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The impact of big data analytics and artificial intelligence on green supply chain process integration and hospital environmental performance

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Abstract

Big data analytics and artificial intelligence (BDA-AI) technologies have attracted increasing interest in recent years from academics and practitioners. However, few empirical studies have investigated the benefits of BDA-AI in the supply chain integration process and its impact on environmental performance. To fill this gap, we extended the organizational information processing theory by integrating BDA-AI and positioning digital learning as a moderator of the green supply chain process. We developed a conceptual model to test a sample of data from 168 French hospitals using a partial least squares regression-based structural equation modeling method. The findings showed that the use of BDA-AI technologies has a significant effect on environmental process integration and green supply chain collaboration. The study also underlined that both environmental process integration and green supply chain collaboration have a significant impact on environmental performance. The results highlight the moderating role of green digital learning in the relationships between BDA-AI and green supply chain collaboration, a major finding that has not been highlighted in the extant literature. This article provides valuable insight for logistics/supply chain managers, helping them in mobilizing BDA-AI technologies for supporting green supply processes and enhancing environmental performance.

Keywords: big data analytics; artificial intelligence; environmental performance; green supply chain process; green digital learning; organizational information processing theory; healthcare

1. Introduction

Due to the rapid spread of information technology, big data has gained strategic importance and has become one of the most valuable assets for many companies (Papadopoulos & Gunasekaran, 2018; Dubey et al., 2019a). Big data includes heterogeneous formats and is characterized by volume, variety, velocity, and veracity (Tao et al., 2018). The accumulation of data has led many companies to develop analytical means (big data analytics [BDA]) to transform the data into useful information that can improve decision-making and support the performance of their supply chains (Hazen et al., 2014; Papadopoulos et al., 2017). Research exploring the impact of big data on the supply chain is still in its infancy, especially for the environmental dimension. With a few exceptions (e.g., Dubey et al., 2019a), empirical studies that have shown the impact of big data on the integration of green practices and environmental performances are still rare (Song et al., 2017).

The green supply chain (GSC) is considered in the literature as an organizational element supporting circular economy (Dubey et al. 2016a; Liu et al., 2017; Gupta et al., 2019). The GSC has attracted the attention of several researchers and practitioners in recent years under the pressure of regulations and consumer awareness. The integration of the environment into the supply chain is considered by several researchers to be a source of competitive advantage for companies (Yang, 2013; Bentahar and Benzidia, 2018). Improving the environmental performance (EP) of organizations should be considered in all sectors, including the healthcare sector, which is a major source of pollution throughout its supply chain. In the United States, for example, hospitals produce 6,600 tons of waste per day (Kaplan et al., 2012) and consume more energy than any other type of commercial building (Singer & Tschudi, 2009). The pollution generated by hospitals causes numerous risks related to pathological, pharmaceutical, chemical, radioactive, and safety aspects (Kaplan et al., 2012).

In general, green initiatives in hospitals are either part of a *reactive* approach in response to pressure from regulations mainly centered on waste reduction (Chaerul et al., 2007) or a *voluntary* approach restricted to a limited range of environmental practices in the hospital supply chain. One of the main reasons for environmental delays in the healthcare supply chain is that hospitals are evolving in a fuzzy environment characterized by ambiguities in objectives and uncertainties in consequences regarding care activities and logistics operations (Shen et al., 2013). Moreover, there is a lack of capacity to measure and exploit qualitative and quantitative data from diverse internal and external sources to support green practices in hospitals (Oruezabala & Rico, 2012; Campion et al., 2015). Balan and Conlon (2018) claim that it is time for hospitals to adopt a computerized approach using more practical big data to give their GSCs greater visibility. This would make it increasingly advantageous for hospitals to learn how the concepts and approaches of BDA can be used to develop environmental practices. Furthermore, BDA can positively support the large-scale group decision making (LSGDM) approach in circular economy implementation in hospitals (de Sousa Jabbour et al., 2018), which in turn reduces relational conflicts and task conflicts among multiple stakeholders, such as suppliers, physicians, nurses, supply chain managers, and patients (Jabbour et al., 2019; Liu et al. 2019).

From this same perspective, in many countries, the hospital sector has engaged in a wave of digitalization and adoption of BDA technology in recent years. In France, the government seems to be aware of the technological opportunity and is adopting a new strategy, “My health 2020,” which aims to move the hospital toward a connected organization. The government is investing, for example, in major big data projects such as ConSoRe and Health Data Hub. Big data sources in hospitals can rely on a variety of technological equipment, such as electronic patient records, cloud computing, smartphones, tablets, and smartwatches. These technological sources play an essential role in improving clinical care (Wu et al., 2017). Big data is usually analyzed using artificial intelligence (AI) methods that are capable of handling a huge amount of data for the benefit of medical research. However, though research on the link between BDA and AI is abundant at the medical level, it is scarcely mobilized in the improvement of hospital supply chain processes and, in particular, green practices. Our study focused on the role of BDA associated with AI (BDA-AI) to improve EP in hospitals, an issue that, to our knowledge, remains little studied.

The literature has also discussed the connection between BDA and supply chain process integration as a means to develop organizational performance. This involves both external integration based on the collaborative capacity of supply chain members (Hazen et al., 2014; Gunasekaran et al., 2017) and interfunctional integration to ensure an effective decision-making process (Hofmann, 2017). This is, therefore, an important area for exploration, since failed supply chain integration has a negative impact on performance (Narayanan et al., 2011). Nevertheless, the combination of these three mechanisms, namely BDA-AI, internal and external integration, and the impact on EP, has rarely been studied. Our study was the first to examine this relationship in the context of hospitals.

Furthermore, the literature on the capacity of BDA has tended to focus on the technical side and computing capacity to improve the supply chain process. The empirical results of some studies also underline the importance of investing in other complementary and intangible resources, such as human resource skills (Singh & El-Kassar, 2019; Mikalef et al., 2020). The literature has largely focused on the direct role of organizational learning in developing collaborative supply chains and improving performance (Wadhwa et al., 2006; Sendlhofer & Lernborg, 2018). However, the mobilization of organizational learning to support green practices in supply chains is not yet clearly understood. Our study examined the moderating role that can be played by organizational and interorganizational learning to support managers in the decision-making process and help them succeed in "going green." Based on the previous studies, we suggest that the learning process in the supply chain can take a digital form. In fact, digital learning has become more popular recently in several domains, including health and safety in the workplace, fire and safety in buildings, and labor rights (Burke, 2016). Several advantages are offered by this mode of learning, namely cost reduction, flexibility, and reduced employee travel (Clarke et al., 2005). This virtual mechanism is all the more important given the complex, sensitive nature of the health sector, which is subject to increasing regulatory pressure (Sendlhofer & Lernborg, 2018). However, as underlined by Marra et al. (2012), there is no evidence that digital technology in itself contributes to the performance of an organization. Moreover, the lack of social interactions risks leading to a low unnoticed understanding (Wang, 2008). To address this tension and fill this theoretical gap, the main objective of our study was to understand how the capacity of BDA-AI technology, supported by a green digital learning orientation (GDLO), can offer an external collaborative opportunity and better interfunctional integration to improve hospitals' EP.

The organizational information processing theory (OIPT) has been used extensively in investigating the manufacturing supply chain (Huang et al., 2014) and, in a few rare cases, in the study of the hospital supply chain (Srivastava and Singh, 2020). However, this theory has not yet been empirically applied to the specific topic of hospital green supply chain. Given the complexity of the hospital supply chain, the uncertainty of managing several flows (i.e., patients, drugs, laundry, catering, and waste), and the coordination of various interdependent processes (i.e., medical units, pharmacy, supply, transport, production), it was appropriate to employ OIPT as a theoretical framework.

