organisations optimise resources, forecast operating room demands, and improve patient pathway management and logistics (Dash et al., 2019). Finally, BDAC can facilitate the integration of environmental approaches into the organisation's internal processes and supply chain and enhance hospitals' environmental performance (Benzidia et. al., 2021).

Apart from rare exceptions (e.g. Benzidia et al., 2021), few empirical studies have explored the application and assimilation of BDAC in healthcare OSCM and its impact on environmental innovation and organisational performance. Moreover, practitioners are still sceptical about the impact of big data on organisational environmental performance (Sharma et al., 2014). Thus, there is a strong need to understand how big data can facilitate the decision-making process linked to environmental issues within the healthcare sector.

2.3 Green process innovation

For several years, the management of green innovations has been gaining importance both in practice and academia in response to environmental awareness and the effects of climate change pressures. These considerations have led organisations to integrate sustainability into their strategic plans through innovative environmental measures as part of their OSCM. Green innovation has thus proven to be a response to popular issues in recent decades, related in particular to global warming and environmental challenges (Khan & Johl, 2019). Chen et al., (2006, p. 534) define green innovation as 'hardware or software innovation that is related to green products or processes, including the innovation in technologies that are involved in energy saving, pollution prevention, waste recycling, green product designs, or corporate environmental management'. Green innovation has been associated with other concepts such as sustainable, ecological, and environmental innovation, which have similar characteristics (Nguyen Dang et al., 2022; Tariq et al., 2017). Chen et al. (2006) distinguished four types of green innovation: product, process, service, and organisational innovation. In this study, we focus on process innovation, defined as changes in manufacturing processes and systems, to ensure energy saving, pollution prevention, and waste recycling (Li et al., 2016, p. 1092). Beyond manufacturing processes and systems, researchers such as Roberts (2003) and have expanded the application of green process innovation to other operations such as green procurement and green logistics. The hospital sector continues to lag behind other industries regarding green innovation. Consequently, studies remain limited, and further research is required, particularly given hospitals' significant environmental impact. In response to escalating environmental threats, green innovation has been gaining momentum in recent years. In France, several hospitals are attempting to implement green process innovations based on technologies that reduce excessive energy consumption and manage waste effectively while using fewer resources. The green process innovation that we advocate can eventually translate into investments in hospital OSCM. This includes all medical activities such as pharmacy and operating rooms and support activities such as logistics and transportation. Additionally, the health crisis caused by COVID-19 has accelerated the use of green innovation in the healthcare supply chain. Several developed countries, including France, have lifted all financial constraints to combat this pandemic and have turned to innovative practices that allow hospitals to evolve towards green organisations.

2.4 Data-driven innovation

Despite growing interest from researchers and practitioners, empirical research on the role of BDAC as a facilitator of innovation in OSCM remains very limited. More specifically, research on the relationship between BDAC and green process innovation in hospitals remains in its infancy. However, our review of the literature allows us to identify various studies offering an understanding of the data-driven innovation approach (DDI). Researchers view DDI as a new paradigm of knowledge assets where BDAC plays an essential role in the innovation activities of a company (Hagstorm, 2012). DDI not only affects existing operations but also contributes to the creation of new processes, products and business models (Akter et al., 2021; Babu et al., 2021).

The application of BDAC has produced innovative effects in several sectors. Drawing on a systematic literature review and a qualitative analysis, the conceptual framework constructed by Babu et al. (2021) highlights the key role of BDAC in the implementation of process and product innovations in manufacturing industries. In the hospital sector, owing to technological developments in medical activities, the use of BDAC is being assimilated and offers hospitals a new way to stimulate innovation in, for example, personalized medicine or pharmaceutical activities. However, the application of BDAC in hospital OSCM remains very limited and underused despite the potential of the existing sources of data.

Furthermore, other research studies consider BDAC as a lever for green innovation and sustainable development of OSCM (Govindan et al., 2018; Song et al., 2019). Despite the potential positive influence of BDAC on innovation, the practical implications and the empirical evidence of this proposition remain underdeveloped (Johnson et al., 2017). This observation can be explained by the importance of other variables such as technical skills, human resource practices and the commitment of management to promoting innovation (Gunasekaran et al., 2017; Jabbour et al., 2019).

3 Conceptual framework and research hypotheses

This study proposes a conceptual framework and empirically tests the association between BDAC use, internal environmental integration, green process innovation, and environmental performance (see Fig. 1). Our study postulates that the relationship between internal envi-

