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Generative Artificial Intelligence as a Strategic Engine for Manufacturing Execution System Optimization and Sustainable Digital Enterprise Transformation

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ABSTRACT: The rapid evolution of artificial intelligence has fundamentally redefined the way organizations conceptualize, design, and execute digital transformation strategies. Among the most consequential developments in this domain is the emergence of generative artificial intelligence, particularly large language models, which extend beyond traditional predictive analytics toward creative, adaptive, and context-aware decision support. In manufacturing-intensive enterprises, the integration of generative artificial intelligence into Manufacturing Execution Systems represents a critical inflection point in the broader journey toward intelligent, autonomous, and sustainable production. This research article develops a comprehensive theoretical and empirical synthesis of how generative artificial intelligence can be used to optimize Manufacturing Execution Systems through digital manufacturing configuration recommendation mechanisms, building directly on the conceptual and operational foundations articulated by Chowdhury, Pagidoju, and Lingamgunta (2025). By situating their model within a wider body of interdisciplinary scholarship on artificial intelligence, digital business models, strategic management, sustainability, and organizational governance, this study constructs a holistic framework for understanding how language-model-driven systems can reshape production planning, resource allocation, workflow orchestration, and strategic alignment.

The article argues that Manufacturing Execution Systems are no longer merely operational tools for shop-floor control but have evolved into strategic platforms that mediate between enterprise planning systems, supply chain networks, and real-time production intelligence. Generative artificial intelligence enables these platforms to move from reactive monitoring to proactive configuration, learning from historical data, contextual signals, and strategic objectives to generate optimal manufacturing scenarios. Drawing on theoretical insights from artificial intelligence research, organizational theory, sustainability governance, and business model innovation, this study examines how generative artificial intelligence supports dynamic reconfiguration, reduces uncertainty, enhances customer responsiveness, and improves environmental performance. It also interrogates the ethical, managerial, and institutional challenges associated with delegating configuration authority to algorithmic agents.

Using a qualitative, literature-grounded methodological approach, this research synthesizes evidence from existing studies to develop interpretive results regarding performance gains, strategic flexibility, and governance implications of generative artificial intelligence in Manufacturing Execution Systems. These results demonstrate that generative artificial intelligence, when embedded into digital manufacturing infrastructures, transforms enterprises into adaptive systems capable of aligning operational decisions with long-term strategic and sustainability goals. The discussion advances a critical perspective on how these technologies alter power relations, knowledge production, and managerial accountability, offering a roadmap for future research and practice. Ultimately, this study contributes to both the artificial intelligence and operations management literatures by providing a theoretically rich and practically relevant understanding of generative artificial intelligence as a central pillar of intelligent manufacturing transformation.

Keywords: Generative artificial intelligence, Manufacturing Execution Systems, digital manufacturing, enterprise systems, sustainability, business model innovation, intelligent operations

INTRODUCTION

The digital transformation of industrial enterprises has been a central theme in management, information systems, and engineering research for several decades. What began as a movement toward computer-integrated manufacturing and enterprise resource planning has evolved into a complex ecosystem of cyberphysical systems, cloud-based platforms, and artificial intelligence-driven analytics. Within this evolving landscape, Manufacturing Execution Systems occupy a pivotal role as the operational nerve center of modern factories, linking enterprise-level planning with real-time shop-floor execution. Historically, these systems were designed to collect data, monitor performance, and enforce predefined workflows. However, as production environments have become more volatile, customized, and sustainability-sensitive, the limitations of static and rule-based execution systems have become increasingly apparent (Feuerriegel, Shrestha, von Krogh, and Zhang, 2022).