Based on OIPT and a survey from 168 hospitals, our study contributes to a better understanding of the mechanisms through which BDA-AI technologies impact EP in a complex context. Our study built and empirically tested a conceptual model that shows that BDA-AI technologies improve internal and external environmental integration in supply chain processes and further contribute to EP. The study extended the OIPT model beyond classical technological infrastructure and organizational mechanisms by integrating BDA-AI as innovative technology enabling decision-making in GSC processes. Another extension was the positioning of digital learning as a moderator of the GSC process.

This article is organized as follows: Section 2 presents the theoretical framework of the study. Section 3 develops the hypotheses and conceptual model. Section 4 details the research methodology and explains the data sources and data analysis. Section 5 presents the empirical results, and Section 6 discusses these results before concluding with limitations and proposing avenues for future research.

2. Theoretical framework

2.1. Big data analytics

Given the recent popularity of BDA and the diversity of its application, it is difficult to reach a consensus on its definition. Generally, BDA is defined as "a new generation of technologies and architectures, designed to economically extract value from very large volumes of a wide variety of data, by enabling high velocity capture, discovery and/or analysis" (Mikalef et al., 2018, p. 2). It requires innovative technological forms of information processing for better understanding and decision-making (Hofman, 2018) and thus allows companies to obtain competitive advantages (Gunasekaran et al., 2017; Rialti et al., 2019). These advantages include the management of skills, supply chain management, and company performance (Mikalef et al., 2020).

Big data analytics has gained ground, thanks to its capacity to use techniques that enable managers to make better decisions based on proof rather than human judgment or intuition (Brynjolfsson et al., 2011). It requires setting up specific tools to manage the potential data volume and thus identify trends, detect models, and collect valuable results (Zhong et al., 2017). Technological progress has greatly increased the importance of big data in the process of decision-making of companies (Chen et al., 2012). To obtain valuable information, technologies such as smartphones and RFID, cloud computing, and the internet of things (IoT) offer significant advantages in terms of integration and real-time data processing and analysis (Zhang et al., 2017; Pan et al., 2017). This information asset requires the deployment of innovative technological infrastructures capable of quickly analyzing diverse big data in a scalable, precise way (Priya & Ranjith Kumar, 2015). Several technological platforms (e.g., Apache Hadoop, Storm, S4, Dremel) are associated with big data and can support companies in increasing their processing capacity. Choi et al. (2018) have categorized data processing schemes into three types, namely batch processing, real-time flow processing, and interactive processing. The technological sources associated with BDA can also cover several fields of analysis, such as predictive, normative, and descriptive analysis (Chen et al., 2012).

One of the challenges faced by organizations in the use of BDA technologies is the subjectivity and uncertainty of the results, which may have come from the wrong sources (Wang et al., 2019). Another challenge may relate to the confidentiality and security of shared data, which remains a high concern in sectors such as healthcare. This situation requires the mobilization of technology in accordance with standards but also human skills capable of mastering the technological characteristics linked to BDA (Hazen, 2014).

Big data analytics enables organizations to make efficient decisions related to green operations in the supply chain by combining tools, techniques, and processes (Srinivasan &

Swink, 2018). However, the impact of big data on decision-making processes regarding green supply chain integration and environmental performance is not well established in the literature (Song et al., 2017).

2.2. Organizational information processing theory

The OIPT maintains that an organization evolves in a system, integrating several internal and external processes characterized by their complexity and uncertainty (Thompson, 1967). The theory provides a solid basis for explaining the concept and organizational behavior of companies through information processing mechanisms. Gattiker and Goodhue (2004) identified several sources of uncertainty, such as hierarchical reference and standard operational procedures, the instability of the supply chain environment, and the level of interdependence between sub-units.

As the volume of data managed by companies increases, so does their use of information processing, requiring the involvement of several internal and external entities (Galbraith, 1977; Srinivasan & Swink, 2018). This volume of data requires greater visibility to ensure that decision-making is effective. According to Wong et al. (2015), an organization's capacity to process data could be increased by an improved culture of sharing mutually useful interorganizational information to strengthen the collaborative environment and reduce uncertainties related to coordination. Premkumar (2000) adds that the lack of an information-processing culture in an uncertain environment generates significant costs for organizations. Recent studies have found that the capacity to process information improves the performance and enhances the competitive advantage of the company (Bartnik and Park, 2018; Dubey et al., 2019b). In the healthcare sector, information processing capacity improves the management of operations and patient service quality based on knowledge and the use of the appropriate technology (Srivastava and Singh, 2020).

Various studies have referred to the role of technological infrastructure as a mechanism that can increase organizations' information-processing capacities (Galbraith, 1974). In this respect, we maintain that the use of BDA-AI technology can help organizations cultivate and exploit the additional information required to make internal and external supply chain decisions. This study supports previous studies that typically examined the use of information technologies such as BDA and enterprise resource planning (ERP) by companies to increase their capacity to process information, building on OIPT approaches (Galbraith, 1974; Dubey et al., 2019b).

In hospital organizations, supply chain operations depend on several uncertain conditions that change in line with patient demand and the unpredictability of medical activities. These uncertainties or perturbations may complicate the capacity to effectively process information and make decisions on the implementation of environmental approaches. In addition, hospitals share a high degree of interdependence between their different units, which increases organizational complexity. In this respect, the deployment of BDA is potentially very useful in supporting decision-making processes by making adjustments to actions to improve hospitals' EP. However, given the complexity of the healthcare supply chain, including diverse groups, operations, and actors (Ageron et al., 2018; Bentahar, 2018), evidence of the capacity of BDA-AI in processing environmental information through the hospital supply chain to obtain environmental performance has not yet been provided.

2.3. Green supply chain in hospitals

With the transition of linear economy to circular economy, private and public organizations need to develop green approaches and redesign their supply chain. The GSC is defined as "integrating environmental thinking into supply-chain management, including product design, material sourcing and selection, manufacturing processes, delivery of the final product to the consumers as well as end-of-life management of the product after its useful life" (Srivastava, 2007). Several studies have contributed to understanding GSC practices in hospitals, but the literature remains unconsolidated. A study by Johnson (2010) concluded that hospitals tend to look for greener alternatives but they remain limited to certain activities and do not cover the entire supply chain. Balan and Colon (2018) encourage organizations to work together to implement a green approach because the high number of actors, the ambiguity of goals, and the complexity of the healthcare system make it difficult to evaluate green initiatives in the supply chain. The hospital supply chain includes different flows, such as patients, bed logistics, waste, laundry, catering, and medical supplies and devices. Hospital supply chains also fully integrate different processes, such as the management of purchases and provisions, internal and external transportation, storage, production, and all medical care activities (Feibert & Jacobsen, 2015; Benzidia et al., 2019). The LSGDM approach reconciles divergent interests of various groups and supports the engagement of stakeholders in implementing circular economic practices within a fuzzy environment (Liu et al., 2019, Shen et al., 2019). Traditional information technologies (e.g., ERP) and advanced technologies (e.g., BDA, AI) provide hospital groups with the capacity to improve the management of flows, processes, and intra- and inter-organizational relationships.

The healthcare supply chain lags behind compared to supply chains in other sectors and is characterized by poor integration of activities, limiting the dissemination of green practices (Johnson, 2010). The management of waste flows, for example, constitutes a major challenge for hospitals, because it involves a rigorous process of collection, sorting, transport, storage, processing, and disposal. This challenge is linked to the increasing quantities of infectious waste generated, coupled with the danger they may present to medical staff, patients, visitors, and the environment (Chaerul et al., 2007). A study carried out by Campion et al. (2015) on Brazilian hospitals suggests that the dependency on disposable items should also be addressed and that reusable alternatives should be proposed, identifying cotton materials as a subject of concern in individual disposable packaging. Kwakye et al. (2010) mention that the reprocessing of medical equipment is a relatively new ecological practice that has attracted a great deal of attention. These authors claim that over 25% of U.S. hospitals use reprocessing as a means to reduce the volume of disposable waste generated.