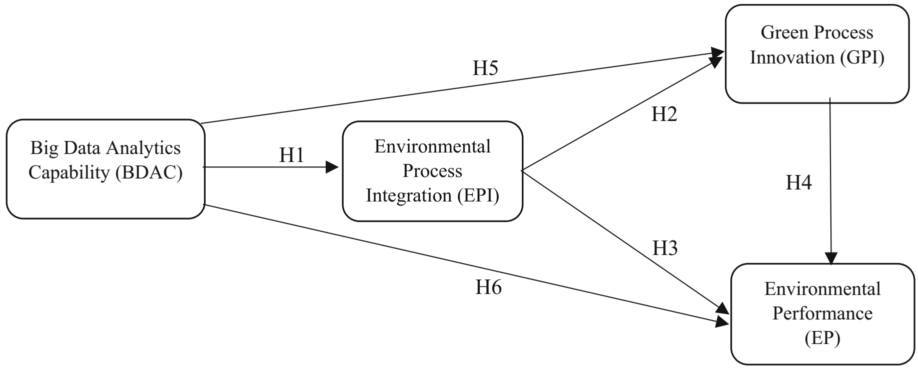

Fig. 1 Conceptual model

ronmental integration and environmental performance will be strengthened by the mediating role of green process innovation. Based on the theoretical arguments that identified the external factors of the dynamic environment, this research focuses on healthcare organisations, which, due to strong pressure from their external environment, need to adopt innovative solutions to improve the environmental practices of OSCM. Further, the literature suggests that in a dynamic environment, companies can draw on their technological capacity to confront the instability of their environment. Specifically, as suggested by Chen et al. (2015), we assert that BDAC technology represents an important technical value in confronting such a changing environment (Wamba et al., 2020). Therefore, researchers have conceptualised BDAC as a technology opportunity that can enable hospitals to integrate internal operations better. Thus, BDAC can help hospitals not only to strengthen the ties between their internal teams regarding environmental issues but also to improve their environmental performance (Benzidia et al., 2021).

The literature affirms that robust IT infrastructures facilitate the recording and control of information about organisational processes, making their formalisation more viable (McAfee, 2002; Whitaker et al., 2007). Pagell (2004) finds that the presence of IT infrastructure pushes an enterprise towards full process integration and resolves information fragmentation. Studies maintain that technological infrastructures are necessary for internal supply chain process integration, especially in complex organisations with excessive transaction data (Wamba & Mishra, 2017). This finding applies to hospitals that produce large and complex datasets and comprise multiple departments and services with different preferences and priorities. Therefore, the decision-making process requires a consensus between the medical and managerial teams to define environmental strategies (Jabbour et al., 2019). Madanian et al. (2019) find that access to knowledge from other hospital departments remains limited because data have not been sufficiently valued due to difficulties in management, evaluation, and analysis. In our study, we adopt the dynamic capabilities view, an extension of the resource-based view (RBV), to explain firms' competitive advantage in volatile markets and highly dynamic environments (Winter, 2003). Specifically, we argue, based on the RBV, that an organization can create capabilities to respond to rapidly changing ecological constraints. Moreover, we construe innovative capability as one of the two main dynamic capabilities for ensuring firm performance (Darroch, 2005). Innovative capability is a dynamic capability that consists of the mobilization of practices and solutions to transform processes, products and services. Specifically, green innovation capability is composed of environmentally friendly practices throughout the hospital OSCM that act as key mechanisms to drive innovation. Following the RBW, we conceptualize BDAC as a dynamic capability that contributes to processes of analysis, coordination, and internal integration, which ultimately leads to increased levels of innovation capabilities (Mikalef et al., 2019) and improved green performance. The use of analytical techniques such as BDAC appears to be a fundamental solution that can allow healthcare managers to improve their data processing capacity and make their internal processes operationally efficient and more environmentally friendly (Benzidia et al., 2021; Wang et al., 2016). Based on these arguments, we propose the following hypothesis:

H1 The use of BDAC has a positive impact on environmental process integration.

Internal integration has often been considered a driver of product and process innovation (Droge et al., 2004). It has been associated with product innovation by considering that successful product development can be achieved only if the organisation can effectively integrate internal functional units (Weng et al., 2015). However, little research has explored the link between internal integration and process innovation (Ettlie & Reza, 1992). Further, from the environmental standpoint, the association between internal integration and green process innovation has not been sufficiently examined in the literature (Wu, 2013). The scant research on this association has obtained mixed results. For example, Wong et al. (2020) found that internal integration does not influence green process innovation. Rather, this association required other intermediate factors such as supplier and customer integration. Other research considers environmental integration as an important factor for investing in green innovation. Shrivastava (1995) contends that internal environmental integration aligns departmental strategies and goals and allows for the allocation of resources to achieve green innovation.

In this study, we adopt the definition of internal integration put forth by Du et al. (2018): 'the degree of connection, coordination, and information sharing of functional strategies, development, and improvement activities performed by each department in the green innovation process'. Therefore, we postulate that internal integration increases the likelihood of improving green process innovation through mega data analytic capability. Given the environmental constraints that hospitals face, we argue that organisations that engage in the green innovation process procure more value by intensifying their internal integration. Hence, we propose the following hypothesis:

H2 Environmental process integration supports the integration of green process innovation.

