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OPTIMIZING BIG DATA CAPABILITIES AND MANAGEMENT IN MANUFACTURING FIRMS. A SOCIOTECHNICAL PERSPECTIVE

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ABSTRACT. *The rapid growth in digital transformations in businesses has increased the volume of data available to firms for analysis. This change has led to a rise in the uptake of big data analytics (BDA) in different business dimensions to enhance organizational performance, creating significant opportunities for integration within manufacturing systems. By using a sociotechnical perspective, we explore the interplay between social and technical aspects of BDA using a qualitative systematic review of 86 studies. The findings indicate that manufacturing firms have to optimize both social and technical factors in BDA systems to enhance their performance. While advanced analytical capabilities of BDA like prescriptive analytics improve operational performance, manufacturing firms should also invest in enhancing their human resource capabilities, organizational culture, and information governance to align them with the requirements of BDA. In that regard, this study provides scholars and practitioners with an understanding of how to optimize big data capabilities within manufacturing firms and a basis for further research on BDA adoption.*

KEYWORDS: big data analytics; sociotechnical perspective; qualitative systematic review.

JEL classification : C55, D70, L86, P2.

Introduction

Since the turn of the 21st century, the term ‘big data’ has gained significant popularity both in academia and in business, attracting significant interest from researchers and practitioners (Wamba *et al.*, 2017). The interest stems from an increase in the volume of data arising from the digital transformations that form part of modern businesses (Grover *et al.*, 2018). Due to the large volume of data being processed, the term big data is used to describe the size, volume, and complexity of the datasets (Wamba *et al.*, 2017). As a result, users need to utilize advanced analytical techniques and systems to generate valuable insights from the data (Chen *et al.*, 2012). In the business field, advanced analytical and processing techniques are broadly referred to as big data analytics (BDA) (Grover *et al.*, 2018). In a manufacturing context, BDA is broadly defined as the ability of a firm to collate, process, and interpret large volumes of data from internal or external sources to derive valuable insights that enhance the quality of managerial decisions and operating performance (Minelli *et al.*, 2013; Akter *et al.*, 2016; Moktadir *et al.*, 2019). The large data sets generated regularly within the manufacturing cycle can provide significant value to companies by providing information to enhance robustness and efficiency (Alexopoulos *et al.*, 2022). Even though such potential benefits exist, the adoption of BDA in the manufacturing cycle is still relatively low among firms (Yadegaridehkordi *et al.*, 2018).

Traditionally, the manufacturing sector encountered a major challenge of increased complexity in various processes, which hindered their effective management (Kozjek *et al.*, 2020). The complexities stemmed from incomplete information on aspects of the production process and an incomplete knowledge of such processes (Peklenic, 1995; Suh, 2005). The modern manufacturing sector is facing a different challenge. There are large volumes of various types of data about the manufacturing process, which are continuously increasing. However, the data remains unexploited due to the inability to extract useful information or the failure to understand the potential that the data has for enhancing manufacturing performance and overall firm performance (Kozjek *et al.*, 2020). There is a need to optimize manufacturing processes by not only reducing the incompleteness of information but also by gaining additional knowledge about manufacturing to improve efficiency and its business value.

From a technical perspective, BDA comprises different types of analytics, including autonomous, prescriptive, descriptive, and predictive, which are distinguished by varying degrees of intelligence capabilities. The variability among the technical aspects confers varying degrees of competitive advantages for businesses (Davenport, Harris, 2017). Various studies have established that besides the technical aspects of BDA, social factors such as employee skillsets are crucial to derive the expected competitive advantages (Grover *et al.*, 2018; Aldossari *et al.*, 2023). The growing body of information systems (IS) research has established that social factors are essential to the successful utilization of technical systems within organizations (Surbakti *et al.*, 2020). There are complementary elements between the social aspects of a business and its information technology (IT) assets, which have to operate in tandem (Schryen, 2013). Considering that there are significant opportunities in BDA, firms around the world have invested significant amounts of money in establishing frameworks that would enhance the utilization of their data assets. However, Grover *et al.* (2018) established that the success of firms varies in deriving useful outputs from their data through BDA. There has to be a mechanism that bridges the gaps between social factors that are essential to BDA and its technical output in areas such as manufacturing (Krishnamoorthi, Mathew, 2018). Additionally, firms struggle with establishing the relevant financial value of BDA given that it is intangible and there are no standardized models for such an assessment (Grover *et al.*,

2018). Even though such a challenge is prevalent, establishing the mechanisms through which BDA can generate value for firms is crucial for them to generate its potential benefits (Côte-Real *et al.*, 2017).

