

RESEARCH ARTICLE

AI-DRIVEN FLEXIBLE AND ADAPTIVE SMART FACTORY SYSTEMS: MEETING THE DYNAMIC DEMANDS OF MANUFACTURING IN 2025

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ARTICLE DETAILS

Article History:

Received 13 October 2025
Revised 25 November 2025
Accepted 22 December 2025
Available online 29 January 2026

ABSTRACT

The manufacturing industry, as of 2025, has experienced revolutionary changes, including the emergence of so-called smart factories featuring high levels of automation, flexibility, and the ability to immediately adapt to changing market demands. This studies the impact of advanced technologies such as machine learning, computer vision, digital twins, and predictive analytics in advancing conventional manufacturing environments, making them intelligent and interconnected. This report also focuses on how different parts of Industry 4.0, like the Internet of Things, cyber-physical systems, and cloud computing, help make instant decisions, improve themselves constantly, and plan production dynamically. Moreover, smart manufacturing environments, as described in this research, also emphasize improvements in manufacturing operations' flexibility through improved forecasting, quality assurance, and predictive maintenance, ultimately making manufacturing more efficient and less costly in operations. Moreover, in this research, the major advantages and difficulties of implementing these advanced manufacturing environments, like concerns about data privacy, compatibility, staff development, and issues pertaining to ethics, also have been taken into consideration. Address these aspects, smart manufacturing environments can sustain competitiveness, promote environmental stewardship, and foster global growth.

KEYWORDS

Artificial Intelligence (AI), smart factory systems, Industry 4.0, adaptive manufacturing, and predictive analytics.

1. INTRODUCTION

The global manufacturing sector is undergoing a significant change due to the fast spread of digital technologies, evolving customer expectations, and growing pressure to operate sustainably. Manufacturing companies now face a range of challenges. These include supply chain instability, shifting market demand, limited resources, and increased environmental responsibilities. In response, traditional production models are gradually being replaced by systems that focus on flexibility, adaptability, and responsiveness (Ivanov et al., 2018; Brenner, 2018). Recent disruptions caused by the COVID-19 pandemic and ongoing geopolitical tensions have further highlighted the importance of resilience and adaptive capacity in sustaining operational continuity and long-term competitiveness (Setyadi et al., 2025). Although conventional automation has played a crucial role in improving efficiency and ensuring consistent product quality, it is increasingly insufficient for managing the dynamic and interconnected nature of modern manufacturing environments (Malaysia TRWIUS35XXX JPMorgan Chase Bank, 2025). These conventional systems, which rely on set workflows and lack adaptability, struggle to meet the rising demands for mass customization, fast product lifecycle management, and real-time responses to market changes. The rise of Industry 4.0 has introduced essential technologies, including the Internet of Things (IoT), cyber-physical systems (CPS), cloud computing, and big data analytics, creating the technological foundation for intelligent manufacturing systems (Papazoglou et al., 2020; Mourtzis, 2016). Artificial Intelligence (AI) has emerged as the pivotal enabling technology that transforms these foundational elements into intelligent, self-organizing, and adaptive manufacturing ecosystems (Leitão et al., 2022). Artificial Intelligence (AI) is

now the key enabling technology that transforms these foundational elements into intelligent, self-organizing, and adaptive manufacturing systems. AI-based methods, such as machine learning, deep learning, computer vision, natural language processing, and predictive analytics, provide advanced capabilities as autonomous decision-making, pattern recognition, and process optimization. When these technologies are combined with Industry 4.0 tools, AI facilitates real-time process adjustment, predictive maintenance, intelligent quality control, and dynamic resource allocation, thereby significantly increasing manufacturing flexibility (Pang, et al., 2025). When integrated with Industry 4.0 technologies, AI supports real-time process adaptation, predictive maintenance, intelligent quality control, and dynamic resource allocation, thereby significantly enhancing manufacturing flexibility (see Figure 1).