Internal process integration refers to the degree of harmonisation of functional areas within the enterprise (Narayanan et al., 2011). The literature suggests that achieving internal integration is crucial in the overall integration of supply chain processes. Internal process integration is essential in complex supply chains such as hospitals due to their highly interdependent functions and heterogeneous stakeholders. Additionally, internal teams do not have sufficient knowledge of other functional areas (Benzidia et al., 2021).

It is widely recognised that organisations that operate in an integrated cross-functional process improve their performance (Flynn et al., 2010; Narayanan et al., 2011). In the environmental domain, studies suggest that the environmental performance of organisations depends on the level of inter-functional integration (Chen et al., 2015; Dubey et al., 2015; Pham & Pham, 2021; Shah & Soomro, 2020). However, empirical evidence of improved environmental performance resulting from corporate environmental integration is considerably limited. For Kang et al. (2018), internal integration reflects a firm's decisions to improve its environmental practices. This approach prevents disconnection and fragmentation between processes and functional barriers (Yang et al., 2013). Specifically, environmental integration allows teams to continuously explore ways to reduce environmental impacts in their operations, which contributes to improving environmental practices (Sroufe, 2003).

In this study, we advance that strong internal integration should be extended to the overall hospital process, including managerial and medical activities. It would also allow cross-functional hospital teams to play a significant role in decision-making related to the environment and engage in common goals. Hence, we propose the following hypothesis:

H3 Environmental process integration has a positive effect on environmental performance.

There is mixed evidence on the effects of green process innovation (Wong et al., 2020). Green innovation, especially green process innovation, requires firms to mobilise significant resources with a high risk of failure because it is difficult to achieve significant economic benefits in the short term (Rui & Lu, 2021). Studies on the effect of green innovation and performance have often examined multiple categories of innovation. In this study, we analyse only the effect of green process innovation on hospital environmental performance. Chen et al. (2006), among other researchers, report that green process innovation helps organisations meet the requirements of regulatory standards and minimise environmental risks, which, in turn, improves environmental performance and corporate image. Zhao and Sun (2016) confirmed that the implementation of green process innovation enables organisations to reduce environmental risks, pollution, and other negative effects. Therefore, companies increase their financial and social performance through waste and cost reduction (Weng et al., 2015). Environmental innovation and, more specifically, process-related innovation have also been examined as a mediator to measure the effect of environmental performance. However, this particular relationship has not been sufficiently explored in the literature. For example, Seman et al. (2019) found a mediating effect of green innovation on the relationship between green supply chain management and environmental performance in 123 manufacturing organisations in Malaysia. Eiadat et al. (2008) examined the positive effect between green suppliers and green processes, which, in turn, increases environmental performance. Given the dynamic environment of hospitals, we predict that the integration of internal environmental processes not only influences environmental performance but also indirectly encourages these organisations to adopt a green innovation strategy. Therefore, green process innovation should have a mediating effect that enhances the environmental performance of such organisations. Based on the above discussion, we propose the following hypothesis:

H4 Green innovation has a mediating effect on hospitals' environmental performance.

Recently, some studies have focused on the role of BDAC in the innovation process and highlighted its importance in improving manufacturing operations and product added value (El-Kassar & Singh, 2019). The results show that BDAC technology can significantly support the development of green innovation. However, to date, there is insufficient evidence resulting from rigorous empirical testing of the benefits of BDAC and the green innovation process. Moreover, most of the research on the BDAC and GPI relationship has examined manufacturing industries; few results have been published in the health field (Benzidia et al., 2021).

Waqas et al. (2021) advance that BDAC provides emerging technological resources to manage big data effectively, and stimulates green innovation in the Chinese manufacturing industry. Capurro et al. (2022) argue that BDAC can generate new heterogeneous knowledge and ideas that often facilitate the development of innovation and the redefinition of firm-customer relationships. Further, BDAC is useful for understanding customer behaviors and changes that propel businesses to adapt their innovation process as the market evolves (Maglio & Lim, 2016). We can thus extend the previous hypothesis to test the direct impact of BDAC and the green innovation process in hospital organizations:

H5 The use of BDAC positively influences the green innovation process.

Recent literature increasingly acknowledges that the use of BDAC is becoming a contributing factor to overcoming technological challenges (Song et al., 2019). Big data are seen as a new trend in strategic management that organizations can use to improve corporate sustainability and especially environmental performance (Calza et al., 2020; Dubey et al., 2019a, 2019b). Positive outcomes include reducing energy consumption, gas or solid emissions, pollution, resource waste, and other adverse environmental effects (Belhadi et al., 2020). Big data have been shown to affect environmental performance by reducing energy consumption and energy costs (Zhang et al., 2018), for example. Benzidia et al. (2021) affirm that BDAC is a trend to develop credible sources of information from big data that supports decision making and improves environmental performance in hospitals. Other researchers have demonstrated the potential of BDAC in enhancing monitoring, visualization, and analysis techniques to reduce waste and improve energy efficiency (Belhadi et al., 2020). Although a growing body of literature is presenting results showing that BDAC can help improve environmental performance, the studies mostly provide conceptual and anecdotal evidence and theoretical propositions (Mishra et al., 2020; Song et al., 2017). Hence the following hypothesis:

H6 The use of BDAC positively influences environmental performance.