Numerous past studies have investigated the role of BDA in firm performance, but there have been inconsistent results (Torres *et al.*, 2018). Some studies have shown that BDA enhances management capabilities through evidence-based decision-making, which enhances business performance (Karaboga *et al.*, 2023). The finding highlights that firms that integrate BDA in the decision-making process increase their output. LaValle *et al.* (2011), in their comparative analysis of top-performing firms versus low-performing organizations globally, determined that the successful entities adopted more advanced data analytical approaches than their peers. However, other studies (Ghasemaghahi, 2019) established that there is no direct correlation between firm performance and BDA utilization. Such mixed results have led to confusion on the role of BDA in creating competitive advantages for firms, which has led to a derailment in its adoption, especially in manufacturing processes. In that regard, there is a research gap that needs to be filled through a comprehensive investigation. Specifically, the optimization of big data capabilities in specific aspects of a firm. This research builds on sociotechnical theory with the aim of answering the following questions:

1. What are the primary social and technical factors affecting BDA and their role in bolstering the performance of firms in the manufacturing process?
2. Do the technical aspects of BDA have an impact on firm performance, specifically manufacturing efficiency?

Based on the established benefit of BDA in enhancing firm performance (Grover *et al.*, 2018; Côte-Real *et al.*, 2017; Karaboga *et al.*, 2023), we define business value as the impact of BDA on improving the operational or financial performance of a firm, whereby we focus on its operational contribution. To bridge the gap created by the inconsistencies in individual studies, a qualitative systematic review of 86 studies was done (Paré *et al.*, 2015). The rest of the paper is organized as follows: A theoretical background on the role of BDA in creating business value is discussed in Part 2. Discussion of research variables in Section 3. A presentation of the methodology is in Part 4, followed by a qualitative systematic review in Part 5. Lastly, the conclusion for the research and the implications for future research are in Part 6.

1. Theoretical Background

1.1 Big Data Analytics

BDA has widely been used to refer to the collection, storage, and analysis of large volumes of data from multiple sources with the aim of deriving a competitive advantage over rival firms (Kude *et al.*, 2017). Goes (2014) describes big data as a high volume of observational data that is used to enhance decision-making. BDA is the process of collecting, consolidating, analyzing, and exploiting large volumes of data from independent and mixed sources to establish patterns that can improve managerial decision-making (Wamba *et al.*, 2017). The continued digital transformation in various aspects of businesses has contributed to the rapid growth in data volumes (Grover *et al.*, 2018). Variety, velocity, and volume are the three main attributes of big data, whereby volume represents the magnitude of data sets, velocity is the speed at which data is generated and processed for decision-making, and variety relates to the heterogeneity of the sources (Davenport, 2012; Hashem *et al.*, 2015; Gandomi, Haider, 2015; Ghasemaghahi, Calic, 2020). Relational databases like enterprise

resource management systems are able to generate structured data, while unstructured data stems from multiple endpoints like e-commerce platforms and social networks. Gandomi, Haider (2015) note that only 5% of the data available to firms is structured, with the rest requiring extensive data analysis.

The availability of large volumes of unstructured data has increased the demand for BDA to leverage the capabilities of big data to provide information that can support evidence-based decision-making (Seddon *et al.*, 2017; Dwivedi *et al.*, 2022). Primarily, the datasets are essential in establishing new patterns and relationships that can improve managerial decisions (McAfee *et al.*, 2012; Walker, 2014). BDA systems are founded on data collection and statistical analysis, with different concepts being used to describe their level of intelligence complexity (Chen *et al.*, 2012; Someh *et al.*, 2019). Basic systems provide descriptives that allow researchers to assess relationships or trends from historical data, while sophisticated options can present prescriptive or predictive analytics (Lepenioti *et al.*, 2020). Complex augmented analytics are able to operate autonomously by leveraging the capabilities of artificial intelligence to self-learn and self-optimize (Davenport & Harris, 2017). This study adopts the technical ranking of BDA systems to assess the contribution of BDA technical capabilities to firm performance.

Various studies have analyzed the role of BDA in generating business value, which provides insights into some of its social and technical factors (Zhu *et al.*, 2021), but without clearly evaluating the positive or negative impacts (Božič, Dimovski, 2019b). For the technical aspects, most studies have focused on specific elements of BDA, such as its modeling frameworks (Ghasemaghahi, 2019), which creates a gap in understanding whether the technical complexity of BDA has an impact on its business value. There is no qualitative systematic review available that analyzes the cumulative impact of social and technical factors on the big data capabilities and management in manufacturing firms. Therefore, this research seeks to fill that gap by providing an analysis of the impact of social and technical factors on the performance of manufacturing firms.

