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Generative artificial intelligence in manufacturing: opportunities for actualizing Industry 5.0 sustainability goals

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Abstract

Purpose – This study offers practical insights into how generative artificial intelligence (AI) can enhance responsible manufacturing within the context of Industry 5.0. It explores how manufacturers can strategically maximize the potential benefits of generative AI through a synergistic approach.

Design/methodology/approach – The study developed a strategic roadmap by employing a mixed qualitative-quantitative research method involving case studies, interviews and interpretive structural modeling (ISM). This roadmap visualizes and elucidates the mechanisms through which generative AI can contribute to advancing the sustainability goals of Industry 5.0.

Findings – Generative AI has demonstrated the capability to promote various sustainability objectives within Industry 5.0 through ten distinct functions. These multifaceted functions address multiple facets of manufacturing, ranging from providing data-driven production insights to enhancing the resilience of manufacturing operations.

Practical implications – While each identified generative AI function independently contributes to responsible manufacturing under Industry 5.0, leveraging them individually is a viable strategy. However, they

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synergistically enhance each other when systematically employed in a specific order. Manufacturers are advised to strategically leverage these functions, drawing on their complementarities to maximize their benefits.
Originality/value – This study pioneers by providing early practical insights into how generative AI enhances the sustainability performance of manufacturers within the Industry 5.0 framework. The proposed strategic roadmap suggests prioritization orders, guiding manufacturers in decision-making processes regarding where and for what purpose to integrate generative AI.

Keywords Generative AI impact, Industry 5.0, Resilience, Sustainable development goals, Digital transformation, Human centric
Paper type Article

Quick value overview

Interesting because: The study applies paradox theory as a framework to understand how generative artificial intelligence (AI) can enhance sustainability values in Industry 5.0. It investigates the integration of generative AI in manufacturing, focusing on its impact on sustainability performance within the framework of Industry 5.0. It emphasizes exploring how generative AI can effectively address sustainability paradoxes, such as balancing innovation with environmental stewardship and optimizing resource usage while minimizing negative social impacts. We delve into the specific functions of generative AI that, if leveraged correctly, can boost sustainability values while mitigating potential adverse effects, offering novel insights into the intersection of technology and sustainability in manufacturing.

Theoretical value: Generative AI plays a pivotal role in advancing Industry 5.0 via various functions such as enhancing customer support and quality management. However, integrating AI into manufacturing poses challenges. For instance, obtaining extensive, high-quality datasets is difficult and costly. Compatibility issues between AI algorithms and legacy systems require significant modifications. Collaborative partnerships with AI experts and vendors can facilitate knowledge transfer and skill development. Fostering a culture of innovation and continuous learning encourages openness to new technologies. Overcoming these challenges enables companies to leverage generative AI for innovation and efficiency in manufacturing.

Practical value: Manufacturers should adopt a cautious approach to integrating generative AI, prioritizing targeted implementations for specific purposes like risk mitigation and operational resilience. This phased approach, aligned with Industry 5.0 goals, allows for strategic leveraging of AI functions based on immediate needs and resource capacities. Generative AI can offer economic viability without sacrificing sustainability objectives, fostering a balanced approach to business practices. Manufacturers must prioritize user-friendly design and accessibility to bridge the digital divide. Proper governance and collaboration among stakeholders are essential to maximize generative AI's potential for sustainable growth while mitigating risks like job displacement and widening inequalities. By embracing inclusivity and responsible innovation, generative AI can drive efficiency and sustainability in manufacturing.

1. Introduction

The emergence of Industry 5.0 has sparked both enthusiasm and skepticism (Hein-Pensel *et al.*, 2023; Xian *et al.*, 2023). Industry 5.0 presents itself as a fusion of technology-driven advancements and a socially motivated framework, attempting to bridge the gap between digital innovation and human-centric values (Renda *et al.*, 2022). However, the perceived idealism of Industry 5.0 goals and objectives is criticized recurrently (Ghobakhloo *et al.*, 2023a). Skeptics argue that the underlying technologies are more futuristic than realistic, and many companies are far from incorporating them into their operations (Narkhede *et al.*, 2023). While scholars were struggling with conceptualizing Industry 5.0 and its feasibility, generative AI entered the scene as an unexpected catalyst. In the latter part of 2022, generative AI experienced transformative global diffusion and gained prominence, with widespread development and integration observed in various business contexts (Ooi *et al.*, 2023). However, a notable gap exists in the discourse, which concerns the limited attention that has been given to the integration of generative AI into the manufacturing sector and its expected impact on the performance of manufacturers.

To delve into the knowledge gap about the role of generative AI in reshaping manufacturing, it is imperative to understand the controversy surrounding Industry 5.0. At its core, Industry 5.0 embodies a mixed framework, blending the technological advancements of Industry 4.0 with socially driven objectives (Sindhwani *et al.*, 2022). This amalgamation is both its strength and weakness. Critics argue that the inclusive sustainability goals set by Industry 5.0 are often more idealistic than practical (Longo *et al.*, 2020). It is further argued that the promised technologies are yet to mature into viable and widespread solutions (Ghobakhloo *et al.*, 2023b). Also, companies are hesitant to fully embrace the underlying technologies, citing various challenges, including cost implications, implementation complexities and the need for extensive workforce retraining (Mukherjee *et al.*, 2023). This gap further relates to the complex mechanisms crucial for deploying the Industry 5.0 framework in the manufacturing sector. Industry 5.0's vision for a harmonious blend of advanced technologies with inclusive sustainability relies on various enabling systems (Ghobakhloo *et al.*, 2023b). These systems involve many mechanisms, such as responsible technology implementation or reshaping corporate governance (Maddikunta *et al.*, 2022; Verma *et al.*, 2022). However, empirical research does not demonstrate how these enabling mechanisms can be effectively established within the manufacturing landscape. In other words, this gap signifies a lack of hands-on, real-world studies that guide manufacturers in navigating and implementing these complex mechanisms (Hein-Pensel *et al.*, 2023). Therefore, Industry 5.0 stakeholders, particularly manufacturers, struggle with translating the theoretical concept of Industry 5.0 into tangible actions within the manufacturing sector. On top of the existing knowledge gap in establishing enabling mechanisms, the limited commercialization of anticipated technologies is another major barrier. Notably, most emerging technologies of Industry 5.0, like cognitive cyber-systems or adaptive robotics, are far from widespread adoption within mainstream manufacturing firms (Müller, 2020; Valette *et al.*, 2023). This discrepancy has further pushed the realization of Industry 5.0 into the future. This issue underscores that, beyond theoretical frameworks, the commercialization and integration of pivotal Industry 5.0 technologies are prerequisites for bridging the gap between vision and reality in manufacturing.

Under such circumstances, generative AI emerges as a game-changer that could redefine the narrative of Industry 5.0. While generative AI has made significant strides in other business sectors (Prasad Agrawal, 2023), its potential within manufacturing remains relatively unexplored, at least within academia. The transformative capabilities of generative AI lie in its ability to generate content, ideas and solutions autonomously, providing a dynamic and adaptive framework that can be tailored to the unique challenges of manufacturing processes (Budhwar *et al.*, 2023; Wang *et al.*, 2023). Drawing on such valuable capabilities, it is logical to assume that generative AI may be valuable to the sustainable manufacturing industry of the future promised under the Industry 5.0 framework. Indeed, the manufacturing sector is traditionally characterized by structured processes, precision and efficiency (Bendoly *et al.*, 2023). Generative AI, with its capacity for learning and adaptation, may have the potential to enhance these characteristics, bringing about a new era of intelligent manufacturing (Badini *et al.*, 2023). From design optimization to predictive maintenance, generative AI can possibly be leveraged to streamline operations, reduce waste and improve overall efficiency (Castañé *et al.*, 2023). Moreover, its capacity to analyze vast datasets in real-time may allow for data-driven decision-making (Kar *et al.*, 2023), a crucial aspect in achieving the sustainability goals outlined by Industry 5.0 (Xu *et al.*, 2021). While generative AI holds speculative promises for responsible manufacturing within the context of Industry 5.0, the intricate mechanisms through which this technology might actualize the vision of Industry 5.0 remain largely unknown. This uncertainty underscores the need for focused empirical research to unravel the nuanced interactions and dependencies between generative AI and the key components of Industry 5.0, especially in the context of responsible manufacturing.

The present study strives to fill this knowledge gap by offering early empirical insights into utilizing generative AI within manufacturing and examining how these applications align with Industry 5.0 objectives. This research identified and analyzed eight case companies that have actively incorporated generative AI into their operations and implemented formal mechanisms to measure the impact on manufacturing performance under the Industry 5.0 framework. Drawing insights from experts within these companies, the study goes beyond description to develop a strategic roadmap that systematically outlines how the implications of generative AI in manufacturing can be harnessed to maximize its contribution to the Industry 5.0 sustainability objectives.