Artificial intelligence has emerged as a critical enabler of the next generation of manufacturing systems, promising to transform how organizations sense, interpret, and act upon complex operational data. Early applications of artificial intelligence in manufacturing focused primarily on predictive maintenance, quality inspection, and demand forecasting, relying on machine learning models trained on historical datasets (Jordan and Mitchell, 2015). While these approaches delivered measurable efficiency gains, they were fundamentally constrained by their reliance on predefined objectives and static model structures. The rise of generative artificial intelligence, particularly large language models, represents a qualitative shift in this paradigm, enabling systems not only to predict outcomes but also to generate novel configurations, strategies, and recommendations in response to changing conditions (Feuerriegel, Hartmann, Janiesch, and Zschech, 2024).

Within this context, the work of Chowdhury, Pagidoju, and Lingamgunta (2025) marks a significant milestone by demonstrating how large language models can be embedded into Manufacturing Execution Systems to provide digital manufacturing configuration recommendations. Their research shows that generative artificial intelligence can interpret complex production requirements, machine capabilities, and resource constraints to propose optimized manufacturing scenarios, thereby reducing setup times, minimizing waste, and improving throughput. This approach reframes Manufacturing Execution Systems as intelligent advisors rather than passive controllers, capable of engaging in a form of operational reasoning that resembles human expert decision-making. By integrating natural language understanding with domain-specific manufacturing knowledge, generative artificial intelligence creates a new interface between human managers and digital production systems, expanding the scope of what can be automated and optimized (Chowdhury, Pagidoju, and Lingamgunta, 2025).

The theoretical significance of this development extends far beyond the boundaries of manufacturing engineering. Scholars of information systems and strategic management have long argued that the value of digital technologies lies not in their technical features but in their capacity to reshape organizational routines, decision rights, and value creation mechanisms (Grover and Kohli, 2012). Generative artificial intelligence, by virtue of its ability to synthesize heterogeneous data sources and articulate context-sensitive recommendations, challenges traditional hierarchies of expertise and authority within organizations. In manufacturing settings, where decisions about process design, scheduling, and resource allocation have historically been the domain of experienced engineers and supervisors, the introduction of algorithmic configuration agents raises fundamental questions about trust, accountability, and the nature of managerial work (Jo, 2023).

At the same time, the integration of generative artificial intelligence into Manufacturing Execution Systems aligns closely with broader societal and economic imperatives for sustainability and resilience. Manufacturing remains one of the largest contributors to global carbon emissions, resource depletion, and environmental degradation. As firms face increasing regulatory and stakeholder pressure to adopt sustainable practices, the ability to optimize production configurations in real time becomes a strategic necessity rather than a technical luxury (Di Vaio, Palladino, Hassan, and Escobar, 2020). Generative artificial intelligence offers a powerful mechanism for balancing competing objectives such as cost efficiency, customer responsiveness, and environmental impact, enabling firms to explore trade-offs and identify configurations that align with sustainable governance principles (Hristov, Chirico, and Ranalli, 2022).

Despite these transformative potentials, the scholarly understanding of generative artificial intelligence in Manufacturing Execution Systems remains fragmented and underdeveloped. Much of the existing literature on artificial intelligence in business focuses on high-level conceptual frameworks, ethical guidelines, or isolated use cases, rather than on integrated, system-level analyses of how generative models interact with core operational infrastructures (Dwivedi et al., 2021). Similarly, research on Manufacturing Execution Systems has traditionally emphasized technical integration and performance metrics, with limited attention to the cognitive and strategic dimensions introduced by generative artificial intelligence. The study by Chowdhury, Pagidoju, and Lingamgunta (2025) provides a crucial starting point, but its implications for organizational theory, business models, and sustainability governance have yet to be fully explored.

This article seeks to address this gap by developing a comprehensive, theoretically grounded, and empirically informed analysis of generative artificial intelligence as a driver of Manufacturing Execution System optimization and digital enterprise transformation. Drawing on an extensive body of interdisciplinary literature, the study situates the digital manufacturing configuration recommendation framework proposed by Chowdhury, Pagidoju, and Lingamgunta (2025) within broader debates about artificial intelligence, business value, and sustainable governance. By synthesizing insights from information systems, management, and sustainability research, the article aims to articulate how generative artificial intelligence reshapes not only how manufacturing systems operate, but also how organizations think, decide, and compete in a digitally mediated economy (Enholm, Papagiannidis, Mikalef, and Krogstie, 2022).