4 Methodology

The research model involves the use of structural equation models. In this study, we mobilised the analysis according to the covariance structures: the partial least squares (PLS) approach.

Beyond its predictive capacity (Chin, 1998), the use of this approach is justified by its suitability to exploratory research, which is relevant for our research on new BDAC technology.

Furthermore, the PLS approach can be used regardless of sample size (Hair et al., 2017) and particularly with small sample sizes, which is the case in this study. Indeed, the model evaluation framework is based on the use of resampling methods to evaluate standard errors. Notably, the PLS approach examines the measurement models by a block of indicators. Therefore, the number of observations required is determined by that of parameters to be estimated simultaneously. Thus, the PLS method is less sensitive to sample size.

4.1 Sample and procedure

To test the hypotheses of our conceptual model, we used data collected by a survey conducted in 2020 among supply chain executives within hospitals. We selected executives involved in OSCM. A list of hospitals was identified from information provided by the French Hospital Federation (FHF), the French federation of clinics and Private Hospitals (FHP), and other hospitals. We collected the responses to an online survey conducted using Sphinx software.

We received 123 usable questionnaires, and the response rate was 31%. According to Malhotra and Grover (1998), this response rate is considered acceptable for statistical analysis. The details of responses usable for data analysis are presented in Table 1.

Table 1 Data characteristics

Demographic Characteristics	Number of respondents	Percentage of respondents (%)
Experience of the manager		
≤ 1 year	7	6
Between 1 and 5 years	31	25
> 5 years	85	69
Hospital status		
Private	66	54
Public	53	43
Other	4	3
Number of beds		
≤ 199	8	7
Between 200 and 499	55	45
Between 500 and 999	41	32
Between 1000 and 2000	13	11
> 2000	6	5

4.2 Non-response bias

Data collection by the survey can present problems related to participant non-response and the bias this generates (Armstrong & Overton, 1977; Chen & Paulraj, 2004). To assess the non-response bias, as suggested by Chen and Paulraj (2004), we divided the responses of our sample into two groups according to the date of receipt of the questionnaire: late respondents and early respondents (Armstrong & Overton, 1977). Both the groups include 40 respondents each. We performed a student's t-test on the responses of the two groups, which revealed no statistically significant difference between the two groups (Armstrong & Overton, 1977).

Additionally, we performed Levene's variance homogeneity test. The criterion for passing the test is the absence of a significant difference between the values ($p > 0.05$). The results showed no difference between the two groups. Therefore, we concluded that non-response bias is not a serious issue in this study.

4.3 Common method bias

We collected data for this research through a self-administered questionnaire. Several studies have associated the risk of common method variance (CMV) with the use of self-reported measures of the same sample (Podsakof & Todor, 1985). Therefore, it is essential to determine to what extent the correlations between variables are due to CMV.

To minimise the risk of a common method, we took several precautions. Following the recommendations of Podsakoff et al. (2003), we first improved the construction of measurement scales. To facilitate an improved understanding of the answers, we avoided vague concepts and made the questions specific, simple, and concise (Tourangeau et al., 2000). We also counterbalanced the orders of measurement of the dependent and independent variables. Finally, to minimise apprehension among the respondents, we protected their anonymity and reassured them by specifying that there is no right or wrong answer. These procedures contributed to minimising methodological biases at the stage of reporting or editing responses.

We also performed statistical analyses to assess the possible effect of CMV, using several tests recommended in the literature (Podsakoff et al., 2003; Tehseen et al., 2017). We first performed Harman's single-factor test, which uses principal component analysis in SPSS to check whether a single general factor results from most of the covariance between measures. Harman's one-factor method accounts for only 43.7% of the explained variance. Accordingly, no factor emerged that represents most of the covariance, which indicates that CMV is not an issue in this study (Chang et al., 2010).

We also used the confirmatory factor analysis (CFA) marker technique of latent factors to test the effects of CMV (Podsakoff & Todor, 1985; Podsakoff et al., 2003). This method consists of adding a general factor to group together all items of the tested hypothetical models. This general factor uses the score of the first unturned factor that is obtained during principal component analysis. Using SmartPLS, we compared the difference between the R^2 values before and after adding the general factor. The result of this test shows that the addition of this general factor leads to a slight increase in the R^2 value of the endogenous construct (< 0.01), indicating that the potential effect bias of the common method is minimal in the study.

We also checked the multicollinearity between variables by applying the collinearity approach proposed by Kock and Lynn (2012) and calculating the variance inflation factor (VIF). The results were between 1.80 and 2.27. According to Kock (2013), values below the threshold of 3.3 are acceptable and indicate the absence of multicollinearity between the variables. On this basis, multicollinearity is not an issue in this study. Overall, this confirms the absence of bias due to a method factor.