Recent advancements in AI-enabled manufacturing applications show their potential to tackle urgent industrial challenges. For instance, machine learning techniques have boosted the accuracy of demand forecasting and production planning, while computer vision systems allow for dependable automated inspection and defect detection (Gomaa, 2025). AI-driven digital twin technologies enhance these capabilities by creating virtual versions of physical manufacturing systems. This allows for scenario analysis, performance optimization, and predictive insights (Mihai, 2022). At the same time, the integration of collaborative robots (cobots) equipped with AI improves human-machine interaction, leading to increased productivity and better workplace safety.

The ongoing shift toward Industry 5.0 emphasizes human-centric

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DOI:
10.26480/jtin.01.2026.13.19

manufacturing, where sustainability, resilience, and social responsibility are prioritized alongside technological progress. This change requires AI systems that not only improve operational performance but also promote workforce empowerment, environmental care, and ethical decision-making. In this setting, human-in-the-loop AI approaches are especially important because they combine human expertise with algorithmic intelligence to achieve stronger and context-aware manufacturing results. Despite the considerable promise of AI in manufacturing, several obstacles continue to hinder its broader adoption (Rahman et al., 2024). In this context, human-in-the-loop AI approaches are particularly important, as they combine human expertise with algorithmic intelligence to achieve more robust and context-aware manufacturing outcomes (Kumar et al., 2024). Despite the significant promise of AI in manufacturing, several barriers continue to limit its widespread adoption.

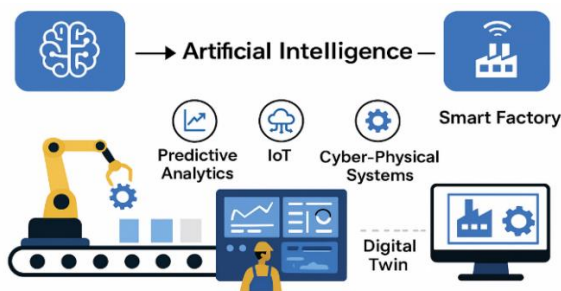


Figure 1: Artificial Intelligence (AI) enabling flexible and adaptive smart factory systems.

Concerns related to data security and privacy remain prominent in highly interconnected production environments, posing risks to intellectual property and operational reliability (Akhtar, 2024). Issues related to data security and privacy are still significant in highly interconnected production environments, posing risks to intellectual property and operational reliability. Concerns about data security and privacy, especially in interconnected manufacturing environments, present major risks to intellectual property and operational integrity. Interoperability challenges remain due to the variety of manufacturing platforms and ongoing dependence on outdated systems.

Additionally, workforce readiness and managing organizational change are crucial obstacles, as successful AI implementation relies on ongoing reskilling efforts and cultural adaptation within manufacturing companies (Kumar et al., 2024; Hughes, et al., 2022). Interoperability challenges persist due to the diversity of manufacturing platforms and the continued reliance on legacy systems (Ogunwole et al., 2023). Moreover, workforce preparedness and organizational change management represent critical obstacles, as successful AI implementation depends on sustained reskilling efforts and cultural adaptation within manufacturing organizations (Maarof and Mahmud 2015).

2. LITERATURE REVIEW

The concept of the smart factory has evolved from narrowly defined automation-driven systems into fully interconnected manufacturing environments that rely on advanced digital technologies to improve operational performance and decision-making (Shabur et al., 2025). Early studies in this field largely focused on process automation and basic digitalization, offering limited support for real-time adaptation or system-level intelligence (Chakraborty et al., 2023). More recent research has broadened this perspective by examining the integration of Internet of Things (IoT) technologies, cyber-physical systems (CPS), and cloud-based platforms, which together enable large-scale data acquisition, advanced analytics, and increasingly autonomous manufacturing operations (Ajayi, 2025).