This study contributes to research and practice by bridging critical gaps in understanding generative AI application in the context of Industry 5.0 and responsible manufacturing. Through empirical insights drawn from eight case companies actively using generative AI, the study offers a practical foundation for manufacturers, outlining how generative AI can be strategically leveraged to align with the Industry 5.0 framework.

2. Literature review

Industry 5.0, characterized by a shift toward more sustainable and human-centric manufacturing, has been the subject of ongoing debate regarding its definition (Huang *et al.*, 2022). The conceptualization of Industry 5.0 became more standardized around 2022 when the European Commission, in a policy brief, asserted that Industry 4.0 was no longer adequate as a framework for Europe's future industry (Renda *et al.*, 2022). Instead, Industry 5.0 was introduced as a transformative framework designed to complement Industry 4.0 (Leng *et al.*, 2022), specifically addressing environmental and social challenges associated with the previous industrial revolution (Ivanov, 2023). This shift marked a pivotal moment in the discourse surrounding the evolution of manufacturing paradigms, emphasizing the need for a more holistic and socially responsible approach (Carayannis and Morawska-Jancelewicz, 2022).

Within the Industry 5.0 landscape, various emerging and futuristic technologies have been identified as key constituents (Xu *et al.*, 2021). These may include cognitive cyber-physical systems, smart materials and adaptive robotics (Maddikunta *et al.*, 2022; Müller, 2020). However, until recently, many of these technologies and their applications remained largely theoretical, struggling to progress beyond the conceptual stage due to challenges in commercialization. This limitation prompted criticism regarding the practicality and feasibility of Industry 5.0 (Ghobakhloo *et al.*, 2023c). Unexpectedly, the breakthrough in the commercialization of generative AI has emerged as a pivotal technology driver for Industry 5.0. This shift has instilled hope for the materialization of Industry 5.0, offering a tangible pathway forward for integrating advanced technologies into manufacturing practices (Kar *et al.*, 2023). The commercial viability of generative AI has become a game-changer, propelling the industry toward a new era of sustainable and human-centric manufacturing (Ooi *et al.*, 2023).

A comparative analysis between generative AI and other emerging technologies in manufacturing reveals a distinct shift from Industry 4.0 to Industry 5.0, with generative AI emerging as the primary driver of industrial transformation in the latter (Ghobakhloo *et al.*, 2024).

While Industry 4.0 was largely characterized by the dominance of Internet of Things (IoT) devices and connectivity (Xu *et al.*, 2021), Industry 5.0 marks a resurgence of technologically driven evolution, with generative AI at the forefront (Yang *et al.*, 2024). Unlike traditional AI systems, generative AI possesses the unique ability to autonomously generate new content, designs and solutions, revolutionizing product development, production management and supply chain management (Bendoly *et al.*, 2023; Bilgram and Laarmann, 2023). While other technologies such as IoT, robotics and additive manufacturing play crucial roles in Industry 5.0 (Huang *et al.*, 2022), it is the transformative potential of AI that drives the most significant advancements and innovations in this context. As generative AI continues to evolve, it is poised to become increasingly integral to Industry 5.0 initiatives (Ghobakhloo *et al.*, 2024), fueling continuous improvement and innovation across all facets of production, from design optimization to predictive maintenance and beyond.

Generative AI is a subset of AI techniques that aim to create models capable of generating new, original data, typically in the form of images, text or other types of content (Prasad Agrawal, 2023). Generative AI has gained widespread attention in the industrial domain, particularly for its diverse applications in tourism (Dogru *et al.*, 2023) and marketing (Peres *et al.*, 2023). Generative AI's disruptive impact in the industrial and business domains stems from its ability to transform various aspects of operations (Kanbach *et al.*, 2023). One key benefit lies in its capacity for content creation, allowing businesses to automate the generation of diverse and complex materials, from designs and prototypes to marketing content. This not only expedites the creative process but also enhances productivity (Fui-Hoon Nah *et al.*, 2023). Generative AI contributes significantly to product design and optimization, enabling the exploration of innovative ideas and efficient iteration of designs (Bilgram and Laarmann, 2023). Moreover, its predictive capabilities are crucial in forecasting trends, demand and potential issues, facilitating informed decision-making (Chen *et al.*, 2023). Overall, its versatility, from creative tasks to predictive analytics and process improvement, positions generative AI as a game-changer with broad-reaching implications for industrial and business practices (Kar *et al.*, 2023). In addition, the implementation of generative AI can be relatively accessible compared to other emerging technologies. Generative AI tools and platforms are usually designed to streamline the development process, providing user-friendly interfaces and pre-built models that reduce the technical barriers to adoption (Prasad Agrawal, 2023). This accessibility and the growing availability of cloud-based services make this technology more feasible for a broader range of companies (Dogru *et al.*, 2023). While the costs associated with generative AI implementation can vary depending on factors like the complexity of use cases and customization requirements, the technology's increasing maturity and widespread availability contribute to its perceived affordability compared to certain cutting-edge technologies. Companies may find generative AI more approachable for integration, making it an attractive choice for those seeking advanced capabilities without extensive resource investments (Prasad Agrawal, 2023).

Indeed, a plethora of commercially available generative AI products are tailored explicitly for manufacturing purposes, addressing needs ranging from product design to simulation, optimization and predictive modeling (e.g. https://tulip.co/). However, in the academic context, the exploration of generative AI's role in manufacturing is still nascent. While industry discussions report practical implementations, academia is gradually delving into a more systematic examination of the scattered yet promising contributions of generative AI within manufacturing contexts. This increasing academic interest reflects a growing acknowledgment of the technology's transformative potential in manufacturing.

The scholarly literature reveals that most academic contributions in this context relate to the generative design AI application for product design (Bendoly *et al.*, 2023; Castañé *et al.*, 2023).

In addition, there have been other sporadic reports on the implications of generative AI in the manufacturing context, such as using ChatGPT to generate optimized Gcode in the 3D printing context (Badini *et al.*, 2023). Recent studies also consider generative AI a fundamental technology of Industry 5.0 (Ghobakhloo *et al.*, 2023a, b, c). Nonetheless, the literature fails to practically explain how integrating generative AI into manufacturing operations can contribute to sustainability goals under the Industry 5.0 framework.

3. Theoretical background

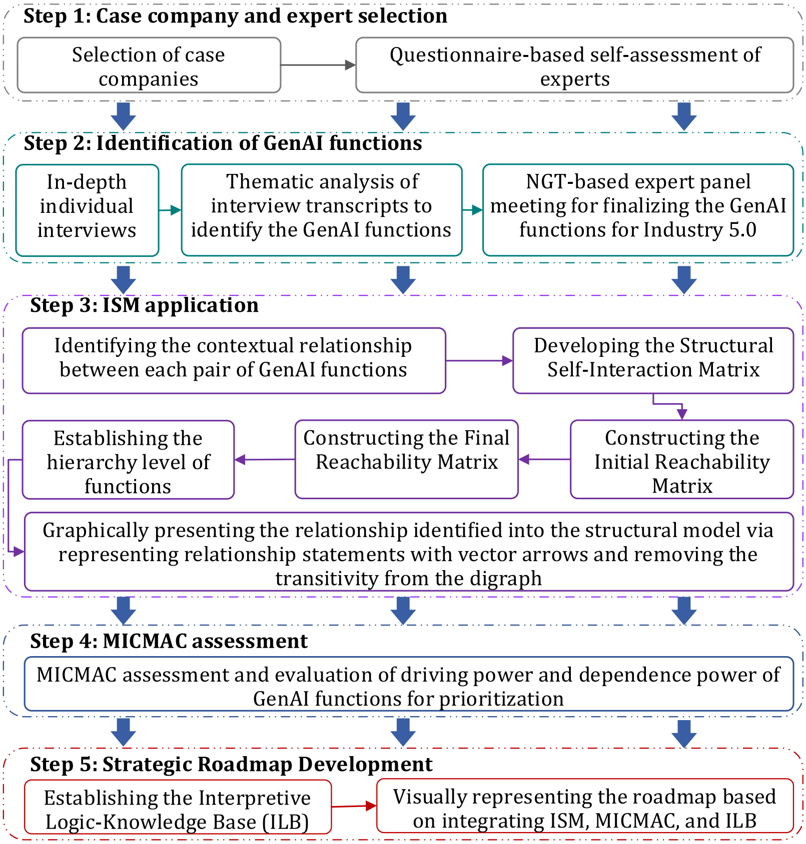
This study draws on paradox theory (Ozanne *et al.*, 2016) to structure the research into the relationships between the utilization of generative AI and the sustainability performance of manufacturers within the framework of Industry 5.0. Paradox theory provides a lens to understand and manage the inherent tensions and contradictions that arise in the pursuit of sustainability goals through technological innovation (Singh *et al.*, 2024). By applying paradox theory, this research aims to explore how manufacturers can effectively leverage generative AI technologies to enhance sustainability performance while navigating the complex interplay of competing demands and objectives.

