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Development of an Artificial Intelligence-Based Green Smart Manufacturing Framework for Sustainable Industrial Transformation

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ABSTRACT

Manufacturing industries are facing increasing pressure to enhance productivity and operational efficiency while simultaneously reducing environmental impacts and supporting sustainable development goals. In response to these challenges, Artificial Intelligence (AI) has emerged as a transformative technology capable of enabling intelligent, data-driven, and environmentally responsible manufacturing systems. This study aims to develop a Green Smart Manufacturing Framework based on Artificial Intelligence that integrates sustainability principles with smart manufacturing technologies to support sustainable industrial transformation. The framework was developed using the Design Science Research (DSR) methodology, which involved problem identification, literature analysis, framework design, development, and expert-based validation. The findings identified three core dimensions of Green Smart Manufacturing, namely Green Manufacturing, Smart Manufacturing, and AI Capability, which were integrated into a unified framework architecture. The study contributes to the existing body of knowledge by extending Green Manufacturing theory through the integration of Artificial Intelligence and sustainability concepts within a comprehensive smart manufacturing architecture.

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1. INTRODUCTION

The manufacturing sector plays a pivotal role in global economic development by contributing significantly to industrial productivity, employment generation, and technological innovation. However, rapid industrialization has also intensified environmental concerns, including excessive energy consumption, greenhouse gas emissions, material waste generation, and inefficient utilization of natural resources. According to international sustainability reports, manufacturing activities account for a substantial proportion of global carbon emissions and industrial energy demand, making the sector a critical target for environmental improvement initiatives. As governments and industries worldwide strive to achieve sustainable development goals and carbon neutrality targets, there is an increasing need to transform conventional manufacturing systems into environmentally responsible and resource-efficient operations(Almeida et al., 2013).

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The emergence of Industry 4.0 has accelerated the digital transformation of manufacturing environments through the integration of advanced technologies such as the Internet of Things (IoT), cyber-physical systems, cloud computing, big data analytics, and automation(Xu et al., 2018). More recently, Industry 5.0 has expanded this paradigm by emphasizing human-centricity, resilience, and sustainability in industrial operations. These developments have encouraged manufacturers to seek innovative approaches that not only improve operational efficiency but also minimize environmental impacts. Consequently, the concept of Green Manufacturing has gained considerable attention as a strategic approach to reducing waste, optimizing resource utilization, lowering carbon emissions, and promoting environmentally sustainable production practices throughout the product lifecycle.

Alongside the advancement of smart manufacturing technologies, Artificial Intelligence (AI) has emerged as a transformative tool capable of enhancing manufacturing performance through intelligent decision-making and process optimization. AI technologies, including Machine Learning, Deep Learning, Reinforcement Learning, Predictive Analytics, Computer Vision, and Digital Twins, enable manufacturers to analyze large volumes of operational data, predict equipment failures, optimize production schedules, monitor energy consumption, and improve product quality in real time. These capabilities provide significant opportunities for achieving both economic and environmental objectives simultaneously. For example, predictive maintenance systems can reduce machine downtime and unnecessary energy consumption, while AI-based production planning can minimize material waste and improve resource efficiency.

Research on sustainable manufacturing, Industry 4.0, and Artificial Intelligence (AI) has expanded significantly during the last decade as industries seek to improve productivity while reducing environmental impacts. One of the earliest streams of research focused on the role of Industry 4.0 technologies in achieving sustainable manufacturing objectives(Sharma et al., 2021). Jamwal, Agrawal, Sharma, and Giallanza (2021) conducted a comprehensive systematic review examining how Industry 4.0 technologies including Artificial Intelligence, the Internet of Things (IoT), Cyber-Physical Systems, Big Data Analytics, and Digital Twins contribute to manufacturing sustainability. Their study demonstrated that digital technologies can improve resource efficiency, energy management, and production flexibility. Nevertheless, the authors emphasized that existing implementations often focus on specific technologies rather than providing an integrated sustainability-oriented framework.