4.4 Instrument and scale development

To examine the conceptual model, a questionnaire and measurement scales were designed. The questionnaire was developed in several stages: The initial construction of the questionnaire with the choice of measurement scales, a pre-test and a pilot test to verify the reliability and validity of each construct. First, a thorough review of the literature was conducted to differentiate the concepts addressed. We consequently arrived at the definitions of the constructs and the first list of items for each construct. We used five-point Likert scales ranging from "1 = strongly disagree" to "5 = strongly agree" to evaluate the questionnaire items. The second stage of development consisted in submitting the initial instrument to nine experts. Three types of experts were consulted: (1) academics conducting research on the topic of healthcare supply chain and technology management (n = 2); (2) research professionals familiar with the use and development of questionnaires (n = 2); and (3) supply chain executives within hospitals (n = 5).

The purpose of this pre-test was to verify the relevance of the items and whether the various items of an instrument are representative of the construct(s) being measured (content validity) (DeVellis, 2012). The pretest also assessed the comprehensibility and acceptability of the questionnaire, and its relevance to its objectives (face validity). Some ambiguous phrases due to translation in the scale items were found and subsequently revised for clarity. Experts' comments were analyzed and the questionnaire was adjusted accordingly. The last step in the development of our questionnaire consists of a pilot test. With the help of experts and based on personal contacts, we compile a list of supply chain professionals within hospitals representing our target. These professionals agreed to participate in this pilot test. We received 29 usable questionnaires out of the 35 questionnaires sent by e-mail. We found the pilot sample size to be adequate for this test. According to some researchers (Connelly, 2008), the sample size of the pilot study should be 10% of the sample size of the main study. This group of target participants is not included in the main survey.

We perform a Principal Component Analysis (PCA) by SPSS to assess the reliability of the constructed items. The reliability test shows that the Cronbach's alpha value for this pilot study is 0.8 after the items with lower internal consistency have been deleted. The list of final measurement items used in the study is presented in Table 2.

All questions are written in the local language, French; therefore, we use a back translation process to provide an appropriate correspondence between English and French (Malhotra et al., 1996). We conduct a test in which a group of bilingual participants is given both the translated version and the original version of the questionnaire and asked to evaluate the degree of similarity between the two versions. The final drafting of the questionnaire takes the difficulties identified into consideration. To ensure that respondents do not sense the inherent logic of each construct based on the order of items in the questionnaire, we shuffle the questions pertaining to each construct.

5 Data analysis

Testing the research hypotheses formulated within the framework of the conceptual model was based on the SmartPLS method. As advocated by Chin (1998), data analysis was organised into two stages: evaluating the measurement model and testing structural relationships.

5.1 Measurement model evaluation

This step consisted of verifying the reliability and validity of the scales used in this work. All constructs used in the model were reflective constructs. For each construct, we evaluated the validity and reliability of the measurements.

5.1.1 Convergent validity

First, we checked that the items converged on their respective construct. Analysis using Cronbach's alpha and item-constructed correlation was performed to refine the measures and eliminate items that may cause deterioration in the alpha coefficient. Consequently, we eliminated items that have a factor contribution of less than 0.7 (or loading $\lambda < 0.7$). These are thus considered by Tenenhaus et al. (2005) to have a good level of reliability. Convergent validity was also measured using the extracted mean–variance (AVE) (Chin, 1998). The AVE for each dimension ranged from 0.738 to 0.777, all above the commonly recommended 0.50 threshold.

5.1.2 Reliability analysis

To measure the internal consistency of each construct, we examined the composite reliability using the coefficient rho (ρ) of Dillon and Goldstein (Nunnally, 1978). The four constructs of our model demonstrated satisfactory results, all exceeding the value of 0.7.

Both the convergent validity and the reliability of all scales returned satisfactory results (see Table 3). Additionally, the study of cross-loadings unambiguously underlined the correctness of the specification of the tested scale structures.

Table 2 Constructs and items used in the survey

Construct & Derivation	Indicator	Measures
Big data analytics capability (BDAC), adapted from Srinivasan and Swink (2018), Dubey et al. (2019a, 2019b)	BDAC1	Use of advanced analytical techniques (e.g. simulation, optimisation, regression) to improve decision-making
	BDAC2	Use of multiple data sources to improve decision-making
	BDAC3	Use of data visualisation techniques (e.g. dashboards) to assist decision-makers in understanding complex information
	BDAC4	Deployment of dashboard applications/information in communication devices (e.g. smartphones, computers) of the OSCM
Environmental process integration (EPI), adapted from Narayanan et al. (2011), Graham (2018)	EPI1	Active knowledge sharing across internal functions to minimise our plant's environmental impact
	EPI2	Active cooperation across internal functions to minimise our plant's environmental impact
	EPI3	Use of cross-functional teams in process integration improvement
	EPI4	Data integration among internal functions
	EPI5	Real-time integration and connection among all internal functions
Green Process Innovation (GPI), adapted from Chiou et al. (2011), El-Kassar and Singh (2019)	GPI1	Less consumption of natural resources during production
	GPI2	Recycling, reusing, and remanufacturing
	GPI3	Focus on using renewable technology
	GPI4	Redesigning manufacturing and logistics processes for environmental effectiveness
Environmental performance (EP), adapted from Paillé et al. (2014), Singh and El-Kassar (2019)	EP1	Decrease in air emissions
	EP2	Decrease in hazardous wastes
	EP3	Establishment of partnership with many green suppliers
	EP4	Increase in compliance with global environmental regulations
	EP5	Increase in the environmentally friendly purchase rate of goods and materials (e.g. medicines)
	EP6	Reduction of environmental accident risks such as medical waste leakage, poisoning, or radiation emissions