Paradox theory posits that organizations often face inherent tensions or contradictions, such as stability vs change or exploration vs exploitation, which must be managed effectively for success (Farrukh and Sajjad, 2024). Building on this theory to study the positive contributions of generative AI to the sustainability performance of manufacturers involves recognizing and leveraging the paradoxes inherent in both sustainability and technological innovation (Lim *et al.*, 2023). Generative AI, with its ability to optimize designs, streamline processes and analyze complex data, presents opportunities to address sustainability challenges in novel ways (Bilgram and Laarmann, 2023). For instance, by embracing the paradox of innovation vs sustainability, manufacturers can use generative AI to develop eco-friendly products and processes that enhance resource efficiency and minimize environmental impact. Similarly, by navigating the paradox of centralized control vs decentralized autonomy, organizations can establish clear sustainability goals while empowering cross-functional teams to explore innovative applications of generative AI throughout the value chain (Fosso Wamba *et al.*, 2024). Moreover, by embracing the paradox of exploitation vs exploration, firms can leverage generative AI to simultaneously optimize existing operations and explore new sustainable business models. Through this integrative approach informed by paradox theory, manufacturers can unlock the full potential of generative AI to drive positive sustainability outcomes while navigating the complexities of organizational dynamics and stakeholder expectations.

Therefore, we drew on paradox theory as an exploratory basis to understand the mechanisms through which generative AI may address the sustainability paradox, namely, the challenge of simultaneously enhancing socio-economic and environmental values while minimizing potential negative impacts. This approach allows us to examine how generative AI can catalyze positive socio-economic and environmental outcomes within the context of Industry 5.0, shedding light on its potential to navigate and mitigate sustainability challenges effectively.

4. Methodology

Given the emerging nature of generative AI applications in manufacturing within the academic realm (Castañé *et al.*, 2023), this study embraced an exploratory research method, integrating both quantitative and qualitative elements (Sale *et al.*, 2002). Expert interviews were selected as a primary data collection method to capture rich and context-specific insights from practitioners at the forefront of generative AI implementation in European manufacturing companies. These interviews were designed to capture the purposes for which generative AI has been implemented and to assess its effectiveness in meeting these objectives. The study conducted interviews with eight experts, each representing a manufacturing company that had prior experience utilizing generative AI. To enhance the robustness and generalizability of the findings, careful consideration was given to the selection of these experts. The participants were chosen to represent a diverse array of factors, including the size of their respective manufacturing enterprises, the specific sectors within the manufacturing industry they operated in and their geographic locations across Europe. This strategic approach ensured that the insights gleaned from the study would encompass a broad spectrum of perspectives, spanning different organizational scales, industrial contexts and regional influences within the manufacturing landscape. After identifying the case companies and experts, several expert panel meetings were organized that drew on the nominal group technique (NGT) to ensure systematic and rigorous consensus-building among diverse experts. Interpretive structural modeling (ISM) was further employed to transform expert opinions into a coherent and actionable roadmap systematically. Figure 1 represents the research design and underlying steps.



Source(s): The authors

Figure 1.
An overview of research design

4.1 Participant selection

In collaboration with the research consortium, the study identified 11 European companies that successfully integrated generative AI into their operational frameworks and expressed intentions to align with Industry 5.0 principles. With a geographical focus on European manufacturers and support from an EU-funded project, invitations were extended to experts knowledgeable about AI-generative applications, resulting in the participation of 8 out of the 11 identified companies. This process further entailed a qualification step that used a self-assessment questionnaire to ensure the expertise and readiness of participating experts. This process showed that all experts have a robust understanding of generative AI and a willingness to engage.

4.2 Generative AI functionality identification

In-depth individual interviews with the eight qualified experts were conducted to identify the specific purposes for which generative AI was employed within their respective companies. Thematic analysis of interview transcripts identified ten distinct functionalities [1] of generative AI, representing the collective rationale for its integration and diverse applications within the operational landscapes of the participating companies. Next, the research team organized the first expert panel meeting to present and discuss the ten identified functions. Using the NGT for the expert panel meetings facilitated a structured and rigorous approach to extract reliable and valid expert opinions. During this meeting, experts collectively deliberated on the appropriateness of labels and operationalizations for each function, as well as how these functions could contribute to the goals of Industry 5.0. The outcome was a shared consensus among experts regarding the naming and operational definitions of the 10 generative AI functions and their alignment with Industry 5.0 objectives. This iterative process ensures the robustness of the methodology and the reliability of the derived insights. These functions are briefly introduced and discussed in the following.

Advanced customer support (ACS): Trained on vast datasets, generative AI can comprehend and generate human-like responses to diverse customer queries. In the manufacturing context, this means that customers can receive more detailed and tailored support, whether it is troubleshooting issues with products, obtaining detailed information about specifications, or seeking guidance on usage and maintenance. Generative AI can simulate natural language interactions, offering a seamless experience for customers. Moreover, by leveraging machine learning and constantly updating their knowledge base, generative AIs can adapt to evolving products and customer needs. This ensures manufacturers can provide efficient, highly adaptive and personalized support, ultimately enhancing customer satisfaction and loyalty. The technology's ability to handle complex queries and its continuous learning capacity position generative AIs as valuable assets for manufacturers aiming to deliver a superior and responsive customer support experience. Aligned with the customer-centricity of Industry 5.0, generative AI can provide sophisticated and personalized customer assistance, contributing to a more humanized and tailored interaction between manufacturers and customers.

Agile production decisions (APD): Generative AI delivers this function by enabling a dynamic interplay of real-time insights, enhanced decision-making efficiency and streamlined data accessibility. Generative AI significantly minimizes human errors by providing instantaneous data insights, fostering a more informed decision-making process essential for Industry 5.0's vision of adaptive and responsive production systems. This multifaceted function also amplifies shop-floor decision-making efficiency by automating routine tasks and facilitating streamlined data accessibility, ensuring that human operators can efficiently interpret and leverage information. Economically, the combined impact contributes to operational efficiency, cost-effectiveness and heightened competitiveness.

Socially, the function cultivates a safer and more engaging work environment, allowing human operators to focus on tasks that harness their cognitive strengths.

Advanced quality management (AQM): By harnessing the power of machine learning algorithms, generative AI can analyze vast datasets to identify intricate patterns, potential defects and areas for improvement in the manufacturing processes. Generative AI contributes to predictive quality analytics through continuous learning and adaptation, allowing manufacturers to foresee and address potential issues before they escalate. Generative AI can integrate with sensors and IoT devices to collect and analyze data from various stages of production, providing a comprehensive view of the entire manufacturing ecosystem. This enables manufacturers to optimize processes, minimize defects and enhance overall product quality. Generative AI's ability to self-improve over time also ensures a dynamic and responsive approach to quality management. By automating or at least streamlining tasks such as defect detection, root cause analysis and quality prediction, generative AI empowers manufacturers to excel in quality assurance and management. Aligned with Industry 5.0 values and through its capacity to enhance quality and prevent defects in manufacturing, generative AI plays an essential role in waste reduction, consequently serving environmental goals. By preventing suboptimal production, it contributes to ecological sustainability and yields economic benefits through increased profitability and enhanced product impact. From a social perspective, the emphasis on quality ensures customer satisfaction, fostering positive relationships and bolstering the brand's reputation in the market.

Advanced training and knowledge transfer (ATK): This function is a key enabler for upskilling and reskilling initiatives by providing invaluable guidance to less experienced operators, guiding them on the intricacies of efficiently managing complex production operations. The generative AI models act as personalized tutors, offering high-probability suggestions on various domains such as equipment adjustments, maintenance schedules and even optimal spare parts purchases. The adaptive feedback loop enables operators to interact, seek clarification and receive real-time responses, fostering a dynamic and responsive learning environment. Moreover, generative AI's continuous learning capability ensures that the knowledge base remains current and relevant. These dynamic training mechanisms not only enhance the skill set of less experienced operators but also accelerate their learning curve in adapting to sophisticated production processes and work routines. Economically, this function streamlines the training process, reducing the time and resources traditionally required for upskilling, thus contributing to cost-effectiveness. Socially, it fosters a collaborative learning environment, empowering less-experienced operators with the expertise of their more seasoned counterparts.

Data-driven production insights (DPI): Through this function, generative AI empowers manufacturers with real-time, data-driven insights into their operations. This capability allows the swift analysis of vast data volumes, enabling the identification of trends and the extraction of meaningful insights. Manufacturers can comprehensively understand their processes and make informed decisions seamlessly. The real-time insights derived from generative AI contribute to economic sustainability by optimizing production efficiency, minimizing waste and reducing operational costs. This function also allows for leveraging data for agile and responsive manufacturing. Socially, it fosters safer working environments as real-time data enables rapid response to potential hazards. Environmentally, by facilitating efficient resource utilization, this function reduces the ecological footprint of manufacturing processes.