The concept of intelligent manufacturing supported by Digital Twin technology has also received considerable attention. Tao et al. (2021) reviewed the application of digital twins in sustainable intelligent manufacturing and highlighted their potential for real-time monitoring, predictive analysis, and process optimization. The study concluded that digital twins can significantly improve manufacturing sustainability by enabling better control of resources, reducing operational waste, and supporting predictive maintenance. However, the review noted that the integration of AI-driven sustainability indicators within digital twin environments remains underdeveloped.

In the area of predictive maintenance, Pech, Vrchota, and Bednář (2021) explored intelligent sensors and predictive maintenance systems in smart factories. Their findings demonstrated that AI-based predictive maintenance can reduce machine downtime, improve equipment reliability, and minimize unnecessary energy consumption. While the study highlighted the economic benefits of AI-enabled maintenance systems, its primary focus remained operational efficiency rather than broader environmental sustainability objectives.

Research on green manufacturing frameworks has also advanced considerably. In a systematic literature review, Dallasega and colleagues (2023) analyzed 189 studies related to green manufacturing and proposed a framework outlining the primary influences, elements, and outcomes of green manufacturing practices. Their review revealed that green manufacturing contributes not only to environmental performance but also to operational and organizational improvements. Nevertheless, the proposed framework did not explicitly incorporate Artificial Intelligence as a core mechanism for decision-making and optimization.

The relationship between Industry 4.0 technologies and green supply chains has attracted increasing scholarly attention. Morella, Lambán, Royo, Sánchez, and Latapia (2023) systematically reviewed the application of Industry 4.0 technologies in green supply chain management. Their findings showed that technologies such as IoT, AI, and Big Data Analytics can enhance supply chain transparency, resource management, and environmental performance. However, the study primarily focused on supply chain processes and did not develop a unified manufacturing framework integrating sustainability metrics with intelligent operational control.

Similarly, Labaran and Masood (2023) examined Industry 4.0-driven green supply chain management in the renewable energy sector. Their review highlighted the importance of digital technologies in supporting sustainability objectives and reducing environmental impacts across supply networks. The authors emphasized the need for future research on integrated frameworks capable of connecting sustainability goals with real-time intelligent decision-making systems.

Despite the growing body of literature on smart manufacturing, green manufacturing, and artificial intelligence applications, existing studies often address these domains separately. Research on AI-driven predictive maintenance primarily focuses on enhancing equipment reliability and operational efficiency, with limited consideration of broader sustainability outcomes. Similarly, studies on green manufacturing emphasize environmental performance indicators such as waste reduction and energy efficiency but frequently lack advanced AI-enabled decision support mechanisms. Smart factory frameworks developed within the Industry 4.0 context often prioritize connectivity, automation, and data exchange while paying insufficient attention to environmental sustainability objectives(Oláh et al., 2020). Furthermore, existing Industry 4.0 and Industry 5.0 frameworks generally do not provide comprehensive integration of intelligent decision-making capabilities, green performance metrics, and smart manufacturing technologies within a unified framework.

This fragmentation in the literature reveals a significant research gap. While numerous studies have investigated the individual contributions of AI, smart manufacturing, and green manufacturing, limited research has proposed an integrated framework that systematically combines environmental sustainability indicators, artificial intelligence capabilities, and smart manufacturing infrastructures. As a result, industries lack comprehensive guidance for implementing intelligent manufacturing systems that simultaneously achieve operational excellence and sustainability goals.

To address this gap, this study proposes the development of a Green Smart Manufacturing Framework based on Artificial Intelligence(Li et al., 2021). The proposed framework integrates AI-driven decision support, environmental sustainability metrics, and smart manufacturing technologies into a cohesive structure that supports sustainable industrial transformation. By combining real-time monitoring, predictive analytics, intelligent optimization, and sustainability assessment mechanisms, the framework aims to facilitate data-driven decision-making while promoting environmentally responsible manufacturing practices.

The objectives of this research are fourfold. First, the study seeks to identify the key dimensions and components of green smart manufacturing based on existing literature and industrial requirements. Second, it aims to develop an integrated Artificial Intelligence-based Green Smart Manufacturing Framework that incorporates sustainability and smart manufacturing principles. Third, the study intends to validate the proposed framework through expert evaluation and/or case study analysis. Finally, it seeks to assess the potential contribution of the framework to improving sustainability performance in manufacturing environments.