2. Dimensions of Big Data Analytics

We analyze the manufacturing business value of BDA using the well-defined IS framework that comprises both social and technical factors (Schryen, 2013). Additionally, we adopt the sociotechnical theory as analyzed by Bostrom and Heinen (1977) to understand the impact of the above factors on firm performance. In the IS business framework, there is the assumption that information technology resources provide a competitive advantage since they influence firm performance (Melville *et al.*, 2004). However, the sociotechnical theory views IT as a composite of social and technical factors (Bostrom, Heinen, 1977). The technical factors relate to all the technological aspects of the system that are essential to its optimal functioning, while the social factors refer to the human aspects of the system, including their skills and the organizational structure (Bostrom, Heinen, 1977). By using that multidimensional approach to analyze big data capabilities in manufacturing firms, we seek to enhance the understanding of the social and technical factors that dictate the integration of BDA in such firms.

2.1 Big Data Analytics and Manufacturing Firm Performance

Past studies have shown that technology investment decisions are affected by multiple factors, with the expected business value being a major consideration (Anand *et al.*, 2020). In

most cases, such decisions are anchored on specific aspects of organizational performance (Dong *et al.*, 2021). In that regard, we focus on the social and technical aspects as determining factors of the contribution of BDA to manufacturing firm performance also referred to as its business value in this research. Previous studies on the topic have analyzed the benefits of BDA based on multiple indicators of firm performance at different levels, including operational, financial, and market performance. Some studies conceptualized firm performance at the market level, such as sources of competitive advantage, share performance, and the success of new products or services (Gupta *et al.*, 2019; Wang *et al.*, 2019; Shan *et al.*, 2019; Côte-Real *et al.*, 2020), or customer-focused indicators like customer satisfaction (Ferraris *et al.*, 2019). Ji-fan evaluated firm performance based on financial indicators like return on investment, profitability, and revenue, while Ghasemaghahi (2018) considered operational performance through the evaluation of firm agility and the effectiveness of decision-making. A common aspect of all the above studies is that they conceptualized firm performance based on broad indicators, which is different from the narrow approach we adopt for this research. We will consider the operating indicators within the manufacturing cycle analyzed in the selected primary studies. Therefore, business value in the manufacturing sector will encompass productivity and supply chain efficiency due to the integration of BDA in the manufacturing cycle.

2.2 Social and Technical Aspects of Business Data Analytics

The social and technical aspects of BDA are conceptualized as independent variables in our research model, as shown in *Table 1*. The two aspects are extensively analyzed in relation to BDA in the selected literature. Most studies recognize the technical and human resource aspects of BDA as essential factors for firms to change and adapt to constantly changing operating environments (Ghasemaghahi, 2017). The resource-based view of BDA as a composite of technological and human aspects is in line with the tenets of the sociotechnical theory that views IT systems as comprising both social and technical aspects (Bostrom, Heinen, 1977). Broadly, the technical system comprises the hardware, tools, methods, and software that are essential for the utilization of the technology (Lyytinen, Newman, 2008). There is consistency in studies evaluating BDA and firm performance to classify assets and tools of the BDA system as its technical aspects (Torres *et al.*, 2018; Shan *et al.*, 2019; Côte *et al.*, 2020), which implies that our study considers the BDA system and its purpose as a single focus area. The task-level components of BDA are analyzed in this research based on the four levels of complexity outlined by Davenport and Harris (2017), which range from descriptive systems as the most basic to autonomous systems as the most sophisticated. Such an approach conforms to the task-level components encompassed in the sociotechnical theory. In that regard, we aim to evaluate whether there is variability in the impact of the BDA systems at different levels of advancement on manufacturing performance, which leads to the inclusion of descriptive, predictive, prescriptive, and autonomous levels as variables in our analysis model. However, since prescriptive and autonomous levels in BDA are relatively new and have not been widely adopted in organizations, they are analyzed as a single variable (Lepenioti *et al.*, 2020).

We analyze the social aspect of BDA as well as the organizational structure and human factors. The IS framework comprises all people involved with the technology system, including managers, users, and customers (Lyytinen, Newman, 2008). For this research, human resources and organizational structure are considered to be the most social aspects of BDA. Human resources, including management capabilities, refers to attributes such as

skillsets that are considered to be essential to the generation of value from the utilization of BDA (Fink *et al.*, 2017; Božič, Dimovski, 2019a). The managerial capabilities are the decision-making frameworks and the capability of managers to accomplish essential tasks through BDA, like planning and coordination of organizational operations (Aker *et al.*, 2016). For managers to be able to generate value from BDA, they have to have the ability to acquire, synthesize, and create actionable decisions from the insights it provides (Anand *et al.*, 2016).