The central research problem addressed in this article is therefore not merely whether generative artificial intelligence can improve Manufacturing Execution System performance, but how and why it transforms the strategic and organizational logic of manufacturing enterprises. This problem is particularly salient in an era characterized by volatile demand, fragmented supply chains, and heightened sustainability expectations, where traditional planning and control mechanisms struggle to cope with complexity and uncertainty (Rodriguez and Peterson, 2024). By focusing on the generative, configurational, and advisory capabilities of large language models, this study advances a more nuanced understanding of artificial intelligence as a socio-technical system that co-evolves with organizational structures and strategic priorities.

The remainder of this article is organized around a detailed methodological synthesis, interpretive results, and an extended discussion that integrates multiple scholarly perspectives. Throughout the analysis, the insights of Chowdhury, Pagidoju, and Lingamgunta (2025) serve as a conceptual anchor, demonstrating how generative artificial intelligence can be operationalized within Manufacturing Execution Systems to achieve measurable and strategic outcomes. In doing so, this research contributes to the growing literature on intelligent manufacturing and digital business by offering a deeply elaborated account of generative artificial intelligence as a cornerstone of the next generation of enterprise systems.

METHODOLOGY

The methodological foundation of this research is grounded in an interpretive, theory-driven synthesis of interdisciplinary literature, designed to capture the complex, socio-technical dynamics of generative artificial intelligence in Manufacturing Execution Systems. Given the emergent nature of large language model applications in industrial contexts, traditional quantitative meta-analysis techniques are ill-suited to capturing the richness of conceptual innovation and organizational transformation described in recent studies. Instead, this research adopts a qualitative, integrative approach that combines systematic literature review principles with critical theory building, enabling a deep exploration of how generative artificial intelligence reshapes digital manufacturing architectures (Sarker, 2022).

The first step in this methodological process involved the identification and selection of relevant scholarly sources. The reference corpus provided for this study includes foundational works on artificial intelligence, business value, sustainability, and organizational strategy, as well as the pivotal contribution by Chowdhury, Pagidoju, and Lingamgunta (2025) on generative artificial intelligence for Manufacturing Execution System optimization. These sources were treated not as isolated empirical reports but as interconnected theoretical artifacts that collectively illuminate the evolving role of artificial intelligence in enterprise systems. By situating the digital manufacturing configuration recommendation model within this broader intellectual landscape, the study ensures that its analysis is both grounded and expansive (Feuerriegel, Hartmann, Janiesch, and Zschech, 2024).

The analytical procedure followed a multi-stage interpretive coding and synthesis process. In the first stage, key constructs and themes related to generative artificial intelligence, Manufacturing Execution Systems, sustainability, and business model innovation were extracted from each source. This included concepts such as algorithmic decision-making, digital configuration, strategic alignment, environmental governance, and organizational learning. Particular attention was given to how Chowdhury, Pagidoju, and Lingamgunta (2025) conceptualize the role of large language models as configuration advisors within Manufacturing Execution Systems, as this framework serves as the focal point for the study's theoretical integration.

In the second stage, these constructs were compared and contrasted across the literature to identify convergences, tensions, and gaps. For example, while business-oriented studies emphasize the value creation and competitive advantages of artificial intelligence (Enholm et al., 2022), ethical and governance-focused works highlight the risks of opacity, bias, and accountability loss (Attard-Frost, De los Rios, and Walters, 2023). By mapping these perspectives onto the digital manufacturing configuration context described by Chowdhury, Pagidoju, and Lingamgunta (2025), the analysis reveals how generative artificial intelligence simultaneously enables operational excellence and introduces new governance challenges.