Table 3 Results of the measurement model

Constructs	Items	Loadings	Cronbach's Alpha	Rho A	Composite reliability (ρc)	AVE
Big Data Analytics Capability (BDAC)	BDAC1	0.897	0.887	0.903	0.923	0.750
	BDAC2	0.902				
	BDAC3	0.908				
	BDAC4	0.744				
Environmental Process Integration (EPI)	EPI1	0.857	0.911	0.920	0.934	0.738
	EPI2	0.879				
	EPI3	0.807				
	EPI4	0.845				
	EPI5	0.905				
Green Process Innovation (GPI)	GPI1	0,816	0.893	0.896	0.926	0.757
	GPI2	0.896				
	GPI3	0.909				
	GPI4	0.854				
Environnemental Performance (EP)	EP1	0.893	0.943	0.943	0.954	0.777
	EP2	0.887				
	EP3	0.892				
	EP4	0.851				
	EP5	0.893				
	EP6	0.874				

5.1.3 Discriminant validity

To check the external validity, we examined the discriminant validity of each construct. This test aimed to ensure that reflective items, which are intended to measure a certain construct, differed from those not supposed to measure that construct (Straub et al., 2004).

In the context of the PLS approach, this implied that a construct must share more variance with its measures than it shares with other constructs in the same model. The latent variables could therefore be correlated with each other, but they must measure different concepts. Accordingly, it must be possible to discriminate against them.

To assess discriminant validity, we used the recent heterotrait−monotrait ratio of correlation (HTMT) approach (Henseler et al., 2015), which is more efficient than the initial approach proposed by Fornell and Larcker (1981). According to Gold et al. (2001), HTMT results should not be > 0.9, although some authors suggest a threshold of 0.85 as an empirical rule for discriminant validity (Kline, 2011). All the corresponding indices showed an index greater than 0.85 and were therefore considered satisfactory (see Table 4).

The results indicated that the validity and reliability of the constructs were adequate for testing and analysing the structural model.

Table 4 Heterotrait-Monotrait (HTMT)

Constructs	BDAC	EPI	GIP
Big Data Analytics Capability (BDAC)			
Environmental Process Integration (EPI)	0.535		
Green Process Innovation (GPI)	0.838	0.583	
Environmental Performance (EP)	0.760	0.582	0.717

5.2 Model testing results

5.2.1 Structural model evaluation

To validate the research model, we used the four-step PLS approach. First, we estimated the quality of the model, then its predictive validity, followed by a bootstrap procedure to estimate the structural coefficients. Finally, a control test was performed to determine the effects of size and hospital status.

Regarding the quality of the fit, Tenenhaus et al. (2005) proposed the overall goodness-of-fit validation index (GoF). The GoF in the current model reflects the high quality of construction for the external and internal models (0.504). This value is the geometric mean of the average commonality and the average R^2 of the endogenous latent variables (Henseler & Sarstedt, 2013; Wetzels et al., 2009). According to Tenenhauss GoF guidelines, a GoF value greater than 0.36 represents a large fit (Kock, 2013); therefore, it indicates that the overall quality of the model was satisfactory.

To determine predictive validity, we used the Stone−Geisser Q^2 coefficient by applying the blindfolding technique (Geisser, 1974). This test measures the quality of each structural equation. As recommended by Henseler et al. (2009), a research model with Q^2 statistics greater than zero is considered to have predictive relevance (Chin, 1998; Henseler et al., 2009). The results of this technique implied that the Q^2 indices were positive and different from zero (Q^2 value > 0.17). These results indicated that the model had predictive validity (Hair et al., 2017).

Finally, we examined the level of significance of the estimation parameters (path coefficient) of the relationships between the latent variables. To this end, a systematic bootstrap procedure was undertaken with 5000 replications to calculate critical values and verify that the confidence intervals did not surround zero. All the obtained structural coefficients were statistically significant and thus helped validate the formulated research hypotheses.

5.3 Hypotheses testing

As shown in the table, the research hypothesis H1 is validated. Indeed, the value of BDAC has a positive impact on environmental process integration. That is, the use of BDAC by a healthcare facility improves collaboration in the supply chain and internal integration between departments and thus supports the decision-making process for environmental initiatives.

The results show a positive influence of environmental process integration on the innovation process (H2). Effective environmental process integration encourages the establishment of green innovation processes, for example, the use of renewable technologies. Environmental process integration also has a direct impact on environmental performance (H3).