Table 1. Independent variables in the research model

Independent Variables	Variable	Definition
BDA Technical Aspects	Level of Analytical Advancement	A study that analyzes the relationship between task-level technical aspects of BDA and firm performance.
BDA Social Aspects	Human Resources	A study that analyzes human resources, management capabilities, or both in relation to BDA.
	Organizational Structure	A study that analyzes data-driven culture or information governance in relation to organizational decision-making

Source: created by the author.

Organization structure represents the formal work environment in the firm and the communication and authority dimensions, including culture (Lyytinen, Newman, 2008). Primarily, having a evidence-based decision-making culture and an information governance framework are considered critical aspects of BDA business value creation (Grover *et al.*, 2018; Shamim *et al.*, 2020). Past studies have shown that having such a culture significantly enhances decision-making (Mikalef *et al.*, 2018; Wamba *et al.*, 2020). Shamim *et al.* (2020) also determined that information governance facilitates effective decision-making by promoting accurate analysis of data, which also leads to improvements in firm performance, especially in dynamic business environments. In line with those prior studies, we adopt data-driven culture and information governance as essential components of the organizational element of the social system of BDA.

3. Qualitative Systematic Review

We conducted a qualitative systematic review to analyze empirical evidence on the expected benefits of BDA in manufacturing from different studies. Since the conceptualization of the synthesis of qualitative studies in 1988 (Noblit, Hare, 1988), qualitative systematic review has become well established in research methodology, and it continues to evolve (Seers, 2015). The approach has been extensively utilized in different fields, including pharmacology, healthcare, and business (Paré *et al.*, 2007; Gülmezoglu *et al.*, 2013). In IS-related studies, the use of qualitative reviews has gained significant attention due to its ability to resolve inconsistencies in findings prevalent among individual studies (Mikalef *et al.*, 2018; Korherr, Kanbach, 2023). The objective of a qualitative systematic review is to interpret the existing studies, leading to the development of new understandings that can be used to develop new theories to understand or predict behavior (Seers, 2015).

Qualitative systematic reviews are an effective approach for synthesizing quantitative empirical studies to draw relevant conclusions (Noblit, Hare, 1988). The approach seeks to establish the direction of an effect, the size of the effect, the consistency of the effect across studies, and the strength of the evidence of the effect (Paré *et al.*, 2015). A narrative and

subjective approach is utilized that integrates the findings of the selected studies (Paré *et al.*, 2015). In BDA research, the method is highly effective due to the large number of studies available for systematic review. With the inconsistencies identified in individual studies on the effect of social and technical factors on the benefits of BDA, we consider the use of qualitative systematic reviews to be appropriate.

3.1 Selection of Studies

For this research, we adopt the 7 steps of a qualitative synthesis by Nobit and Hare (1988), which are getting started, selecting the relevant studies, analyzing the studies, establishing the relationship between the studies, integrating the studies into each other, synthesizing the findings, and expressing the findings (Seers, 2015). Considering that BDA research encompasses multiple fields, including business, computer sciences, mathematics, and management, we conducted a similar interdisciplinary search of relevant literature to ensure we captured a large number of studies. A three-step approach—database search, eligibility analysis, and selection—was used to search and select relevant studies for inclusion in the research, which enabled us to capture a wide range of studies on BDA. The goal was to ensure that a comprehensive collection of literature was achieved that enhanced the extent of the research while minimizing publication bias. Such a bias often arises when specific studies are preferred due to the significance of their results to the research topic, while those with insignificant findings are ignored (Rothstein *et al.*, 2005). To ensure that our research does not suffer from the same limitation, all studies that were identified through the key word search were included in the primary screening process based on the relevance of each study to the topic.

The first step in the selection of studies was to develop a protocol to guide the search, as recommended by Higgins and Green (2008). The protocol was based on the primary research question, which is: *What are the primary social and technical factors affecting BDA and their role in bolstering the performance of firms in the manufacturing process?* The question was relevant in assessing the eligibility for inclusion of all studies identified from a key word search. We utilized the key words big data, analytics, and data analytics on leading scholarly databases, which were Google Scholar, Science Direct, Scopus, and the Association of Information Systems (AIS) library. Each of the databases contains numerous papers from leading journals, conferences, and unpublished sources such as dissertations, without specific limitations on specific topics. Alongside the three search key words highlighted above, other terms such as manufacturing efficiency, business value, business intelligence, analytics capability, firm performance, and manufacturing performance were adopted to create search strings to tailor the search findings. As a result, the first search yielded 475 articles, after which 124 duplicates were eliminated. A detailed screening was done for the remaining 351 papers based on their titles, abstracts, and relevance to the research topic. The eligibility and inclusion criteria used for the articles were their focus area, the quality of qualitative or quantitative research, and the assessment of the variables presented in *Table 1*. As a result, 86 papers fulfilled the eligibility criteria and were included in the qualitative systematic review. They were coded based on their attributes, including publication type, authors, and study focus. The study focus coding primarily sought to categorize the papers based on their main research area.