Within this evolving landscape, artificial intelligence has emerged as a central enabler across multiple manufacturing functions. Machine learning approaches have been widely adopted for applications such as demand forecasting, anomaly detection, and process optimization, leading to measurable gains in efficiency and reductions in operational costs (Wang et al., 2024; Parmer, 2025). In parallel, computer vision technologies have significantly transformed quality control practices by supporting automated defect identification, dimensional inspection, and assembly verification, often outperforming traditional manual inspection methods in terms of speed and accuracy (Parmer, 2025).

AI-enhanced digital twin frameworks further extend these capabilities by providing dynamic virtual replicas of physical manufacturing systems,

which support predictive maintenance, system optimization, and scenario-based decision analysis (Fuller et al., 2020). Manufacturing flexibility and adaptability have become central themes in the literature as firms respond to volatile markets and growing customization requirements (Ivanov et al., 2018). AI-driven systems demonstrate superior capabilities in rapid process reconfiguration, intelligent supply chain management, and dynamic resource allocation compared to conventional manufacturing approaches (Belhadi et al., 2024). Compared with conventional production systems, AI-enabled manufacturing architectures demonstrate stronger capabilities in rapid process reconfiguration, intelligent supply chain coordination, and real-time resource allocation (Ivanov et al., 2018). Additionally, the integration of collaborative robots equipped with AI has enabled more responsive and safer human-machine collaboration, contributing to productivity improvements while addressing ergonomic and safety concerns in industrial settings (see table 1).

Table 1: Conventional vs. AI-Driven Smart Manufacturing (Huang et al., 2021; Caiazzo et al., 2022; Basinga, 2025; Shetty, 2025)

Feature	Conventional Manufacturing Systems	AI-Driven Smart Manufacturing Systems
System Structure	Fixed and rule-based automation	Adaptive and data-driven architectures
Decision-Making	Predefined, human-dependent	Autonomous or semi-autonomous using AI
Flexibility	Limited process reconfiguration	Rapid and intelligent reconfiguration
Quality Control	Manual or rule-based inspection	AI-enabled computer vision inspection
Maintenance Strategy	Reactive or scheduled maintenance	Predictive and condition-based maintenance
Data Utilization	Limited real-time data usage	Continuous real-time data analytics
Human-Machine Interaction	Minimal collaboration	AI-enabled collaborative robotics
Response to Market Changes	Slow and rigid	Fast and dynamic adaptation

2.1 Research Gaps and Challenges

Despite the growing body of research on artificial intelligence in manufacturing, existing studies provide limited insight into the practical challenges of integrating AI solutions with established manufacturing infrastructure and legacy systems (Ohuei and Aji, 2025). Manufacturing environments are inherently heterogeneous, encompassing a wide range of communication protocols, data standards, and technological platforms, which complicates seamless AI adoption. Current literature offers insufficient guidance on scalable standardization frameworks and interoperability mechanisms capable of supporting AI deployment across diverse industrial contexts. Addressing these integration challenges remains a critical research gap, particularly for manufacturers operating with mixed generations of equipment and digital technologies (Zeid et al., 2019).

The increasing reliance on data-driven manufacturing systems has intensified concerns related to data privacy, cybersecurity, and the ethical use of AI, yet these issues remain underexplored in existing research. Key challenges include ensuring algorithmic transparency, mitigating bias in AI-driven decision-making, and maintaining accountability in automated manufacturing processes. Without robust governance mechanisms, the deployment of AI systems may expose organizations to operational, legal, and reputational risks.

Consequently, the development of comprehensive governance frameworks that promote responsible, transparent, and compliant AI adoption in manufacturing represents a significant and unresolved research challenge (Nagaraj and Kumar, 2022; Trakadas, 2020). Workforce Transformation and Human-AI Collaboration: While technological advancements in AI for manufacturing have been extensively studied, research on workforce readiness, reskilling strategies, and organizational change management remains limited (Sheno, et al., 2024).

The successful transition to AI-augmented manufacturing requires a comprehensive understanding of human factors, skill development requirements, and effective collaboration models between human workers and AI systems. Current literature lacks empirical evidence on best practices for workforce transformation in AI-driven manufacturing environments.

