Exploring the Landscape of Big Data and Artificial Intelligence Applications in Manufacturing Small-Sized Enterprises: Insights from Italian Business-to-Business companies

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Abstract

This study investigates the utilization and prospective adoption of big data (BD) and artificial intelligence (AI) applications within small-sized manufacturing enterprises (SMEs), with a particular focus on Italian SMEs operating in business-to-business markets. The research aims to discern the level of interest among these enterprises in such applications, as well as to delineate any variances in implementation maturity. Furthermore, the study endeavours to uncover the challenges inherent in the integration of BD-AI applications within these contexts. A qualitative inquiry involving a panel of 12 experts was conducted to identify potential applications utilized by manufacturing SMEs. Qualitative analysis reveals burgeoning interest in BD-AI applications for predictive maintenance and energy efficiency. However, despite the allure of these applications, various challenges hinder their seamless implementation. Interestingly, specific applications, such as production scheduling optimization and root-cause analysis, garnered negligible interest, while uncertainty surrounds applications for predictive quality control and environmental impact reduction. This research represents a pioneering effort in shedding light on an underexplored domain. The findings contribute to a deeper understanding of BD-AI application dynamics within manufacturing SMEs and offer actionable insights for managerial decision-making and resource allocation in the realm of BD-AI applications.

Keywords

Artificial Intelligence; Big Data; manufacturing sector; SME.

1. Introduction

Big data (BD) and artificial intelligence (AI) have garnered increasing interest in both academic and managerial circles, positioning themselves as key scientific themes of our era (Diebold 2012). BD and AI are interdependent, with AI enhancing the efficiency of BD analysis concerning user interactions, computing, and storage resources (Reis et al. 2021). Laney (2001) characterized BD using the 3Vs: volume, velocity, and variety. BD encompasses both structured and unstructured data in various formats, including text, sound, video, and images (Jayagopal and Basser 2022). Consequently, advanced technological capabilities are essential for collecting and analyzing BD to support effective decision-making, and AI is predominantly used for these tasks (Iafrate 2018).

In recent years, BD and AI have been explored across numerous applications and processes, particularly in digital marketing (Malik et al. 2022), where vast amounts of data are gathered from millions of internet-connected users. Similarly, manufacturers, such as those in the automotive and consumer electronics sectors, collect extensive data from smart technologies embedded in their products globally. While firms like Amazon, Google, LinkedIn, and Facebook are often associated with BD and AI, the manufacturing sector may actually store more data than any other industry (Nedelcu 2013). This sector generates data from various internal sources, including machinery, assembly lines, measurement instruments, tools, robots, sensors, and numerous digital technologies. Manufacturers are now integrating data from shop floors with software systems and ERP modules. Despite the growing number of publications on BD and AI applications in manufacturing, operations, and supply-chain management, research in this field is still limited (Lamb and Singh 2017). Some scholars argue that research on BD-AI applications in production lags behind studies in IT, finance, and marketing (Weng and Weng 2013; Lamb and Singh 2017; Kumar et al. 2022).

Focusing on production management within business-to-business manufacturers, the existing research becomes even scarcer, especially concerning small- and medium-sized enterprises (SMEs). SMEs often face significant challenges when adopting new technologies (Maroufkhani et al. 2020; Wang and Wang 2020). For instance, a typical manufacturing SME with limited resources may struggle with BD and AI management, as their traditional ERP and software systems are typically based on standard relational databases suited only for structured data (Ekren and Erkollar 2020).

2. Literature review

There is an extensive body of literature focused on the applications of big data (BD) and artificial intelligence (AI) in the manufacturing sector. These applications are integral to initiatives like Industry 4.0, Made in China 2025, the Advanced Manufacturing Partnership (USA), and Society 5.0 (Japan) (Azeem et al. 2022). Various authors have explored how BD and AI present challenges, benefits, and future prospects for manufacturing businesses (Khan et al. 2017; Lamba and Singh 2017; Nagorny et al. 2017; Javaid et al. 2020; Azeem et al. 2021). One of the pioneering papers by Khan et al. (2017) delved into the impacts of BD on production management, illustrating how the combination of BD and AI can influence business intelligence, simulations and optimizations, product quality improvement, machine health prediction, and production planning.

