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AI-Augmented Manufacturing and Logistics Analytics Review

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Abstract-* *Artificial intelligence (AI) is transforming the way that manufacturing and logistics functions operate, helping companies to gain a competitive advantage from an ever-increasing amount of complex data that is now available in real-time. Even though much research and investment has been made, there is little consistency within and across both of these interrelated areas in synthesizing the empirical evidence regarding AI augmentation. It is a paper that gives an overview of the literature in the form of a narrative empirical research analysis and explores the role of AI in improving the analytics-driven decision making in manufacturing operations and logistics systems. The review is based on peer-reviewed studies published from 2015 to 2024 from the Scopus, Web of Science and Google Scholar databases which were identified as five thematic areas namely, applications of Artificial Intelligence in manufacturing, applications of Artificial Intelligence in logistics and supply chain, analysis frameworks for supporting the augmentation with Artificial Intelligence, human-AI collaboration, and barriers to the implementation of Artificial Intelligence. The results indicate that AI augmentation is consistently found to have a positive effect on the operational performance in both areas, with predictive maintenance, demand forecasting, and warehouse automation being the areas with the most empirical support. The human-AI collaboration is a complex but fruitful model, especially in decisions support applications, whereas limitations in data quality and infrastructure and costs of implementation remain an obstacle to adoption, particularly in small and medium sized enterprises (SMEs) and developing economy contexts. The review helps fill a gap in the literature by summarising the existing evidence on these topics in an integrated thematic synthesis, by highlighting the gaps in the research and by proposing a research pathway focused on novel contexts and methodological approaches. The implications for manufacturing companies, logistics companies, and technology policy makers looking to responsibly and effectively use AI as an augmentation tool are significant.

Keywords: artificial intelligence (ai); manufacturing operations; logistics and supply chain management; ai augmentation; human–ai collaboration; predictive analytics; operational performance.

I. INTRODUCTION

AI and cutting-edge manufacturing and logistics technologies are poised to become one of the most impactful technology shifts of the early twenty-first century. In the industrial world, AI is no longer an accessory, but an integral part of the strategic management of operations thanks to the abundance of data, the accessibility of the computing infrastructure and the development of machine learning algorithms. The manufacturing and logistics industry is using AI powered analytics to boost factory productivity, minimise waste, optimize supply chains and ensure more agility in meeting customer demand (Bag et al., 2021; Jan et al., 2023). Although there is a considerable amount of investment and empirical research in this area, there is still a lot of disintegration in the literature. Research often focuses on a restricted scope of application areas, individual industries or single technologies, but has lacked an integrated view of how the use of AI augmentation works between manufacturing and logistics. Therefore, there is a need for a review to bring together evidence from both sectors, highlight any common themes and highlight what still needs to be done in the research base. This review is necessarily limited to empirical research on the use of AI-augmented analytics in the manufacturing and logistics settings, for the 2015-2024 timeframe, which is when AI tools are maturing within the Industry 4.0 paradigm. This paper aims to achieve four objectives: firstly, it aims to map the existing empirical evidence on the use of AI in manufacturing and logistics analytics; secondly, it investigates the analytics frameworks that underpin AI augmentation; thirdly, the paper looks at the evidence with respect to human-AI collaboration and implementation

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barriers; and fourthly, it aims to highlight areas for further investigation of research gaps.

II. CONCEPTUAL BACKGROUND AND THEORETICAL FRAMING

2.1 Defining Key Terms

AI augmentation is different from AI automation, where AI tools support and augment human cognitive and operational abilities and not replace the human effort completely. For manufacturing and logistics settings, this involves AI-powered systems for decision support, predictive analysis, and smart analytics, which enhance the decision-making and performance of human workers (Alenizi et al., 2023). Manufacturing analytics refers to the use of data processing and analytic techniques like machine learning, computer vision, and statistical modelling for manufacturing processes, like quality control, maintenance planning, and production scheduling. Logistics analytics, on the other hand, involves leveraging data to make informed decisions and optimise various aspects of the supply chain, such as demand forecasting, inventory management, route planning, and warehouse management.