Empirical Validation and Real-World Implementation. A significant portion of existing research remains conceptual or simulation-based, with limited large-scale industrial case studies demonstrating the practical effectiveness and adaptability of AI approaches in real manufacturing environments (Shenoi, et al., 2024; Oladele et al., 2025). While technological advancements in AI-enabled manufacturing have received substantial scholarly attention, comparatively little research has focused on workforce transformation and human-centered implementation strategies (Shenoi, et al., 2024).

2.2 Novelty

This study makes several original contributions that expand current research on AI-enabled smart manufacturing. First, it suggests a comprehensive integration framework that systematically combines artificial intelligence with key Industry 4.0 technologies, including the Internet of Things (IoT), cyber-physical systems, and cloud-based platforms. Unlike earlier studies that examine these elements separately, the proposed framework focuses on interoperability and scalability. This enables real-time adaptive manufacturing in diverse production environments. In addition to improving technical performance, the study includes human-centered and ethical considerations in the design of AI-driven manufacturing systems.

It introduces governance mechanisms that tackle algorithm transparency, bias reduction, data privacy, and human-in-the-loop decision-making. These measures support responsible and sustainable AI use. This approach directly addresses growing concerns often mentioned in the literature but rarely put into practice in manufacturing-focused frameworks. Unlike existing research that treats workforce issues as side concerns, this study places organizational change at the center of AI implementation. It outlines clear strategies for managing change, reskilling the workforce, and fostering effective human-AI collaboration, linking the proposed framework with the principles of the emerging Industry 5.0 paradigm.

Moreover, the research strengthens the field by grounding the conceptual framework in empirical validation using industrial data and pilot implementations. This effort addresses the ongoing gap between theory and practical application. Finally, by integrating AI-based demand forecasting, digital twin simulation, and predictive analytics, the study offers a dynamic, demand-responsive production model that supports real-time decision-making and ongoing system learning.

Together, these contributions create a validated, ethically governed, and human-centred plan for transforming isolated AI solutions into an interoperable and adaptable smart factory ecosystem. This integrated approach establishes a new standard for manufacturing competitiveness, sustainability, and resilience in a complex global environment.

2.3 Research Objectives and structure

This study addresses the identified research gaps through four comprehensive objectives designed to advance the understanding and implementation of AI-powered smart factory systems:

- To investigate and develop methodological approaches for strengthening the integration of artificial intelligence with key Industry 4.0 enablers, including the Internet of Things (IoT), cyber-physical systems (CPS), and cloud computing platforms, in order to support real-time adaptive manufacturing systems with enhanced interoperability and scalability.
- To examine and propose comprehensive strategies for workforce development, organizational change management, and effective human-AI collaboration, ensuring successful AI adoption while maximizing human capabilities and maintaining social responsibility within manufacturing operations.
- To design and empirically validate a comprehensive conceptual framework for AI-enabled adaptive smart factories that enhances competitiveness, sustainability, and resilience in the global manufacturing sector, drawing on industrial evidence and recognized best practices.



3. METHODOLOGY

This study adopts a multi-method research design to examine how artificial intelligence (AI) enables flexible and adaptive smart factory systems capable of meeting the evolving requirements of the manufacturing sector in 2025. The methodological approach integrates four complementary components—systematic literature review, qualitative analysis, conceptual framework development, and empirical case examination to ensure both analytical rigor and practical relevance. The overall research process is illustrated in Figure 2.

