Artificial Intelligence Adoption in the Manufacturing Sector: Challenges and Strategic Framework

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ABSTRACT

In today's competitive business landscape, manufacturing organizations are increasingly recognizing the potential of artificial intelligence (AI) to enhance productivity, efficiency, and cost-effectiveness. Despite AI's transformative applications across various sectors, its adoption within the manufacturing industry remains underexplored, with many firms facing unique challenges such as organizational complexity, legacy systems, and a shortage of specialized digital skills. This study conducts a comprehensive literature review to identify the key factors influencing AI adoption in manufacturing, categorizing them into technological, organizational, and external dimensions. Technological factors include perceived benefits, system compatibility, data quality, cost and IT infrastructure, while organizational factors encompass top management support, employee competencies, and organizational readiness. External influences involve government regulations, competitive pressures, and vendor support. By synthesizing findings from multiple empirical studies, we develop a conceptual framework based on the Technology-Organization-Environment (TOE) model, highlighting how these dimensions interact to shape AI adoption decisions. The proposed framework highlights the critical role of leadership commitment, strategic alignment of AI initiatives, and the necessity for robust technological infrastructure. It also emphasizes the impact of external factors such as supportive government policies and market competitiveness on accelerating AI integration. The study's implications are significant for academics seeking to fill research gaps, industry practitioners aiming for successful AI implementation, and policymakers interested in fostering an environment conducive to technological advancement. While the framework offers a structured approach to understanding AI adoption in manufacturing, the study acknowledges the need for empirical validation. Future research should test the framework across different manufacturing sectors and regions to account for industry-specific factors and regional variations. By addressing these areas, organizations can better navigate the complexities of AI adoption, enhancing competitiveness and innovation in the manufacturing sector.

Keywords: Artificial intelligence, Manufacturing sector, Organizational readiness

INTRODUCTION

In today's competitive business environment, organizations must adopt strategies that enhance productivity, efficiency, and cost-effectiveness to stay competitive (Ahmad et al., 2020). One practical approach is through advanced digital strategies, particularly artificial intelligence (AI) (Verhoef et al., 2021). AI, defined as systems that perform tasks requiring human intelligence—such as decision-making, problem-solving, and pattern recognition—can significantly boost productivity and help decision-makers respond swiftly to challenges (Dwivedi et al., 2021); (Duan et al., 2019); (Puklavec et al., 2018)). These systems learn from data, adapt over time, and deliver outputs like predictions, recommendations, and decisions (the International Organization for Standardization (ISO), 2022); (Feingold, 2023).

AI's ability to exceed human cognitive and computational limits has enabled transformative applications across healthcare, marketing, education, and manufacturing (Dwivedi et al., 2021). In manufacturing, AI technologies like automation, predictive maintenance, and supply chain optimization are revolutionizing productivity and efficiency (Czarnitzki et al., 2023); (Merhi & Harfouche, 2023). Understanding AI adoption across different regions and sectors within manufacturing is essential for identifying common challenges and developing strategies that can be applied across a range of organizations.

While existing research emphasizes the importance of organizational readiness and leadership in AI adoption, significant challenges—such as limited resources and technological complexity—remain (Ghani et al., 2022). Additionally, AI adoption rates vary significantly by region and organization size, warranting further investigation (Kinkel et al., 2022). Although this study provides a global overview, future research could benefit from focusing on specific regions or sectors to uncover unique challenges and opportunities.

To understand the factors influencing AI adoption in manufacturing, this study applies the Technology-Organization-Environment (TOE) framework, a model developed by Tornatzky & Fleischer, (1990). The TOE framework categorizes these factors into three contexts: technological, organizational, and environmental, all of which play a critical role in AI adoption.

Technological factors refer to the current technologies available to the organization, including system compatibility, data quality, and IT infrastructure (Czarnitzki et al., (2023). These elements determine an organization's ability to integrate AI effectively, as demonstrated by the growing need for robust IT systems among medium-sized manufacturers (Merhi & Harfouche, (2023). The perceived benefits and availability of AI technologies are central to this context, helping firms assess the feasibility and value of adoption.