Based on these objectives, the research addresses the following questions: (1) What key components should constitute an effective Green Smart Manufacturing Framework? (2) How can Artificial Intelligence technologies support green manufacturing practices and sustainability objectives? and (3) How effective is the proposed framework in enhancing environmental, operational, and economic performance within manufacturing systems? By answering these questions, the study contributes to the growing body of knowledge on sustainable digital transformation and provides practical guidance for organizations seeking to implement AI-enabled green smart manufacturing strategies.

2. RESEARCH METHOD

This study employs the Design Science Research (DSR) methodology to develop and validate a Green Smart Manufacturing Framework based on Artificial Intelligence (AI)(Mehdiyev & Fettke, 2020). Design Science Research is particularly suitable for framework development studies because it focuses on creating innovative artifacts that address practical and theoretical problems while contributing to scientific knowledge. The methodology provides a systematic process for identifying

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problems, designing solutions, developing frameworks, demonstrating applicability, evaluating effectiveness, and communicating research outcomes. The research process consists of six stages: problem identification, objective definition, framework design, framework development, demonstration, and evaluation.

The first stage involves problem identification, where the challenges associated with conventional manufacturing systems are analyzed. These challenges include excessive energy consumption, high carbon emissions, inefficient resource utilization, and significant material waste generation. Simultaneously, the study examines the limitations of existing smart manufacturing and green manufacturing frameworks, particularly the lack of integration between environmental sustainability objectives and AI-driven decision-making capabilities. Based on these identified challenges, the second stage defines the research objectives, which focus on developing a comprehensive framework that integrates sustainability principles, smart manufacturing technologies, and artificial intelligence techniques to support sustainable industrial transformation.

Data collection is conducted using multiple sources to ensure the comprehensiveness and reliability of the framework(Roller & Lavrakas, 2015). The primary source of information consists of a systematic review of scientific literature retrieved from major academic databases, including Scopus, Web of Science, IEEE Xplore, and ScienceDirect. These databases are selected because they contain high-quality peer-reviewed publications related to sustainable manufacturing, Industry 4.0, Industry 5.0, Artificial Intelligence, Digital Twins, and smart manufacturing systems. The literature review aims to identify the key concepts, technologies, dimensions, indicators, and best practices relevant to green smart manufacturing.

In addition to literature sources, expert knowledge is incorporated into the framework development process. Experts may include manufacturing managers, sustainability specialists, AI engineers, industrial consultants, and academic researchers with extensive experience in manufacturing and digital transformation. Their expertise provides practical insights into the applicability and relevance of the proposed framework within real industrial environments. Furthermore, industrial case studies from sectors such as automotive manufacturing, electronics production, food processing, and smart factory operations may be examined to understand real-world implementation challenges and opportunities.

The framework development process consists of four major steps(Parviainen et al., 2017). The first step involves identifying the dimensions of Green Manufacturing. Through literature analysis and expert consultation, several sustainability-related dimensions are identified, including energy efficiency, carbon emission reduction, waste minimization, resource optimization, circular economy practices, and environmental performance monitoring. These dimensions represent the environmental sustainability objectives that manufacturing organizations seek to achieve.

The second step focuses on identifying Smart Manufacturing dimensions(Xia et al., 2019). This stage examines the technological enablers associated with Industry 4.0 and Industry 5.0. Key components include the Internet of Things (IoT), Cyber-Physical Systems (CPS), cloud computing, Big Data Analytics, Digital Twin technology, intelligent automation, advanced robotics, and real-time monitoring systems. These technologies provide the digital infrastructure necessary for collecting, processing, and managing manufacturing data across production environments.

The third step involves identifying the Artificial Intelligence components required to support intelligent decision-making(Gupta et al., 2007). Several AI capabilities are incorporated into the framework, including predictive maintenance, demand forecasting, process optimization, quality prediction, anomaly detection, energy consumption forecasting, and autonomous decision support systems. These AI technologies enable manufacturers to transform operational data into actionable insights that improve productivity while supporting sustainability goals.

