# The role of absorptive capacity and big data analytics in strategic purchasing and supply chain management decisions


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## Abstract

Big data analytics (BDA) is widely used in sales, marketing, distribution, and finance; however, its implementation in supply chain management, specifically in purchasing and supply management (PSM), has been slow and uneven. This study investigates the impact of BDA on strategic PSM decisions and how it interacts with a company's absorptive capacity. We conducted a survey of 222 purchasing and supply chain managers in international companies across various industries. Using structural equation modeling, we found that the exploration, assimilation, and transformation capabilities of purchasing departments are crucial in facilitating the use of BDA for strategic decision-making in PSM. Companies that excel in BDA in the PSM space are better equipped to capitalize on new and existing knowledge sources, which improves their performance. However, only businesses with the right resources can fully leverage BDA for high-level strategic decision-making; when BDA is applied to operational PSM activities, the desired effects may not be achieved.



**Keywords:** Absorptive capacity; Big data analytics; Knowledge management; Purchasing management; Supply chain management


## Highlights

- Adequate absorptive capacity is necessary for PSM to benefit from big data analytics.
- Data acquisition, assimilation, and transformation drive the use of BDA in PSM.
- BDA can significantly improve purchasing organizations' ability to exploit knowledge.
- Strategic purchasing decision-making using big data analytics improves performance.
- Operational purchasing activities do not benefit to the same degree.

## 1. Introduction

Big data analytics (BDA), a hot topic in the fields of innovation, strategy, and operations management, is attracting increased attention in the field of supply chain management (SCM) (Richey et al., 2016). The many processes involved in SCM, such as demand planning, materials management, transportation, and inventory management, all contribute to the massive amount of data being generated, which makes BDA an ideal tool for the prediction, analysis, and optimization of SCM operations (Richey et al., 2016). To improve market performance in the face of intense competition and an uncertain business environment, businesses must use empirical sources of data to inform their operations (Sanders, 2016). Studies in the literature have shown that information systems, such as business intelligence insights, analytics, and prediction tools, are crucial in optimizing the decision-making process and business operations of modern organizations. (Raman et al., 2018).

In this study, our primary focus is on the information systems that are currently available for SCM, with a particular emphasis on purchasing and supply management (PSM). PSM encompasses activities that involve 1) strategic planning for current and future needs, and 2) operational purchasing of goods and services from external suppliers (Spina et al., 2013). Studies in the literature have demonstrated that PSM can have a significant influence on the success of a company's supply chain as well as the performance of the company (González-Benito, 2007; Patrucco et al., 2023). In many industries, purchasing organizations contribute to innovation (Patrucco et al., 2022a), help build organizational resilience (Pereira et al., 2020), enable better production performance, and ultimately maximize organizational results. Consequently, purchasing departments and PSM activities have become more important and are increasingly recognized as strategic peers to their marketing, manufacturing, and finance counterparts. Due to their strategic role, many companies are focusing on how to develop a more effective PSM decision-making process (Patrucco et al., 2023); in this sense, understanding how BDA can contribute to this effectiveness is at the top of managers' agenda (Moretto et al., 2017). PSM activities produce a massive amount of internally generated data (such as spend data, contract data, and supplier performance data), which can be easily integrated with data from external sources of information (Moretto et al., 2017). Purchasing organizations are able to gain additional knowledge to support spend analysis and classification, supply network design and relationship management, supply market intelligence, and risk management by making use of BDA in conjunction with more or less complex techniques to analyze structured and unstructured data (e.g., Arvidsson et al., 2021; Hallikas et al., 2021; Handfield et al., 2019; McKinsey, 2021).

When examining the effectiveness of advanced technologies in organizations, it is crucial to consider the role of individuals and their ability to utilize knowledge effectively (Mahmood and Mubarik, 2020). Value creation and extraction from BDA depend not only on data and technology availability but also on organizations' capacity to transform strategic information into actionable knowledge for informed decision-making (Roberts et al., 2012; Wang and Byrd, 2017; Wang et al., 2019). Here, absorptive capacity (AC) plays a vital role.

AC can be defined as "*the ability of a firm to recognize the value of new, external information, assimilate it, and apply it to commercial ends*" (Cohen and Levinthal, 1990, p. 128). Initially used to explain organizational learning dynamics (Tu et al., 2006), AC is also recognized as a complementary resource and an enabler of information systems adoption (Roberts et al., 2012). In the context of information systems literature, the management of knowledge processes and capabilities are frequently associated with the innovative use of technologies (Roberts et al., 2012; Wang et al., 2014). This holds true, especially for BDA, as its value lies in transforming extensive and complex data into meaningful insights and actionable information that drive business value. Organizations with higher AC possess a clearer understanding of their data needs, how data can contribute to their business objectives, and the advantages of utilizing data analytics for informed decision-making. They are also more likely to possess the necessary technology, skilled workforce, and streamlined processes to effectively analyze big data and integrate new knowledge into their existing operations, and thereby foster innovation and growth.

The novelty of this paper lies in the integration of the two previously discussed aspects. While previous studies have explored various applications of BDA in different contexts (Božič and Dimovski, 2019; Neirotti et al., 2021; Wang and Byrd, 2017), empirical evidence remains scarce in the field of SCM, particularly in the PSM domain. Furthermore, few studies have examined the relationship between knowledge management, BDA applications, and strategic decision-making, despite the potential significance of this connection (Bag et al., 2023).

This study aims to contribute to this field by starting from the theoretical premise that AC and knowledge management capabilities are prerequisites for organizations to derive value and create new knowledge from data generated by supply chain processes. Specifically, to understand how such capabilities impact the use of BDA in supporting decision-making processes in PSM, we consider the four typical dimensions of AC (Lane et al., 2006; Zahra and George, 2002): (1) the ability to identify new and external knowledge (i.e., acquisition capabilities); (2) the ability to assimilate external knowledge (i.e., assimilation capabilities); (3) the ability to transform external knowledge into new knowledge (i.e., transformation capabilities); and (4) the ability to apply the assimilated and newly generated knowledge (i.e., exploitation capabilities).

Our research objective is to answer the following research question: What is the relationship between the AC components of a purchasing organization and the use of BDA to support strategic PSM activities?

We collected survey responses from 222 purchasing and supply chain managers across various industries and company sizes. The respondents evaluated their purchasing organization's characteristics and the extent to which BDA supported PSM activities and decisions. Using covariance-based structural equation modeling (CB-SEM), we tested the relationships and found that higher levels of acquisition, assimilation, and transformation capabilities are precursors for the utilization of BDA in strategic PSM decision-making. Furthermore, our results demonstrate that the use of BDA in PSM enhances exploitation capabilities, and acts as a mediator for the positive relationship between BDA and performance improvement. While acquisition, assimilation, and transformation capabilities continue to drive greater BDA use in operational decision-making, they do not directly contribute to exploitation capabilities and performance improvement.

These findings significantly advance the theoretical and practical understanding of the role of BDA in SCM. First, our research empirically supports studies that explored how organizations can leverage BDA for strategic decision-making thanks to knowledge management capabilities and processes (e.g., Lozada et al., 2023). Second, it enhances our understanding of how organizations can harness the power of BDA in PSM, an under-researched area within SCM (Arvidsson et al., 2021). Organizations that have matured in their ability to utilize BDA for strategic decision-making and rely on strong purchasing AC are the ones that can truly benefit from the performance enhancements derived from these technologies.

The article is structured as follows. Section 2 presents the theoretical background, hypothesis development, and the overall research model. Section 3 describes the characteristics of the survey instrument and the data collection process, while Section 4 presents the statistical results. Section 5 discusses the main findings and its theoretical and practical implications, and Section 6 discusses the main limitations, and suggests opportunities for future research.

## 2. Theoretical background, research model and hypotheses

### 2.1 Big data analytics in supply chain management

The most widely accepted definitions of big data are based on three Vs (e.g., Kwon et al., 2014): volume, variety, and velocity, which represent the magnitude, structural heterogeneity, and continuous stream that define this type of data, respectively. Later, the three Vs were expanded to include value (i.e., how to utilize the data), veracity (i.e., how to ensure data accuracy), and variability and complexity (i.e., how to integrate multiple data sources) (Wamba et al., 2015). Over the past decade, big data research has flourished in the field of management, and yielded invaluable insights in a variety of disciplines.

The earliest applications of BDA focused primarily on either information systems, such as fraud detection (Abbasi et al., 2012), or on a marketing level, customer journey behavior (Leeflang et al., 2014). Numerous studies have also investigated the role of big data in driving business model innovation (Ciampi et al., 2021; Trabucchi et al., 2017; Trabucchi and Buganza, 2019). SCM has increasingly attracted the attention of scholars and practitioners in terms of the application of BDA (Tiwari et al., 2018). Through the use of sensors, barcodes, radio frequency identification (RFID), and automated systems, supply chains in various industries are now able to collect a vast amount of data and information—a valuable resource for identifying areas for improvement in several SCM processes (i.e., demand management, purchasing management, production management, inventory management, and distribution management; Waller and Fawcett, 2013). This has made data an indispensable source of competitive advantage (Sanders, 2016).