Another challenge for hospitals is the greening of the upstream supply chain. A study by Malik et al. (2016) recommends that hospitals should place greater emphasis on their purchasing strategy, particularly in terms of selecting suppliers, because it offers a proactive opportunity and reduces healthcare supply chains' carbon footprint. The construction of hospital buildings is a subject that has also attracted research (Johnson, 2010). The literature has identified the absence of a design approach that respects sustainable building requirements. According to the Environmental Protection Agency (EPA), hospitals consume the highest amount of energy among commercial buildings after the catering industry (Johnson, 2010).

Despite the awareness of hospital managers about green issues and their growing interest in environmental approaches, their endeavors to implement environmental approaches remain restricted. Thus, BDA-AI offers a viable opportunity for integrating environmental approaches in the internal and external supply chains, thereby reducing waste and air pollution.

2.4. BDA-AI and hospitals

Research and the application of BDA and AI in healthcare have developed over recent years. Artificial intelligence technology has opened up numerous opportunities in the healthcare sector, such as in-depth learning to interpret automated biomedical images in radiology, pathology, dermatology, ophthalmology, and cardiology (Wang et al., 2019). The advantages generated in these domains are numerous: improved processes, real-time responses to situations, optimization of resources and costs, and effective healthcare (Raghupathi & Raghupathi, 2014; Nilashi et al., 2016). In addition to its benefits for medical care, the combination of BDA and AI offers promising opportunities for medical research. In the area of hospital pharmacies, the combination of AI and BDA has already been proved effective, notably in the design and development of new drugs (Wang et al., 2019). Other benefits of AI include very precise forecasts of ambulatory hospital visits (Hadavandi et al., 2012). Thus, thanks to this capacity to process information, hospitals can better plan these resources in terms of staff needed to care for patients (doctors, nurses, nursing assistants) and anticipate their need for such items as equipment and drugs for a given period. These results offer a considerable advantage for managing flows and processes in the hospital supply chain in terms of managing purchases and supplies of hospital goods and equipment, transport and storage, internal production, and management of waste sorting and treatment. In fact, big data exploited via AI can be interfaced with applications such as ERP software to improve decision-making and proactively develop a policy on green practices.

Our study looked at AI technology, which can be used alongside BDA in a hospital environment characterized by existing technological AI practices. Despite the wide range of sources available, hospital managers do not sufficiently exploit these data to support green decision-making. In addition, despite the opportunities offered by BDA-AI, several organizations have failed to use it efficiently in the diffusion of green supply chain practices (Dubey et al., 2019c). Given the dynamic and uncertain character of the hospital context, we propose the idea that BDA-AI technologies should develop the information-processing capacity to support the decision-making process in the best possible way (Dubey et al., 2019b).

3. Conceptual framework and hypotheses

3.1. **Conceptual framework**

Big data analytics associated with artificial intelligence plays a critical role in GSC management by eliminating information asynchronization and managing complex environmental data (Wu and Pagell, 2011). It provides insights for decision-making processes to improve GSCM and enhance environmental performance (Dubey et al., 2016b). Furthermore, BDA-AI is a key construct to manage intra- and inter-organizational environmental issues.

Academics have recognized the use of BDA in the internal integration of the environment in various supply chain activities, such as production, storage, and waste management, thereby enhancing environmental performance (Lee and Klassen, 2008). The application of BDA-AI has been extended to green practices in the external supply chain by integrating supplier selection and eco-design to strengthen environmental performance (Raut et al. 2019). Indeed, BDA-AI supports internal green operations and collaboration with suppliers, which lead to reduced waste, carbon emissions, and environmental risks (Singh et al., 2018; Liu et al., 2018). Despite these academic investigations and scholarly attention, the interaction between BDA-AI and its impact on the green supply chain and environmental performance remains in its infancy (Sing et al. 2017; Dubey et al. 2019c).

Our conceptual model was founded on the OIPT (Galbraith, 1974; Tushman and Nadler, 1978). This theory defines how the structure of an organization should respond to uncertainty to achieve optimal performance. The OIPT emphasizes that a company evolves in a system, integrating several internal and external processes characterized by complexity and uncertainty (Thompson, 1967). Based on this theory, we constructed a conceptual model that allows the explanation of the organizational behavior of companies through information processing mechanisms enabled by using BDA-AI technology.

In our model, we established links between the use of BDA-AI technology by hospitals and their EP. We outlined that BDA-AI helps hospitals to process data needed to make internal and external green supply chain decisions to strengthen environmental performance. The model establishes a direct link between BDA-AI and green supply chain collaboration (GSCC). Furthermore, we considered BDA-AI technology as a way to share real-time knowledge among internal functions and to make decisions for EPI. We developed our hypotheses on the impacts of a moderating variable, namely the GDLO. We anticipated a moderating effect of the GDLO on the relationship between BDA-AI and EPI and GSCC.

In the model, we considered the BDA-AI as well as all the variables as reflective constructs. Figure 1 presents the conceptual model as well as the set of hypotheses resulting from the review of the literature.

---Figure 1 --

3.2. **Hypotheses**

The use of BDA in the GSC is increasingly popular and has grown significantly in numerous domains over recent years (Mitra & Datta, 2013; Papadopoulos et al., 2017). The literature has empirically proved that the use of BDA improves visibility and integration in GSCs and increases the availability of valuable information (Song et al., 2017). Within the circular economy, green supply chain collaboration refers to the extent to which companies and their suppliers participate in improving green decision-making and performance, including the design of green products, the supply, production, and recycling of components, and the management of waste and reuse throughout the life cycles of flows (Zhu et al., 2012). Involvement and collaboration between members of the supply chain represent a major challenge that makes it harder to obtain sustainable results (Kamble et al., 2020; Centobelli et al. 2020). Put another way, the development of the GSC can be improved when suppliers adopt practices that both respect the environment and respond to the requirements of their clients (Singh & El-Kassar, 2019).
Big data analytics can benefit from smart technologies to improve sustainability in the product design process (Zhang et al., 2017; Dubey et al., 2019c). Singh et al. (2018) developed a new decision-aid system capable of measuring greenhouse gas emissions and carbon footprints in

the process of selecting suppliers by combining BDA, cloud computing technology, and methods used in operational research (AHP, DEMATEL, and TOPSIS).

Following the same rationale as information processing, we support the idea that the use of BDA technologies help hospitals to exploit and process data from external and internal sources and also creates opportunities for collaborating with suppliers in the environmental decision-making process. On the basis of the above discussion, we proposed the following hypothesis:

Hypothesis 1: BDA-AI–enabled decisions will have a positive effect on GSCC.

Environmental process integration is a matter of concern for companies when organizing their communication resources and sharing information among departments (Graham, 2018). Environmental process integration is similar to interfunctional integration reported in previous studies, which suggest that the various functions should operate as part of an integrated process (Flynn et al., 2010; Narayanan et al., 2011).

The literature reveals that technological infrastructures are required for the integration of the internal supply chain process (Pagell, 2004; Zhu et al., 2012). The use of information technologies has been empirically proven to improve coordination, standardization, and cooperation among internal functions (Zhao et al., 2011). Managers can make use of information technologies for modelling and simulations to improve their capacity to process, and analyzing data may help them to make their internal supply chain processes (i.e., logistics, storage, planning, supplies) operationally effective and more eco-friendly (Wang et al., 2016). As a consequence, the use of BDA technologies creates greater visibility for interfunctional flows and a common alignment with the organization’s objectives (Hofmann, 2017). Dubey et al. (2019a) suggest that companies can use technologies such as AI to interpret and combine complex information from diverse sources. Decisions thus become increasingly efficient, which reduces uncertainty and fosters a climate of trust among internal managers (Chen et al., 2012; Vecchiato, 2012).