The fourth step integrates the identified Green Manufacturing dimensions, Smart Manufacturing technologies, and Artificial Intelligence capabilities into a unified conceptual framework(Ghita et al., 2021). The proposed framework is structured as an interconnected system consisting of data acquisition, smart monitoring, AI analytics, intelligent decision support, manufacturing operations, and sustainability performance assessment layers. The framework illustrates how real-time manufacturing data collected through IoT devices and cyber-physical systems can be processed using AI algorithms to support sustainable operational decisions.

To ensure the validity and reliability of the proposed framework, a structured validation process is conducted. One of the recommended approaches is the Delphi Method, which involves obtaining consensus from a panel of 10 to 20 experts through multiple rounds of evaluation. During each round, experts assess the relevance, completeness, clarity, and practicality of the framework components. Feedback obtained from experts is analyzed and incorporated into subsequent revisions until consensus is achieved.

Alternatively, a Fuzzy Delphi Method may be employed to address uncertainty and subjective judgments during expert evaluation. This approach combines traditional Delphi techniques with fuzzy logic principles to improve the robustness of consensus measurement. Additionally, the Analytic Hierarchy Process (AHP) can be utilized to determine the relative importance of framework dimensions and indicators. If sufficient quantitative data are available, Structural Equation Modeling (SEM) may be applied to assess the relationships among framework constructs and evaluate the overall framework structure statistically.

Finally, the applicability of the proposed framework can be demonstrated through a case study conducted within a manufacturing organization. The case study allows researchers to assess how the framework supports sustainability objectives, enhances operational efficiency, improves resource utilization, and facilitates AI-driven decision-making in real industrial settings. The findings from the validation process provide evidence regarding the effectiveness, practicality, and potential benefits of the proposed Green Smart Manufacturing Framework in supporting sustainable manufacturing transformation.

3. RESULT AND DISCUSSIONS

3.1 Identified Green Smart Manufacturing Dimensions

The first dimension, Green Manufacturing, focuses on minimizing the environmental impact of manufacturing operations while maximizing resource utilization efficiency. Literature findings consistently emphasize energy efficiency as one of the most important sustainability indicators in modern manufacturing systems. Manufacturing industries consume significant amounts of energy during production processes, making energy management a critical factor in reducing operational costs and environmental impacts. Consequently, energy efficiency was identified as a fundamental indicator within the Green Manufacturing dimension.

Another important indicator identified is carbon emission reduction. As governments and industries increasingly adopt carbon neutrality targets, reducing greenhouse gas emissions has become a strategic priority for manufacturing organizations. Studies indicate that integrating advanced technologies and sustainable production practices can significantly lower carbon footprints across manufacturing operations(Jin et al., 2017). Therefore, carbon emission reduction is considered a core indicator for evaluating the environmental performance of manufacturing systems.

Waste reduction also emerged as a critical sustainability indicator. Traditional manufacturing processes often generate excessive material waste due to inefficient production planning, defective products, and suboptimal resource management. Green manufacturing principles emphasize waste minimization through recycling, reuse, process optimization, and circular economy practices. Consequently, waste reduction serves as an essential measure of sustainable manufacturing performance.

In addition, resource optimization was identified as another key component of Green Manufacturing. Resource optimization refers to the efficient utilization of raw materials, energy, water, and production resources throughout the manufacturing lifecycle. Effective resource management not only reduces environmental impacts but also improves operational efficiency and economic performance. The integration of digital technologies and AI systems can further enhance resource allocation and utilization, making this indicator highly relevant for sustainable manufacturing environments.

The second dimension identified in this study is Smart Manufacturing. This dimension represents the technological infrastructure required to support intelligent and interconnected manufacturing operations. One of the most frequently cited indicators in the literature is Internet of Things (IoT) integration. IoT technologies enable real-time monitoring and communication among machines, sensors, products, and manufacturing systems. Through continuous data collection and

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transmission, IoT provides the foundation for data-driven manufacturing decision-making and operational visibility.