SCM scholars have referred to BDA solutions as "*a revolution that will transform supply chain design and management*" (Waller and Fawcett, 2013, p. 77). Several studies have focused on the impact of BDA on different SCM processes. Scholars have also examined the issue of enhancing supply chain structure and capabilities to exploit big data more effectively by focusing on IT infrastructure requirements (e.g., Zhong et al., 2016), necessary technical capabilities (such as analytics and visualization techniques; e.g., Arunachalam et al., 2018; Nguyen et al., 2018), and suitable network and organizational structures (e.g., Wamba and Akter, 2019; Srinivasan and Swink, 2018).

The use of BDA to support production management decisions has received the most research interest (Nguyen et al., 2018). Authors have discussed the application of prescriptive analytics in production planning and inventory management (e.g., Hofmann, 2017; Papadopoulos et al., 2017), and how BDA can support quality control and decisions related to equipment maintenance (Hazen et al., 2014; Zhang et al., 2017). Several SCM scholars have also focused on BDA applications in logistics and transportation management, particularly on how BDA can support logistics network design and the optimization of transportation routes (Mehmood et al., 2017; Neilson et al., 2019). The contribution of BDA to demand management is another well-researched topic that focuses on how BDA can help improve the accuracy of forecasting models and the alignment between forecasted demand and internal capacity (e.g., Hofmann and Rutschmann, 2018).

Despite the increasing digitalization of PSM activities (Hallikas et al., 2021; Patrucco et al., 2020; Seyedghorban et al., 2020), SCM research has paid much less attention to the application of BDA in this domain. While empirical evidence exists in the areas of supplier selection and evaluation (e.g., Lamba and Singh, 2019) and supplier risk management (e.g., Araz et al., 2020), research on BDA in PSM remains scattered, especially regarding the role of these technologies in supporting strategic decision-making (Arvidsson et al., 2021). Theoretical and empirical evidence on how to incorporate BDA into the PSM decision-making process is still lacking; therefore, in the context of the strategic role that purchasing organizations play for businesses, this should be considered from a research perspective (McKinsey, 2021).

## 2.2 The interplay between big data analytics and absorptive capacity

"*In the coming years, most intelligent organizations will need to blend technology-enabled insights with a sophisticated understanding of human judgment, reasoning, and choice. Those that do it successfully will have an advantage over their rivals*" (Schoemaker and Tedlock, 2017, p. 27).

Although BDA in SCM has received increasing attention due to the possibility of obtaining value from a massive and growing volume of data and gaining a commanding competitive advantage in the planning and execution of complex processes, supply chains in many industries are still lagging behind in their use, particularly in supporting decision-making processes (KPMG, 2018). Previous research has identified several obstacles to effective BDA implementation, including the inability to build suitable high-quality databases, data security concerns, and the complexity of BDA techniques (Alharthi et al., 2017). Studies in the literature on information systems have emphasized the significance of knowledge management capabilities in relation to the adoption of innovative technologies when discussing these enablers and barriers (e.g. Mahmood and Mubarik, 2020; Roberts et al., 2012; Wang et al., 2014). In the case of BDA, there is still a need to learn how the insights generated by these technologies can be exploited by articulating them with the skills of individuals and other processes involving the acquisition, organization, and application of knowledge (Lozada et al., 2023). Recent SCM literature has also promoted a need for increasing appropriate knowledge management skills in organizational resources to extract value from BDA, especially in PSM (Arvidsson et al., 2021; Öhman et al., 2021). Big data cannot be used as a direct input for decision-making due to its complexity. It must be interpreted, and in order to do that, organizations require competent individuals who can use the appropriate data as a starting point, correctly apply data analysis techniques, and interpret the data in the context of organizational policies and the business environment (Lozada et al., 2023). AC represents a key organizational capability to do this (Lam et al., 2017).

AC represents a dynamic capability through which organizations acquire, assimilate, transform, and apply external knowledge to create a competitive advantage (Zahra and George, 2002). By growing their AC capabilities, organizations are able to amplify the knowledge produced by individuals and transform it into an organizational asset (Božič and Dimovski, 2019; Neirotti et al., 2021; Wang and Byrd, 2017).

Previous studies articulated AC through four sub-components—acquisition, assimilation, transformation, and exploitation (Cohen and Levinthal, 1990; Zahra and George, 2002)—although assimilation and transformation have also been considered together (e.g., Todorova and Durisin, 2007).

The role of AC in the adoption of advanced technologies is theoretically supported by several studies in the information systems literature (e.g., Ardito et al., 2021; Saraf et al., 2013). Some studies have shown that the processes of acquiring, assimilating, and exploiting unique and novel knowledge enable the use of technology in novel ways (Wang et al., 2014). Similarly, research has demonstrated that greater digital skills positively impact AC, thereby enhancing organizational performance (Bolvar-Ramos et al., 2013), and that AC is essential for establishing technology infrastructure that generates organizational value (Elbashir et al., 2011).

In the context of BDA, there are even more compelling reasons why AC represents a crucial element. First, AC, as defined by Cohen and Levinthal (1990), encompasses a firm's ability to recognize the value of new, external information, assimilate it, and apply it for commercial purposes. BDA involves the processing of vast amounts of data to extract valuable insights, making AC highly relevant in extracting meaningful information from big data. Second, Zahra and George (2002) reframed AC theory to emphasize its dynamic nature, moving beyond a static ability to a set of active organizational routines. These routines serve as mechanisms that facilitate knowledge acquisition, assimilation, transformation, and application, thereby creating dynamic capabilities. This redefined perspective on AC is crucial as it recognizes the ongoing and evolving processes of learning and adaptation, which are inherent in organizations operating in a rapidly changing environment. In the context of BDA, this conceptualization holds great significance. BDA involves the handling of vast volumes of structured and unstructured data from diverse sources; however, the data are only valuable if an organization can effectively utilize it. Only organizations with structured routines to organization to acquire, assimilate, transform, and apply knowledge derived from BDA can effectively use these technologies.

This is even more important in the context of SCM processes, where the critical information required to improve supply chain performance is primarily accessible from external sources and not readily available for decision-making (Handfield et al., 2019). As BDA can provide crucial new information that can be used to support strategic decision-making in SCM, companies must have structured routines to enable the organization to acquire, assimilate, transform, and apply knowledge derived from BDA to make more effective SCM decisions (Wang et al., 2016). The interplay between AC and BDA is thus crucial for leveraging BDA effectively to enhance performance in the area where BDA is introduced. It empowers organizations to convert raw data into actionable insights that drive decision-making and strategy, thereby creating dynamic capabilities (Božič and Dimovski, 2019; Ardito et al., 2021). This is especially true for the PSM process, where the AC of purchasing departments has frequently been linked to a company's capacity to capture external knowledge and use it to introduce innovations, thereby favoring the success of these innovation initiatives and enhancing performance (e.g., DiFrancesco et al., 2022; Kauppi et al., 2013; Knoppen et al., 2022; Patrucco et al., 2022a; Picaud-Bello et al., 2022).

Using the research model depicted in Fig. 1, we contribute to the literature by connecting BDA and knowledge management using PSM as the unit of analysis. We base our model on two theoretical premises: the AC of PSM is related to BDA adoption and associated benefits, and to obtain these benefits, companies should invest in and utilize BDA to support strategic decision-making and activities, as opposed to operational ones.

To theorize how purchasing AC relates to the use of BDA to support strategic PSM activities, we are aligned with prior research (e.g., Flatten et al., 2011) that regarded AC as a second-order construct that builds, integrates, and reconfigures underlying first-order capabilities to create and deploy new knowledge. However, while previous studies considered the relationship between AC and BDA, and viewed AC as a unique construct (e.g., Božič and Dimovski, 2019; Elbashir et al., 2011; Wamba and Akter, 2019), our theoretical argument is based on the idea that the three different components of AC play a different role in the use, adoption, and value creation from BDA for strategic decision-making (e.g., Wang et al., 2014). Particularly, we argue that not all AC components represent antecedent or subsequent organizational technology adoption capabilities (ideas that were proposed, under different theoretical lenses, by previous studies (e.g., Cepeda-Carrion et al., 2012; Setia et al., 2013; Mahmood and Mubarik, 2020). Instead, our model considers the capabilities of knowledge acquisition, assimilation, and transformation as drivers of BDA adoption, while the final component, knowledge exploitation, represents a capability that can be strengthened by BDA, and also facilitates performance improvement. The model's main hypotheses are discussed next.

**[Insert Fig. 1 here]**

### 2.3 Hypotheses development

Acquisition capabilities constitute the first component of AC. Acquisition refers to the ability to identify and acquire externally generated knowledge to execute internal operations (Zahra and George, 2002). According to Camisón et al. (2018), these capabilities are essential for acquiring external information and expanding a company's current knowledge. In the context of BDA, the ability to scout and identify external information and integrate it with internal knowledge improves information system capabilities (Cepeda-Carrion et al., 2012), enabling organizations to compile better data sets that can be used as input for various analytics techniques (Wamba et al., 2017). The ability of purchasing organizations to collect and combine internal and external purchasing and supplier data (e.g., commodity prices, supplier performance, and supplier costs) is a prerequisite for the application of analytics in PSM (e.g., Wamba and Akter, 2019; Hallikas et al., 2021; Öhman et al., 2021). Therefore, we formulate our first hypothesis as follows:

**H1.** Greater knowledge acquisition capabilities of the purchasing department positively impact the use of BDA for strategic PSM activities.