Acharya et al. (2018) report that BDA supported by new technologies is a means for sharing knowledge and making decisions within organizations. Data and knowledge need to be shared in real time among internal functions to understand the changing situation and adapt to it in an appropriate way, particularly in dynamic organizations (Singh & El-Kassar, 2019). Hence, we proposed the following hypothesis:

Hypothesis 2: BDA-AI–enabled decisions will have a positive effect on EPI.

Although GSCC has become a widely debated subject in academic research, no previous study has focused on how internal integration related to green collaborations with suppliers is taken into account in hospital management. Many studies have noted the direct impact of internal integration on external integration (Flynn et al., 2010). In this area, the literature suggests that the evolution of environmental practices in an external direction is only possible when companies possess the capacity to internally coordinate and integrate their processes (Koufteros et al., 2005). Internal environmental integration allows companies to avoid any disconnection and fragmentation between processes (Yang et al., 2013). In addition, companies should reinforce the connection with teams and encourage them to interact with each other (Swink et al. 2005). As a result, companies will have the capacity to communicate and resolve problems with their partners efficiently.

Zhao et al. (2011) add that technological resources can play a key role in sharing information and knowledge with suppliers. This technological capacity allows data stored internally to be used with precision and in real time in a synchronized process that encourages close external collaboration.

In this hypothesis, we maintained that internal environmental integration has a positive effect on external environmental collaboration for green performance in hospitals. Thus, we proposed the following hypothesis:

Hypothesis 3: EPI is positively associated with GSCC.

Companies focused on learning are always looking for ways to improve their processes by adopting effective ways to organize themselves into interenterprise and cross-functional teams (Iyer et al., 2019). For Graham (2018), the capacity to learn is an important antecedent for developing a collaborative environmental practice with suppliers. A learning focus leads organizations to collaborate externally and be more cross-cutting internally, which makes it easier to share new knowledge (Kumar et al., 2020). A learning focus also encourages internal teams to voluntarily implement green action to improve EP (Jabbour, 2013). To keep learning up to date, information must be systematically reevaluated and structured, and lessons and learning must be shared among the different organizational services within the organization (Iyer et al., 2019). To this end, our study investigated the moderating effect of GDLO, as intangible resources, in interfunctional management and coordinating external partners through BDA in hospitals. In the United States, for example, the Healthier Hospitals Initiative offers member hospitals opportunities to support green practices through learning programs and interactive webinars. For Sendlhofer and Lernborg (2018), digital learning is more effective because it encourages the participative training of workers, who can either learn on their own or in a group using videos and quiz-type activities. One of the advantages of digital learning is that staff can generally examine their knowledge using progress tests on a computer or a mobile phone. This advantage is subject to new regular directives aimed at protecting the environment and improving health security. In general, digital learning is in place for subjects related to health and safety at work, including industrial safety, risk management, systems security, toxic substances, the disposal and storage of waste, and industrial hygiene (Burke, 2016; Sendlhofer & Lernborg, 2018). Based on these arguments, we proposed the following hypotheses:

Hypothesis 4: GDLO positively moderates the relationship between BDA and GSCC.

Hypothesis 5: GDLO positively moderates the relationship between BDA and EPI.

The literature has highlighted the association between internal environmental integration and collaboration with suppliers to guarantee sustainable EP (Zhu et al., 2012; Gupta et al. 2019). Although this subject has been widely debated in the literature, no studies have focused on this relationship in the hospital sector.

Supplier collaboration implies mutual engagement involving the sharing of resources and decision-making aimed at minimizing environmental impacts on the product development cycle (Yang et al., 2013). In this area, previous studies suggest that companies should invest more in research and development and collaborate with suppliers to foster EP (Zhu et al., 2012). Several studies have proved empirically that supplier collaboration is a key factor for organizations to integrate resources and practices with low-carbon emissions and reduce their environmental and energy footprint (Vachon & Klassen, 2006; Yang et al., 2013). Similarly, Zhu et al. (2012) observe that an external collaborative approach can help companies reduce waste, attain substantial EP, and improve their green image. A GSCC approach strengthens the monitoring level of suppliers who commit to supplying and using equipment and raw materials that respect the environment (Seman et al., 2019). In the hospital sector, the study carried out by Oruezabala and Rico (2012) underlines how difficult it is for hospitals to measure their EP. Their study insists on the rationalization of supplier relations by adopting new forms of cooperation and interaction to improve knowledge on their overall supply. The adoption of a collaborative approach with suppliers seems necessary to improve green hospital practices in terms of purchases and supplies and manage future demand and transport. These practices can improve production (drugs, laundry, catering) and help in the reduction/disposal of hospital waste.

Concerning internal integration, the literature has illustrated that organizations can also ensure performance if the various departments operate as part of an integrated process (Flynn et al., 2010). In this area, research has demonstrated a positive connection between internal integration and EP (Koufteros et al., 2005; Longoni et al., 2018). The results of Zhu et al. (2012) confirm that internal environmental integration can minimize waste and toxic emissions and promote the use of materials that respect the environment in manufacturing companies. For Kang et al. (2018), internal integration reflects a company's decisions to adopt operational practices and act for the environment through an integrated interfunctional process. Aragon-Correa and Sharma (2003) affirm that the interfunctional capacity of companies helps them to achieve proactive EP.

In this article, we maintain that interfunctional, interorganizational collaboration on green issues ensures hospitals' EP. We proposed two alternate hypotheses:

Hypothesis 6: EPI has a positive effect on EP.

Hypothesis 7: GSCC has a positive effect on EP.

4. Methodology

Our study aimed to investigate the mechanisms through which the use of BDA-AI technologies impacts EPI and GSCC and further contributes to EP in a complex context. To investigate the links and complementarities among the variables, we built a conceptual model and tested it empirically using a survey from 168 hospitals. To analyze data, we carried out a partial least-squares (PLS) regression-based structural equation modelling method. The PLS approach was adopted because of its capacity to solve the system of simultaneous equations representing the network of relationships among the variables and, thus, to estimate coefficients that quantify these relationships (Tenenhaus, 1998). We detail the methodological approach in the following subsections.

4.1. Sampling and data collection

We used the survey to test the hypotheses of our conceptual model. We carried out a pre-test with seven experts who had experience in logistics and supply chain management in hospitals. This allowed for clarification of some questions and items. In addition, we consulted four academics conducting research on the topic of healthcare supply chain and technology management to verify the content of the measures. Their suggestions were incorporated into the final survey. A glossary of key terms from our study was provided to respondents to avoid confusion in understanding the questions. Respondents were assured that their identity would be kept confidential.

We used the survey to test the hypotheses of our conceptual model. In order to build our measurement scale, several steps were respected and a pre-test was conducted (Chen and Paulraj, 2004). As a first step, we needed to ensure the validity of the content of the measurement scale. The objective of the content validity tests was to check whether the different items of the questionnaire were a sufficient representation of the phenomenon studied. For this purpose, we reviewed the academic literature to guide us in the development of the questionnaire and the measurement scales of the model variables before purification (Dillman, 1978). At the end of the literature review, a first version of the questionnaire was reviewed and corrected by academics conducting research on the topic of healthcare supply chain and technology management to verify the content of the measures (DeVellis, 2012). A second questionnaire was developed following some corrections and modifications suggested at the end of the pre-test. The questionnaire was then emailed to seven experts who had experience in logistics and supply chain management in hospitals. The experts examined whether the scales covered the constructs studied and submitted their comments on the structure, formulation, and understanding of scales. The comments and advice mainly focused on the formulation of certain statements and the overall presentation of the questionnaire. These comments were included in the final survey instrument.