Organizational factors include internal aspects such as leadership support, employee competencies, and organizational readiness. Strong leadership is key to aligning AI initiatives with business objectives (Ghani et al., (2022). Organizational readiness, particularly the availability of skilled personnel and resources, influences the success of AI implementation (Lada et al., (2023). Larger firms generally have more resources and infrastructure to support AI adoption, while smaller firms often face financial and technical constraints (Kinkel et al., (2022).

Environmental factors encompass external pressures such as government regulations, competitive forces, and vendor support (Ghani et al., (2022). Supportive government policies can accelerate AI adoption by providing incentives and clear regulatory frameworks (Merhi & Harfouche, (2023). Competitive pressure also drives firms to adopt AI to maintain a market edge through innovation and efficiency improvements (Horani et al., (2023). However, excessive regulation can hinder AI adoption, creating uncertainty and delays Horani et al., (2023).

This study aims to contribute to the literature by developing a conceptual framework to help manufacturing decision-makers assess AI adoption. The framework will support more informed decision-making and enable organizations to engage in the AI adoption process more effectively.

AI IN THE MANUFACTURING SECTOR

Empirical research on AI adoption within the manufacturing sector reveals that manufacturers face unique challenges related to organizational complexity, legacy systems, and the requirement for specialized digital skills. Studies applying frameworks like the Technology Acceptance Model, Technology-Organizational-Environmental framework, and Diffusion Of Innovations show that the manufacturing industry encounters challenges distinct from other sectors, primarily because it relies on physical processes and intricate production environments.

Chatterjee et al. (2021) identified organizational complexity as a significant barrier to AI adoption in manufacturing, especially when firms depend on outdated technologies and rigid processes that inhibit the seamless integration of AI. This is due to the prevalence of legacy systems in the sector, which frequently

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require substantial modernization before AI can be effectively integrated. Similarly, Lada et al. (2023) underscored the importance of organizational readiness and top management commitment, highlighting that AI adoption is likely to falter without internal preparedness and leadership support.

Moreover, Kinkel et al. (2022) found that company size and R&D intensity are critical in determining AI adoption success. Larger firms that have more resources and well-developed digital infrastructures are better equipped to implement AI solutions. However, compared with smaller manufacturers, where limited financial and technical resources slow adoption, there is a growing divide in technological competitiveness between large and small firms.

On the technological front, data quality and IT infrastructure are essential enablers. According to Polisetty et al. (2023), data governance and trust in AI systems are key determinants of AI readiness, with accurate, reliable data being crucial for data-driven AI applications like predictive maintenance and process optimization. Furthermore, Merhi & Harfouche (2023) emphasized the necessity of robust IT infrastructure, noting that medium-sized manufacturers often need technology upgrades to facilitate efficient AI integration.

External factors, particularly government regulation and competitive pressure, also play important roles in shaping AI adoption in manufacturing. Ghani et al. (2022) and Merhi & Harfouche (2023) observed that supportive government policies could significantly boost AI adoption, but Horani et al. (2023) found that excessive regulation can become a hindrance. Competitive pressure, on the other hand, tends to be a consistent driver of AI adoption, with manufacturers increasingly turning to AI to enhance efficiency, innovation, and product quality (Horani et al., (2023).

Table 1 provides a summary of the AI adoption studies in the manufacturing sector. A notable gap in the current research is the limited understanding of how AI adoption varies across different geographical regions and industry sectors (Czarnitzki et al., (2023); Horani et al., (2023)).

This gap in evidence, particularly concerning the diverse technological and operational needs of different industries, highlights the importance of investigating AI adoption in the printing sector and understanding the contextual factors that shape its uptake.

Table I Summary of the previous AI adoption studies.

References	**Theory**	**Manufacturing Sector**	**Methodological approach**	**Analysis technique**
Chatterjee et al., (2021)	TAM (Davis, 1989) and TOE (Tornatzky & Fleischer, 1990)	Not specified	Structured questionnaire of 340 respondents of Top and middle level IT managers from Indian manufacturing sector	Partial Least Squares-Structural Equation Modelling (PLS-SEM)
Ghani et al., (2022)	TOE (Tornatzky & Fleischer, 1990)	Industrial products manufacturing	Structured questionnaire of 127 respondents of top managers and lower-level managers from publicly listed Malaysian manufacturing companies	Correlation and regression
Kinkel et al., (2022)	TOE (Tornatzky & Fleischer, 1990)	SME and Large manufacturing Vehicles, Rubber & Plastics, Textile & Clothing, Chemicals & Pharmaceuticals, Mechanical Engineering,	Cross-national survey of 655 managers from China, Poland, Germany manufacturing industry	Regression analysis