3.2 Data Extraction and Synthesis

In order to synthesize the findings of the selected studies, we categorized them into their main concepts, which were added to a Microsoft Excel spreadsheet to facilitate comparison across studies. The translation of the findings was then used to make higher-order interpretations for the research topic. Primarily, we conducted a review of each of the independent variables in the sociotechnical system and how they relate to firm performance as an indicator of manufacturing improvement. Data from the studies was derived based on the two research questions that this review seeks to answer.

4. BDA Capabilities and Firm Performance

The ability of firms to collect and store big data alone is not sufficient to enhance their performance (Wamba *et al.*, 2017). There is a need for firms to leverage specific firm-level resources, including human resource and management capabilities and the technical capabilities of BDA systems (Gupta, George, 2016). BDA capabilities (BDAC) can be an effective source of competitive advantage for businesses if they are leveraged to facilitate and support organizational capabilities (Mikalef *et al.*, 2019). Based on data collected from 88 Italian firms, Ferraris *et al.* (2018) determined that there is a direct positive correlation between advanced BDAC and improvements in firm performance. In another study, Awan *et al.* (2021) determined that BDAC and business intelligence analytics are positively associated with decision-making quality in firms, especially when manufacturing managers utilize data-driven insights. In relation to manufacturing supply chains, BDA technical and managerial capacities have a positive impact on green supply chain integration in firms (Liu *et al.*, 2022). BDAC enhances supply chain resilience by improving the innovative capabilities of firms and the quality of decision-making information (Bahrami, Shokouhyar, 2021). Therefore, firms that are able to increase both their technical and social capabilities in relation to BDAC are able to improve both operational and financial performance.

4.1 BDA Technical Factors and Manufacturing Firm Performance

For this research, we define the technical aspects of BDA as its task-level components, as defined by Davenport and Harris (2017), which range from a descriptive system as the most basic to autonomous as the most sophisticated. The technical aspects relate to the expected output of the system and how it impacts manufacturing firms. Descriptive analytics form the largest usage of BDA systems as they typically relate to basic querying, modelling, and visualization of historical data (Karthikeyan *et al.*, 2019). They are essential in consolidating all the internal and external structured data for a firm that is organized into simplified representations that indicate trends and relationships in past data (Karthikeyan *et al.*, 2019). Firms are able to collect and store manufacturing data continuously throughout the manufacturing process, which can provide useful insights into various manufacturing factors (Dogan, Birant, 2021). In that regard, firms can identify areas that require improvements for effective changes to be implemented throughout the manufacturing process, which ultimately leads to improved firm performance. Neuböck and Schrefl (2015) propose the use of new analysis graphs generated through descriptive analytics to gain production insights like missing materials. Other studies have explored different applications of such analytics: Lee *et al.* (2016) showed that the analytics are useful in analyzing abnormalities within the production process, improving the quality of the manufacturing cycle (Durakbasa *et al.*,

2017), extensive monitoring of industrial processes using multiple data sources (Sanz *et al.*, 2017), estimation of residual fatigue rate in structural components in machines (Mozgova *et al.*, 2018), and automation of industrial equipment and maintenance systems (Ventura *et al.*, 2019). All the above applications of BDA descriptive analytics target process improvements to enhance the efficiency of the manufacturing process as a prerequisite for positive firm performance. However, descriptive analytics are limited to past and current performance (Kunc *et al.*, 2018), which may hinder the ability of firms to anticipate future directions in the manufacturing cycle.