2.2 Theoretical Anchors

This review is based on three theoretical frameworks. First, AI is a key instrument in the implementation of the Industry 4.0 framework, which envisions intelligent production systems that are connected through cyber-physical systems, the Industrial Internet of Things (IIoT) and advanced analytics, empowering them to become self-organising (Zhou et al., 2015; Alenizi et al., 2023). Second, the Resource Based View (RBV) of the firm provides a framework for understanding how AI capabilities can be viewed as resources that can create competitive advantage in organisations if embedded in human resources and processes (Wamba et al., 2020). Evidence for this can be seen from research that shows the ability of companies to use AI systematically rather than as one-off projects to deliver better and more long-lasting performance. Thirdly, the Dynamic Capabilities framework has been developed to build a more complete theory of the RBV, which focuses on the firm's ability to sense, seize and reconfigure their resources to take advantage of changing environments (Teece, 2007). Dynamic capabilities in AI-enhanced manufacturing and logistics are seen in the flexibility and adaptability to update AI analytics with changing demand patterns, supply disruptions, or regulatory changes.

2.3 AI Augmentation versus AI Automation

One key difference in the concept of AI that is important to note in this review is the difference between AI augmentation and AI automation. Automation replaces humans in a defined repetitive task, while augmentation enhances humans' decision-making power and abilities with real-time insight, pattern recognition and predictive foresight. The results of the empirical studies are consistently found to be more successful when using augmentation-based strategies than complete automation in complex operational settings where contextual judgement is still a critical part of the job (Zheng et al., 2024). This distinction is relevant when considering the literature about humanAI collaboration in Section 6.4.

2.4 Analytics within the Manufacturing-Logistics Interface

Manufacturing and logistics are very closely interwoven; in fact, more and more, it is analytics augmented by AI that are encountered at the interface between the two. Logistics scheduling is driven by real-time production data, and logistics analysis data is given back to the production planning. This bi-directional aspect brings both advantages and disadvantages when it comes to implementing AI in an integrated manner or in organizational silos developing analytics systems. Empirical literature referenced in this paper provides examples of the promise and continuing challenge of cross-functional implementation of integrated analytics.

III. REVIEW METHODOLOGY

In this review, the narrative empirical method was used via the peer-reviewed studies published from 2015 up to 2024. The databases were Scopus, Web of Science and Google Scholar. The terms used in the search were such as “AI augmentation”, “manufacturing analytics”, “logistics analytics”, “Industry 4.0”, “predictive maintenance”, “supply chain AI", "demand forecasting" and "human-AI collaboration". Studies were included if they provided original empirical data (quantitative, qualitative or mixed) in the context of manufacturing or logistics. Only conceptual or theoretical papers were not accepted. Grey literature and publications in languages other than English were not included. This review aims to be narrative not systematic; it doesn't create a PRISMA flowchart and selection of studies is based on thematic relevance, not being comprehensive. The innovation of the contribution is not so much in exhaustive search retrieval as in the critical synthesis of evidence on themes.

IV. THEMATIC FINDINGS

4.1 AI Applications in Manufacturing Operations

Empirical evidence shows significant benefits to the use of AI in key manufacturing activities. Perhaps most strongly supported, predictive maintenance uses machine learning models applied to sensor data to consistently prevent unplanned downtime through condition-based maintenance interventions before failure by reducing unplanned maintenance costs and downtime (Achouch et al., 2022; Alshboul et al., 2024). The same study indicates that digital readiness, data access and maintenance organisation culture are essential mediating factors to support a successful implementation, as confirmed by qualitative case study evidence (Hoffmann & Lasch, 2025). AI-based computer vision systems have shown significant advancements in defect detection precision and speed in various industries, including semiconductors, automotive, and food production, in the realm of quality control (QC) (Kusiak, 2023). Empirical studies have also become increasingly interested in implementing optimisation of production using reinforcement learning, noting the significant improvements obtained in dynamic scheduling that are superior to the traditional heuristic approaches (Zhang et al., 2024). In regards to the manufacturing domain, the automotive industry has the highest adoption rates for AI, especially in machine learning and computer vision, whereas the textile industry is lagging behind with infrastructural and budget issues (Scientific Reports, 2025).