The survey was administered with respondents who had the responsibility for logistics and supply chain activities within hospitals. We pre-selected each respondent through closed questions concerning their knowledge of big data functionalities in relation to the supply chain.
We administered the online surveys at French hospitals via the Sphinx software. We relied on the information provided by the French hospital federation (public) and the French federation of private clinics and hospitals. The surveys were returned via email.

Of the 520 surveys distributed, we received 181 completed surveys. We did not integrate 13 surveys because they contained incomplete responses. Thus, the final sample size was 168, which represents a response rate of 32% (Malhotra & Grover, 1998). The hospitals in the sample were private and public and had different sizes in terms of the number of beds and the number of employees. Table 1 provides a detailed synthesis of the descriptive analysis of the answers.

--Table 1 ---

4.2. Non-response bias and common method bias

According to Wagner and Kemmerling (2010), survey research in the field of the supply chain can present problems of non-response. To determine the potential non-response bias, we followed the method of comparing the late and early groups of respondents in our sample (Armstrong and Overton, 1977; Tsou and Hsu, 2015). The early group included 98 respondents and the late group included 70 respondents. The two sub-samples were identified according to the receipt date of the questionnaire. The t-test analysis applied to the responses of the two sub-samples did not reveal any significant statistical difference ($p > 0.05$). Therefore, we conclude that the non-response bias did not affect the model.

To prevent the occurrence of common method bias (CMB), procedure and statistical remedies were implemented (Podsakoff et al. 2003). Several statistical tests were performed to assess the potential of common method variance (CMV). Among these tests, we chose the most commonly used in the supply chain management field (Dubey et al., 2019c; Wamba et al., 2020).

The first test was the Harman's single factor test (Podsakoff et al., 2003; Richardson et al 2009). The literature indicates that the Harman test is the most widely used verification tool for CMB (Podsakoff et al., 2003). The test involved an exploratory factor analysis (EFA) of the main components in which all indicators were grouped into a single dimension. In accordance with established guidelines pertaining to Harman's single-factor test, CMV did not appear to be problematic. A Harman test showed that no single factor explained all of the variances of the items (41%) and that the first factor did not represent the majority of the variance.

We also conducted a second test using the marker-variable technique (Lindell and Whitney, 2001). This test involved using an unrelated variable to partial out the correlations caused by CMB. In addition, we calculated the significance value of the correlations using the equations formulated by Lindell and Whitney (2001). We observed minimal differences between manifest variables as measures for the latent method variable. The analysis showed that various latent variables in our sample did not correlate significantly with correlation coefficients close to zero.

We supplemented the previous tests with a test for pathological collinearity, a sign for CMV, using the full collinearity test by Kock (2015). Kock and Lynn (2012) note that pathological collinearity is suggested by variance inflation factors (VIF) with a higher value than 3.3, indicating that the model could be loaded with CMV. The VIF values should be lower than the 3.3 threshold (Kock, 2015; Hair et al., 2017). This indicates that the model is free from common method bias. Based on these results, we concluded that CMB did not have a significant effect on this study.

4.3. Construct operationalization (measures)

Based on the conceptual model, we designed a survey that covered each of the dimensions examined. The questionnaire items of the survey were adapted from previous studies. For this purpose, several studies were used to operationalize the constructs of the conceptual model. To measure the degree of agreement or disagreement with the questions asked, we used five-dimensional Likert scales, ranging from "1 = strongly disagree" to "5 = strongly agree." All the constructs used in our theoretical framework were operationalized as reflective constructs. The operationalization of our variables is presented in Table 2 below.

--Table 2 --

5. Data analysis

The testing of the research hypotheses in the conceptual model was based on the PLS regression method. This method offered several benefits to our study. On the one hand, it is more adapted to exploratory research, which is relevant for our study on a new BDA technology. The PLS method can thus constitute an interesting alternative to estimate a more general model than SEM (Smart PLS) based on covariance, and it is less impacted by model specification errors (Henseler et al., 2015). On the other hand, it is more suitable for small samples of under 250 observations (Hair et al., 2009).

According to Hulland (1999), evaluating a PLS model requires three main factors: determining the nature of the relationships between the measurements and constructs, evaluating the reliability and validity of the measurements, and evaluating the final model.

5.1. Analysis of measurement validity

The measurement model was evaluated on the basis of the reliability of the internal consistency and the converging validity of measurements associated with the constructs and the discriminant validity. The reliability of internal consistency was verified by Cronbach's alpha and composite reliability (Chin, 1998). The values of the model were greater than 0.7. Therefore, they had a good level of reliability according to Tenenhaus et al. (2005). We verified the converging validity of the measurements by examining the correlations (or loadings) of the measurements with their respective constructs, as displayed in Table 3.

---Table 3 --

The discriminant validity was verified if the shared variance between the latent variable and its indicators (AVE) was greater than the variances (squared correlation) of each variable with the other latent variables (Fornell & Larcker, 1981), as displayed in Table 4.

---Table 4 --

5.2. Model testing results

After examining the quality of the measurement scales used in the theoretical model, we tested our hypotheses. We first examined the results of the tested R^2 model. The results demonstrated that an acceptable part of the variance of the constructs can be explained by the model (R^2 for GSCC = 0.405, R^2 for EPI = 0.559, and R^2 for EP = 0.541). These results were in agreement with the criteria suggested by Chin (1998); as such, the nomological validity of the model was considered satisfactory.

In the next step of the analysis, we examined the significance of the relationships among the variables of the research model presented in Figure 2. The significance of the structural relationships (t values) and the path coefficients are summarized in Table 5.

The relationships among the variables in the structural model were all significant except the moderating role of GDLO between BDA-AI and EPI. More specifically, the value of BDA-AI had a positive impact on GSCC ($\beta = 0.438$; $t = 4.144$) and on EPI ($\beta = 0.619$; $t = 6.697$).

These results validate hypotheses H1 and H2 of our study, respectively. We noted that this impact was greater on EPI than on GSCC. Indeed, the use of BDA-AI by a healthcare facility improves supply chain collaboration and internal integration among departments and thus supports the process of decision-making for environmental initiatives.

The results highlighted a positive influence of EPI on GSCC (H3) ($\beta = 0.259$; $t = 1.1961$). If a company has an effective integration process, this strengthens its green collaboration with external partners, namely the suppliers. We carried out an additional analysis that involved identifying the possible mediating role of GSCC. The Smart PLS module included a parametric test that allowed us to compare the coefficients and parameters of the model with and without mediation (Baron & Kenny, 1986). We compared these coefficients of GSCC on EP and found that a differential effect existed (po.02). This suggests a partial mediating effect of GSCC. In other words, EPI had both a direct and an indirect impact on EP through the mediating role of GSCC.

Our hypothesis H6, which predicted that EPI positively influences EP, was confirmed, and the influence was statistically significant in view of the values taken by the t value ($\beta = 0.563$; $t = 8.070$). This hypothesis indicated that internal information sharing and cross-functional integration encourage healthcare facilities to implement an effective environmental policy. In contrast, GSCC had a significant but low impact ($\beta = 0.250$; $t = 3.199$) on the hospital's EP (H7).

---Table 5 --

The moderation analyses examined the effect of GDLO on the path connecting BDA-AI and GSCC/EPI. The results of the analysis underlined a significant positive impact of GDLO on the relationship between BDA-AI and GSCC (Figure 2). However, we found that the effect of GDLO on the relationship between BDA-AI and EPI was not significant.