Assimilation and transformation capabilities constitute two further components of the AC, where assimilation refers to organizational capacity to understand the information gathered, and transformation refers to the ability to process and interpret the information (Zahra and George, 2002). Due to the difficulty in distinguishing where passive assimilation ends and active transformation begins at an individual level, these two capabilities are frequently grouped together in the management literature (e.g., Todorova and Durisin, 2007) and play a crucial role in technology adoption. To effectively use and create value from BDA, organizations must be able to read, interpret, and use the output generated by the application of analytics techniques to improve their decision-making (Božič and Dimovski, 2019). Before investing in advanced technologies in the context of PSM, companies must ensure that purchasing personnel are able to fully understand, interpret, and strategically apply the output resulting from the application of such technologies (Arunachalam et al., 2018; Arvidsson et al., 2021; Hazen et al., 2014; Wamba et al., 2017). Purchasing organizations with demonstrated organizational learning capabilities drive technology investments to exploit these capabilities (Kauppi et al., 2013). There is evidence that purchasing organizations with greater assimilation and transformation capabilities are also more digitalized (Hallikas et al., 2021). We can assume that these capabilities constitute a second enabler for the implementation of BDA to support strategic PSM decisions. Therefore, we propose the following hypothesis:

**H2**. Greater knowledge assimilation and transformation capabilities of the purchasing department positively impact the use of BDA for strategic PSM activities.

Exploitation capabilities constitute the last component of the AC. Exploitation refers to the organizational capacity to refine, extend, and capitalize on existing knowledge and/or innovate by incorporating knowledge extracted from external sources (Zahra and George, 2002). Through exploitation capabilities, organizations use acquired external knowledge and information to create new competitive advantages within their supply chains and market environment (Tu et al., 2006). When companies invest in advanced technologies, their ultimate goal is to improve their strategic decision-making capabilities, which will have a positive effect on business performance. In the case of BDA, greater adoption of these technologies permits companies to increase the quantity and the quality of information available for strategic decision-making (Richey et al., 2016). This information is also presented with multiple dimensions and levels of analysis, which encourages organizations to utilize it and elaborate on it in a variety of ways (Intezari and Gressel, 2017; Mikalef et al., 2020; Setia et al., 2013). Ultimately, increased BDA usage improves an organization's analytical capabilities, and has a positive effect on the organization's ability to exploit and create value from data analyses. In the context of PSM, the greater use of BDA to support decision-making means that purchasing organizations have better access to high-quality information, thereby enhancing their ability to exploit and utilize this information to improve supply chain performance (Öhman et al., 2021). Therefore, we propose the following hypothesis:

**H3**. Greater use of BDA for strategic PSM activities positively impacts the knowledge exploitation capabilities of the purchasing department.

Studies on BDA and SCM have shown that by investing in these technologies, companies can benefit in two ways: 1) BDA improves their ability to analyze data, gives better meaning to such data, and generates new knowledge, and 2) BDA enables them to make more effective SCM decisions, which ultimately result in enhanced operational performance, such as faster delivery times, lower costs, closer integration with external partners, lower inventory levels, and better management of risks (e.g., Mikalef et al., 2020; Patrucco et al., 2020; Wamba et al., 2017). Adopting BDA to improve purchasing decision-making and the resolution of complex purchasing issues is a supporting tool in PSM, not the solution (Sanders, 2016). The introduction of BDA alone is insufficient to achieve measurable performance gains; however, it induces a change in the organizational context by stimulating the development of new capabilities (Raman et al., 2018). As previously theorized on the adoption of other technologies (e.g., Kauppi et al., 2013), the use of BDA in PSM provides purchasing professionals with access to more valuable, dependable, and up-to-date information in order to develop new knowledge and competitive advantages. As a result, BDA directly contributes to improving the knowledge and information quality within purchasing organizations, thereby enhancing their exploitation capabilities; with this mechanism, organizations can benefit from higher performance enabled by the use of BDA. Therefore, we propose our final hypothesis:

**H4.** Greater knowledge exploitation capabilities of the purchasing department positively mediate the relationship between the use of BDA for strategic PSM activities and BDA's contribution to performance improvement.

## 3. Methodology

Our paper adopts a deductive approach, aligning with the nature and objectives of our research. We build on the established theories of BDA and AC (Lam et al., 2017) and apply these theories to the context of PSM. This approach allows us to test the theoretical premise that AC and knowledge management capabilities are vital for organizations to extract value and generate new knowledge from supply chain data (Lam et al., 2017). We focus specifically on the four principal dimensions of AC and the relationship between these AC components within purchasing organizations, and the use of BDA to support strategic PSM activities.

To test our hypotheses, we employ a structured collection and analysis of the data, which aligns with the deductive approach. Considering the purpose of analyzing the relationships between the variables depicted in Fig. 1, we collected data through an online survey questionnaire specifically designed for this study, and conducted the survey during 2019–2020. This research method enables theory testing (Malhotra and Grover, 1998).

### 3.1 Questionnaire design and validation

Given the scarcity of empirical research on BDA in a PSM context (Arvidsson et al., 2021), the questionnaire was designed using an iterative procedure based on best practices in the literature (DeVellis and Thorpe, 2021; Forza, 2002; Groves et al., 2009) and examples from comparable studies (Bianchi et al., 2019).

A pilot version of the survey was distributed to purchasing professionals in close contact with the research team between November 2019 and February 2020. In this first phase, in an effort to design the most effective survey instrument for large-scale distribution, we wanted to determine whether the PSM practices suggested in the literature were consistent with those of the companies. We solicited participation from 50 respondents (all chief purchasing officers, purchasing directors, or purchasing managers) and collected 34 responses. The majority of the respondents were from the manufacturing industry (30 out of 34). The pilot survey also allowed respondents to provide text-based feedback.

The responses to the pilot survey provided feedback in three areas, with the first pertaining to the obstacles and difficulties in using BDA in PSM. Several respondents cited a lack of skills to identify the right information to feed the analysis and how to use the results to support decision-making as the primary barrier to BDA adoption in purchasing. This finding reinforced the significance of linking AC to BDA. The second finding relates to BDA application areas. Due to the possibility of increasing the knowledge and information available for complex decisions, 31 of the 34 respondents indicated that their organizations utilized BDA to support strategic purchasing activities to varying degrees. The third component relates to the potential impact of implementing BDA for purchasing activities. All the respondents highlighted a direct (and intangible) impact on the ability of purchasing employees to make better decisions, but emphasized an indirect but substantial contribution to a number of operational performance areas, including purchasing costs, supplier quality, and level of service. This exploratory data was incorporated into the initial design of the survey instrument and assisted in its revision.

To achieve maximum clarity and appropriateness of the measures, we conducted follow-up interviews with a subset of the respondents who had participated in the pilot test to ensure we understood their feedback (DeVellis and Thorpe, 2021; Groves et al., 2009). Some items were subsequently eliminated, modified, and added. The revised questionnaire was independently reviewed by two supply chain scholars (external to the research team) to validate the scales, item clarity, and theoretical validity of the construct measures. The questionnaire received final approval after consultation with the ten respondents from the pilot study. The survey was finalized in September 2020. Although the questionnaire was intended to be disseminated internationally from Italy, it was initially developed (and pilot tested) in English, then independently back-translated into Italian to ensure the accuracy of definitions and to identify ambiguous language. The accuracy of both translations was double-checked by a panel of experts (ten respondents proficient in both Italian and English). Appendix A1 provides a summary of the items comprising each construct.

## 3.2 Measures

To measure purchasing AC, we refer to the traditional capability-based conceptualization proposed by Cohen and Levinthal (1990) and Zahra and George (2002). This conceptualization is more in line with the objectives of this study than the one proposed by Tu et al. (2006), and has recently been adopted in SCM studies (e.g., Knoppen et al., 2022). In accordance with this perspective, AC captures the purchasing capabilities to acquire, assimilate, transform, and explore external knowledge and ideas, where assimilation and transformation capabilities can be bundled as part of interrelated knowledge management activities (in line with Todorova and Durisin, 2007).

Regarding the formulation of items for each component of AC in the SCM domain, we adopted the approach proposed by Sáenz et al. (2014) in the context of buyer–supplier relationships and adapted it to the context of the purchasing organization and employees.

As a result, to measure the purchasing department's capabilities to acquire external knowledge, we asked respondents to rate how frequently their company's buyers collected information about customer preferences, supply market structures, new market technologies, and the strategies and policies of competitors. To measure purchasing departments' capabilities to assimilate and transform external knowledge, we asked respondents to rate to what extent their company's buyers frequently communicated with their supervisors, communicated new ideas to other internal departments, supported each other, shared ideas with each other, and were willing to accept changes. Last, to measure purchasing departments' capabilities to exploit external knowledge, we asked respondents to rate to what extent their company's buyers used their knowledge and information to identify opportunities for cost reduction, quality improvements, improving suppliers' level of service, and more effective material planning.