4.2 AI Applications in Logistics and Supply Chain

Demand forecasting is the most mature application of AI in the world of logistics and supply chain management. Historical and real-time data-based neural network models significantly outperform traditional statistical forecasting models: error rates are reduced by significant amounts in retail, pharmaceutical, and industrial supply chains (Feizabadi, 2022; Bottani et al., 2017). In several empirical scenarios, such as reducing delivery times, fuel usage and operational costs, route optimisation is demonstrated to achieve these goals through the use of algorithms like XGBoost and reinforcement learning (Boute et al., 2022; Chen et al., 2024). Combining robotics, computer vision, and IoT sensors, warehouse automation has revolutionized inventory management processes, allowing for real-time tracking and inventory control, and significantly cutting down on manual labour expenses (Li et al., 2024). In many contexts, last-mile delivery is an important cost component, often making up over 50% of overall logistics expenses, but AI-based dynamic routing has started to show tangible benefits in terms of the precision of deliveries and the utilization of resources (Golicic et al., 2023). According to empirical data from leading retailers and logistics companies, AI-driven logistics platforms can cut down on deadhead miles by more than 20% and boost the utilization of trucks by around 15%, resulting in significant cost reductions (IJSAT, 2025).

4.3 Analytics Frameworks Supporting AI Augmentation

The empirical literature refers to three types of analytics for the support of AI technologies for manufacturing and logistics: descriptive, predictive, and prescriptive. Descriptive analytics serves as the operational foundation by combining sensor, transactional and process information to create an up-to-the-minute picture of the states of the system. Predictive analytics uses machine learning and data analysis to look at past data and predict future failures, demand changes and supply disruptions. The highest level of AI analytics, prescriptive analytics, suggests or even makes optimised decisions based on the prediction of outcomes (Smyth et al., 2024; Bousdekis et al., 2020). Empirical research has

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shown that integration of IoT infrastructure with AI analytical systems is one of the key enablers for this evolution in analytics, with the quality and granularity of the data produced by IoT directly influencing the performance of the models. But even research also reports that many organizations are still in the descriptive and predictive phase, and that the lack of data governance standards and a low level of readiness of the organization are limiting the adoption of prescriptive AI (Gröger, 2018; Lade et al., 2017).

4.4 Human-AI Collaboration in Manufacturing and Logistics

In most empirical studies, the role of human workers and AI systems in manufacturing and logistics are found to be complementary rather than substitutional. It can be shown by Industry 5.0 literature that by keeping the human agency in decision making, while enabling the use of AI analytical capacity, better social and operational performance outcomes are achieved than with fully automated systems (Zheng et al., 2024). Empirical studies show that the innovation-enabling potential of AI increases as the job demands become more complex, as workers in complex operational roles use AI tools to augment their cognitive capabilities, not just as efficiency tools (Dong et al., 2024). However, the workforce skills challenge continues to be a challenge: research in manufacturing and logistics contexts reveals substantial differences between the skills of the workforce and the analytical skills needed to collaborate effectively with AI systems. There are interventions and adaptations to human-machine interface design that can be said to be critical mitigating factors, namely upskilling interventions and adaptive human-machine interface designs (Castane et al., 2023). There is also evidence that the adoption rate and willingness to implement transparent AI decision-making protocols (those that allow workers to understand and challenge AI suggestions) are related (Allal-Cherif et al., 2021).

4.5 Barriers and Challenges

There is a common set of barriers to AI augmentation identified from an empirical study in both manufacturing and logistics contexts. The top challenge is data quality, and accessibility, with research highlighting that fragmented, incomplete or poorly labelled datasets can negatively impact the quality of AI models (Hoffmann & Lasch, 2025; Bag et al., 2021). A second big obstacle is infrastructure gaps, such as but not limited to computational resources, legacy system incompatibility, and coverage of IoT sensors, which are barriers especially in SME and developing economy settings (Alenizi et al., 2023). Limited resources make technology purchase, integration and training prohibitive for adoption by resource-constrained organisations. Implementing the changes is further hampered by organisational resistance, which is driven by resistance to change, fear of losing jobs and lack of leadership commitment. Empirical studies from the automotive sector in South Africa illustrate how institutional pressures and organisational flexibility moderate the relationship between AI resource availability and adoption outcomes, underscoring that AI augmentation is as much an organisational challenge as a technological one (Bag et al., 2021).