The use of simulations for optimizing production systems is a well-explored topic in the literature (Gao et al. 2019; Dolgui et al. 2022; Jung et al. 2022; Zhang et al. 2022). These simulations often utilize BD and AI and are based on "digital twin" models, which are virtual replicas of physical entities (Bruckner et al. 2020). Javaid et al. (2020) emphasized the utility of BD-AI in processes such as production deviation and prediction, quality discrimination, and energy efficiency. Azeem et al. (2021) similarly noted the application of BD-AI in predictive manufacturing environments, smart planning and scheduling, quality control, maintenance, and sustainability.

A significant theme in production management literature is the use of BD-AI in predictive maintenance processes. Feng and Shanthikumar (2018) explored how BD-AI could evolve production and operations management research, highlighting the role of AI in improving machine maintenance and root-cause analysis. Polenghi et al. (2021) also noted the shift towards data-driven decision-making in modern maintenance practices. Studies have examined BD-AI for predictive maintenance in various contexts, including cloud-based analytics integration (Daily and Peterson 2017), maintenance policy frameworks (Lee et al. 2017), and multisource heterogeneous information structuring (Yan et al. 2017; Yu et al. 2019). Research has further explored its application across different industries and case studies (Canizo et al. 2017; Sahal et al. 2020; Ayvaz and Alpay 2021; Drakaki et al. 2021; Nordal and El-Thalji 2021), as well as its trends in literature (Sakib and Wuest 2018; Bousdekis et al. 2019; Sajid et al. 2021; Wen et al. 2022).

BD-AI applications in production planning and scheduling have also attracted attention. Zhu et al. (2017) presented an early case study demonstrating how BD can enhance production scheduling. Similar applications have been reported in various contexts, including simplified manufacturing (Ji and Wang 2017), garment manufacturing systems (Dong 2021), and refinery production (Joly et al. 2018). Ji and Wang (2017) combined BD-AI with fault prediction in shop-floor scheduling. Parente et al. (2022) reviewed trends and challenges in Industry 4.0 cybertechnologies for production scheduling, suggesting that BD-AI can significantly support and improve scheduling processes (Parente et al. 2022, p. 5412), a view also expressed by Sokolov and Ivanov (2015).

The role of BD-AI in environmental performance has also been examined. Keeso (2014) was among the first to report on large firms like LinkedIn and BT adopting BD analytics for energy efficiency and environmental performance. Etzion and Aragon-Correa (2016) outlined future research avenues on strategic opportunities in resource allocation and efficiency through BD-AI and environmental management. Subsequent research has confirmed the positive effects of BD-AI on energy efficiency and consumption (Grolinger et al. 2016; Bevilacqua et al. 2017; Belhadi et al. 2018; Liu et al. 2018; Cui et al. 2020; Andrei et al. 2022). Song et al. (2017) discussed the limitations of traditional environmental performance evaluation methods and the importance of BD-AI in improving these evaluations. Su et al. (2020) identified four environmental categories where BD-AI could impact carbon dioxide emissions reduction. Beier (2022) demonstrated how the German automotive sector uses BD-AI to reduce carbon dioxide emissions, introduce environmentally friendly materials and processes, increase energy efficiency, reduce water consumption, and optimize waste management.

However, not all findings are uniformly positive. Edwin Cheng et al. (2021) found no direct effect of BD-AI on sustainable performance in their survey of 320 manufacturing companies. Dubey et al. (2019) also reported no evidence of a moderating role of flexible and control orientation in the relationship between BD-AI and social and environmental performance (Dubey et al. 2019, p. 534).