To measure the use of BDA for purchasing activities, the respondents were first made aware of the meaning of BDA in line with the definition provided by Kache and Seuring (2017), who conceptualized BDA as "*the application of advanced statistics to any kind of electronic communication … [with] the aim to identify behavioral patterns within the data*" (p. 10). Regarding BDA adoption in the purchasing process, we could not find a survey scale in the literature that could be easily adapted or used. Therefore, we searched the literature for articles that defined the structure of the purchasing procedure. Existing classifications of purchasing activities (e.g., Bäckstrand et al., 2019; Luzzini et al., 2014; Moretto et al., 2017; Van Raaij, 2016) included demand planning, category strategy development, supply risk management, spend management, and performance management among the strategic activities. We included all the activities associated with the contract-order-delivery-payment cycle, such as supplier selection and negotiation, order management, logistics management, invoice management, and fraud detection, under operational purchasing. With this distinction in mind, we asked respondents to rate the extent to which their company utilized BDA to support strategic and operational purchasing activities.

To measure BDA's contribution to performance improvement, we referred to earlier studies that distinguished purchasing performance in terms of cost, quality, timeliness, innovation, and sustainability (e.g., Caniato et al., 2014; Maestrini et al., 2018; Richter et al., 2019). In accordance with this, we asked respondents to rate the extent to which the use of BDA in purchasing in their organizations improves the cost of purchases, the productivity of purchasing employees, the cost of the purchasing process, the cost of the inventory, the quality of purchases, the level of innovation of purchases, the processing time of internal purchase orders, the delivery times of suppliers, and the ability of suppliers to meet agreed environmental performance goals. For each question, a five-point Likert scale ranging from strongly disagree (value = 1) to strongly agree (value = 5) was provided. The respondents were also instructed to consider the preceding two years as the time horizon in their answers. The details of the survey items are listed in Table A1 of the Appendix.

In addition to these factors, the questionnaire captured additional firm-level variables, including industry type (manufacturing, service, or construction), number of employees in the organization and purchasing department, turnover, and purchase-to-sales ratio. Respondents were instructed to use the previous year as a point of reference when answering questions regarding these variables.

### 3.3 Sampling and data collection

As our survey assessed the extent of BDA usage for PSM activities of different nature, knowledge management capabilities, and its contribution to improving performance, the ideal respondents were professionals with managerial responsibilities in the purchasing process (in line with the approach adopted to collect the data for the pilot survey). Using the research team's professional contacts, an initial database of buyer companies was compiled to identify potential participants. We used this convenience sampling strategy, as we required only supply chain and purchasing professionals to complete the survey and wanted to ensure a high quality of responses. We also conducted follow-up interviews with the key respondents to clarify some of the evidence resulting from the data collection (DeVellis and Thorpe, 2021; Groves et al., 2009).

In November 2020, potential company participants were contacted via email and, where necessary, by phone to explain the survey project and assess their interest in and availability for participation. The need to have a respondent with managerial responsibilities in the purchasing area was clearly stated in the research project's description so that the person who received the email could forward it in case they did not fit the required profile. Once a respondent agreed to participate, they were assured that their responses would remain confidential, thereby reducing the likelihood of social desirability bias (Groves et al., 2009).

A participation email was sent to 1,026 purchasing and supply chain professionals on the research team's contact list. We received 387 responses between November 2020 and January 2021 (representing a raw questionnaire completion rate of approximately 40%); only 222 were deemed usable for our study after excluding 1) responses with missing values on critical items, and/or 2) unreliable responses (e.g., same values provided to all items), and/or 3) responses were respondents indicated that their company did not use BDA to support PSM activities (value = 1 for the questions "BDA for purchasing activities"). Table 1 provides a summary of the descriptive data for the final empirical sample.

**[Insert Table 1 here]**

Most of the organizations in our sample were from the manufacturing sector and were located in Italy (where the data collection originated). All the responses included in the final sample were provided by C-level purchasing professionals, purchasing managers, or other types of managers in cases where purchasing activities were included under other departments (such as production or manufacturing).

### 3.4 Bias control

Non-response bias was checked through independent sample t-tests between early, late, and non-respondents on control variables such as organization size and revenue (Dalecki et al., 1993). We observed no significant differences between the groups on these key firm characteristics, so non-response bias was not a significant concern.

Social desirability bias was mitigated by ensuring confidentiality and asking general questions about the behavior of the organization and its members, as opposed to direct questions about the respondents' personal behaviors (Groves et al., 2009). In addition, because the institutional items did not relate to individual behaviors or performance, they were less susceptible to social desirability bias (Groves et al., 2009). To avoid a single-source bias, we used a sample of managers from diverse industries and companies of varying sizes (Bianchi et al., 2019; Groves et al., 2009). In addition, we included two instrumental manipulation checks (nonsensical tasks to ensure survey respondents were paying attention) (Groves et al., 2009).

In accordance with the suggestions of Podsakoff et al. (2003), we ensured that common method bias (CMB) was minimized in multiple ways. First, even though the research project was labeled as a comprehensive study to understand the maturity of BDA in PSM, no reference to the model in Fig. 1 was provided, so that the respondents' attention was not drawn to the relationships being targeted in this study. Second, questions were organized in different sections, which prevented respondents from developing their own theories about possible cause-and-effect relationships. Third, some items were reverse coded (i.e., EXP4, AST5, EXL4 in Appendix A1) to balance positively and negatively worded items. Furthermore, the common latent factor and marker variables techniques were applied to assess common method bias statistically. The common latent variable yielded a linear estimate of 0.489, with its variance of 0.239 below the threshold of 0.500. For the marker variable, we selected the level of digitalization of SCM processes, a multi-item construct with no apparent theoretical connection with the constructs in the model. We tested the same model reported in Fig. 1 after introducing an association between this construct and the model's dependent variables (BDA use for strategic purchasing and exploitation capabilities, and BDA's contribution to performance improvement), and these new paths were not significant (without incurring any substantial change in other path values and constructs' correlations). We could conclude that CMB is not a concern for our study based on how the survey procedure was designed and the additional tests.

### 3.5 Approach for model testing

Since the aim of our study was theory testing and confirmation, the four hypotheses were tested using CB-SEM. The model was tested using the maximum likelihood (ML) estimation method, because it can provide more realistic indexes of overall fit and less biased parameter values for paths that overlap with the actual model, compared to other methods such as the generalized least squares and weighted least squares (White, 1982). The ML estimation assumes the variables in the model are (conditionally) multivariate normal, which is valid for our dataset according to the Doornik-Hansen ($p > \chi^2 = 0.307$) and Henze-Zirkler tests ($p > \chi^2 = 0.355$). The analysis was conducted in Stata 17.0.

## 4. Data analysis

### 4.1 Measurement model

Before estimating the path coefficients, we ensured the validity of the measurement model. Table 2 presents the results of the confirmatory factor analysis (CFA). All the measurement model fit indicators suggested a sufficient fit ($\chi^2$/d.f. = 1.76; CFI = 0.958; TLI = 0.949; SRMR = 0.05 RMSEA = 0.059). Convergent validity was confirmed through significant loadings of all the scale items of the hypothesized constructs, as well as through the average variance extracted (AVE), composite reliability (CR), Cronbach's alpha (CA), and omega (OM). Specifically, the AVE values ranged between 52% and 74% (over the 50% threshold), and CR, CA, and OM are higher than 0.7 for all the constructs (Garver and Mentzer, 1999).

**[Insert Table 2 here]**

To determine the discriminant validity of our measurements, we ensured that the square roots of the AVE values exceeded their respective correlations (Fornell and Larcker, 1981). In every instance, this criterion was met, thus establishing validity (Table 3). As an additional test, we calculated the heterotrait-monotrait ratio of correlations (HTMT and HTMT2; see Table 4). For each pair of constructs, the values consistently fell below the 0.9 threshold, thus confirming discriminant validity.

**Insert Table 3 here]**

**[Insert Table 4 here]**

4.2 Structural model

The structural model was tested through path models via CB-SEM. Table 5 shows the structural model's results, including the standardized path coefficients, with the significance based on two-tailed t-tests for our hypotheses.

**[Insert Table 5 here]**

In line with H1 and H2, higher purchasing acquisition capabilities ($\beta = 0.340$, $p < 0.001$) and assimilation and transformation capabilities ($\beta = 0.191$, $p < 0.05$) are associated with the greater use of BDA for strategic purchasing activities. The use of BDA for strategic purchasing activities is positively associated with higher purchasing exploitation capabilities ($\beta = 0.316$, $p < 0.001$); thus, H3 is accepted. The path analysis also shows a positive relationship between the use of BDA for strategic purchasing activities and BDA's contribution to performance improvement ($\beta = 0.383$, $p < 0.001$) and purchasing exploitation capabilities, and BDA's contribution to performance improvement ($\beta = 0.222$, $p < 0.001$). As shown in Table 5, none of the control variables have a significant relationship with BDA's contribution to performance improvement.