---Figure 2 --

---Figure 3 --

6. Discussion

This study extends the OIPT by integrating BDA-AI and digital learning to achieve a deeper understanding of decision-making in support of the GSC process. Based on the conceptual model of Galbraith (1973) and Tushman and Nadler (1978), our study shows that decision-making based on innovative technologies improves the information processing capacities of internal hospital processes. This result reinforces our belief that hospitals with technological means and intelligent analytical capacity can mitigate the uncertainties related to the interdependence among units and to the dynamic environment of patients. This finding of this study is an important contribution because the application of the OIPT in the study of hospital operations remains insufficiently studied. Aligned with the perspective of the OIPT, our findings are also consistent with the discussion in the literature on the need for the development of a supporting IT infrastructure to establish collaborative relationships with stakeholders (Lee et al., 2000; Wong et al., 2000; Wong et al. al. 2015; Jabbour et al. 2019). Accordingly, BDA-AI can enhance the LSGDM approach to the environmental process integration and green supply chain collaboration of hospitals in a fuzzy environment. Hospitals consist of several interest groups with different preferences; hence, the decision-making process requires consensus among stakeholders to ensure the integration of the circular economy philosophy (Jabbour et al., 2019). More specifically, the OIPT insists on the importance of aligning information processing capacities simultaneously at the internal and external levels of the hospital supply chain to strengthen environmental performance.

The study provides valuable insight into how BDA-AI technologies enable EPI and GSCC and impact EP. Furthermore, the study offers new evidence on how the relationship between BDA-AI technologies and the GSC process is moderated by digital learning, a major finding that has not been highlighted in the extant literature. The findings illustrate the relationships among BDA-AI, EPI, GSCC, GDLO, and EP and support our conceptual model. The study presents a valuable contribution to theory and important insight for managers and decision-makers who could encourage hospital transition from linear to circular economy.

Research implications

First, the results of our study show a significant positive relationship between BDA and the GSCC (H1). These results support the propositions of various recent conceptual and empirical studies according to which the use of BDA technologies leads to better collaboration between supply chain stakeholders (Hazen et al., 2014; Dubey et al., 2019b). Our results are also consistent with a recent study in engineering and technology management (Lamba et al., 2019) which demonstrated the impact of BDA in the supplier selection process. This is a major benefit of the BDA-AI for hospital facilities, which operate in an uncertain and dynamic environment.

Second, our study suggests that the use of BDA-AI technology has a positive effect on hospitals' EPI (H2). The result is consistent with previous studies that argue for the use of BDA for effective internal process integration in an uncertain environment (Lee and Klassen, 2008; Narayanan et al., 2011). However, no empirical study has demonstrated the relationship between BDA-AI technologies and environmental internal integration in a hospital context. Furthermore, the literature positions the role of internal integration mainly as a tangible resource and a formative antecedent of the use of BDA (Mikalef et al., 2020). Thus, our study provides a novel contribution to how the use of BDA-AI technologies influences environmental integration in the internal processes of the hospital sector. More specifically, we consider that the existing big data in hospitals represent an asset that requires development in terms of analysis and internal processing to reduce the organizational complexity of hospitals and support GSC initiatives. Activities of the internal processes (quality, purchasing, logistics, production, administration) can benefit from the advanced medical activities in terms of the use of BDA and AI to develop a robust environmental model.

Third, the findings show that GSCC positively influences the environmental performance of hospitals (H7). Indeed, hospitals that collaborate closely with suppliers achieve better green performance. This result is consistent with the theoretical conjectures that the implementation of a collaborative policy allows companies to maintain relationships with suppliers and achieve EP (Vachon & Klassen, 2008; Singh & El-Kassar, 2019). Indeed, supply chain collaboration is a critical process in the hospital sector, which lacks capacity and maturity in the implementation of environmental practices.

Forth, our finding underlines the significant direct and indirect effect of internal integration on the EP of hospitals (H3; H6). This suggests that hospitals that provide strong cross-functional integration enhance collaboration with suppliers and achieve better green performance. This result supports the propositions developed in previous research that consider internal integration as a catalyst for external collaboration and therefore a stimulator of organizational performance (Koufteros et al., 2005; Yang et al., 2013). However, previous studies have not empirically investigated the relationships and complementarities among the BDA-AI, GSCC, EPI, and EP, specifically in the hospital context. While previous studies have supported the future potential of BDA applications in improving visibility to reduce uncertainties in supply chain networks (Dubey et al., 2019b), our study offers a rich contribution according to which BDA-AI participates not only to provide treatment capacities with the supplier network but also to the hospital's internal process by creating a shared vision supporting EP. Thus, our study enriches the extant literature by using a novel conception going beyond the direct relationship between BDA-AI and EP and better capturing the complexity of the reality. Ultimately, this result, which proposes that internal and external integration influences the impact of BDA-AI on environmental performance, is a major contribution of our study.

Fifth, the study provides important insight into digital learning as a moderating construct of the process of GSCC (H4). Several recent studies examining the implementation of supply chain practices have underlined that learning can help organizations find the best ways to work and adopt a proactive environmental policy (Longoni et al., 2018). In the current era of big data, hospitals cannot succeed by only having access to good data and efficient information processing; they should also rely on green digital learning to strengthen collaboration and communication with suppliers and promote the co-construction of common ideas and initiatives for green practices. The recent study by Kumar et al. (2020) shows that learning-oriented organizations open their borders to external sources to identify and assimilate new knowledge. Furthermore, Sendlhofer and Lernborg (2018) recommend the use of digital learning in multidisciplinary and multi-stakeholder organizations. However, these studies have not explored the moderating role of digital learning on the relationship between the use of BDA-AI technologies and the GSC process. Thus, our study offers new empirical evidence on how the combination of BDA-AI and GSCC is moderated by digital learning. The study also extends the limited but growing research on the direct effect of learning orientation on supply chain integration (Mikalef et al., 2020). In this way, the findings contribute to the literature on the central role of the digitalization of learning, which seems necessary to support the knowledge of stakeholders on green practices and the improvement of EP.

Finally, the anticipated moderating effect of GDLO on the relationship between BDA-AI and EPI has not been found (H5). This result may be related to the reduced focus of GDLO on the technical elements and hard skills often mobilized by decision-makers to improve the integration of internal processes. This suggestion needs a deeper understanding and further investigation in future studies.

Managerial implications

Our study provides several implications for hospital managers and decision-makers. First, there is an opportunity for decision-makers to exploit their existing technological capacity in

BDA-AI in the implementation of a proactive environmental policy covering all the activities of the hospital supply chain. Indeed, the use of BDA-AI technologies allows managers to implement new measures and indicators in real time to better visualize and assimilate knowledge on environmental sustainability. This achievement can support circular economy philosophy and policy.

Second, given the heterogeneous nature of hospital activities and limited knowledge in environmental practices, another promising avenue offered by the study to decision-makers is investing in technological learning resources (e-learning and m-learning). This investment could be in line with the current and future objectives of hospitals, which are moving toward a new vision of connected management. However, decision-makers should think about how to harmonize all of the hospital's technological resources in terms of interoperability to fully exploit the data collected. In addition, hospitals are encouraged to strengthen their vigilance to secure the dissemination of confidential data and protect the personal data of patients.

On the external aspect, the adoption of a GDLO seems very beneficial in stimulating a collaborative environmental approach between managers in hospitals and their network of suppliers. Given the large number of hospital suppliers, a GDLO allows for clear communication on the orientation of the hospital and better management of the implementation of the environmental approach in the design, transport, and supply processes. This result seems promising and initiates a future scientific debate on the use of a new model of environmental learning, especially in hospital organizations.