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		Metal Products, and Food		
Czarnitzki et al., (2023)	Production Function Approach (Berndt, 1991)	Agriculture and Food, Textiles and Apparel, Chemicals and Pharmaceuticals. Rubber, Plastics, and Metals, Machinery and Equipment	A cross-sectional survey of 5851 Managers from German manufacturing firms	Production function analysis.
Lada et al., (2023)	Internal-External Factors	Not specified	Structured questionnaire survey of 196 SME owners and managers from Sabah manufacturing sector	Partial Least Squares-Structural Equation Modelling (PLS-SEM)
Merhi & Harfouche, (2023)	TOE (Tornatzky & Fleischer, 1990)	Not specified	Eight experts in analytics, AI and IT from medium-sized manufacturing in the Midwestern US	Analytical Hierarchy Process (AHP)
Horani et al., (2023)	DOI (Rogers, 1995), and TOE (Tornatzky & Fleischer, 1990)	Not specified	Structured questionnaire of 512 respondents of senior IT/IS managers from the manufacturing sector in Jordan	Partial Least Squares-Structural Equation Modelling (PLS-SEM)
Polisetty et al., (2023)	TOE	Not specified	Netnographic of online discussions from social media, forums and blogs focused on AI adoption and questionnaire survey of 866 SME manufacturing managers	Thematic analysis of the netnographic data and Partial Least Squares-Structural Equation Modelling (PLS-SEM)

FACTORS INFLUENCING AI ADOPTION IN THE MANUFACTURING SECTOR

AI adoption in the manufacturing sector is shaped by a complex interplay of technological, organizational, and external dimensions. From a technological perspective, the key drivers include the perceived benefits of AI, such as enhanced operational efficiency and product innovation. However, these advantages must be weighed against challenges like system complexity and compatibility with existing infrastructures (Czarnitzki et al., 2023; Lada et al., 2023). Organizations with strong digital foundations are better equipped to navigate these challenges, while those with less advanced IT capabilities often struggle with the technical demands of AI implementation (Chatterjee et al., 2021; Polisetty et al., 2023).

On the organizational side, factors such as leadership support and the alignment of AI initiatives with strategic business goals are crucial for successful adoption (Ghani et al., 2022; Horani et al., 2023). However, these efforts need to be bolstered by workforce development, as a lack of specialized skills among employees can impede effective AI deployment (Czarnitzki et al., 2023). Fostering a culture of continuous learning and innovation is essential to building the internal capacity required for AI integration.

Externally, government regulations, competitive pressures, and vendor support play significant roles in the adoption process. Regulatory clarity and financial incentives can mitigate perceived risks, encouraging firms to invest in AI technologies (Merhi & Harfouche, 2023). Competitive pressures compel organizations to adopt

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AI to maintain or enhance their market position, while vendor support—through technical assistance and training—helps firms manage the complexities of AI deployment.

The literature review consolidated insights from various relevant studies, filtering and synthesizing the most commonly cited factors to develop a mapping matrix of salient adoption theories (see Table 2). This matrix identifies the key variables and dimensions influencing AI adoption, providing a foundation for a conceptual framework that addresses both internal readiness and external influences.

Table 2: Mapping matrix of the dimensions and independent variables obtained from the various literature review used

Dimension	**Independent Variables (IV)**	**Description**	Chatterjee, S., Rana, et al. (2021).	Ghani, E. K., Ariffin, N., & Sukmadilaga, C. (2022)	Kinkel, S., Baumgartner, M., & Cherubini, E. (2022)	Czarnitzki, D.,et al. (2023)	Lada, S., Chekimaet. al (2023).	Merhi, M. I., & Harfouche, A. (2023)	Horani, et al. (2023).	Polisetty, A., Chakraborty, D., G, S., Kar, A. K., & Pahari, S. (2023).
Technological	Relative advantage	Benefits AI provides over traditional methods.			√			√	√	√
	Costs	Financial impact for AI adoption							√	
	Compatibility	AI fits with current tech and organizational practices				√		√	√	√
	Data	Data quality, quantity, privacy and security						√		
	IT Infrastructure	Hardware, software, networks for AI adoption		√				√		
	Complexity	The difficulties in understanding and using AI solutions	√		√				√	
Organizational	Top Management Support	Leadership commitment for AI adoption.	√	√			√	√	√	
	Employee competencies	Skills required to manage and implement AI effectively.	√		√		√			√
	AI initiative	Strategic alignment ensures AI supports business goals.	√					√	√	
	Organizational readiness.	Organizational capacity to adopt and implement changes through leadership, infrastructure, and adaptability.	√		√	√	√	√	√	√
External	Competitive pressure	External force to maintain competitiveness.	√				Ö	Ö	Ö	