To verify the significance of the mediation effect of purchasing exploitation capabilities, we followed the bootstrapping approach (Hayes, 2009), where we first evaluated the direct and indirect effects of the mediator on BDA's contribution to performance improvement. Next, the indirect effect was assessed through bootstrapping analyses by considering bias-corrected and accelerated confidence intervals (97.5%) for the indirect effects, where mediation is said to occur if the derived confidence interval does not contain zero. The results are reported in Table 6.

**[Insert Table 6 here]**

The mediation tests show that the indirect effect of the use of BDA for strategic purchasing on BDA's contribution to performance improvement is statistically significant ($\beta = 0.073$, $p < 0.05$), and the confidence interval after bootstrapping does not include zero. We conclude that exploitation capabilities positively mediate this relationship, meaning that H4 is accepted.

4.3 The use of big data analytics for operational purchasing

As anticipated in subsection 3.2, the survey instrument also asked the respondents to rate how their company used BDA to support more operational activities included in the purchasing process. Although traditionally, BDA is expected to support strategic decision-making (Richey et al., 2016; Tiwari et al., 2018), due to the scarcity of literature on BDA use in PSM, we considered it useful to run the same model hypothesized in Fig. 1 but for operational purchasing activities. This construct shows good convergent validity (CR = 0.791, CA = 0.752, AVE = 55.75%), including items BDA7, BDA8, BDA9 and BDA10. Instead, BDA11 (i.e., BDA support for fraud detection activities) was dropped following the CFA. Both the measurement ($\chi^2$/d.f. = 2.19; CFI = 0.903; TLI = 0.884; SRMR = 0.071 RMSEA = 0.074) and structural ($\chi^2$/d.f. = 2.16; CFI = 0.901; TLI = 0.890; SRMR = 0.074 RMSEA = 0.073) models have sufficient fit to the data. The results of the path analysis are reported in Fig. 2, in comparison with the results obtained for the main research model.

**[Insert Fig. 2 here]**

In contrast to previous model testing, the results indicate that the use of BDA for operational purchasing is not associated with greater exploitation capabilities ($\beta = 0.106$, $p > 0.05$). The use of BDA for operational purchasing is not significantly related to BDA's contribution to performance improvement ($\beta = 0.088$, $p > 0.05$). Acquisition ($\beta = 0.278$, p 0.01) and assimilation and transformation ($\beta = 0.221$, p 0.05) capabilities continue to be positively associated with greater use of BDA to support purchasing activities.

4.4 Endogeneity test: the use of big data analytics as driver of higher purchasing absorptive capacity

To refine the results, we conducted an additional robustness test to ensure that the relationship between the dependent and independent variables did not influence our research model. We tested an alternative model where BDA use for strategic purchasing is used as an independent variable affecting the three components of the purchasing AC. Fig. 3 presents the results of the path estimates.

**[Insert Fig. 3 here]**

The path estimates gave us poorer fit indices for this model compared to our research model in Fig. 1 ($\chi^2 = 622.17$; $\chi^2$/d.f. = 1.96; RMSEA = 0.066; CFI = 0.895; TLI = 0.884). The improved statistical explanatory power further supports the theoretical validity of the hypotheses in the research model.

## 5. Discussion

The analysis confirmed the hypotheses developed for the interaction between AC components and BDA in the context of PSM. Acquisition, assimilation, and transformation capabilities are essential for organizations to effectively use BDA for strategic PSM activities. These capabilities help organizations explore external environments, assimilate knowledge, and integrate data from multiple sources. Organizations prone to acquiring and assimilating information from the external environment tend to favor BDA for use in decision-making (Božič and Dimovski, 2019), and can later exploit the value of BDA to inform their strategic PSM decisions (Moretto et al., 2017; Neirotti et al., 2021). The use of BDA for strategic PSM activities influences purchasing exploitation capabilities positively, allowing organizations to generate new knowledge, identify opportunities, and create competitive advantages. Performance improvement following the use of BDA for strategic PSM activities is enabled through both direct and indirect effects. Direct contributions came from BDA adoption, while indirect effects are amplified through greater knowledge exploitation capabilities. The model testing confirmed our theoretical arguments, and showed that purchasing AC relates differently to the use of BDA, highlighting the multifaceted relationships between BDA and AC capabilities, as discussed in the non-SCM literature (Božič and Dimovski, 2019; Roßmann et al., 2018; Urbinati et al., 2019; Lozada et al., 2023). BDA adoption for strategic PSM activities was more beneficial than operational activities, as it provided more significant improvements in performance.

These results can be discussed with reference to four main areas of interest.

5.1 Do purchasing acquisition, assimilation and transformation capabilities enable the use of big data analytics for strategic purchasing?

By validating hypotheses H1 and H2, we demonstrate that exploration and assimilation capabilities are the drivers and prerequisites for a greater use of BDA to support strategic PSM activities. Purchasing organizations struggle to incorporate BDA into their decision-making if the organization is not open to exploring the external environment for new supply markets and supply chain knowledge or assimilating such knowledge inflows from the outside. The types of data that are most relevant to their strategic PSM activities are more likely to be known by purchasing departments, with greater knowledge acquisition capabilities. This can assist them in identifying the appropriate data sources for their BDA projects. Through knowledge assimilation and transformation capabilities, they can generate information of a higher quality by integrating data from multiple sources, such as their procurement systems, supplier databases, and external data sources (e.g. market intelligence reports). On the basis of this data, they are able to obtain more in-depth insights through the use of BDA, which can inform strategic PSM decisions. Purchasing organizations with high internal capabilities in the areas of market, technology, and competitor scouting, as well as internal relationship mechanisms based on integration, communication, and mutual support (which can facilitate assimilation and transformation of such knowledge) are more likely to adopt advanced technologies like BDA (Hallikas et al., 2021; Öhman et al., 2021; Rialti et al., 2019; Roßmann et al., 2018). Our endogeneity test revealed that the reverse causality (supported by prior literature such as Setia and Patel, 2013) only applies to assimilation and transformation capabilities. Thus, we conclude that, at least in the context of PSM, the successful implementation of BDA is contingent upon an organizational foundation of acquisition, transformation, and assimilation capabilities.

5.2 Does the use of big data analytics for strategic purchasing influence purchasing exploitation capabilities?

In accordance with previous research (e.g., Intezari and Gressel, 2017), organizations that use BDA for strategic PSM activities experience an improvement in their exploitation capabilities. With this result, we demonstrate that BDA contributes to the purchasing organization's ability to generate new knowledge and identify opportunities in multiple areas using higher-quality information after its application. Using BDA to analyze spend data, for instance, the purchasing department can identify cost-saving opportunities (e.g., where purchasing volume can be consolidated to negotiate better prices, or where inefficient procurement processes can be streamlined to reduce costs). By analyzing process data with BDA, the purchasing department can identify areas for process optimization, such as the identification of procurement bottlenecks and the implementation of process improvements to reduce lead times and increase efficiency. Last, by analyzing supplier data with BDA, the purchasing department can identify areas where suppliers can enhance their performance. In conclusion, the analysis of high-quality data through BDA can be used to generate new knowledge and insights. However, H3 only makes sense if H1 and H2 are also true, highlighting the significance of the interaction between different AC components in the technology's adoption (Cepeda-Carrion et al., 2012; Mahmood and Mubarik, 2020; Mikalef et al., 2020). Knowledge exploitation becomes tangible and effective through the use of BDA, which drives, informs, and empirically validates the weak signals coming from the external environment by enabling a more effective identification of supply chain opportunities to create a competitive advantage for the company (Erevelles et al., 2016; Grover et al., 2018).

5.3 What organizational mechanisms enable performance improvement following the use of big data analytics for strategic purchasing?

When discussing the competitive advantage of using BDA for strategic PSM activities, our findings indicate that the overall (positive) impact on performance improvement results from the simultaneous coexistence of a direct and indirect effect, which supports our hypothesis H4 (Rialti et al., 2020; Roßmann et al., 2018). The adoption of BDA for strategic PSM activities, per se, provides a direct contribution to performance improvement. The adoption of BDA can help purchasing departments improve their performance by increasing efficiency, enhancing supplier management, improving negotiation outcomes, and providing real-time data and insights for agile decision-making. By leveraging BDA effectively, purchasing professionals can drive better results for their organizations (Arvidsson et al., 2021; Moretto et al., 2017). Due to the significant (positive) mediation effect of this variable, greater knowledge exploitation capabilities amplify the effect. This gives further hints on the role of BDA in strategic purchasing decisions. The adoption of BDA requires not only the implementation of appropriate technological infrastructure but also the development of appropriate knowledge management capabilities and competencies among the purchasing professionals. The knowledge exploitation capabilities of purchasing people are essential to fully leverage the potential of BDA for purchasing performance improvement. Only purchasing professionals who are wellversed in BDA and possess the necessary competencies and knowledge can use this high-quality data and information to make more informed strategic decisions that ultimately result in enhanced performance (Hallikas et al., 2021).