Enhanced data quality and consistency (EDQ): Generative AI can deliver this function in various ways. For example, it aids in data augmentation by generating synthetic data and diversifying datasets for better model training. Generative AI contributes to anomaly detection, identifying outliers and maintaining data consistency. It facilitates data cleaning and imputation by predicting missing values, leading to improved dataset integrity. In noise reduction, generative models filter irrelevant information, ensuring cleaner, more focused datasets. Generative AI also ensures consistent scales across the dataset by learning feature distributions through standardization and normalization. Alternatively, generative AI's enhanced labeling and contextual understanding can further contribute to data quality, while privacy-preserving synthetic data addresses confidentiality concerns. This function improves operational efficiency and diminishes the risk of errors associated with manual data handling, ensuring the accuracy and reliability of the insights generated. Generative AI's contribution in this regard not only optimizes the data workflow but also bolsters the foundation for robust decision-making processes within the Industry 5.0 data governance framework.

Generative design optimization (GDO): This function involves deploying generative design algorithms to optimize product design. It concerns making products more economically viable by reducing production costs, enhancing material efficiency for lightweight designs and seamlessly integrating customer preferences. Economically, generative AI enables ways to reduce production costs, enhancing the economic viability of the manufacturing process. Concurrently, the focus on lightweight structures contributes to material efficiency, aligning with economic and environmental objectives. Furthermore, the integration of customer preferences is seamlessly supported by generative AI, ensuring cost-effective customization and delivering personalized, high-quality products that meet consumer demands. Importantly, this function does not merely stop at the production stage. It extends its impact to the end of the product lifecycle. Generative AI minimizes environmental impact throughout the product's life cycle by considering end-of-life factors, such as recyclability and eco-friendly disposal.

Operational resilience (OPR): This function revolves around streamlining data categorization, raising alerts and swiftly delivering context-rich information to operators. This streamlined process facilitates risk identification, error reduction and an overall increase in operational resilience. By categorizing data efficiently, generative AI ensures that critical information is surfaced promptly, aligning seamlessly with the adaptive and responsive production systems envisioned by Industry 5.0. From an economic perspective, this function aids in risk mitigation, averting potential financial implications associated with operational disruptions. On the social front, it contributes to a safer working environment by providing timely alerts to operators, minimizing errors and fostering a culture of disruption resilience. Additionally, the streamlined process has environmental implications in terms of reducing errors and associated resource waste. Generative AI's role in enhancing operational resilience encapsulates a holistic and systematic approach, ensuring a technologically advanced manufacturing ecosystem that is resistant to disruption throughout the business environment.

Operator satisfaction enhancement (OSE): Generative AI delivers this function in myriad ways. AI-optimized workflows directly impact operators by reducing wait times, enhancing task efficiency and providing a more streamlined work environment. Personalized training programs, tailored by generative AI to individual operator needs, contribute to skill development, job satisfaction and a sense of mastery. Real-time feedback mechanisms empower operators by offering immediate insights into their performance, fostering a more engaging and responsive work environment. Furthermore, the introduction of intuitive interfaces directly benefits operators by simplifying machine interactions and reducing the likelihood of errors. Additionally, adaptive automation facilitated by generative AI ensures operators have control over their tasks, contributing to a more satisfying and collaborative work experience. Accordingly, generative AI promotes the social values of Industry 5.0 by fostering a collaborative work culture and facilitating effective communication and responsiveness. The dynamic feedback loop empowered by generative AI enables a continuous exchange of information between managers and operators that strengthens professional relationships and cultivates a close collaboration environment. Therefore, it results in a more engaging and satisfying work environment where employees feel heard, supported and empowered to contribute to the ongoing enhancement of the manufacturing process.

On-demand workforce empowerment (OWE): This function is realized through generative AI's capacity to act as a multilingual internal knowledge base and dynamic assistant, revolutionizing how operators interact with software applications, report production information (e.g. defects) and navigate information seamlessly through a single natural sentence. This function aligns profoundly with Industry 5.0's vision of human–machine collaboration, where technology serves as a facilitator, enhancing operational capabilities. Economically, on-demand empowerment streamlines tasks, contributing to operational efficiency and reducing labor costs. Socially, it empowers operators by simplifying complex processes, fostering a more intuitive and user-friendly work environment. Moreover, the streamlined interactions minimize the potential for errors, further contributing to the socio-environmental sustainability objectives. This function represents generative AI's role in automating tasks and empowering operators in a user-friendly, efficient manner, thereby supporting human-centric operations in the manufacturing landscape.

4.3 Applying ISM

ISM is a decision-making methodology widely used in strategic planning and roadmapping (Ching *et al.*, 2022). It facilitates the analysis of complex systems by identifying and visualizing interdependencies among various factors. ISM provides a structured approach to understanding hierarchical relationships, allowing for prioritizing critical elements and recognizing feedback loops (Dwivedi *et al.*, 2023). Its visual representation aids in communicating complex information, making it a valuable tool for systematically managing complexity and guiding strategic decision-making in roadmapping processes. In implementing ISM for this study, the initial step involved establishing relationships among generative AI's functions using the following coding system (See Table 1):

(1) V: Indication that Function 1 determines Function 2.

(2) A: Denotes that Function 1 is determined by Function 2.

(3) X: Signifies that Function 1 and Function 2 determine each other.

(4) O: Represents that Function 1 is independent of Function 2.

Table 1. The SSIM for generative AI functions

Factors	ACS	APD	AQM	ATK	DPI	EDQ	GDO	OPR	OSE	OWE
ACS	–	O	O	O	A	O	O	O	O	O
APD		–	O	A	A	O	O	V	V	A
AQM			–	O	A	A	O	V	O	O
ATK				–	O	A	O	O	V	V
DPI					–	A	O	V	O	O
EDQ						–	V	O	V	V
GDO							–	V	O	V
OPR								–	O	A
OSE									–	A
OWE										–

Source(s): The authors

In the next step in ISM, these symbolic relationships were translated into the binary initial reachability matrix (IRM) through the following established rules. This IRM, presented in Table 2, formed the initial basis for understanding the direct relationships between SCR functions.

(1) If the SSIM relationship was denoted as "V," the corresponding entry in the IRM was set to 1, while the reverse entry was set to 0.

(2) If the SSIM relationship was marked as "A," the entry in the IRM was set to 0, with the reverse entry set to 1.

(3) If the SSIM relationship was coded as "X," both entries in the IRM were set to 1.

(4) If the SSIM relationship was represented by "O," both entries in the IRM were set to 0.

The subsequent step involved constructing the final reachability matrix (FRM) by applying the transitivity rule to the IRM. The transitivity rule, considering indirect causality, clarified the influence of one generative AI function on another through intermediate functions. Table 3 demonstrated the FRM, including "1*" entries to indicate the presence of the transitivity rule.

The next step entails systematically determining the hierarchical position of each function (Ching *et al.*, 2022). This involves an iterative extraction approach, where reachability, antecedent and intersection sets are first established for each function. The reachability set signifies functions directly influencing a given function, while the antecedent set includes functions determined by it. The intersection set represents the overlap between these sets (Dwivedi *et al.*, 2023). The initial extraction identifies functions with identical reachability and intersection sets. This iterative process repeats, excluding previously extracted functions in each iteration. The resulting table or representation demonstrates how hierarchy levels are iteratively identified. Table 4 represents the hierarchical extraction of generative AI functions. For the present study, this process was completed across five iterations.