	Government roles	Regulation, funding, education, and strategic support.		√	√			√	√	√
	Vendor Support	Technical assistance and collaborative efforts by vendors and partners.	√				√	√	√	

DISCUSSION AND IMPLICATIONS

This review is to understand the AI adoption process in the manufacturing sector by analyzing relevant empirical research. Through the examination of studies, we mapped the key findings across technological, organizational, and external dimensions that influence AI adoption.

The findings highlight that AI adoption in manufacturing is a multifaceted process, shaped by the complex interplay of various factors. Top management support and organizational readiness emerged as critical determinants, emphasizing the importance of leadership commitment and the strategic alignment of AI initiatives (Ghani et al., (2022); Lada et al., (2023). The readiness of an organization to adopt AI depends not only on leadership but also on internal capabilities such as employee competencies and resource availability.

From a technological perspective, factors such as relative advantage and system compatibility are significant drivers of AI adoption. However, challenges such as system complexity and the requirement for robust IT infrastructure often impede progress, especially in firms reliant on legacy systems (Chatterjee et al., 2021); Merhi & Harfouche, (2023). For example, Polisetty et al. (2023) found that medium-sized manufacturers frequently need to upgrade their IT infrastructure to facilitate AI integration, particularly for applications like predictive maintenance and process optimization.

Organizational factors play a key role in AI adoption. For instance, Lada et al. (2023) demonstrated that organizations with strong leadership support and adequate resources are far more likely to successfully adopt AI technologies. The presence of skilled employees and management's commitment to aligning AI with business goals significantly improves the chances of successful integration.

Environmental or External factors—including government policies and competitive pressures—also significantly shape AI adoption. Supportive government regulations can accelerate the adoption process, while excessive regulation may act as a hindrance (Kinkel et al., (2022); Horani et al., (2023). In the United States, for example, government incentives have significantly accelerated AI adoption in the automotive manufacturing sector, illustrating how a favourable regulatory environment can influence technological uptake (Merhi & Harfouche, (2023). Additionally, competitive pressures drive companies to implement AI solutions to remain innovative and efficient in a fast-evolving market Horani et al., (2023).

Based on these insights, we propose a conceptual framework (Figure 1) that integrates the key factors identified in Table 2 by applying the Technology-Organization-Environment (TOE) framework, a widely used model for understanding technology adoption at the organizational level. This framework offers a comprehensive view of the various factors influencing AI adoption in the manufacturing sector, accounting for technological capabilities, organizational preparedness, and external pressures.

The implications of this study are significant for both academia and industry. For researchers, the identified gaps suggest the need for more empirical studies focused on underexplored areas, such as small and medium-sized enterprises (SMEs) in developing economies and the interaction of multiple influencing factors. For practitioners, the study emphasizes that, beyond technological capability, leadership support and organizational readiness are critical components for successful AI integration. Policymakers can also draw valuable insights from the findings, particularly regarding the role of supportive regulations and incentives in facilitating AI adoption, thereby enhancing competitiveness and innovation within the manufacturing sector.

LIMITATIONS AND FUTURE RESEARCH

Although this study developed a conceptual framework based on an established model, a primary limitation is the lack of empirical validation of the proposed framework. Future research should focus on empirically testing the framework to better understand the factors affecting AI adoption, especially in underrepresented manufacturing sectors such as printing. Additionally, the study did not explore the role of industry-specific factors and regional variations in depth, which could be valuable areas for further research.