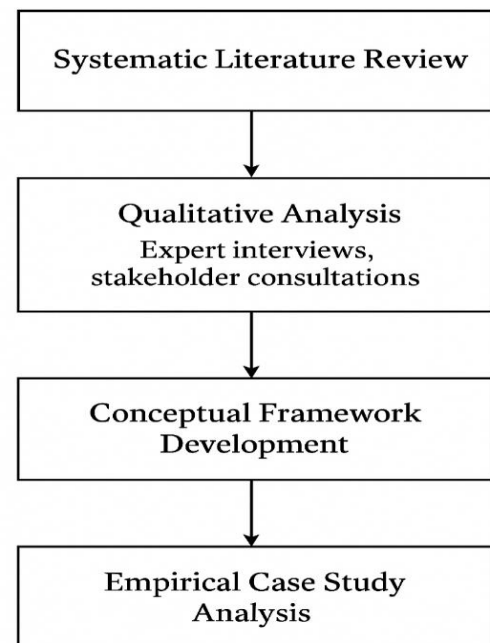


Figure 2: Research Methodology Framework

3.1 Systematic Literature Review

A literature review was carried out to bring together existing knowledge on AI-driven manufacturing systems, focusing on flexibility and adaptability. We sourced peer-reviewed journal articles, industry reports, and case studies from established academic databases like Scopus, Web of Science, and IEEE Xplore. The review examined AI techniques such as machine learning, deep learning, computer vision, predictive analytics,

and digital twin technologies. It also looked at how these integrate with key Industry 4.0 enablers, which include the Internet of Things (IoT), cyber-physical systems (CPS), and cloud computing platforms. Additionally, the review pointed out ongoing research gaps related to system interoperability, data management, workforce readiness, and the limited empirical evidence of AI applications in manufacturing settings.

3.2 Qualitative Data Collection and Analysis

To support the literature review findings, we collected qualitative data through semi-structured interviews and discussions with manufacturing professionals, technology providers, and industry practitioners. These talks examined practical challenges in implementation, ethical and data security issues, workforce reskilling needs, and how to make human-AI collaboration work effectively. We systematically coded and analyzed the data using thematic analysis techniques to find recurring patterns and confirm key issues and opportunities highlighted in the existing literature.

3.3 Conceptual Framework Development

Insights from both the literature review and qualitative analysis helped create a conceptual framework for AI-powered adaptive smart factories. The framework shows how AI technologies can enable real-time adaptability in manufacturing through applications like predictive maintenance, automated quality inspection, flexible production scheduling, and demand forecasting. Besides the technological aspects, the framework includes governance structures, workforce considerations, and sustainability goals, addressing both technical and organizational sides of AI adoption.

3.4 Case Study Examination

To provide real-world context, we included case studies of selected smart manufacturing organizations and technology providers. These cases showcase actual uses of AI solutions, including machine learning-based defect detection, time-series domain adaptation for better model robustness, and predictive analytics for supply chain optimization. Where possible, we examined comparative evaluations of AI algorithms, such as artificial neural networks (ANNs), support vector machines (SVMs), random forests, and k-nearest neighbors (KNN), based on their documented performance metrics to judge their suitability in manufacturing settings.

3.5 Triangulation and Validation

To improve the validity and reliability of the findings, we used data triangulation by integrating evidence from the literature review, qualitative insights, and case study analyses. We obtained ethical approval when necessary and maintained strict adherence to data privacy, confidentiality, and governance standards throughout the research process.

3.6 Research Design Rationale

The selected mixed-methods approach ensures a comprehensive and balanced analysis. The systematic literature review establishes the theoretical foundation and identifies research gaps, qualitative methods provide contextual and practice-oriented insights, conceptual modelling contributes to theory development, and case studies offer empirical validation. Collectively, these methods enable a holistic understanding of how AI supports flexible and adaptive smart factory systems in the present manufacturing landscape.