Predictive analytics build on descriptive analytics based on the assumption that past behavior will be replicated in the future (Dubey *et al.*, 2019). Through predictive analytics, big data collected throughout the organization is transformed into useful information that helps to optimize and enhance organization control (Lee *et al.*, 2013). For that reason, BDA predictive analytics can be a critical tool for increasing organizational output, especially in manufacturing environments where there is significant variability, complexity, and capacity constraints (Zhong *et al.*, 2016). Manufacturing firms can generate significant and positive effects on costs and their operational efficiency through the adoption of BDA predictive analytics (Srinivasan & Swink, 2018; Dubey *et al.*, 2019). Insights generated from such a system can facilitate process improvements within manufacturing firms, which can lead to cost and efficiency benefits. Practical implementations of BDA predictive analytics include process monitoring and control for yield optimization (Kohlert, König, 2016), facilitating the transition of data through machine monitoring (Lin *et al.*, 2016), mass customization (Miškuf, Zolotova, 2016), intelligent product design (Saldivar *et al.*, 2016), predictive modeling to optimize the production process (Stein *et al.*, 2016), predictive maintenance of industrial equipment (Borgi *et al.*, 2017), predictive manufacturing situation alert system (Park *et al.*, 2017), and estimating and predicting the degradation of production equipment (Ruiz-Sarmiento *et al.*, 2020). The studies above indicate that BDA predictive analytics facilitate quality control, demand forecasting, maintenance and supply chain optimization, resource utilization efficiency, and product development improvements, which can create a competitive advantage for a manufacturing firm. They can utilize their past and current data to model future outcomes, leading to enhanced visibility of the manufacturing cycle.

Manufacturing firms often encounter the newsvendor problem, which is the optimal production or order quantity period in a specific product cycle to satisfy an unknown demand without over or underproduction in an environment with constrained resources (Punia *et al.*, 2020). Such a challenge necessitates the adoption of a data-driven solution to minimize the downside risks. Prescriptive analytics provides a potential solution to that manufacturing dilemma by answering the question, What should be done? (Lepenioti *et al.*, 2020). The approach addresses what, when, and why within a business and its relevant domain rules (Poornima, Pushpalatha, 2020). Compared to descriptive and predictive analytics, prescriptive and autonomous analytics are a relatively new area in BDA due to their limited adoption within organizational processes (Lepenioti *et al.*, 2020). Primarily, prescriptive analytics leverage big data to prescribe the most suitable decision options (Šikšnys, Pedersen, 2016). They help capitalize on predicted future outcomes using large volumes of data (Šikšnys, Pedersen, 2016). Firms that integrate prescriptive analytics are able to use BDA to describe future courses of action that may be taken to optimize business processes, leading to the realization of specific objectives (Silva *et al.*, 2021). Typically, practical applications require the association of decision choices with estimated business outcomes. Modeling techniques like scenario scheduling, design experimentation, optimization, and simulation are applied within the prescriptive analytics framework to perform prescriptive actions (Banerjee *et al.*,

2013; Jugulum, 2016). Most studies have explored different applications of prescriptive analytics within industrial environments. The use of algorithms is the leading technique that has been examined in most studies due to the refinement of various algorithms for large-scale utilization (Khayyam *et al.*, 2019; Silva *et al.*, 2020). Other optimization techniques, such as task distribution engines, have been examined in the existing literature to propose the integration of prescriptive analytics to automate and optimize task scheduling and resource planning (Ansari *et al.*, 2019; Fu *et al.*, 2018; Tsouma *et al.*, 2018; Qu *et al.*, 2016). By analyzing data from various sources such as production equipment, supply chain, and historical performance, prescriptive analytics can recommend optimal production schedules, resource allocations, and process parameters (Qu *et al.*, 2016; Richter *et al.*, 2017; Uriarte *et al.*, 2018; Leite *et al.*, 2019; Negri *et al.*, 2019; Li *et al.*, 2020; Milošević *et al.*, 2020). Prescriptive analytics can recommend maintenance schedules and strategies based on equipment condition, usage patterns, and maintenance costs (Romeo *et al.*, 2018; Ansari *et al.*, 2019; Brik *et al.*, 2019; Liang *et al.*, 2019). Other studies have shown that the effective utilization of analytics can enhance energy management, reduce waste and costs, and facilitate a transition to green energy within the manufacturing process (Yeh *et al.*, 2019; Stratigakos, 2023). Prescriptive analytics empowers manufacturing firms to make informed decisions, optimize processes, and drive continuous improvement to enhance performance, competitiveness, and profitability in dynamic business environments.