The third stage involved the construction of an integrative analytical narrative that explains how generative artificial intelligence functions as a mediating technology between strategic objectives and operational execution in manufacturing enterprises. This narrative draws on organizational theory, particularly the concept of dynamic capabilities, to explain how firms can use generative artificial intelligence to reconfigure their production systems in response to environmental change (Fountaine, McCarthy, and Saleh, 2019). It also incorporates sustainability and governance frameworks to show how digital configuration recommendations can be aligned with long-term societal goals (Hristov, Chirico, and Ranalli, 2022).

A key methodological assumption underlying this research is that knowledge about generative artificial intelligence in Manufacturing Execution Systems is socially constructed through scholarly discourse and organizational practice. As such, the study does not seek to test a single causal hypothesis but to build a coherent theoretical model that integrates diverse insights into a unified explanation. This approach is consistent with the interpretive tradition in information systems research, which emphasizes meaning, context, and human-technology interaction as central to understanding digital innovation (Dwivedi et al., 2021).

Nevertheless, this methodology is not without limitations. Because it relies on secondary sources and conceptual synthesis, it cannot provide statistically generalizable claims about the performance impacts of generative artificial intelligence. Instead, its strength lies in its ability to reveal underlying mechanisms, patterns, and implications that may not be visible in isolated empirical studies. By grounding its analysis in the detailed and operationally specific framework of Chowdhury, Pagidoju, and Lingamgunta (2025), the study mitigates the risk of excessive abstraction and ensures that its theoretical claims remain anchored in real-world manufacturing contexts.

In sum, the methodological design of this research enables a deep and nuanced exploration of generative artificial intelligence as a transformative force in Manufacturing Execution Systems. By combining rigorous literature synthesis with critical theoretical integration, the study provides a robust foundation for the interpretive results and discussion that follow, illuminating how digital manufacturing configuration recommendation systems can redefine the strategic and operational logic of contemporary enterprises (Sarker, 2022; Chowdhury, Pagidoju, and Lingamgunta, 2025).

RESULTS

The interpretive results of this research reveal that the integration of generative artificial intelligence into Manufacturing Execution Systems produces a multifaceted transformation that extends across operational performance, strategic flexibility, and sustainability governance. Drawing on the conceptual model and empirical illustrations provided by Chowdhury, Pagidoju, and Lingamgunta (2025), as well as complementary insights from the broader literature, this section describes how digital manufacturing configuration recommendation systems reshape the way manufacturing enterprises plan, execute, and evaluate their production activities.

One of the most salient results is the shift from deterministic, rule-based execution toward probabilistic, context-aware configuration. Traditional Manufacturing Execution Systems rely on predefined process plans, bill of materials, and routing rules that must be manually updated when conditions change. In contrast, the large language model-driven framework proposed by Chowdhury, Pagidoju, and Lingamgunta (2025) enables the system to interpret natural language inputs, production data, and strategic constraints to generate alternative manufacturing scenarios in real time. This capability allows enterprises to explore a wider solution space and to adapt more quickly to disruptions such as machine failures, supply shortages, or sudden changes in customer demand, consistent with the broader promise of artificial intelligence to enhance organizational agility (Feuerriegel, Shrestha, von Krogh, and Zhang, 2022).

Another important result concerns the role of generative artificial intelligence in knowledge integration and transfer. Manufacturing organizations are characterized by highly specialized and often siloed expertise, spanning process engineering, quality management, logistics, and sustainability. The digital manufacturing configuration recommendation approach enables large language models to synthesize these heterogeneous knowledge domains into coherent, actionable recommendations, effectively functioning as a boundary-spanning agent within the organization (Chowdhury, Pagidoju, and Lingamgunta, 2025). This aligns with the literature on artificial intelligence as a mechanism for augmenting human decision-making and facilitating cross-functional collaboration (Fui-Hoon Nah et al., 2023).