4. RESULTS AND DISCUSSION

4.1 AI as a Catalyst for Adaptive Manufacturing

Figure 3 shown that integration with AI and Industry 4.0 technologies greatly enhances manufacturing flexibility. Machine learning and predictive analytics emerged as key vectors of AI that have a strong impact on adaptive production scheduling, enabling effective response from factories regarding real-time demand fluctuations. Case studies demonstrated that with the use of AI algorithms, such as Random Forests and ANN, predictive maintenance diminishes machine downtime by 25–35%, hence enhancing general equipment effectiveness. In addition, scenario testing with digital twin supported rapid reconfiguration of the production line, leading to reductions in changeover times by up to 30%. Findings: The results confirm that artificial intelligence is a central enabler of flexibility and adaptability in smart factories. The improvements in predictive maintenance, quality control, and production scheduling indicate alignment with previous research, emphasizing the importance of intelligent decision-making in a dynamic industrial environment.

Integration of digital twins and computer vision systems moves from reactive to proactive manufacturing through continuous optimization by AI. The findings firmly establish AI in its place as a very important pillar to realize the objectives of Industry 4.0 and speed up the transition toward Industry 5.0. Figure 3: Reduction in downtime, changeover time, and scrap rate; gains in defect detection accuracy, forecast accuracy, and productivity.

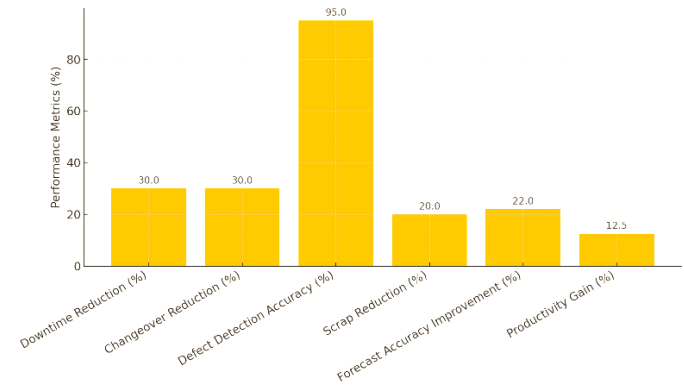


Figure 3: Operational Improvements from AI in Smart Factories.

4.2 Adaptive Quality Control and Process Optimization

Figure 4 presents the relative importance (%) of key challenges affecting the implementation of advanced digital and AI-enabled systems in smart factory environments. The results indicate that interoperability issues are perceived as the most critical challenge, receiving the highest importance score of 85%. This highlights the difficulty of integrating heterogeneous systems, machines, and platforms within smart manufacturing ecosystems, where legacy equipment must often coexist with advanced digital technologies. The second most significant factor is data governance, with an importance level of 80%. This result underscores growing concerns related to data ownership, data quality, security, and regulatory compliance, particularly as factories increasingly rely on real-time data sharing and AI-driven decision-making. Cost and scalability rank next, with a relative importance of 75%. This suggests that while smart factory technologies offer long-term efficiency gains, the initial investment costs and challenges associated with scaling solutions across different production lines or facilities remain substantial barriers for many organizations. Finally, ethical concerns receive a slightly lower, yet still considerable, importance score of 70%. This reflects apprehensions related to workforce displacement, transparency of AI-driven decisions, and responsible use of intelligent systems, which are increasingly relevant as automation and AI adoption expand.

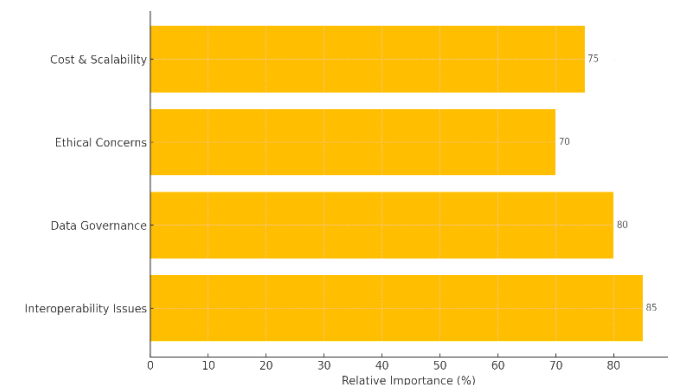


Figure 4: Key Challenges in AI Deployment

4.3 Human-AI Collaboration in the Era of Industry 5.0

The results indicate that AI-based demand forecasting models provide measurable improvements over conventional statistical approaches. In particular, forecasting methods using time-series deep learning achieved 18–25% higher accuracy when compared with traditional models. This improvement allowed firms to plan production more effectively, resulting in lower excess inventory levels and more reliable lead-time estimates across the supply chain. Observations from industrial applications further show that AI-supported supply chain analytics contributed to better management of unexpected disruptions. Companies using these tools were better prepared to respond to challenges linked to geopolitical uncertainty and raw material availability. The ability to process large