4.2 BDA Social Aspects and Manufacturing Firm Performance

We defined the social aspects of BDA as its human resources and organizational structure elements. The human resources aspect of BDA comprises the personnel and management capabilities to manage and operate the technical aspects of the analytics system (Torres *et al.*, 2018; Božič, Dimovski, 2019). Therefore, the term human resource is broadly used to define the human attributes of an organization, including both technical and managerial skills (Mishra *et al.*, 2019). Personnel capabilities refer to the functional, technical, and collaborative expertise of employees within an organization that can be enhanced through education and training programs (Korherr, Kanbach, 2021). Technical skills in the context of BDA relate to the ability to conduct analytics, manage technology aspects, and run projects. Employees should be able to conduct key processes within the BDA system. In the preprocessing of data, employees have to be able to conduct data mining and validation through multiple analytical techniques as a foundational aspect of analytical modeling (Shuradze, Wagner, 2016; Song *et al.*, 2020). During the processing stage, the personnel need to be able to define the data and the desired results to select the appropriate analytical tools such as descriptive statistics, regression, or neural networks (Cheng, Jiang, 2018). De Mauro *et al.* (2018) note that employees have to be aware of the limitations of the analytical techniques adopted during analysis to effectively analyze and implement the findings. As the complexity of the technical aspects of BDA increases, the demand for advanced analytical skills, such as programming, becomes essential to setting up analytical models (Akter *et al.*, 2020a). Moreover, personnel have to possess significant project management skills to enhance collaboration within departments across the manufacturing cycle for effective initiation and completion of performance improvement projects (Akter *et al.*, 2020b).

Beyond the technical skills, personnel have to possess functional expertise in organizational processes, competitive aspects, and resource and capacity constraints (Davenport *et al.*, 2001). Such knowledge is crucial for effective analysis of organizational problems and the formulation of suitable solutions (Wamba *et al.*, 2017). Through such

knowledge, employees can contribute to the integration of BDA within a firm (Saggi, Jain, 2018; Wamba *et al.*, 2017). Ferraris *et al.* (2019) note that a lack of collaboration among organizational departments significantly hinders the adoption of BDA for project-oriented applications. The willingness to share information across departments is crucial to ensuring that BDA is successful (Olszak, 2014). Upadhyay and Kumar (2020) state that organizations have to ensure that they promote a free flow of information across departments and frequent collaboration on projects.

Management capabilities refer to the ability to utilize BDA to accomplish managerial tasks like planning and coordination (Aker, 2016). For that reason, managers have to enhance their understanding of analytical methods to understand the data-based recommendations in their roles (Ransbotham *et al.*, 2015). Yasmin *et al.* (2020) highlight that while the technical aspects of BDA are a hindrance to its adoption, the managerial challenge is a bigger problem. Most studies agree that the capabilities of the management team are crucial to the success of firms in the era of BDA (Olszak, 2014), who have to be comfortable with applying analytical methods in their decision-making frameworks (Ransbotham *et al.*, 2015). McAfee and Brynjolfsson (2012) argue that big data alone is not sufficient to provide a competitive edge to a firm since it requires effective organizational leadership for its optimal utilization. A close and constructive collaboration between data managers and functional managers is crucial to developing the required big data skills within an organization (Gupta, George, 2016). In highly dynamic operating environments, managers have to supervise the work of BDA teams (Shokouhyar *et al.*, 2020). They will need to have the technical knowledge to allocate adequate resources to such teams and offer managerial support (McLaughlin, 2017).

At the organization level, a data-driven culture is essential to capitalize on the potential benefits of BDA (Grover *et al.*, 2018; Shamim *et al.*, 2020). The lack of an appropriate organizational culture significantly hinders the ability of firms to exploit the benefits of BDA (Barton, Court, 2012). The creation of a data-driven culture is characterized by the utilization of data to make decisions and not personal instincts (Dubey *et al.*, 2018; Pedro *et al.*, 2019) and an adherence to data outcomes even when they contradict personal decisions (Chen *et al.*, 2015; Mikalef *et al.*, 2019). An executive commitment to evidence-based decision-making that leverages data capabilities is a suitable indicator of such a culture within an organization (Gong, Janssen, 2020), and it facilitates the acceptance of BDA at other organizational levels (Cao *et al.*, 2019). With an established data-driven culture, information governance is also important (Shamim *et al.*, 2020). McLaughlin (2017) determined that stakeholder management and communication are crucial to data collection and utilization. Additionally, contracts for data quality management have to be in place to maintain high-quality and relevant data in BDA (Shamim *et al.*, 2020). Such contracts define the responsibilities and procedures of all parties to ensure that high-quality data is collected and integrated into BDA (Janssen *et al.*, 2017). Information governance frameworks also enhance organizational capabilities in relation to the BDA life cycle (Mikalef *et al.*, 2020). BDA social aspects affect how its technical aspects are managed and utilized. The two dimensions are highly interdependent, which necessitates manufacturing firms striking a balance between them to improve their operational and financial performance.