The final step in executing ISM is constructing the interpretive model. Doing so first involves structuring the functions based on identified hierarchy levels. This structuring ensures that the model accurately represents the relationships and dependencies among functions (Dwivedi *et al.*, 2023). The number of placement levels in the structural model corresponds to the number of hierarchy levels identified. The placement order within the model is established as the inverse of the iterative extraction order (Ching *et al.*, 2022). Functions extracted earlier, signifying higher dependence, are positioned at the higher placement levels, while functions extracted in later iterations, indicating greater

Factors	ACS	APD	AQM	ATK	DPI	EDQ	GDO	OPR	OSE	OWE
ACS	1	0	0	0	0	0	0	0	0	0
APD	0	1	0	0	0	0	0	1	1	0
AQM	0	0	1	0	0	0	0	1	0	0
ATK	0	1	0	1	0	0	0	0	1	1
DPI	1	1	1	0	1	0	0	1	0	0
EDQ	0	0	1	1	1	1	1	0	1	1
GDO	0	0	0	0	0	0	1	1	0	1
OPR	0	0	0	0	0	0	0	1	0	0
OSE	0	0	0	0	0	0	0	0	1	0
OWE	0	1	0	0	0	0	0	1	1	1

Source(s): The authors

Table 2.
The IRM for generative AI functions

Factors	ACS	APD	AQM	ATK	DPI	EDQ	GDO	OPR	OSE	OWE	*Driving power*	*Rank*
ACS	1	0	0	0	0	0	0	0	0	0	*1*	*7*
APD	0	1	0	0	0	0	0	1	1	0	*3*	*5*
AQM	0	0	1	0	0	0	0	1	0	0	*2*	*6*
ATK	0	1	0	1	0	0	0	1*	1	1	*5*	*3*
DPI	1	1	1	0	1	0	0	1	1*	0	*6*	*2*
EDQ	1*	1*	1	1	1	1	1	1*	1	1	*10*	*1*
GDO	0	1*	0	0	0	0	1	1	1*	1	*5*	*3*
OPR	0	0	0	0	0	0	0	1	0	0	*1*	*7*
OSE	0	0	0	0	0	0	0	0	1	0	*1*	*7*
OWE	0	1	0	0	0	0	0	1	1	1	*4*	*4*
Dependence power	*3*	*6*	*3*	*2*	*2*	*1*	*2*	*8*	*7*	*4*		
Driving power	*5*	*3*	*5*	*6*	*6*	*7*	*6*	*1*	*2*	*4*		

Source(s): The authors

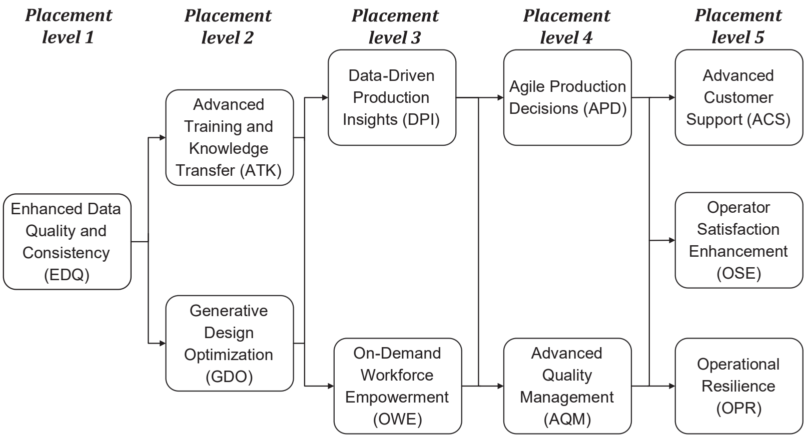
Table 3.
The FRM for generative AI functions

Functions	Reachability set	Antecedent set	Intersection set	Level
Iteration I				
ACS	ACS	ACS, DPI, EDQ	ACS	*I*
APD	APD, OPR, OSE	APD, ATK, DPI, EDQ, GDO, OWE	APD	
AQM	AQM, OPR	AQM, DPI, EDQ	AQM	
ATK	APD, ATK, OPR, OSE, OWE	ATK, EDQ	ATK	
DPI	ACS, APD, AQM, DPI, OPR, OSE	DPI, EDQ	DPI	
EDQ	ACS, APD, AQM, ATK, DPI, EDQ, GDO, OPR, OSE, OWE	EDQ	EDQ	
GDO	APD, GDO, OPR, OSE, OWE	EDQ, GDO	GDO	
OPR	OPR	APD, AQM, ATK, DPI, EDQ, GDO, OPR, OWE	OPR	*I*
OSE	OSE	APD, ATK, DPI, EDQ, GDO, OSE, OWE	OSE	*I*
OWE	APD, OPR, OSE, OWE	ATK, EDQ, GDO, OWE	OWE	
Iteration II				
APD	APD	APD, ATK, DPI, EDQ, GDO, OWE	APD	*II*
AQM	AQM	AQM, DPI, EDQ	AQM	*II*
ATK	APD, ATK, OWE	ATK, EDQ	ATK	
DPI	APD, AQM, DPI	DPI, EDQ	DPI	
EDQ	APD, AQM, ATK, DPI, EDQ, GDO, OWE	EDQ	EDQ	
GDO	APD, GDO, OWE	EDQ, GDO	GDO	
OWE	APD, OWE	ATK, EDQ, GDO, OWE	OWE	
Iteration III				
ATK	ATK, OWE	ATK, EDQ	ATK	
DPI	DPI	DPI, EDQ	DPI	*III*
EDQ	ATK, DPI, EDQ, GDO, OWE	EDQ	EDQ	
GDO	GDO, OWE	EDQ, GDO	GDO	
OWE	OWE	ATK, EDQ, GDO, OWE	OWE	*III*
Iteration IV				
ATK	ATK	ATK, EDQ	ATK	*IV*
EDQ	ATK, EDQ, GDO	EDQ	EDQ	
GDO	GDO	EDQ, GDO	GDO	*IV*
Iteration V				
EDQ	EDQ	EDQ	EDQ	*V*

Source(s): The authors

Table 4. Hierarchy level for the generative AI functions

independence, are placed at the lower placement levels. Next, the contextual relationships between each pair of functions should be represented using vector arrows. These arrows indicate the directional influence or determination between functions across consecutive placement levels. Finally, the transitivity effects among functions are removed, ensuring that vector arrows do not represent indirect influences. This process results in a structured interpretive model, visually capturing the hierarchical dependencies and contextual relationships among the analyzed functions. Figure 2 illustrates the structural model explaining how generative AI functions interact while contributing to Industry 5.0 goals.

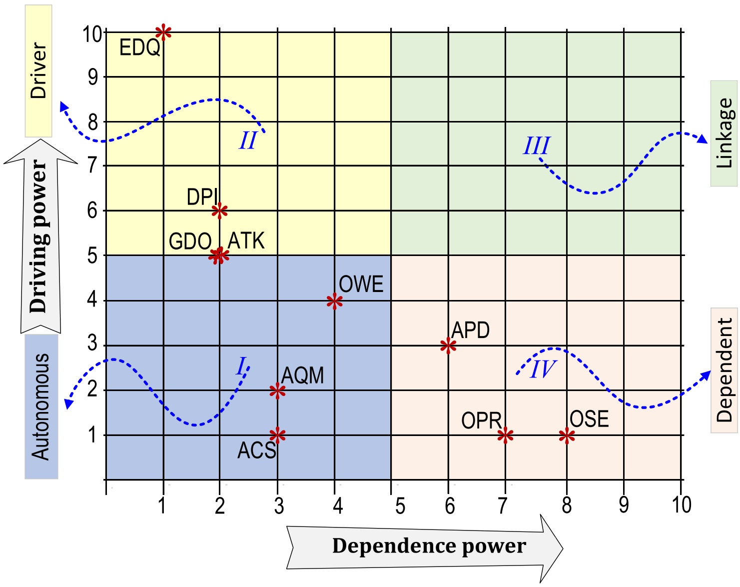


Source(s): The authors

Figure 2.
The study's structural model for generative AI contributions to Industry 5.0

4.4 MICMAC analysis

MICMAC is a complementary step to ISM in strategic roadmapping. In this phase, a comparative visual analysis is undertaken to gauge the relational scope of each system element within a complex system. MICMAC establishes a Cartesian coordinate system to classify system elements into four quadrants based on their driving and dependence powers computed in the FRM. The autonomous quadrant signifies functions with weak driving and dependence powers. As Figure 3 implies, ACS, AQM and QWE are the autonomous functions of generative AI. The driver quadrant includes functions with high driving power and low



Source(s): The authors

Figure 3.
MICMAC assessment

dependence power, pinpointing pivotal functions propelling others. ATK, GDO, EDQ and DPI are the driver functions of generative AI. The third quadrant is the linkage quadrant, which includes elements with substantial driving and dependence powers. Figure 3 signifies the lack of linkage functions in the study. Conversely, the dependent quadrant incorporates functions with limited driving power but substantial dependence power, indicating their reliance on driver functions. APD, OSE and OPR are the dependent functions of generative AI.

4.5 Constructing the strategic roadmap

The study followed the strategic roadmapping guideline by Ghobakhloo *et al.* (2023b) to develop the strategic roadmap for generative AI contributions to Industry 5.0 objectives. Consistently, the promised roadmap was developed through a multi-step process that integrated findings from ISM, MICMAC analysis and the interpretive logic-knowledge base (ILB). Initially, the ISM methodology was employed, leveraging expert interviews, expert panel meetings and structural modeling to identify the contextual relationships among various functions of generative AI within manufacturing processes. The resulting structural model illustrated the interdependencies and hierarchies among these functions. To enhance the insights gained from ISM, the MICMAC analysis was conducted to provide a comparative analysis of the driving and dependent powers of each generative AI function. This analysis categorized the functions into quadrants, such as autonomous, driver, linkage and dependent, shedding light on their relative influences and dependencies. By categorizing functions, MICMAC helped with the prioritization of the functions.