Finally, faced with the COVID-19 health crisis, there is a deep awareness by policy makers of the need to mobilize all means and resources to change the current hospital strategy based mainly on cost reduction. It is becoming central to systematically integrate environmental culture into practices as well as into the hospital's strategic projects. Managers can take this opportunity by strengthening digital learning and by acquiring BDA-AI technologies that support them in the achievement of an ambitious environmental strategy.

7. Limitations and future research avenues

Our study was limited to the learning orientation at the environmental level; however, with the progression of digital strategies in hospitals, it would be interesting for future studies to explore the learning orientation at the analytical level of big data in areas such as basic statistics, data mining, and AI. Furthermore, it would be interesting to study the complementarity between a classical and digital learning program in improving green practices in the supply chain.

Our results provide promising conclusions on the technological and learning role in the use of BDA-AI. However, it would be interesting to investigate other constructs, such as the leadership of logistics/supply chain managers or the commitment of top management in relation to the supply chain process. Such a perspective would enable an understanding of other organizational factors influencing the development of an environmental strategy, particularly in a complex organization that lags considerably behind in the implementation of green practices.

The degradation of the environment has increased consumer awareness of green practices. Pagell and Wu (2009) state that in the face of shifting consumer demand, most companies are subject to hostile competitive pressure to improve their environmental performance and maintain their share of the market. Consequently, many of them have integrated new environmental ideas in their supply chain operations. In the healthcare sector, the idea of eco-care is starting to emerge, and it is likely to become critical for hospitals in the coming years, with a new generation of patients who are more sensitive to the environment. Thus, in future studies, the construct of GSCC should be extended to integrate patient collaboration. An empirical study should investigate the effect of BDA-AI capabilities on patient involvement in hospital green practices: eco-design, clean production, reverse logistics, and transportation. We think that a longitudinal study with several respondents from the same organization would make it possible to better observe the unfolding of a process and improve reliability and validity of constructions (minimizing/reducing CMB) (Ketokivi and Schroeder, 2004; Podsakoff and Organ, 1986; Guide and Ketokivi, 2015).

BDA-AI allows the adoption of an efficient decision-making model to face the dynamic context of hospitals encompassing multi-product, multi-period, and multi-supplier characteristics. This study highlights how the successful deployment of BDA-AI technology can facilitate collaboration with suppliers and ensure the ecological transition of hospitals. For example, BDA-AI offers decision-makers an opportunity to adopt a decision-support system for the selection of suppliers based on environmental criteria and converging with the interests of other stakeholders (patient expectations, environmental standards, etc.). Managers can also rely on BDA-AI technologies to measure greenhouse gas emissions and carbon footprints for each supplier, which, in turn, helps to reconcile environmental and economic goals. Finally, while we are experiencing the COVID-19 health crisis, which is disrupting interorganizational relations, companies are increasingly moving toward virtual and environmental supply chains. Hospital managers can use this opportunity to create a digital and intelligent environment (a smart hospital supply chain) in terms of sharing and using data to support environmentally friendly practices.

Finally, our conclusions are specific to the French healthcare sector and thus could be different for other countries, depending on their technological capabilities and green organizational culture applied to supply chain operations. Future research should complement and consolidate our results by investigating hospitals of other advanced and developing countries on a European or international scale.

8. Conclusion

With the exception of a few studies of a conceptual nature or that fall within medical sciences research, this study is the first academic attempt based on OIPT to highlight the link between the challenges of managing BDA-AI through the supply chain process to improve the EP of hospitals. The study contributes to the growing but limited research on the application of BDA-AI technologies for EP in the circular economy context. The paper also has some limitations.

The research framework of this study offers a complete overview of operation processes as well as hospital flows using a large sample. Such a perspective can sometimes be difficult to use when trying to draw exploratory conclusions. To address this limitation, an additional exploration could concentrate on a single flow (catering, waste, medication) or a single internal activity (transport, pharmacy) as part of a longitudinal qualitative study. This approach could provide an in-depth understanding of how hospitals can accelerate the operation of BDA-AI technology and draw interesting conclusions from a technological and managerial point of view.

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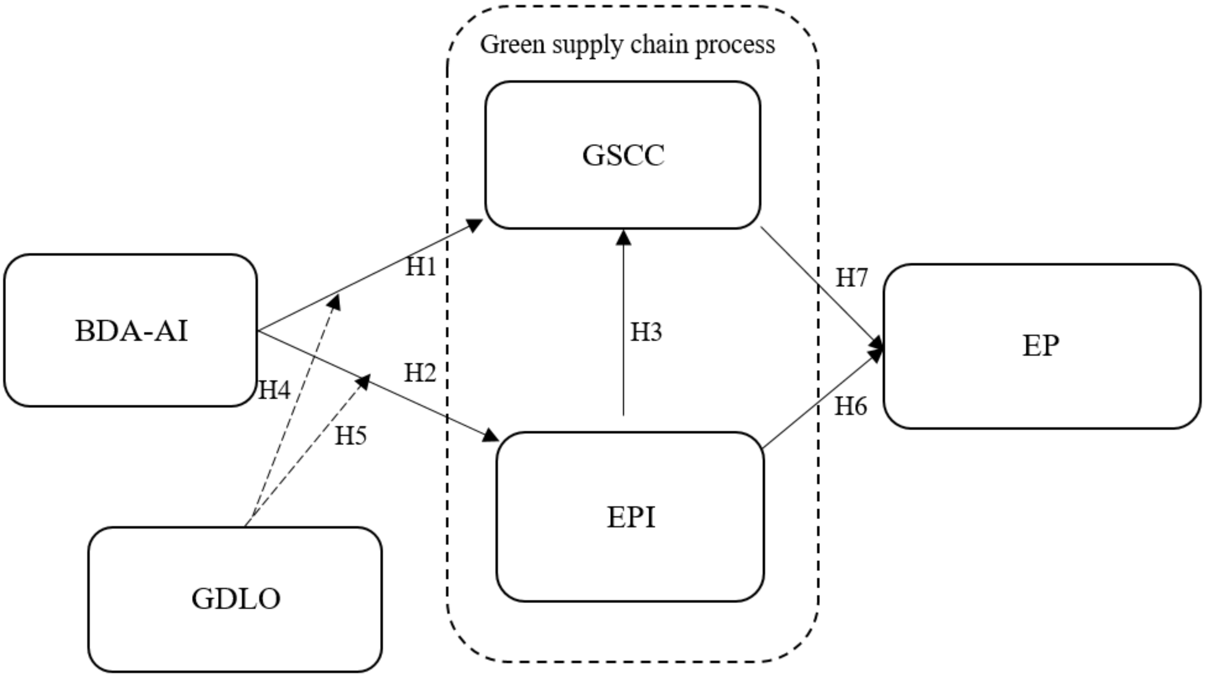