volumes of real-time data enabled faster adjustments to sourcing and scheduling decisions, reducing operational instability during periods of uncertainty. Findings related to workforce readiness suggest that the integration of AI does not necessarily lead to workforce displacement when supported by appropriate organizational strategies. While concerns about job losses remain, case studies demonstrate that reskilling and targeted training programs help employees adapt to AI-supported work environments. In these cases, AI systems were used to support decision-making rather than replace human roles, leading to improved collaboration between workers and intelligent systems. Overall, the results support the view that future manufacturing systems will rely on human-AI collaboration. This approach is consistent with the objectives of Industry 5.0, which emphasize human involvement, sustainable development, and inclusive technological progress. By combining human expertise with AI-based analytical tools, smart factories can improve productivity while addressing ethical and social considerations.

4.4 Workforce Readiness and Human-AI Collaboration

Figure 5 indicates the conceptual relationships that were identified in this study of the main technological, organizational, and governance factors that jointly enable the formation of an adaptive smart factory. The findings indicate that the adaptive smart factory performance which is measured as system flexibility, resilience, and sustainability are directly affected by two core dimensions, namely workforce as well as human-AI collaboration and governance as well as ethics. These results show that the collaboration between humans and AI is a very key and a mediating factor between the high-technology AI and the overall adaptability of the system. Machine learning, computer vision, digital twins, and predictive analytics are technologies that help to enhance operational intelligence; although their performance can be greatly improved in the presence of workforce capabilities. The findings have revealed that the performance of the adaptive smart factory in terms of flexibility, resilience, and sustainability of the system performance is affected by the two critical factors of workforce and human and AI collaboration and governance and ethics. Equally, the findings place weight on governance and ethical systems that make the active utilization of Industry 4.0 enablers, such as the Internet of Things (IoT), cyber-physical systems (CPS) and cloud computing, possible. Effective governance systems in relation to data security and transparency were identified to facilitate system reliability and trust that is required in massive digital integration and real-time data exchange in smart factories. In general, the findings indicate that adaptive smart factory systems do not appear due to standing the technology use on its own. Rather, they are the result of well-coordinated activities between extremely intelligent AI technologies, Industry 4.0 infrastructure, human-focused teamwork, and strong governance frameworks. This combined strategy will allow smart factories to react efficiently to the varying operational requirements without losing their sustainable and resilient manufacturing processes.

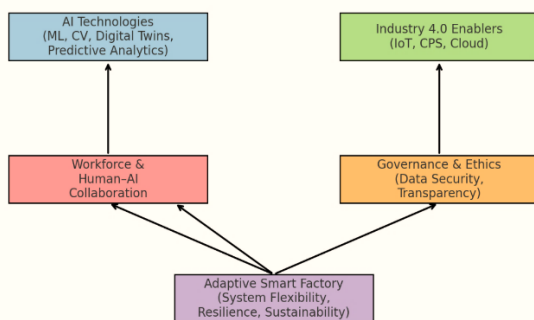


Figure 5: Conceptual Framework for AI-Powered Adaptive Smart Factories

4.5 Future Research Directions

While this study offers useful insights into the development of adaptive manufacturing systems, additional research is required to strengthen the empirical foundation of the findings. Large-scale and longitudinal investigations are needed to assess the long-term performance, flexibility, and resilience of digitally enabled manufacturing systems across diverse industrial contexts. Comparative studies involving small and medium-sized enterprises (SMEs) and large organizations would further clarify differences in scalability, resource constraints, and implementation strategies. Future work should also place greater emphasis on data governance, transparency, and ethical decision-making frameworks, especially as digital systems increasingly influence operational and