ILB serves as a repository for interpretive knowledge and logic extracted from expert insights. Throughout the NGT-based expert panel meetings, experts were engaged in describing the meaning of each contextual relationship, providing collective interpretations. The ILB helped enhance the roadmapping by explaining the functionality of identified contextual relationships and offering additional qualitative depth derived from expert perspectives (see Table 5).

Therefore, the roadmapping process involved synthesizing the identified functions, their relationships and their relative influences to construct a detailed strategic roadmap. This roadmap, presented in Figure 4, provides a visual and conceptual guide outlining the key steps, priorities and considerations for leveraging generative AI in manufacturing toward the objectives of Industry 5.0. The integration of these methodologies ensured a systematic approach to developing a strategic roadmap for the effective integration of generative AI within the Industry 5.0 framework. The implications of the roadmap are discussed in the following section.

5. Discussion

Generative AI has recently emerged as a pivotal technology within the Industry 5.0 landscape. In contrast to other advanced technologies in Industry 5.0, generative AI stands out not as a conceptual idea but as a concrete technological option that manufacturers are actively integrating into their operational frameworks.

To explore how generative AI seamlessly fits into the manufacturing context aligned with Industry 5.0, the study employed a hybrid roadmapping methodology. This strategic roadmap provided a comprehensive overview of how various generative AI functions contribute to realizing the sustainability objectives of Industry 5.0. The study identified ten crucial functions, ranging from data-driven production insights to enhanced quality management, each playing a vital role in improving manufacturing processes. While these functions are individually noteworthy, their true significance lies in the interdependence and

Contextual relationship	Enabling role
Agile production decisions (APD)	
ADP → OPR	Facilitating swift responses to potential risks and disruptions; identifying and mitigating risks promptly, thereby enhancing the overall resilience of the manufacturing process
ADP → OSE	Reducing wait times, enhancing task efficiency and providing a more streamlined work environment for operators, contributing to overall satisfaction and a positive work culture
Advanced quality management (AQM)	
AQM → OPR	Identifying intricate patterns, potential defects and areas for improvement in manufacturing processes proactively; contributing to predictive quality analytics and addressing quality issues before they escalate
Advanced training and knowledge transfer (ATK)	
ATK → APD	Improving decision-making efficiency by upskilling and providing guidance to operators on efficiently managing complex production operations; enhancing the analytical capabilities of operators, contributing to more informed and effective production decisions
ATK → OSE	Offering personalized training programs, tailored guidance and real-time feedback; empowering operators via continuous learning loop, enhancing their skills and fostering a more engaging and responsive work environment
ATK → OWE	Streamlining tasks and improving operational efficiency; Simplifying complex processes, fostering a user-friendly work environment and minimizing errors in collaboration with human operators
Data-driven production insights (DPI)	
DPI → ACS	Addressing customer queries with up-to-date and accurate information, contributing to a seamless and responsive customer support operations
DPI → APD	Providing real-time data-driven insights and swift analysis of vast data volumes, leading to the identification of trends and meaningful insights and contributing to informed decision-making and overall efficiency in production decision processes
DPI → AQM	Streamlined and continuous analysis of data from various production stages, leading to predictive quality analytics and helping identify and address potential defects and areas for improvement
DPI → OPR	Improved risk identification, error reduction and supplying of context-rich information to operators, contributing to a more responsive and adaptive manufacturing system
Enhanced data quality and consistency (EDQ)	
EDQ → AQM	Improving the quality and consistency of data used in advanced quality management processes via data augmentation, anomaly detection and cleaning, leading to enhanced dataset integrity and reliability for machine learning algorithms in quality management
EDQ → ATK	Streamlining the training process by providing high-quality, consistent data. Enhanced data quality contributes to better model training, reducing the time and resources required for upskilling and ensuring the accuracy of training data for knowledge transfer
EDQ → DPI	Ensuring data quality and consistency, which supports efficient analysis of vast data volumes, allowing manufacturers to comprehensively understand their processes and make accurate decisions
EDQ → GDO	Ensures high-quality data for generative design algorithms; increasing the accuracy in the exploration of design possibilities; Supporting generated designs to not only be optimal in performance but also be aligned with specific industry and environmental goals

Table 5.
The ILB

(*continued*)

Contextual relationship	Enabling role
EDQ → OSE	Ensuring the accuracy and reliability of generated insights, thus boosting the AI-optimized workflows, personalized training and real-time feedback mechanisms, contributing to a more satisfying and engaging work environment for operators
EDQ → OWE	Facilitates seamless interactions with software applications, reporting production information and navigating information, contributing to a user-friendly and efficient work environment
Generative design optimization (GDO)	
GDO → OPR	Optimizing product designs processes and ensuring that generative designs are tailored for optimal performance, responsive to dynamic market demand and satisfy value proposition and differentiation requirements
GDO → OWE	Boosts mechanisms empowering R&D and new product design teams, allowing them to focus on creativity and be more efficient
On-demand workforce empowerment (OWE)	
OWE → APD	Simplifying operators' active participation in decision-making processes; streamlining of tasks, making the decision-making processes more efficient; Providing employees with the most up-to-date information to inform their decisions
OWE → OPR	Providing context-rich information, thus, enabling operators to respond swiftly to risks and disruptions, further enhancing the adaptability and responsiveness of production systems
OWE → OSE	Optimizing and simplifying operational processes for employees as well as enabling immediate and constructive information feedback to operators about their performance, resulting in a supportive work environment that reduces the burden of reparative tasks and fosters a sense of mastery among the workforces

Source(s): The authors

Table 5.

complementarity observed among them. For example, enhanced data quality (EDQ) and consistency emerges as a cornerstone function due to its fundamental nature and achievable characteristics. Beyond its standalone contributions, EDQ initiates a cascading effect wherein improved data quality sets the stage for improved training and knowledge transfer, agile production decisions and operational resilience. In simpler terms, when these generative AI functions are leveraged together, their impact is more than just the sum of their individual effects. Indeed, leveraging these functions collectively provides super additive effects, meaning their combined contributions to Industry 5.0 are greater than what each function could achieve alone. The collaborative synergy of these functions amplifies generative AI's overall contributions, emphasizing the need for manufacturers to recognize and harness these mechanisms to extract the maximum benefits from generative AI.

However, it should be noted that the priorities identified in the roadmap, reflecting the relational importance of functions, emphasize the enabling power of the functions and suggest a logical sequence for implementation. Yet these priorities are distinct from the strategic importance of functions. For instance, if achieving operational resilience through generative AI holds the highest strategic significance for a particular organization, prioritizing generative AI integration for that specific purpose becomes strategically imperative, notwithstanding its relational importance in the roadmap. Strategic considerations should guide the alignment of generative AI functions with organizational goals, ensuring that the chosen priorities align with broader strategic objectives rather than solely reflecting their relational significance.

Overall, the strategic roadmap developed addresses the critical significance of the synergistic interactions among generative AI functions, providing a detailed guide on how

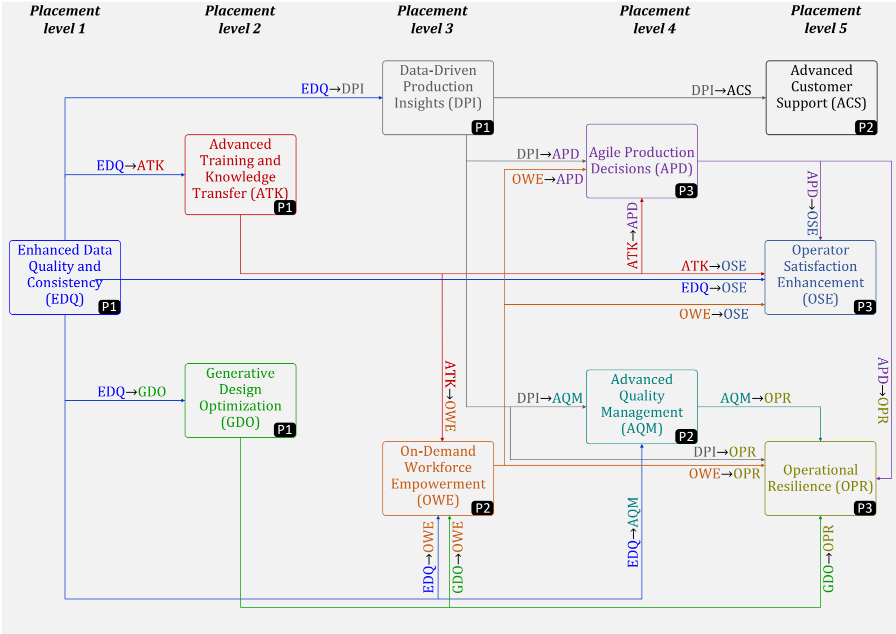


Figure 4.
The strategic roadmap for leveraging generative AI functions for Industry 5.0 objectives

Note(s): P1, First priority function; P2, Second priority function; P3, Third priority function
Source(s): The authors

manufacturers can navigate and capitalize on these dynamics. It provides an understanding of how these functions can be strategically deployed in a sequential manner, creating a deliberate cascade of benefits. By delineating the specific pathways of interaction and dependencies, the roadmap can be a compass for manufacturers, guiding them through a strategic sequence that maximizes the additive effects of generative AI functions. This approach goes beyond isolated implementations, offering a comprehensive strategy that transforms these functions from individual contributors into a powerful collective force, contributing more to Industry 5.0 objectives than the sum of their standalone impacts.