3. Methodology

In the initial stage of our research, we conducted qualitative semi-structured interviews with a panel of 12 experts using the Delphi method. The interviews were guided by four main questions derived from our literature review, allowing the interviewees to discuss their areas of expertise freely. This approach facilitated an in-depth debate on the issues. For example, to gather information on predictive processes, we asked:

What do you think are/will be the impacts of BD-AI in relation to simulation and optimization?
To obtain additional valuable insights not covered in the literature review, we posed a broader question:

What do you think will be the general impacts of BD-AI on production management?

We informed the expert panel that the discussion would focus strictly on shop-floor processes, excluding areas such as logistics, and would be centered on manufacturing SMEs.

The Delphi method involves conducting two or three rounds of interviews with sector experts (Robinson 1991). There is no strict rule regarding the number of experts, though Linstone (1978) suggested a minimum panel size of seven. For our study, we selected 12 experts, ensuring a balance of skills and expertise to cover all relevant issues. Among the interviewees, four were BD-AI experts working as system integrators and solution providers, four were manufacturing and operations management consultants, and the remaining four were production managers from Italian manufacturing companies undergoing significant digital transformations, particularly in shop-floor processes.

Each interview in the first round lasted approximately 45 minutes and was recorded using an iPhone. The recordings were transcribed, and the text was coded and categorized into theoretical themes through thematic context analysis. This process involved:

- Assigning codes to the interview text to describe the content
- Searching for patterns in the codes and grouping them into themes

- Reviewing the themes
- Labeling the themes

4. Findings

From the first round of interviews, we assigned 29 codes to the transcribed text. In the second round of the Delphi method, we asked the 12 experts to identify patterns in the codes and group them into themes. In the third round, the experts reviewed these themes, and we identified nine definitive theoretical themes, listed in the last column of the below table and labeled as T_X. These nine themes represent the main BD-AI applications impacting production management, according to the 12 experts.

Table 1: Coding qualitative data from the interviews with the panel of 12 experts

Question **(referring to production management)**	**Code**	**Initial coding**	**Grouping**	**Theoretical themes**
What do you think are/will be the impacts of BD-AI in relation to simulation and optimisation?	A_1	Digital twin simulation	$T_1 \{A_1A_3A_4A_6A_8A_{13}A_{15}A_{16}A_{20}A_{21}A_{22}A_{23}A_{28}\}$	Production routing simulation
	A_2	Linking production deviations to scheduling		
	A_3	Scheduling potential deferments		
What do you think are/will be the impacts of BD-AI in relation to predictive processes?	A_4	Learning from historical production troubleshooting	$T_2 \{A_6A_7A_{12}A_{13}A_{14}A_{17}A_{18}\}$	Machine parameters and yield optimisation
	A_5	Anticipating future performance		
	A_6	Predicting process behaviour		
What do you think are/will be the impacts of BD-AI in relation to production planning and scheduling?	A_7	Predicting and preventing bottlenecks	$T_3 \{A_1A_2A_3A_4A_6A_7A_8A_9A_{15}A_{16}\}$	Production scheduling optimisation
	A_8	Reducing unplanned postponement events		
What do you think are/will be the impacts of BD-AI in relation to environmental management (including energy management)?	A_9	Real-time product deviation and routing adjustments	$T_4 \{A_5A_6A_{11}A_{12}A_{14}A_{16}\}$	Predictive and preventive maintenance
	A_{10}	Solving potential production problems before they occur		
What do you think are/will be the general impacts of BD-AI on production management?	A_{11}	Planning preventive scheduled maintenance based on process evolution	$T_5 \{A_5A_{10}A_{11}A_{16}A_{17}A_{18}A_{28}\}$	Predictive quality control
	A_{12}	Early warning from machinery and assembly lines		
	A_{13}	Machine and station parameters optimisation and adjustment	$T_6 \{A_6A_7A_8A_{10}A_{12}A_{16}A_{17}A_{18}A_{25}A_{26}\}$	Root-cause analysis and identification
	A_{14}	Increasing machine yield and overall equipment effectiveness		
	A_{15}	Calculating possible trajectory of the production flow	$T_7 \{A_6A_{12}A_{13}A_{14}A_{17}A_{18}A_{19}A_{20}A_{23}A_{24}\}$	Resource consumption optimisation
	A_{16}	Real-time detection of abnormalities and undesirable events	$T_8 \{A_{12}A_{13}A_{18}A_{19}A_{20}A_{23}A_{24}A_{28}\}$	Reduction of environmental impacts
	A_{17}	Predicting process variability		
	A_{18}	Predicting the evolution of the most relevant process variables		
	A_{19}	Predicting potential environmental impacts	$T_9 \{A_{12}A_{13}A_{18}A_{19}A_{20}A_{23}A_{27}A_{29}\}$	Energy efficiency
	A_{20}	Running simulations based on previous data		
	A_{21}	Trail-and-error on production processes		
	A_{22}	Finding similar behaviours and patterns		
	A_{23}	Machine parameters optimisation for reducing consumption of resources		
	A_{24}	Machine parameters optimisation for reducing air and water pollution		
	A_{25}	Finding root causes through pattern recognition		
	A_{26}	Solving most production problems		
	A_{27}	Optimising energy efficiency		
	A_{28}	Analysing and preventing production risks		
	A_{29}	Energy consumption control		