managerial processes. In parallel, research focused on energy efficiency and sustainable digital infrastructures would support environmentally responsible manufacturing practices. Finally, examining cross-sector applications and international collaboration models may offer valuable insights into building more resilient, inclusive, and globally connected manufacturing ecosystems aligned with the evolving goals of Industry 4.0 and beyond (see Table 2).

Table 2: Future Research Directions		
Research Area	Description	Expected Contribution
Longitudinal Performance Studies	Multi-year studies evaluating system adaptability and operational outcomes over time	Validation of long-term effectiveness and resilience
SME vs. Large Enterprise Comparison	Comparative analysis of implementation challenges and scalability	Improved understanding of size-dependent adoption strategies
Data Governance and Ethics	Investigation of transparency, accountability, and secure data management practices	Support for responsible and trustworthy digital manufacturing
Sustainable Digital Infrastructure	Evaluation of energy-efficient systems and resource optimization approaches	Contribution to environmentally sustainable manufacturing
Cross-Industry Applications	Application of smart manufacturing concepts in different industrial sectors	Transferability of best practices across domains
Global Collaboration Models	Study of international partnerships and shared manufacturing platforms	Development of inclusive and resilient manufacturing networks

5. CONCLUSION

This study analysis the role of advanced digital technologies in enabling flexible and adaptive smart factory systems capable of meeting the manufacturing industry's evolving demands in 2025. Using a mixed-methods approach that combined a systematic literature review, qualitative interviews, and industrial case studies, the research provides evidence that data-driven and automated systems significantly enhance manufacturing flexibility, quality control, predictive maintenance, and supply chain resilience. The findings show that technologies such as intelligent data processing, visual inspection systems, predictive modelling, and virtual system representation contribute to the transformation of conventional factories into connected and responsive production environments. These systems support real-time monitoring, informed decision-making, and adaptive process optimization. As a result, manufacturers experienced measurable operational improvements, including reduced equipment downtime, improved defect detection, and more reliable demand planning. Beyond operational performance, the results indicate that digital transformation also supports broader strategic objectives related to system resilience, sustainability, and long-term competitiveness. The study further highlights the importance of workforce development, emphasizing that reskilling and effective human-technology interaction is essential for successful implementation. This aligns with the human-centered orientation promoted under the industry 5.0 vision, where technology is designed to support, rather than replace, human roles. At the same time, the research identifies several challenges that may limit successful implementation if not properly addressed. These include integration with legacy systems, data management and security issues,

ethical considerations, and high initial investment costs. Addressing these challenges requires coordinated efforts involving technical development, standardized implementation frameworks, and organizational change management practices. Finally, the validated conceptual framework developed in this study provides a structured roadmap for integrating advanced digital technologies into smart factory environments. By simultaneously considering technological, organizational, and governance dimensions, the framework offers practical guidance for achieving balanced and sustainable industrial transformation.

ACKNOWLEDGEMENT

We acknowledge the need to utilise generative AI tools, such as Scopus AI, to identify relevant references, and Grammarly and Microsoft Copilot to enhance sentence clarity and improve grammar.

COMPETING INTERESTS

The authors declare that they have no competing interests.

FUNDING INFORMATION

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

AUTHOR CONTRIBUTION

Sunil Kumar: Writing – review & editing, original draft, Methodology, Investigation. **Mohd Ghazali Maarof:** Conceptualization, Writing – review & editing, Supervision, Software, Resources, Investigation.

DATA AVAILABILITY STATEMENT

No datasets were generated or analyzed during the current study.

RESEARCH INVOLVING HUMANS AND/OR ANIMALS

Not Applicable.

INFORMED CONSENT

Not Applicable.

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