5.1 Navigating generative AI's potential

Generative AI technologies are poised to revolutionize manufacturing with their diverse technical capabilities, as observed within the insights from the case companies. These innovations enable accelerated product design iterations by swiftly generating numerous design alternatives, thus expediting the development process. Additionally, generative AI facilitates virtual prototyping, allowing for rapid iteration and testing without the need for physical prototypes, thereby reducing costs and time to market. Furthermore, these technologies optimize manufacturing processes by simulating various scenarios and identifying the most efficient setups, leading to improved productivity and resource utilization. Real-time quality control is also enhanced as generative AI algorithms analyze vast datasets of product images or sensor data to swiftly detect defects or anomalies, ensuring higher product quality standards.

However, the participating experts believed that generative AI technologies encounter significant limitations and challenges in manufacturing applications. One prominent challenge is the requirement for extensive and high-quality datasets for effective training, which can be scarce or costly to obtain in certain manufacturing domains. On a technical level, compatibility issues between AI algorithms and legacy manufacturing systems may arise, necessitating significant modifications or upgrades to existing infrastructure. Moreover, ensuring the interpretability of AI-generated outputs can be difficult, as the rationale behind generated designs or decisions can be opaque, hindering user understanding and trust. Computational constraints also pose a significant barrier, as training and running complex generative AI models require substantial computational resources, which may not be readily available, particularly for smaller manufacturing firms. Alternatively, organizational barriers, such as resistance to change and a lack of expertise in AI implementation, can impede progress. Culturally, shifting toward a data-driven decision-making approach may encounter resistance from entrenched practices and attitudes. Additionally, the scholarly literature argues that regulatory and ethical concerns surrounding intellectual property rights, safety implications and data privacy necessitate careful consideration and adherence to evolving standards and guidelines (Fui-Hoon Nah *et al.*, 2023). The interview with experts revealed that case companies have adopted several best practices to address these challenges. For example, they prioritized thorough assessment and planning to identify potential technical hurdles and develop tailored solutions. Collaborative partnerships with AI experts and vendors facilitated knowledge transfer and skill development within the case companies. Furthermore, fostering a culture of innovation and continuous learning encouraged openness to adopting new technologies and methodologies. By embracing these strategies, the case companies managed to overcome some of the integration challenges and leverage generative AI to drive innovation and efficiency in manufacturing processes.

Looking ahead, experts believe that development trajectories for generative AI technologies in manufacturing are promising yet require targeted efforts to overcome existing challenges. Integration with other advanced technologies such as reinforcement learning could yield hybrid models with enhanced capabilities and versatility. Furthermore, developments in edge computing and data augmentation techniques can offer potential solutions to computational constraints and data scarcity issues, enabling more widespread adoption and application of generative AI in manufacturing. Experts also widely believe that collaboration across academia, industry and regulatory bodies is essential to unlocking the full potential of generative AI technologies in the manufacturing context while addressing associated challenges responsibly.

5.2 Ethical considerations

While the participating experts widely acknowledged the benefits of generative AI for the case companies, they stressed the paramount importance of ethics and transparency in decision-making processes as AI systems wield significant autonomy in generating data, designs and decisions. As a result, the implementing companies have been significantly concerned with the opacity of generative AI's decision-making mechanisms. Consistently, experts highlighted the importance of transparent AI systems that elucidate the algorithms and inputs underpinning decisions, promoting accountability and trust. Fairness emerges as a central consideration, with experts highlighting the imperative to mitigate potential biases inherent in training data or embedded within AI algorithms. Biases within these systems can perpetuate disparities in manufacturing processes, influencing product quality, resource allocation and workforce dynamics. Consequently, experts emphasized the necessity of rigorous evaluation and validation of AI models to identify and rectify biases pre-deployment. Participating experts also argued that achieving transparency and fairness in generative AI systems necessitates interdisciplinary collaboration and sustained dialogue among internal and external stakeholders, from internal experts to technology providers. Under such circumstances, transparency mechanisms such as explainable AI techniques can enable stakeholders to scrutinize and interpret AI-generated outputs, promoting accountability and informed decision-making (Kim *et al.*, 2020). Additionally, proactive measures encompassing diverse and inclusive data collection strategies, algorithmic auditing and bias detection algorithms are indispensable in fostering fairness and mitigating biases within AI-driven manufacturing processes (Raji *et al.*, 2020).

5.3 The sustainability considerations

The findings outline that the integration of generative AI into manufacturing processes carries the promise of significant economic, environmental and social implications. Economically, the adoption of generative AI could lead to remarkable boosts in productivity and efficiency. Through expedited design iterations and process optimization, manufacturers can expect reduced production costs and increased competitiveness in the market. Furthermore, the ability to swiftly customize products to meet consumer demands opens new avenues for revenue generation. In terms of environmental impact, the optimization facilitated by generative AI holds the potential to minimize resource consumption and waste generation. By optimizing material usage and streamlining production processes, manufacturers can contribute to sustainability goals by reducing their environmental footprint. Generative AI in manufacturing may enhance the social aspect of work by offering advanced training experiences and improved man-machine integration. Through AI-driven simulations and virtual environments, operators receive interactive training, accelerating learning and upskilling efforts. AI assistance systems on the factory floor augment decision-making, reducing errors and boosting productivity. Collaborative robots with generative AI capabilities further enhance efficiency and safety. Additionally, generative AI fosters innovation by empowering operators with real-time insights for proactive process optimization.

Conversely, while the benefits are substantial, there are potential negative impacts associated with the widespread implementation of generative AI in manufacturing. Socio-economically, the automation enabled by AI technologies may lead to job displacement, particularly for workers engaged in repetitive tasks. This could result in unemployment and income inequality if adequate retraining and support programs are not implemented. Moreover, the reliance on AI-driven decision-making introduces the risk of algorithmic biases and errors. If these biases go unchecked, they could perpetuate social inequalities or lead to suboptimal outcomes in manufacturing processes. Additionally, concerns over data privacy and security loom large, with the potential for unauthorized access to sensitive manufacturing data or breaches in AI systems. Without robust safeguards in place, such breaches could have severe consequences for both manufacturers and consumers, undermining trust in AI-driven systems and hindering their adoption. Therefore, while the potential benefits of generative AI in manufacturing are vast, careful consideration of the negative sustainability impacts is imperative to ensure responsible and sustainable implementation.

5.4 Future scalability and application

The future scalability of generative AI functions identified for manufacturing sustainability is poised to revolutionize various facets of production, from customer support to workforce empowerment. For example, by leveraging advancements in machine learning and data analytics, these functions hold the promise of enhancing operational efficiency, quality management and workforce satisfaction even more. In the customer support context and as Industry 5.0 technologies unfold, virtual assistants powered by generative AI will offer deeper personalized assistance, leveraging natural language processing to address customer inquiries across multiple channels.

As the manufacturing landscape continues its trajectory of evolution, the anticipated future development of generative AI applications is poised to adapt dynamically to emerging technologies and evolving industry requirements. Through a holistic approach that melds technological advancements with deep industry insights, AI stands to catalyze a profound revolution in how goods are produced. This evolution entails the seamless integration of generative AI with cutting-edge technologies such as IoT, big data analytics and advanced robotics, enabling comprehensive solutions that optimize efficiency, quality and sustainability throughout the manufacturing value chain. With the proliferation of IoT devices in manufacturing environments, generative AI applications are expected to harness real-time data streams from sensors to drive proactive optimizations and predictive maintenance strategies, fostering agility and responsiveness. Furthermore, by leveraging the synergies between generative AI and big data analytics, manufacturers can glean valuable insights from vast datasets, empowering informed decision-making and strategic process optimization in rapidly changing market landscapes. Advancements in robotics and automation are expected to offer new horizons for generative AI, with collaborative robots equipped with AI capabilities envisioned to enhance productivity and safety, while generative AI algorithms optimize robotic motion planning and control, minimizing energy consumption and cycle times. Importantly, a collaborative approach involving close cooperation with domain experts and stakeholders should be in place to ensure that generative AI solutions are not only technologically advanced but also aligned with the practical needs of diverse manufacturing sectors. Overall, the future of generative AI in manufacturing is characterized by its adaptive capability to anticipate and embrace emerging trends, driving continuous improvement and innovation across production processes to enhance efficiency, quality and sustainability under the Industry 5.0 agenda.