5.4 Why should companies adopt big data analytics for strategic purchasing?

While hypotheses H1 and H2 are applicable to both strategic and operational purchasing—highlighting the importance of acquisition, assimilation and transformation capabilities for the successful adoption of BDA for PSM activities (Ciampi et al., 2021)—H3 and H4 are invalid when BDA is used for operational PSM activities. These results are pertinent (and unique) in the context of SCM and BDA in general, as previous research on the interrelationship between BDA and operational activities may have suggested a positive interaction between BDA and operations improvement (Yu et al., 2022). We demonstrate empirically that, in the context of PSM, the use of BDA for operational activities has no positive relationship with either exploitation capabilities or the contribution of BDA to performance. These results shed additional light on the role of BDA in supporting SCM processes (PSM, in particular). PSM activities related to contract management, order management, logistics management, and invoice management generate data, but do not necessitate strategic or complex decisions that may require the use of advanced analytics techniques. Therefore, the improvement in knowledge management capabilities and performance resulting from the adoption of BDA in this area appears to be negligible (e.g., Arunachalam et al., 2018; Nguyen et al., 2018). To summarize, exploration, assimilation, transformation, and exploitation capabilities are therefore essential to extract the power of the BDA technologies, as a tool to assist managers in the context of strategic purchasing decisions instead of supporting daily operational purchasing activities (Grover et al., 2018; Moretto et al., 2017). Nonetheless, this does not imply that businesses should only utilize BDA for strategic PSM activities. In organizations characterized by purchasing operations with a high degree of complexity and a large number of actors (such as hospitals or construction companies), the use of BDA can still be advantageous at the operational level due to their capacity to reduce the complexity of operational activities (e.g., Yu et al., 2022).

5.5 Theoretical implications

Since the first empirical investigation of BDA in PSM was either purely conceptual or exploratory in nature (Arvidsson et al., 2021; Moretto et al., 2017; Öhman et al., 2021), our study  additional insight into the role of BDA in the field of SCM. To better understand the role of AC in driving the effective use of BDA in PSM decision-making, we propose a new empirical perspective on the significance of AC in interacting with BDA, by separating AC components.

Indeed, we show that in the context of PSM, the capabilities of acquisition, assimilation, and transformation function as antecedents for BDA, while BDA strengthens the exploitation capabilities of the companies as a result of their ability to support the strategic PSM decisions (Neirotti et al., 2021; Roßmann et al., 2018). Our research shows that businesses cannot just use BDA as a quick fix to boost PSM and supply chain performance; rather, they need to have the ability to integrate it into an environment, that in itself is flexible and ambidextrous (e.g., Patrucco et al., 2020, 2022b). By complementing existing business decision-making procedures, BDA improves procurement's ability to capitalize on opportunities (Patrucco et al., 2022a). Therefore, BDA will contribute more to performance enhancements, the more fully developed the exploitation capabilities of purchasing activities are (Difrancesco et al., 2022). Since technologies may not always be able to manifest an immediate benefit in terms of performance, this finding has theoretical relevance for BDA, SCM, and, more generally, innovation management. Our conclusion also holds true in settings where human beings and technological systems are highly interactive (Marzi et al., 2022). In this paper, we highlight the importance of further investigating how BDA interacts with the knowledge management capabilities already present within businesses (AlNuaimi et al., 2021).

By re-examining the effect of BDA on performance from the perspective of AC (Rialti et al., 2019; Roßmann et al., 2018), this study adds to the existing body of literature on BDA and its role in facilitating managers' decision-making with a special emphasis on SCM. We offer a theoretical perspective that has not been explored in previous research in the context of SCM, noting the function of BDA as a supporting tool that works in synergy with capabilities already developed internally by the companies. We also inform academics and industry professionals on the many ways in which BDA can boost performance, thereby clarifying the role it plays in facilitating day-to-day operations.

Our findings contribute to the literature on knowledge management, SCM, and BDA; their managerial implications are discussed below.

5.6 Managerial implications

Managers working with BDA should find our research helpful in determining whether or not to acquire BDA capacity and, if so, how to more effectively incorporate BDA into their organizations' decision-making procedures.

First, our research alerts managers to the fact that, without sufficient AC among purchasing professionals, implementing BDA tools and technologies may not yield the desired results. To reap the benefits of BDA, businesses must first develop a set of non-technical capabilities for internal BDA integration. Purchasing departments need to cultivate the skills of knowledge discovery, adaptation, and integration. To achieve AC, organizations must foster an atmosphere that encourages employees to constantly monitor the marketplace, communicate with one another, and pool their expertise. Managers are advised to invest in knowledge acquisition, assimilation, and transformation capabilities. This can be achieved by fostering a culture of continuous learning, promoting the sharing of knowledge and best practices, and encouraging cross-functional collaboration. Training programs and workshops can also be organized to enhance employees' skills in these areas. Managers should encourage a data-driven culture within the organization by emphasizing the importance of using BDA in strategic PSM activities. This includes setting expectations for data-driven decision-making, incorporating data analytics into the decision-making process, and rewarding employees who successfully leverage BDA insights for strategic purposes.

Therefore, incorporating BDA into purchasing should not be seen as a means to endow the organization with the ability to comprehend the competitive environment, but rather as a tool to aid in the development of a mature and sensible purchasing department. BDA and the potential enhanced sensing capabilities it may provide will be of greatest use to purchasing organizations with robust exploration, assimilation, and transformation capabilities. Therefore, companies are further motivated to direct their attention toward developing more mature purchasing departments that exhibit high exploitation capabilities in order to reap the benefits of BDA and contribute even more to performance improvement. In a well-established purchasing department, the immediate benefit of BDA may be its contribution to performance improvement; however, in the long run, the positive effect of BDA can be amplified by the organization's improved knowledge management capabilities, which are reinforced by the virtuous circle of BDA. But if the purchasing department has not worked knowledge management capabilities of its people, BDA will not pay off.

Organizations need to ensure that they have the necessary infrastructure and tools in place to support the adoption and effective use of BDA. This may include investing in advanced analytics software, hardware, and data storage solutions, as well as ensuring that the organization's IT systems can support BDA initiatives.

## 6. Conclusions

In recent years, it has become abundantly clear that supply chains play a crucial role in fostering innovation capabilities and the long-term performance of businesses (González-Benito, 2007; Freije et al., 2021; Patrucco et al., 2023). This is even more significant with the introduction of BDA, which substantially redesigned the SCM processes' activities, transforming them from operational functions to essential strategic ones (KPMG, 2018; McKinsey, 2016). BDA helps the SCM process become a cost-saving area by suggesting the potential for forecasting and analytic management of both inbound and outbound supply chain activities (Sanders, 2016; Yu et al., 2022). BDA application could enhance strategic decisions in the supply network design, supplier relationship management, and supplier performance management domains (Öhman et al., 2021). Using BDA to inform strategic PSM decisions presents an opportunity to enhance the performance of this process and the company's supply chain as a whole (Kamble and Gunasekaran, 2020; Patrucco et al., 2023). Given the scarcity of empirical research in this area, our study investigates the relationship between BDA and the PSM decision-making process through the lens of purchasing AC and its components (Neirotti et al., 2021; Patrucco et al., 2022; Wang and Byrd, 2017), arguing that capturing and creating value from BDA is contingent not only on data availability but also on companies' capacity to explore, assimilate, transform, and exploit data value.

This study has several limitations that indicate avenues for future research. First, although we believe the results (focused on PSM) to be generalizable to other supply chain areas, to ensure generalizability to the SCM field, the interaction between AC and BDA should also be studied in other supply chain processes. Second, while our quantitative methodology allowed us to identify the relationships between BDA and the purchasing AC components, the exclusive use of a deductive approach focused on testing preexisting theoretical hypotheses. Future research could explore alternative approaches, such as inductive or theory-building approaches, to generate new insights into why or how these relationships develop. A qualitative approach (e.g., a case study) would be more appropriate to examine how exploration, assimilation, and transformation capabilities lead to increased BDA use and to understand why and how the mediating effect of exploitation capabilities arises in practice. A qualitative methodology would also capture how BDA helps to build and improve the exploitation capabilities of the purchasing department. Third, our survey construed BDA as an all-inclusive technology, without taking into account that its adoption could involve a variety of techniques and degrees of complexity (e.g., prescriptive, descriptive, and optimization techniques). Future research could investigate whether different or similar effects result from the use of distinct analytics techniques. Last, our sample is skewed toward Italian companies, necessitating validation in other geographic contexts to ensure the global applicability of the results.