Table 5 Standardised structural estimates and hypotheses tests

Hypothesis	Effect of	On	β	Std. dev	t-Values	*p*-values	Result
H1	BDAC	EPI	0.492***	0.074	6629	0.000	Supported
H2	EPI	GPI	0.207**	0.065	3157	0.002	Supported
H3	GPI	EP	0.215*	0.101	2116	0.034	Supported
H4	EPI	EP	0.217**	0.072	2991	0,003	Supported
H5	BDAC	GPI	0.670***	0.059	11,460	0.000	Supported
H6	BDAC	EP	0.429***	0.091	4728	0,000	Supported

*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$

Hypothesis H4, which predicts that the innovation process positively influences EP, is statistically significant given the values taken by the value t. This indicates that the green innovation process improves the capacity of healthcare establishments to implement an effective environmental policy.

Finally, the hypotheses linking BDAC to green innovation processes (H5) and environmental performance (H6) are statistically significant given the t-values obtained. In the hospital field, BDAC sheds light on the market evolution and how to improve the innovation process. BDAC strategies to facilitate managers' decision making can enhance environmental performance (Table 5).

5.4 Mediation analysis

The SmartPLS module includes a parametric test to compare the coefficients and parameters of the model with and without mediation. Thus, we followed the approach of Baron and Kenny (1986) to understand the direct effects of independent and dependent variables in the absence of mediators.

The value of the path coefficient representing the direct effect is 0.546, and t = 8.904. This shows that, in the absence of mediators, the direct effect between the concepts of environmental process integration (independent variable) and environmental performance (dependent variable) is significant. Subsequently, we integrated the mediating variable 'green innovation process', and the comparison revealed a differential effect. This suggests a partial mediating effect of the innovation process β = 0,215. In other words, environmental process integration has both a direct and an indirect impact on environmental performance through the mediating role.

We also analyze the mediation effect for the relationships between BDAC and environmental performance as well as BDAC and Green process innovation (GPI). The results of these analyses show a weaker indirect impact (po.01) compared with the direct effects of BDAC on Green process innovation (GPI). In other words, the Environmental Process Integration (EPI) variable plays a partial mediating role between BDAC and GPI.

The results of these analyzes show that BDAC has both a direct and indirect impact on environmental performance (EP). The direct impact is greater than the indirect impact by 0.148. The results also show a lower indirect impact (po.03) compared to the direct effects of BDAC on environmental performance (EP) by integrating the mediating variable "environmental process integration" (EPI). Hence, as demonstrated by several researchers (Mishra & Singh, 2018), BDAC is an organizational capability that is technologically capable

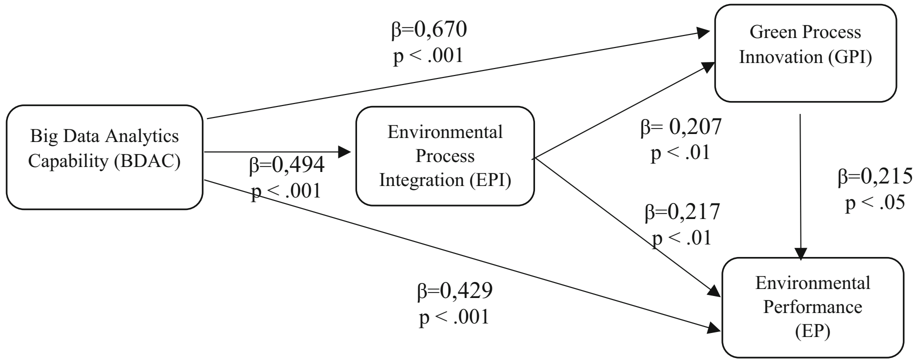

Fig. 2 Structural estimates

of rapidly processing large volumes of diverse data to obtain valuable information. It thus enables hospitals to improve their environmental performance through the reduction of waste in the food supply chain, for example. This impact can also be achieved through environmental innovation and better integration (EPI).

To test the effects of external variables on our structural model, we include two control variables: hospital size and hospital status. Hospital size, measured by the number of beds, allows us to consider the role of size in explaining environmental performance. The variable hospital status is also incorporated to test whether the difference between private and public hospitals could influence the results.

The empirical results confirm no impact of hospital size on performance environmental ($\beta = 0.024$; $p = 0.70$). The results are also non-significant for the variable hospital status ($\beta = 0.083$; $p = 0.22$) (Fig. 2).

6 Discussion and implications

This study attempts to fill the gaps in the literature mentioned above by investigating whether investing in BDACs can lead to improved green innovation and hospital performance. Although the literature on the analysis of the role of BDACs in corporate environmental strategy has been growing in recent years, research with theoretical foundations and empirical tests in hospital OSCM is lacking. Thus, the study provides the OSCM research community with a framework and an empirical understanding of BDAC in relation to environmental practices and innovations for improving the environmental performance of healthcare organisations. Thus, the study contributes to the literature on BDAC, green OSCM, and healthcare management.