The results also indicate that generative artificial intelligence enhances the strategic alignment of Manufacturing Execution Systems with broader business objectives. By incorporating cost, quality, delivery, and sustainability metrics into its configuration logic, the system can generate production plans that reflect not only operational constraints but also strategic priorities such as customer profitability and environmental impact (Lueg and Ilieva, 2024). This integration transforms the Manufacturing Execution System from a tactical tool into a strategic platform, capable of supporting high-level decision-making and long-term planning, as envisioned in contemporary models of AI-powered organizations (Fountaine, McCarthy, and Saleh, 2019).

A further result concerns the implications for sustainability governance. The literature on sustainable business models emphasizes the need for real-time, data-driven insights to balance economic and environmental objectives (Di Vaio et al., 2020). The generative artificial intelligence framework described by Chowdhury, Pagidoju, and Lingamgunta (2025) provides precisely such a capability, enabling enterprises to simulate the environmental consequences of different manufacturing configurations and to select options that minimize waste, energy consumption, and emissions. This supports the development of what Hristov, Chirico, and Ranalli (2022) describe as sustainable governance, in which digital technologies are used to embed environmental considerations into everyday managerial decisions.

However, the results also highlight significant challenges and tensions. One such tension arises from the opacity and autonomy of generative artificial intelligence systems. While large language models can generate sophisticated and contextually appropriate recommendations, their internal reasoning processes are often difficult to interpret, raising concerns about trust, accountability, and ethical responsibility (Jo, 2023). In the manufacturing context, where errors can have costly and potentially dangerous consequences, this lack of transparency poses a substantial barrier to full automation, echoing broader debates about the governance of artificial intelligence in business (Attard-Frost, De los Rios, and Walters, 2023).

In summary, the results demonstrate that generative artificial intelligence, as operationalized in the digital manufacturing configuration recommendation framework of Chowdhury, Pagidoju, and Lingamgunta (2025), delivers significant benefits in terms of flexibility, integration, and sustainability alignment. At the same time, it introduces new organizational and ethical complexities that must be carefully managed. These findings set the stage for a deeper theoretical and practical discussion of how generative artificial intelligence can be responsibly and effectively embedded into Manufacturing Execution Systems.

DISCUSSION

The findings of this study invite a profound reconsideration of the theoretical foundations of Manufacturing Execution Systems, artificial intelligence, and organizational strategy. By embedding generative artificial intelligence into the core of digital manufacturing infrastructures, enterprises are not merely upgrading their technological capabilities but are fundamentally transforming the way decisions are made, knowledge is produced, and value is created. The framework proposed by Chowdhury, Pagidoju, and Lingamgunta (2025) exemplifies this transformation by demonstrating how large language models can act as cognitive agents that mediate between strategic intent and operational reality.

From a theoretical perspective, this development aligns with the concept of dynamic capabilities, which emphasizes the ability of firms to sense, seize, and reconfigure resources in response to environmental change (Fountaine, McCarthy, and Saleh, 2019). Generative artificial intelligence enhances all three of these capabilities. It improves sensing by integrating real-time data from machines, supply chains, and markets; it supports seizing by generating optimized configuration recommendations; and it enables reconfiguration by dynamically adjusting production plans as conditions evolve (Chowdhury, Pagidoju, and Lingamgunta, 2025). In this sense, the Manufacturing Execution System becomes an active participant in strategic adaptation, rather than a passive executor of predefined plans.

At the same time, the integration of generative artificial intelligence challenges traditional assumptions about managerial control and expertise. Classical theories of management assume that strategic decisions are made by human actors who possess tacit knowledge, experience, and ethical judgment. When large language models begin to generate production configurations and strategic recommendations, the locus of decision-making shifts toward a hybrid human-machine system (Fui-Hoon Nah et al., 2023). This raises important questions about accountability and governance. If a generative model recommends a configuration that leads to quality failures or environmental harm, who is responsible: the engineers who trained the model, the managers who deployed it, or the algorithm itself? These questions echo broader concerns in the ethics of artificial intelligence, which emphasize the need for transparent, accountable, and fair AI systems (Attard-Frost, De los Rios, and Walters, 2023).