## FIGURES

**Fig. 1**. Research model

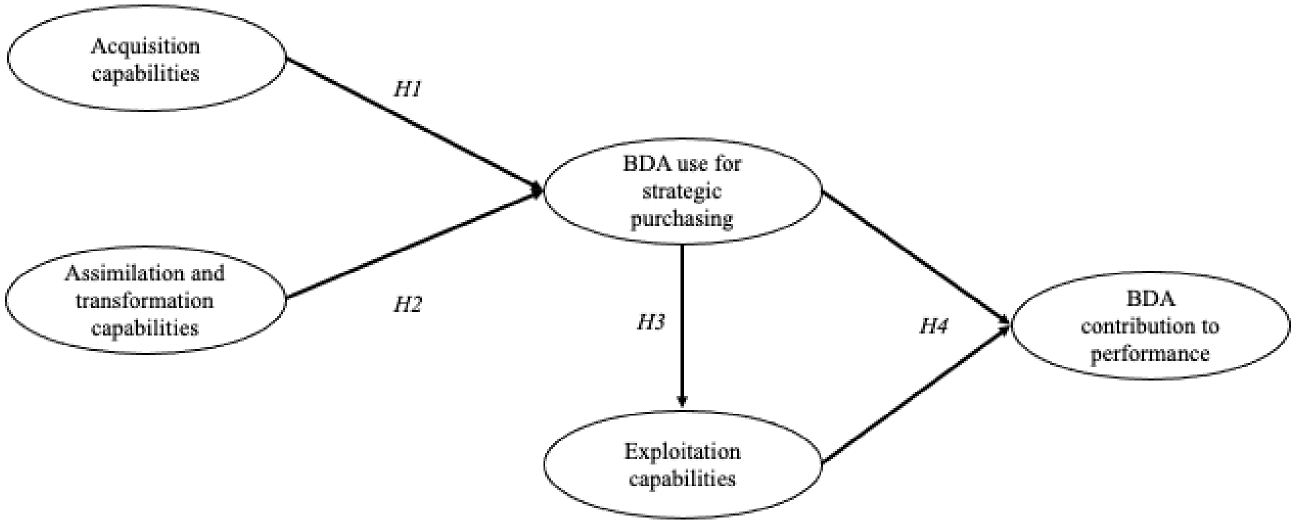


**Fig. 2.** BDA use in PSM: strategic vs. operational activities (Note: standard estimates shown; *p<0.5; **p<0.1; ***p<0.001; value of t-statistics in brackets).

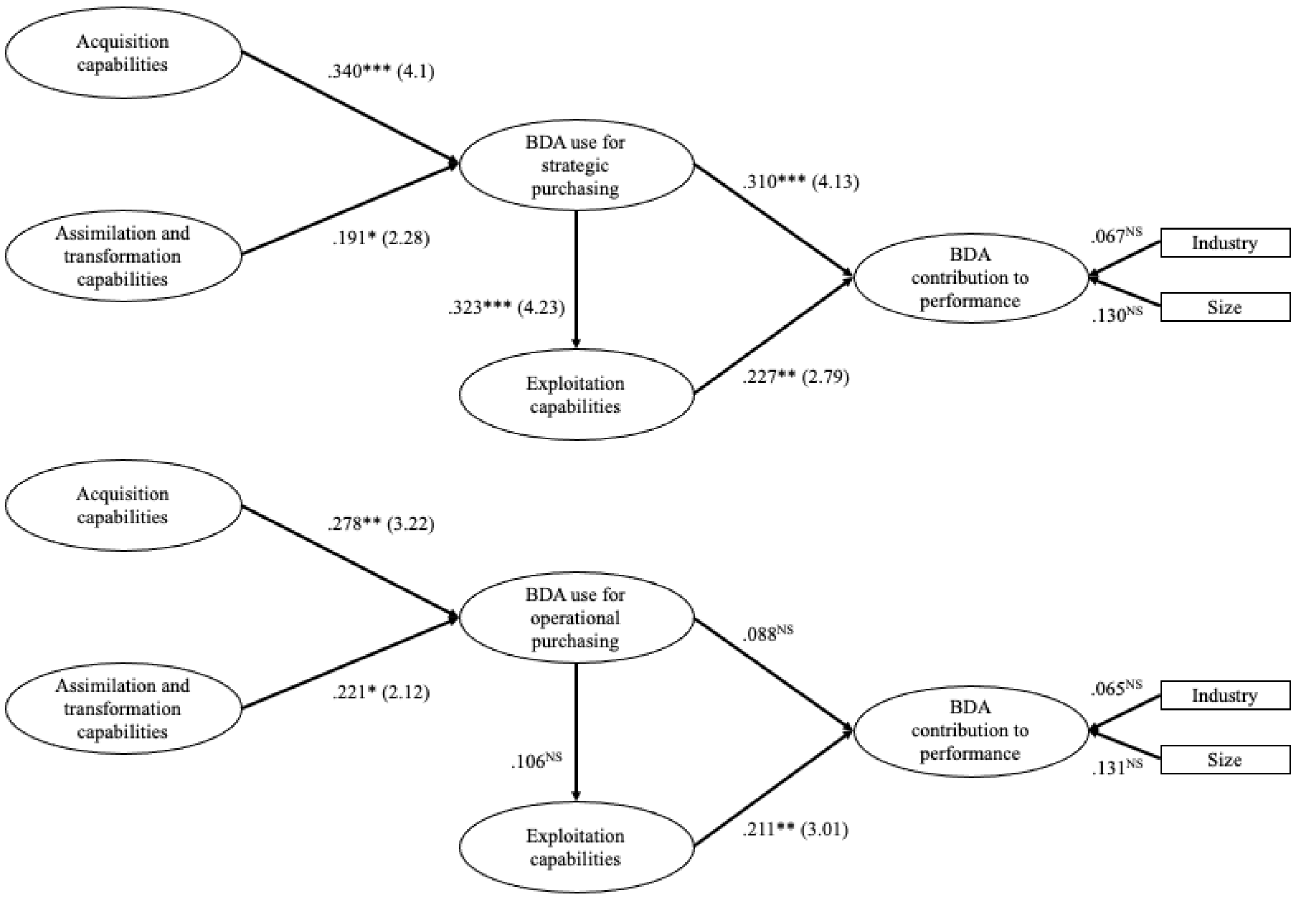
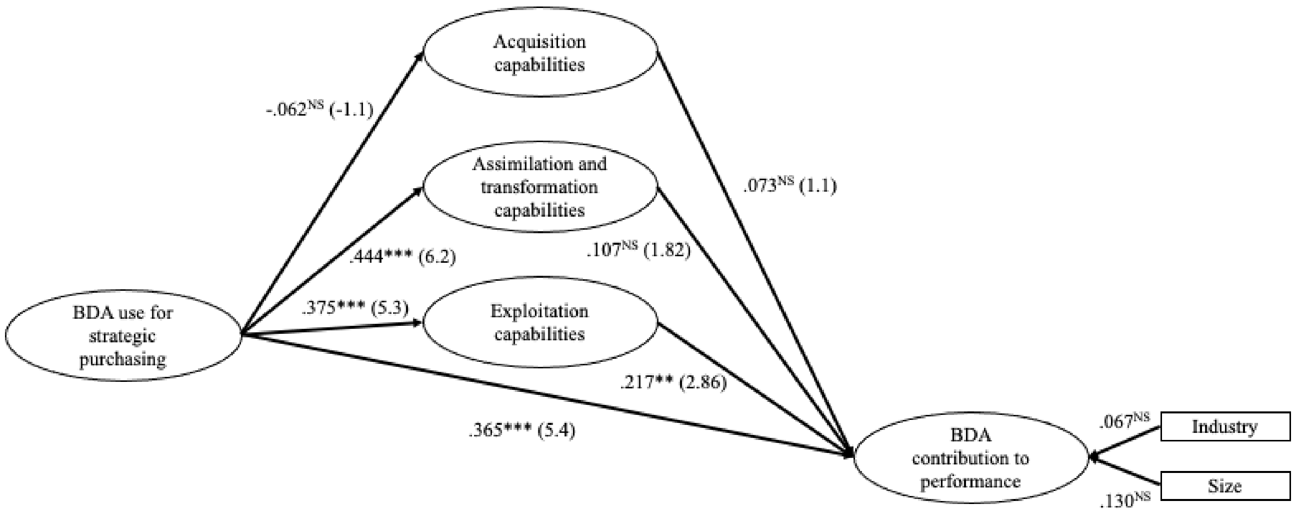


**Fig. 3.** BDA use in PSM: endogeneity test (Note: standard estimates shown; *p<0.5; **p<0.1; ***p<0.001; value of t-statistics in brackets).



## TABLES

**Table 1**. Descriptive statistics of buying company respondents.

| | | |
|---|---|---|
| **Industry** | | |
| Manufacturing | 154 | *69.4%* |
| Service | 43 | *19.4%* |
| Project | 23 | *10.4%* |
| **Company HQ** | | |
| Italy | 137 | *61.7%* |
| Rest of the world | 85 | *38.3%* |
| **Respondent role** | | |
| Senior management: purchasing (e.g., CPO, head of purchasing, head of supply chain) | 22 | *9.9%* |
| Middle management: purchasing (e.g., purchasing manager, category manager) | 153 | *68.9%* |
| Other managers (e.g., head of supply chain, production manager, supply chain manager) | 47 | *21.2%* |
| **Size (employees)** | | |
| < 50 | 64 | *28.8%* |
| 50–250 | 21 | *9.5%* |
| 251–500 | 25 | *11.3%* |
| 501–1,000 | 37 | *16.7%* |
| > 1,000 | 75 | *33.8%* |
| **Revenues (million $)** | | |
| < 10 | 21 | *9.5%* |
| 11–50 | 41 | *18.5%* |
| 51–250 | 60 | *27.0%* |
| 251–500 | 19 | *8.6%* |
| > 500 | 81 | *36.5%* |