Conclusion, Limitations, and Future Research Directions

Conclusion

In this study, we conducted a qualitative systematic review of empirical evidence on the optimization of big data capabilities in manufacturing firms from a sociotechnical perspective. We provided an in-depth review of the social and technical attributes that are crucial to enhancing the performance of manufacturing firms in the BDA context. Through this research, we enrich the literature on BDA integration in manufacturing firms by establishing a consistent view of the role of such factors, and we advance the utilization of qualitative systematic review in IS research. Referring to our first research question, we identify that social and technical factors are crucial to the integration and utilization of BDA within manufacturing firms. We established that social and technical aspects of BDA are interdependent to maximize its business value in such firms. The technical capabilities of the BDA system influence its applicability within various manufacturing contexts, with advanced capabilities like prescriptive analytics encompassing a wide range of analytical applications. Social factors, which are personnel skills, management capabilities, a data-driven culture, and information governance, are essential to the operationalization of BDA within manufacturing firms. They are required to collect and validate data, process the data, interpret data insights from BDA, and make data-driven decisions. These findings are consistent with the sociotechnical view of IS as a composite of social and technical aspects. Manufacturing firms need to have sufficient technical and social capabilities to optimize their operations, leading to the generation of business value.

In relation to our second research question, we sought to examine whether the technical capabilities of BDA have an effect on manufacturing firm performance. We establish that advanced task-level aspects of BDA, like prescriptive analytics, provide enhanced operating capabilities compared to basic aspects like descriptive analytics. Each level is limited to specific analytical capabilities and decision-maker involvement in analytical modeling and insight analysis. For manufacturing firms to optimize their operations, they need to adopt BDA systems that facilitate decision-making, enhance adaptability to changes in consumer needs, and support product and service improvement. Overall, this study contributes both to theory and practice on BDA by expanding the knowledge base and providing insights into the successful utilization of BDA in manufacturing firms.

Limitations and Future Research Directions

Despite having made significant efforts to transparently and consistently apply our research strategy throughout the qualitative systematic review, there is always a risk of unintentional neglect of a source or the interpretation of selected studies. The publication bias problem was also a limiting factor, but we addressed it by using well-accepted databases, documenting the literature search, and only including the most relevant studies in our sample. It is possible that a different group of researchers may have a different literature sample due to the possibility of researcher bias in the selection and use of search strings in different databases. However, we ensured that we strictly adhered to the qualitative systematic review methodology to obtain and structure studies for review (Paré *et al.*, 2015). Another limitation relates to the scope of our study, which does not focus on any specific geographical area. We intended to develop a taxonomy that is applicable to the manufacturing industry in general. Such an approach may fail to capture firm-specific capabilities and how they impact BDA

optimization. Nevertheless, our ambition was to provide a framework that can be applied across all firms within the manufacturing sector. Future research should provide insights into firm-level social and technical factors that affect BDA integration in manufacturing industries by using both quantitative and qualitative methods. Furthermore, additional variables, including the impact of outsourcing BDA technical and managerial capabilities on manufacturing firm performance, need to be analyzed. More research is required on advanced analytics like autonomous systems and the role of artificial intelligence in the manufacturing ecosystem.

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GAMYBOS ĮSTAIGŲ DIDELIŲ DUOMENŲ GALIMYBIŲ IR VALDYMO OPTIMIZAVIMAS. SOCIOTECHNINĖ PERSPEKTYVA**Xiaoli Zhao****SANTRAUKA**

Spartus skaitmeninių transformacijų augimas versle padidino duomenų, kuriuos įmonės turi analizuoti, kiekį. Dėl šio pakeitimo padaugėjo didelių duomenų analizės (BDA) panaudojimas įvairiose verslo dimensijose, siekiant pagerinti organizacijos našumą, sukuriant dideles integracijos į gamybos sistemas galimybes. Taikant sociotechninę perspektyvą, tyrinėjama socialinių ir techninių BDA aspektų sąveiką naudojant kokybinę sistemine 86 tyrimų apžvalgą. Išvados rodo, kad gamybos įmonės turi optimizuoti tiek socialinius, tiek techninius BDA sistemų veiksmus, kad pagerintų savo veiklą. Nors pažangios BDA analitinės galimybės, pavyzdžiui, įsakmioji analizė, gerina veiklos rezultatus, gamybos įmonės taip pat turėtų investuoti į savo žmogiškųjų išteklių pajėgumų, organizacinės kultūros ir informacijos valdymo gerinimą, kad atitiktų BDA reikalavimus. Atsižvelgiant į tai, šis tyrimas suteikia mokslininkams ir praktikams supratimą, kaip optimizuoti didelių duomenų pajėgumus gamybos įmonėse, ir pagrindą tolesniems BDA pritaikymo tyrimams.

REIKŠMINIAI ŽODŽIAI: didelių duomenų analizė; sociotechninė perspektyva; kokybinė sistemine apžvalga.