CONCLUSION

The multifaceted nature of AI adoption in manufacturing, demonstrating that success depends on the synergistic alignment of technological capabilities, organizational readiness, and external support. By identifying key factors and research gaps, this study provides a foundation for future research to develop tailored frameworks that address the specific challenges of the manufacturing sector. Based on the TOE model, the proposed framework offers a structured approach to understanding how technological benefits, organizational capabilities, and external pressures interact to shape AI adoption in manufacturing. The insights derived from this research contribute to the existing literature and provide practical guidance for decision-makers aiming to foster effective AI integration in the manufacturing industry.

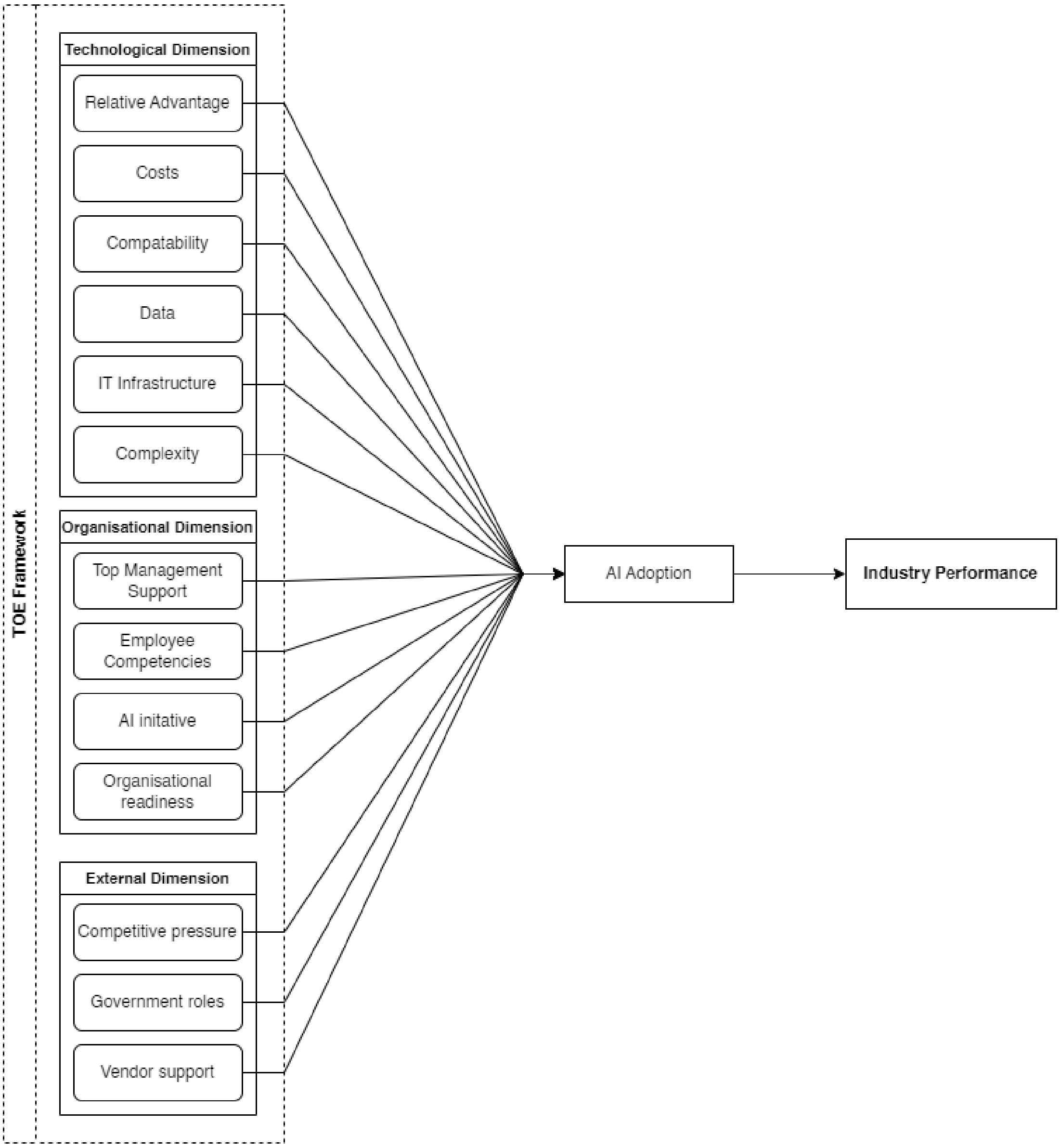

Figure 1: Conceptual Framework of AI adoption in Manufacturing

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