The discussion also highlights the implications of generative artificial intelligence for business model innovation. Scholars have argued that artificial intelligence enables firms to move from product-centric to service-centric and data-driven business models (Di Vaio et al., 2020). In manufacturing, the ability to dynamically configure production processes based on customer-specific requirements supports the emergence of mass customization and servitization strategies (Rodriguez and Peterson, 2024). The digital manufacturing configuration recommendation system described by Chowdhury, Pagidoju, and Lingamgunta (2025) provides the operational backbone for such strategies, enabling firms to offer tailored solutions without sacrificing efficiency or sustainability.

Sustainability represents another critical dimension of this transformation. The literature on sustainable governance emphasizes the importance of integrating environmental considerations into core business processes rather than treating them as peripheral compliance issues (Hristov, Chirico, and Ranalli, 2022). Generative artificial intelligence makes this integration feasible by allowing Manufacturing Execution Systems to evaluate the environmental impact of alternative configurations in real time. This capability supports what might be described as algorithmic sustainability, in which digital agents actively optimize for ecological as well as economic objectives, aligning with the broader vision of artificial intelligence as a tool for achieving the Sustainable Development Goals (Di Vaio et al., 2020).

Despite these promising implications, the discussion must also confront the limitations and risks of generative artificial intelligence in Manufacturing Execution Systems. One major limitation is the dependence on high-quality data and domain knowledge. Large language models are only as good as the data on which they are trained, and manufacturing environments are notorious for data silos, inconsistencies, and legacy systems (Sarker, 2022). If the underlying data is incomplete or biased, the configuration recommendations generated by the system may be suboptimal or even harmful, undermining trust and adoption.

Another limitation concerns organizational readiness. The deployment of generative artificial intelligence requires not only technical integration but also cultural and structural change. Managers and engineers must be willing to share decision authority with algorithmic agents and to adapt their roles accordingly (Feuerriegel, Shrestha, von Krogh, and Zhang, 2022). This transition can be particularly challenging in manufacturing firms with deeply entrenched routines and hierarchical structures. As Frey and Osborne (2017) have argued, the automation of cognitive tasks has profound implications for employment, skills, and organizational identity, which must be carefully managed to avoid resistance and social disruption.

Future research should therefore explore how generative artificial intelligence can be designed and governed in ways that maximize its benefits while minimizing its risks. This includes the development of explainable and transparent configuration algorithms, the integration of ethical and sustainability constraints into model training, and the creation of organizational structures that support human-machine collaboration (Jo, 2023; Attard-Frost, De los Rios, and Walters, 2023). By building on the pioneering work of Chowdhury, Pagidoju, and Lingamgunta (2025), scholars and practitioners can advance toward a more intelligent, responsible, and sustainable model of digital manufacturing.

CONCLUSION

This article has provided an extensive and theoretically grounded analysis of generative artificial intelligence as a transformative force in Manufacturing Execution System optimization and digital enterprise strategy. By integrating the digital manufacturing configuration recommendation framework developed by Chowdhury, Pagidoju, and Lingamgunta (2025) with a broad body of interdisciplinary scholarship, the study has demonstrated how large language models enable manufacturing systems to move beyond static control toward dynamic, intelligent, and sustainable configuration. The findings underscore that generative artificial intelligence reshapes not only operational efficiency but also strategic alignment, organizational governance, and environmental performance. As manufacturing enterprises continue to navigate an increasingly complex and sustainability-driven global economy, the integration of generative artificial intelligence into core execution systems will be a defining factor in their long-term competitiveness and resilience.

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