**Table 2**. Construct validity and reliability.

| Construct | Factor loadings | Average variance explained | Composite reliability | McDonald's omega | Cronbach's alpha |
|---|---|---|---|---|---|
| *Acquisition capabilities* | | 52.55% | 0.767 | 0.831 | 0.822 |
| ACQ2 | 0.751 | | | | |
| ACQ3 | 0.789 | | | | |
| ACQ4 | 0.624 | | | | |
| | *Note*: ACQ1 dropped by CFA | | | | |
| *Assimilation and transformation capabilities* | | 55.62% | 0.790 | 0.798 | 0.797 |
| AST1 | 0.732 | | | | |
| AST2 | 0.710 | | | | |
| AST3 | 0.792 | | | | |
| | *Note*: AST4 and AST5 dropped by CFA | | | | |
| *BDA use for strategic purchasing* | | 60.05% | 0.856 | 0.828 | 0.816 |
| BDA3 | 0.720 | | | | |
| BDA4 | 0.660 | | | | |
| BDA5 | 0.878 | | | | |
| BDA6 | 0.823 | | | | |
| | *Note*: BDA1 and BDA2 dropped by CFA | | | | |
| *BDA contribution to performance impact* | | 55.10% | 0.907 | 0.918 | 0.916 |
| PERF1 | 0.814 | | | | |
| PERF2 | 0.797 | | | | |
| PERF4 | 0.795 | | | | |
| PERF5 | 0.848 | | | | |
| PERF8 | 0.810 | | | | |
| PERF9 | 0.846 | | | | |
| | *Note*: PERF3, PERF6 and PERF7 dropped by CFA | | | | |
| *Exploitation capabilities* | | 74.31% | 0.897 | 0.897 | 0.894 |
| EXL1 | 0.822 | | | | |
| EXL2 | 0.900 | | | | |
| EXL3 | 0.863 | | | | |
| | *Note*: EXL4 dropped by CFA | | | | |

**Table 3**. Correlation matrix and discriminant validity

| Variables | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| 1. Acquisition capabilities | *0.725* | | | | | | |
| 2. Assimilation and transformation capabilities | 0.499*** | *0.746* | | | | | |
| 3. BDA use for strategic purchasing | 0.356** | 0.313** | *0.775* | | | | |
| 4. Exploitation capabilities | 0.531*** | 0.274** | 0.285** | *0.862* | | | |
| 5. BDA contribution to performance improvement | 0.394*** | 0.246** | 0.554*** | 0.275** | *0.742* | | |
| 6. Industry | $0.101^{NS}$ | $0.103^{NS}$ | 0.257** | $0.119^{NS}$ | $0.127^{NS}$ | - | |
| 7. Company size (employees) | 0.143* | 0.162* | 0.266** | 0.201** | $0.097^{NS}$ | $0.065^{NS}$ | - |

Note: square root of the AVE on the diagonal; *p<0.5; **p<0.1; ***p<0.001.

**Table 4.** HTMT and HTMT2 (in brackets).

| **Variables** | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| 1. Acquisition capabilities | - | | | | |
| 2. Assimilation and transformation capabilities | 0.551 (0.528) | - | | | |
| 3. BDA for strategic purchasing | 0.294 (0.275) | 0.561 (0.491) | - | | |
| 4. Exploitation capabilities | 0.385 (0.366) | 0.379 (0.361) | 0.386 (0.381) | - | |
| 5. BDA contribution to performance improvement | 0.306 (0.277) | 0.371 (0.318) | 0.387 (0.351) | 0.367 (0.362) | - |

**Table 5**. Path analysis estimates

| | BDA use for strategic purchasing | Exploitation capabilities | BDA contribution to performance improvement |
|---|---|---|---|
| *Independent variables* | | | |
| Acquisition capabilities | 0.340***(4.1) | | - |
| Assimilation and transformation capabilities | 0.191* (2.28) | | - |
| BDA use for strategic purchasing | - | 0.323*** (4.23) | 0.310*** (4.13) |
| Exploitation capabilities | - | | 0.227**(2.79) |
| *Control variables* | | | |
| Industry: manufacturing | - | | 0.067$^{ns}$ (0.49) |
| Size (employees) of company | - | | 0.130$^{ns}$ (1.51) |
| *Fit indices* | | | |
| Chi-Square | | 304.49 | |
| Chi-Square/d.f. | | 1.97 | |
| RMSEA | | 0.059 | |
| CFI | | 0.927 | |
| TLI | | 0.916 | |
| SRMR | | 0.076 | |

Note: standard estimates shown; *p<0.5; **p<0.1; ***p<0.001; value of t-statistics in brackets.

**Table 6**. Mediation tests

| | **Direct effect** | **Indirect effect** | **Bootstrapping confidence intervals for indirect effects** | **Total effect** |
|---|---|---|---|---|
| BDA for strategic purchasing<br>Exploitation capabilities | 0.323*** (4.23) | - | - | 0.323** (3.24) |
| BDA for strategic purchasing<br>BDA contribution to performance improvement | 0.310*** (4.13) | 0.073* (2.18) | [0.041; 0.094] | 0.383*** (4.57) |

Note: standard estimates shown; *p<0.5; **p<0.1; ***p<0.001; value of t-statistics in brackets.

**APPENDIX**

**Table A1**: Items included in the questionnaire.

| Construct | Item | Label | Mean | SD |
|---|---|---|---|---|
| **Acquisition capabilities** | Our buyers frequently collect information about preferences of our customers | ACQ1 | 3.15 | 1.26 |
| | Our buyers frequently collect information about supply markets structures | ACQ2 | 3.78 | 1.05 |
| | Our buyers frequently collect information about new technologies | ACQ3 | 3.39 | 1.18 |
| | Our buyers rarely collect information about strategies and policies of our competitors *(reverse-coded)* | ACQ4 | 2.95 | 1.20 |
| **Assimilation and transformation capabilities** | Our buyers and their supervisors communicate frequently among themselves | AST1 | 4.01 | 1.06 |
| | Our buyers communicate new ideas to other internal departments | AST2 | 3.89 | 1.02 |
| | Our buyers are supportive of each other | AST3 | 4.06 | 1.02 |
| | Our buyers share ideas freely with each other | AST4 | 4.03 | 0.97 |
| | Our buyers are reluctant to accept changes *(reverse-coded)* | AST5 | 3.71 | 1.13 |
| **Exploitation capabilities** | Our buyers use their knowledge and information to identify opportunities for cost reduction | EXL1 | 3.91 | 1.07 |
| | Our buyers use their knowledge and information to identify opportunities for quality improvement | EXL2 | 3.65 | 1.10 |
| | Our buyers use their knowledge and information to identify opportunities for supplier's level of service improvement | EXL3 | 3.68 | 1.04 |
| | Our buyers rarely use their knowledge and information to identify opportunities for better material planning (*reverse-coded*) | EXL4 | 3.64 | 1.05 |
| **BDA use for strategic purchasing activities** | Our company uses BDA to support category management and strategy definition activities | BDA1 | 2.88 | 1.29 |
| | Our company uses BDA to support demand planning and forecasting activities | BDA2 | 3.09 | 1.31 |
| | Our company uses BDA to support spend analysis and cost management activities | BDA3 | 3.17 | 1.37 |
| | Our company uses BDA to support supply risk management activities | BDA4 | 2.75 | 1.35 |
| | Our company uses BDA to support supplier performance management activities | BDA5 | 3.16 | 1.23 |
| | Our company uses BDA to support purchasing process performance management activities | BDA6 | 3.21 | 1.28 |
| **BDA use for operational purchasing activities** | Our company uses BDA to support supplier selection and negotiation activities | BDA7 | 3.01 | 1.26 |
| | Our company uses BDA to support order management activities | BDA8 | 2.81 | 1.28 |
| | Our company uses BDA for logistics and delivery management activities | BDA9 | 3.09 | 1.21 |
| | Our company uses BDA to support invoice management activities | BDA10 | 2.82 | 1.17 |
| | Our company uses BDA to support fraud detection activities | BDA11 | 2.12 | 1.34 |
| **BDA contribution to performance improvement** | In our company, the use of BDA in purchasing contributes to improve the cost of purchases | PRF1 | 3.07 | 1.28 |
| | In our company, the use of BDA in purchasing contributes to improve the productivity of purchasing employees | PRF2 | 2.90 | 1.35 |
| | In our company, the use of BDA in purchasing contributes to improve the cost of the purchasing process | PRF3 | 2.86 | 1.32 |
| | In our company, the use of BDA in purchasing contributes to improve the cost of the inventory | PRF4 | 3.05 | 1.28 |
| | In our company, the use of BDA in purchasing contributes to improve the quality of purchases | PRF5 | 2.77 | 1.30 |
| | In our company, the use of BDA in purchasing contributes to improve the level of innovation of purchases | PRF6 | 2.63 | 1.24 |
| | In our company, the use of BDA in purchasing contributes to improve the processing time of internal purchase orders | PRF7 | 2.87 | 1.37 |

| | | | | |
|---|---|---|---|---|
| | In our company, the use of BDA in purchasing contributes to improve the delivery times of suppliers | PRF8 | 2.94 | 1.37 |
| | In our company, the use of BDA in purchasing contributes to improve the ability of suppliers to meet agreed environmental performance goals | PRF9 | 2.76 | 1.28 |

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