6. Conclusions

The present study investigated the trajectory of generative AI functions in the manufacturing sector within the Industry 5.0 framework. The insights provided may hold significant implications for advancing theoretical understanding, guiding practical implementation and charting directions for future research endeavors.

6.1 Contributions to theory and practice

This study provides a pioneering contribution to the knowledge base by explaining the pivotal role of generative AI in responsible manufacturing. The theoretical contribution of our study lies in the application of paradox theory to understand how manufacturers can effectively leverage generative AI to enhance the values crucial to Industry 5.0. By adopting paradox theory as a framework, the study identified key functions of generative AI that, if utilized effectively, can not only amplify sustainability values but also mitigate potential negative effects of this technology. Through this lens, the study contributes to the existing body of knowledge by providing insights into the complex interplay between technological innovation and sustainability within the context of Industry 5.0. Specifically, the study shed light on how organizations can navigate inherent tensions and contradictions, such as the balance between innovation and sustainability, centralized control and decentralized autonomy and exploitation and exploration when implementing generative AI technologies. By elucidating these dynamics, our study offers theoretical insights that can inform strategic decision-making and organizational practices aimed at maximizing the positive impacts of generative AI while minimizing unintended consequences. Furthermore, our research underscores the importance of considering broader societal and environmental implications in the adoption of advanced technologies, thereby advancing theoretical discourse on the intersection of technology, sustainability and organizational behavior. Overall, our study contributes to a deeper understanding of how generative AI can be harnessed as a transformative tool to drive sustainable development in the era of Industry 5.0, offering theoretical foundations for future research and practical implications for industry stakeholders.

The research identifies and operationalizes ten distinct functions through a systematic examination, shedding light on how generative AI acts as a key catalyst in advancing the Industry 5.0 framework. This theoretical advancement enhances our comprehension of generative AI's potential in manufacturing, laying a robust foundation for future research endeavors. The operationalization of these functions delivers actionable insights for scholars, industry practitioners and policymakers aiming to integrate generative AI to strategically promote sustainable and innovative manufacturing practices.

Manufacturers are advised not to pursue the all-encompassing integration of generative AI for various purposes hastily. The case companies showcased the benefits of utilizing generative AI for individual purposes. For instance, firms employing generative AI for risk mitigation and operational resilience have witnessed notable improvements in averting potential financial implications linked to operational disruptions and fostering a safer working environment. While these targeted implementations have proven advantageous, the strategic roadmap suggests that, when resources allow, a more inclusive integration in the identified order could amplify these effects even further. This phased approach allows manufacturers to leverage generative AI functions strategically based on their immediate needs and resource capacities, gradually building towards a comprehensive and synergistic deployment that aligns with Industry 5.0 goals.

Secondly, generative AI is a tangible technological choice accessible to most manufacturers, offering unique features such as ease of integration and operation. A critical benefit observed among participating firms is that generative AI functions do not necessitate sacrificing economic gains to promote the environmental or social values of Industry 5.0. Generative AI can strike a healthy balance among various sustainability objectives, pushing them all forward, albeit incrementally. This characteristic aligns with the evolving ethos of sustainable and responsible business practices, providing manufacturers with a pragmatic solution that enhances operational efficiency and contributes positively to broader sustainability goals without compromising economic viability. The study reveals that generative AI's user-friendly features and compatibility with economic interests make it a feasible and appealing choice for manufacturers aiming to gradually and economically embrace the principles of Industry 5.0. It is important to note that the case companies studied in this research viewed generative AI as a potential strategic option for several reasons, with a key consideration being the prevailing belief that generative AI would be relatively easy to implement among end-users in manufacturing environments, facilitating effortless usage. However, during the implementation stage, it became evident that this assumption might not always hold true. Therefore, manufacturers must recognize the importance of user-centric design in generative AI tools and their accessibility to non-experts. This is particularly vital for ensuring that the benefits of AI in manufacturing are widely accessible and that the digitalization gap can be addressed to some extent. By prioritizing user-friendly design and accessibility, manufacturers can enhance the usability and effectiveness of generative AI tools, ultimately maximizing their potential impact on manufacturing processes and bridging the digital divide within the industry.

Third, generative AI not only offers socio-economic benefits at both micro and macro levels when governed and managed effectively but also holds the potential to optimize production processes, diminish waste and bolster resource efficiency, thus fostering environmental sustainability. Generative AI can pinpoint areas for process optimization, identify opportunities for energy conservation and streamline waste management practices.

Consequently, these capabilities can culminate in substantial enhancements to the environmental impact of manufacturing operations. However, it is crucial to acknowledge that generative AI also poses challenges and risks that can potentially undermine sustainability efforts if not properly managed by manufacturers and other stakeholders. The disruptive nature of generative AI, coupled with its potential to automate tasks traditionally performed by human workers, raises concerns about job displacement and income inequality, particularly in regions heavily reliant on manufacturing industries. Moreover, the proliferation of generative AI technologies may exacerbate existing disparities in access to technology and digital skills, further widening the digital divide and hindering socio-economic development in marginalized communities.

To address these sustainability challenges, manufacturers and policymakers must adopt a proactive approach to governance and regulation, ensuring that the deployment of generative AI technologies aligns with broader sustainability goals and ethical principles. This requires robust frameworks for data privacy, security and algorithmic transparency, as well as measures to mitigate the social and economic impacts of automation on workers and communities. Additionally, investments in education and workforce development are essential to equip individuals with the skills and knowledge needed to thrive in an increasingly automated and digitalized manufacturing landscape. Furthermore, collaboration and stakeholder engagement are key to fostering responsible innovation and ensuring that the benefits of generative AI are equitably distributed across society. Manufacturers, researchers, government agencies and civil society organizations must work together to identify and address potential risks and unintended consequences of generative AI deployment while maximizing its potential to drive sustainable economic growth, innovation and social progress. By adopting a holistic and inclusive approach to governance and management, generative AI has the potential to become a powerful tool for advancing sustainability goals and creating a more equitable and resilient manufacturing sector.

6.2 Limitations and future research directions

While this study sheds insights into the integration of generative AI within the manufacturing sector, certain limitations need acknowledgment. Firstly, the research primarily focuses on European companies, which might restrict the generalizability of the findings to a broader global context. Cultural, regulatory and industry-specific variations outside of Europe could influence the dynamics of generative AI implementation.

Secondly, it is crucial to note the optimistic orientation of this study, emphasizing successful generative AI integration cases. Implementing generative AI can pose significant challenges, and outcomes may not always align with sustainability parameters. Future research should explore cases where generative AI implementation faced hurdles or yielded less favorable results to ensure a comprehensive understanding. Analyzing successful and unsuccessful cases would provide a more nuanced view of the complexities and potential drawbacks of generative AI integration in manufacturing settings. In light of these limitations, future research directions should also develop robust frameworks for assessing the risks and challenges of generative AI implementation. Investigating the factors contributing to both success and failure will contribute to a more balanced and realistic comprehension of the implications of generative AI on sustainability within Industry 5.0 frameworks.

On top of these, future research is advised to address various concerns about generative AI's role in manufacturing. An imperative area of investigation is the ethical considerations and societal impacts of generative AI implementation in manufacturing, examining privacy issues, potential job displacement and broader societal consequences. Future research endeavors should also include a comprehensive assessment of the regulatory and policy implications governing generative AI integration in manufacturing, proposing recommendations for effective policy development. Finally, addressing the challenges and opportunities for small and medium-sized enterprises in adopting generative AI is essential, considering factors like resource constraints, scalability issues and adaptability to different operational scales.

In charting future research directions and considering the methodological constraints of the present study, several avenues could deepen our understanding of generative AI's impact on manufacturing. Firstly, predictive analytics could be integrated to forecast the scalability and potential ramifications of generative AI across various manufacturing settings. Secondly, the incorporation of advanced data visualization tools could facilitate clearer communication of intricate insights to stakeholders with varying technical backgrounds, enhancing comprehension and decision-making in this context. Thirdly, adopting a longitudinal study approach would enable tracking the evolution and long-term efficacy of generative AI, providing insights into adaptation and sustainability. Additionally, a comparative case analysis contrasting adopters and non-adopters of generative AI could yield nuanced insights into its comparative advantages and challenges. Expanding the geographic scope beyond Europe would enrich the understanding of cultural and regulatory influences on generative AI adoption and performance. In means future research endeavors should strive for a more diverse and inclusive sample, encompassing a global spectrum of manufacturing contexts, to enhance the external validity of the findings. Lastly, integrating secondary data sources, such as industry reports and academic literature, could enrich the contextual understanding of generative AI's broader implications in the manufacturing landscape.

Note

1. In the context of this study, the term "functionalities" is synonymous with "functions," referring to the mechanisms and operational ways through which generative AI contributes to sustainability objectives of Industry 5.0.

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