5. Discussion and conclusions

We explored two main research questions: What kinds of BD-based and AI-based applications are manufacturing SMEs using or considering for production management? What challenges do these enterprises face when implementing these applications?

To address these questions, we interviewed a panel of 12 experts. The results provided several novel insights, allowing us to theorize varying levels of interest and maturity in implementing these applications.

Our findings confirmed that BD and AI applications are increasingly being used for energy efficiency and predictive and preventive maintenance. These applications have garnered significant interest, and there is considerable experience in using them for production management. Looking ahead, some companies are considering implementing BD-AI predictive applications for assembling stations, as well as dynamically adjusting scheduling for preventive maintenance, a concept referred to as 'dynamic preventive scheduled maintenance.'

Respondents also indicated intentions to use BD-AI for production routing simulation and resource consumption optimization, despite anticipating significant challenges. Production routing simulation, often based on 'digital twin' applications, typically uses historical data. However, respondents expressed the need for more dynamic and intelligent applications that can adapt simulations based on real-time events.

Additionally, companies are interested in developing BD-AI applications to predict raw material costs and facilitate agile purchasing from various suppliers. This need is particularly driven by current supply chain difficulties due to the COVID-19 pandemic and geopolitical events.

When classifying applications by interest and maturity, machine parameters and yield optimization using BD-AI were considered moderately relevant. Respondents felt that these applications should be embedded within machinery.

Conversely, BD-AI applications for production scheduling optimization and root-cause analysis were deemed less important. Respondents suggested that lean production practices, rather than complex BD-AI applications, would be more effective in resolving production scheduling issues and bottlenecks. For root-cause analysis, respondents believed that the trend of producing small batches of diverse products introduced many new problems and root causes. Thus, they felt that human experience and intuition were more effective than any BD-AI application.

BD-AI applications for predictive quality control and reducing environmental impacts did not elicit statistically significant interest. For predictive quality control, respondents' companies prefer traditional model-based applications over BD-driven ones due to the challenge of handling large amounts of unstructured data. This challenge was also noted in discussions about root-cause analysis and identification. Regarding BD-AI applications for reducing environmental impacts, respondents expressed a greater interest in traditional software and automatic equipment to monitor and control process parameters in compliance with environmental legislation, rather than investing in BD-AI solutions. Consequently, they have not implemented, nor do they plan to implement, BD-AI applications for this purpose.

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