Figure 1: Conceptual model

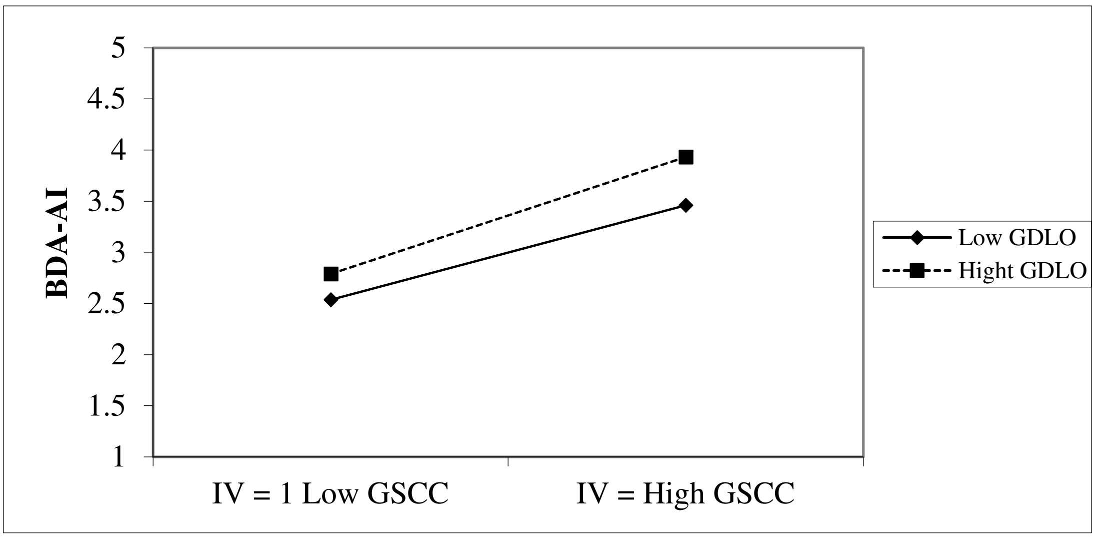

Figure 2. Moderating effect of GDLO on the relationship between BDA-AI and GSCC

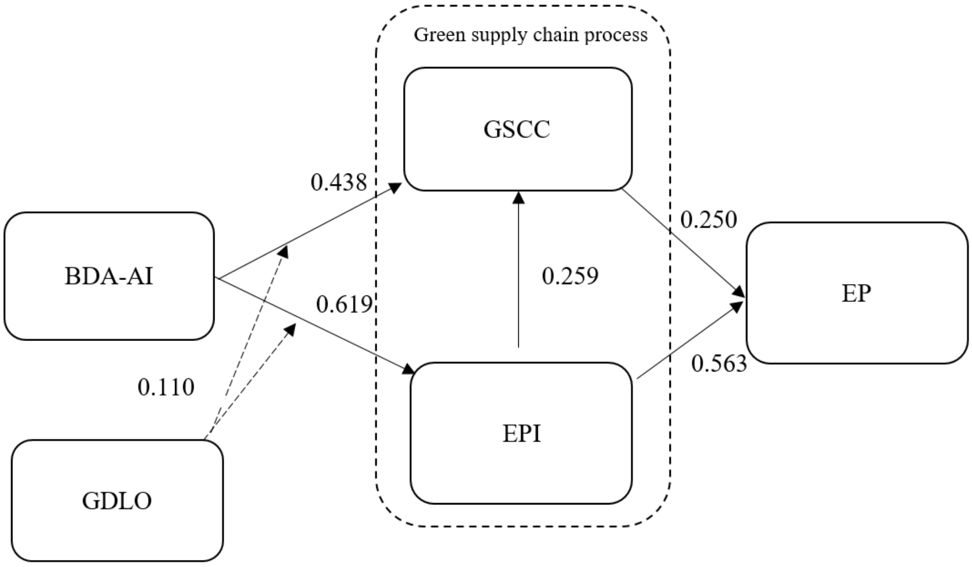

Figure 3. Structural estimates

Table 1. Data characteristics

Demographic characteristics	Number of respondents	Percentage of respondents
Gender		
Male	114	68%
Female	54	32%
Experience of the manager		
≤ 1 year	12	7%
Between 1 and 5 years	81	48%
> 5 years	75	45%
Hospital status		
Private	68	40%
Public	87	52%
Other	13	8%
Number of beds		
≤ 199	30	18%
Between 200 and 499	58	35%
Between 500 and 999	55	33%
Between 1000 and 2000	15	9%
> 2000	10	6%

Table 2. Constructs/Items

Construct & Derivation	Indicator	Measures
Big data analytics-artificial intelligence (BDA-AI), adapted from Srinivasan & Swink, 2018; Dubey et al., 2019b	BDA1	Use of advanced analytical techniques (e.g., simulation, optimization, regression) to improve decision-making
	BDA2	Use of multiple data sources to improve decision-making
	BDA3	Use of data visualization techniques (e.g., dashboards) to assist decision-maker in understanding complex information
	BDA4	Deployment of dashboard applications/information in communication devices (e.g., smart phones, computers) of the GSC process
Environmental process integration (EPI), adapted from Narayanan et al., 2011; Graham, 2018	EPI1	We actively share knowledge across internal functions in order to minimise our plant's environmental impact
	EPI2	We actively cooperate across internal functions in order to minimise our plant's environmental impact
	EPI3	The 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 supply chain collaboration (GSCC), adapted from Singh & El-Kassar, 2019	GSCC1	Supplier selection on environmental criteria
	GSCC2	Advising suppliers on environmental technical issues
	GSCC3	Engaging suppliers in product eco-design & development
	GSCC4	Appraising environmental performance of the suppliers
Green digital learning orientation (GDLO), adapted from Hult et al., 2003; Iyer et al., 2019	GDLO1	The sense around here is that green digital learning is an investment, not an expense in the era of big data
	GDLO2	The ability to green digital learn is a key to improve our supply chain process in the era of big data
	GDLO3	We have specific mechanisms for sharing lessons green digital learned in supply chain process in the era of big data
Environmental performance (EP), adapted from Longoni et al., 2014; Singh & 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. Measurement model

Construct	Items	Factor Loadings	Alpha	Rho A	Composite reliability (ρc)	AVE
Big Data Analytics-AI (BDA-AI)	BDA1	0,892	0.912	0,917	0,938	0.792
	BDA2	0,902				
	BDA3	0,932				
	BDA4	0,831				
	BDA5	0,885				
Environmental Performance (EP)	EP1	0,901	0,937	0,94	0.950	0.762
	EP2	0,901				
	EP3	0,880				
	EP4	0,924				
	EP5	0,757				
	EP6	0,867				
Environmental Process Integration (EPI)	EPI1	0,885	0,935	0,937	0.951	0.796
	EPI2	0,916				
	EPI3	0,838				
	EPI4	0,923				
	EPI5	0,894				
Green Supply Chain Collaboration (GSCC)	GSCC1	0,889	0,899	0,903	0.930	0.768
	GSCC2	0,898				
	GSCC3	0,835				
	GSCC4	0,881				
Green Digital Learning orientation (GDLO)	GDLO1	0,802	0,813	0,82	0,89	0,729
	GDLO2	0,906				
	GDLO3	0,851				

Table 4. Discriminant validity

Construct	BDA-AI	EPI	GSCC	GOLO	EP	CR	AVE
Big Data Analytics -AI (BDA-AI)	**0.890**					**0.938**	**0.792**
Environmental Process Integration (EPI)	0.725	**0.892**				**0.951**	**0.796**
Green Supply Chain Collaboration (GSCC)	0.561	0.577	**0.876**			**0.930**	**0.768**
Green Digital Learning orientation (GDLO)	0.56	0.558	0.505	**0.854**		**0.890**	**0.729**
Environmental Performance (EP)	0.76	0.707	0.574	0.497	**0.873**	**0.950**	**0.762**

Note: The square root of the AVE is reported on the diagonal, while the latent construct correlations are reported off-diagonals.

Table 5. Path coefficients estimates

Hypothesis	Effect of	On	β	Std. dev.	t-Values	p-Values	Result
H1	BDA-AI	GSCC	0,438	0.111	4.144	0.000	Supported
H2	BDA-AI	EPI	0,619	0.097	6.967	0.000	Supported
H3	EPI	GSCC	0.259	0.132	1.961	0.050	Supported
H4	GDLO*BDA	GSCC	0.110	0,061	1,711	0,088	Supported
H5	GDLO*BDA	EPI	0.070*	0.044	1.555	0.121	Not supported
H6	EPI	EP	0.563	0.563	8.070	0.000	Supported
H7	GSCC	EP	0.250	0.078	3,199	0,001	Supported

*p > 0.1