V. CROSS-CUTTING THEMES AND SYNTHESIS

The empirical evidence points to three cross-cutting patterns, which have been synthesised as a result of the thematic findings. Secondly, the benefits of AI augmentation are not guaranteed and will vary depending on the readiness of the organization and its data systems, as well as how much human-AI integration is in place. High performance results in studies are generally found in well-resourced, mature data organisations in highly industrialised countries. Second, the focus on data quality as the ground level of success for AI, irrespective of application area or analytics tier is consistent across themes. Third, there are differences in the level of empirical maturity, demonstrated in the literature: the logistics domain has a more consistent and generalised empirical base, for example in predictive maintenance and route optimisation; the manufacturing domain is more diverse in terms of outcomes, for example in production optimisation. Taken together, the evidence shows that AI augmentation is going strong in both areas; but that to fully realize its potential both technological infrastructure and organizational capabilities need to be sustained.

VI. RESEARCH GAPS AND FUTURE DIRECTIONS

This review identifies a few key research gaps. The huge concentration of empirical evidence is in advanced industrial economies such as the United States, Germany, China and South Korea; and not enough evidence from Africa, South Asia and Latin America, where manufacturing and logistic industries are rapidly expanding but are constrained in different ways. The SME context is another context that has not been explored enough: Most studies are carried out in large organisations with a considerable amount of data and technology, and the results of these studies are not of particular relevance for the SME context, as most SMEs belong to this sector and can be found in a large number of economies. Second, methodological gaps present: there is a scarcity of empirical studies following AI augmentation over time (longitudinal), and most studies come from cross-sectional surveys or a single-site case study. Third, other areas of emerging interest, such as generative AI to assist with logistics planning, explainable AI to aid manufacturing quality control and federated learning for cross-firm supply chain optimisation, are now starting to be the subject of empirical research, but are not yet well understood to draw meaningful conclusions. Research in these contexts and methodologies should be prioritized to strengthen the evidence base to be more representative and longitudinally stronger for the globe.

VII. IMPLICATIONS

The results have several applications for manufacturers, logistics companies and technology users. Before adopting AI augmentation, companies must invest in data governance infrastructure, guaranteeing that they have a complete, standardised and accessible data that is suitable for advanced analytics. Empirically linked to improved adoption success rates are human-centred implementation strategies, such as clear communication of AI, adaptive interface design, and upskilling workforce.Human-centred implementation strategies including clear AI communication, adaptive interface design and workforce upskilling are empirically linked to higher rates of success and should be prioritised in technology implementation plans.

The evidence also signals the policymakers and industry groups the importance of creating policies that encourage investment in AI by SMEs and organisations in resource-limited settings, perhaps by implementing shared infrastructure arrangements, technology transfer initiatives, and regulatory sandboxes. The synthesis highlights the importance of a cross-functional approach to AI usage across the manufacturing-logistics interface for operations and supply chain managers, rather than using AI in individual operational areas.

VIII. CONCLUSION

This review has pulled together empirical evidence on the use of AI augmentation in manufacturing and logistics analytics and found it to be a space where there is genuine and increasing productivity gains, implementation challenges remain, and results are far from uniform across organisations and geographies. In organisations with the necessary data infrastructure and organizational capabilities, AI augmentation has proven to be effective in improving operational performance, with its applications such as predictive maintenance, demand forecasting, warehouse automation, and human-centric decision support making a tangible impact. The field is not just a technological phenomenon; it is a sociotechnical transition impacting the human-machine expertise interface in two economically weighty fields of the world. The need for well-designed, contextually relevant, and longitudinal empirical studies with the use of AI technologies is increasing as they develop and spread. AI's path in manufacturing and logistics is a wide one, and the academic world's ability to keep pace must be broad and deep as well.

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