The study findings provide substantial insights and contributions. The paper contributes to the field of healthcare management. In the literature, few studies have investigated the critical role of BDAC in environmental concerns in healthcare OSCM. The studies mainly developed theoretical frameworks embedding Industry 4.0 constructs and digitalisation technologies in relation to sustainability goals in the healthcare industry OSCM (Wang et al., 2018; Dash et al., 2019). In this study, we empirically test a conceptual framework to provide not only a theoretical perspective but also the practical implications of adopting BDAC in a healthcare context.

6.1 Theoretical implications

This article makes original contributions in at least three different directions. Above all, this research contributes to the ongoing debate on the opportunities that BDAC technologies to improve business innovation. The contribution of this research consists of deepening existing research by focusing specifically on green innovation, an area that is relatively unexplored by researchers to date. More specifically, the results of this study provide major insights for hospitals engaging in ecological transition strategies. It highlights the role of BDACs as a dynamic capability participating in the green innovation process, thereby improving the green performance of hospitals. Using survey data from 123 supply chain managers in French hospitals, this study is one of the few to empirically and explicitly explore the antecedents of green innovation with BDACs in the hospital sector. As such, it is different so from the majority of studies in this field, which have been conducted in other sectors, especially in the industrial sector (Wamba et al., 2017; Bresciani et al., 2021; Tian et al., 2022).

Second, as part of the dynamic capabilities theory, we conceptualized the BDAC as an internal skill adapted to a dynamic and turbulent environment (Kohli & Grover, 2008). The theoretical model contributes to theories RBV and dynamic capacities. It also augments the small but growing body of studies that explores the impact of using BDAC technology in operations and green supply chain management (Bag et al., 2020). Indeed, in hospitals that use BDAC technology, it helps managers to implement environmentally friendly practices and encourages the ecological transition of the supply chain of healthcare establishments.

Third, this study contributes to advancing theoretical knowledge on why and how intermediate mechanisms of the internal integration process in the context of BDAC can be leveraged to increase environmental performance. The BDAC improves integration and internal collaboration (Dubey et al., 2019b) through better information sharing to streamline internal communication. This sharing also contributes to the emergence of new ideas by creating a common center of knowledge. In other words, the more hospitals engage in internal integration, the more likely teams are to share their information, allowing managers to drive green strategy and inform decision-making processes. This increases hospitals' willingness to seriously engage in green initiatives and improve environmental performance. These results are consistent with theoretical conjectures that green internal integration is useful for environmental performance (Benzidia et al., 2021). The need for internal integration is mainly related to the multidisciplinary nature of hospitals, which requires knowledge sharing on environmental needs and issues among internal teams. Thus, it can be concluded that investment in BDAC is a proactive technological measure to improve internal integration in order to enhance environmental performance, which is consistent with previous findings (Zhao et al., 2017).

6.2 Managerial implications

Studies show that only 42% of health organisations rigorously adopt BDAC strategies to facilitate managers' decision-making and create value for the organisation (Wang et al., 2018). Thus, managers need to pay attention to BDAC when making strategic decisions in environmental integration and the diffusion of environmental innovation in OSCM.

Managers can harness BDAC not only to integrate environmental approaches in hospital OSCM but also to support green process innovation and consequently achieve high environmental performance. Thus, healthcare organisations should increase their commitments to the green innovation process to successfully implement green innovation practices and enhance their environmental performance.

Further, the results of this study included several proposals and word clusters that can help decision-makers adopt green operations and SC in healthcare organisations. Therefore, managers should concentrate on the strategic and sustainable value of BDAC rather than on the technical issues of implementing BDAC.

Finally, the study enables healthcare practitioners to understand better the role of BDAC in strategic decisions regarding sustainability and achieving the goals of healthcare organisations. To this end, these organisations should create BDAC and AI structures along with a culture of information sharing and train managers to exploit BDAC results. Managers can also build external partnerships to support the implementation of new digitalisation technologies and facilitate organisational change.

6.3 Limitations and future research directions

Although this study contributes to existing literature, it has limitations that open up avenues for future research. First, the study focused on the green innovation process, which is certainly critical to the environmental performance of organisations. However, other types of green innovation, such as green managerial innovation and green product innovation, could complement processes intended to improve environmental performance. Future research could integrate the three types of innovation and study their impact on environmental performance and the competitive advantage provided to organisations.

Second, the study focused on a sample of hospitals in France. Extending the research to other countries in Europe whose environments differ regarding their characteristics could enhance the generalisability of the research findings.

Third, we conducted a quantitative study based on surveys and structural equation modelling. To triangulate the data and understand the phenomenon better, future research could comprise a qualitative study that includes semi-structured interviews with managers. This qualitative study could explore the antecedents of BDAC, such as managerial and technological capabilities.

Data availability The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to information that could compromise the privacy of research participants.

Declarations

Ethical approval We have followed the university ethical approval for collecting datas for the study.

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