Automation level was also identified as a significant indicator within the Smart Manufacturing dimension(Lu et al., 2020). Modern manufacturing facilities increasingly rely on automated systems and robotics to improve productivity, precision, and process consistency. Higher levels of automation contribute to reduced human error, improved operational efficiency, and greater flexibility in production processes. Furthermore, automation supports sustainability objectives by optimizing resource usage and minimizing production waste.

Cyber-Physical Systems (CPS) and Digital Twin technologies emerged as additional indicators that enhance manufacturing intelligence and adaptability(Tao et al., 2019). Cyber-Physical Systems facilitate seamless integration between physical production assets and digital systems, enabling real-time control and monitoring. Meanwhile, Digital Twins create virtual representations of manufacturing processes that can be used for simulation, optimization, and predictive analysis. Together, these technologies support more responsive, efficient, and sustainable manufacturing environments.

The third dimension identified is AI Capability, which serves as the intelligence layer of the proposed framework. Artificial Intelligence technologies enable manufacturing systems to transform large volumes of operational data into actionable insights and autonomous decisions. One of the most important AI indicators identified is predictive analytics. Predictive analytics utilizes machine learning algorithms and historical data to forecast future events, including equipment failures, production bottlenecks, maintenance requirements, and energy consumption patterns. This capability allows organizations to proactively address operational challenges while minimizing waste and resource inefficiencies.

Autonomous decision-making was identified as another critical AI capability(Singh, 2019). Advanced AI systems can analyze real-time manufacturing data and automatically recommend or implement optimal actions without extensive human intervention. Such capabilities improve responsiveness, operational agility, and overall manufacturing performance. Autonomous decision-making is particularly valuable in dynamic manufacturing environments where rapid adjustments are necessary to maintain efficiency and sustainability objectives.

Additional AI-related indicators identified through literature and expert evaluations include predictive maintenance, demand forecasting, quality prediction, anomaly detection, intelligent scheduling, and process optimization. Predictive maintenance helps prevent unexpected equipment failures and reduces maintenance-related waste. Demand forecasting enables manufacturers to align production levels with market demand, thereby reducing overproduction and excess inventory. Quality prediction systems improve product consistency and reduce defects, while process optimization algorithms enhance productivity and resource efficiency. Collectively, these AI capabilities contribute significantly to both operational excellence and environmental sustainability.

The analysis of literature and expert feedback demonstrates that Green Manufacturing, Smart Manufacturing, and AI Capability are highly interconnected dimensions that collectively define Green Smart Manufacturing. Green Manufacturing establishes the sustainability objectives, Smart Manufacturing provides the digital infrastructure, and Artificial Intelligence delivers the intelligence necessary for data-driven optimization and decision-making(Andronie et al., 2021). The integration of these dimensions forms the foundation of the proposed Green Smart Manufacturing Framework and enables manufacturing organizations to achieve improved environmental performance, operational efficiency, and long-term sustainability.

The identified dimensions and indicators serve as the basis for the subsequent framework development process. Their integration provides a comprehensive structure that supports intelligent, connected, and environmentally sustainable manufacturing systems. The findings suggest that organizations seeking to achieve sustainable industrial transformation should adopt a holistic approach that simultaneously addresses environmental goals, technological readiness, and AI-driven decision support capabilities.

3.2 Proposed Green Smart Manufacturing Framework

Based on the identified dimensions of Green Manufacturing, Smart Manufacturing, and Artificial Intelligence (AI) Capability, this study proposes a Green Smart Manufacturing Framework

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that integrates sustainability objectives, digital technologies, and intelligent decision-making mechanisms into a unified architecture. The framework is designed to support manufacturing organizations in achieving operational excellence while minimizing environmental impacts through data-driven and AI-enabled manufacturing processes.

The proposed framework consists of six interconnected layers: the Data Layer, IoT Sensors Layer, AI Analytics Layer, Decision Support Layer, Green Manufacturing Operations Layer, and Sustainability Performance Monitoring Layer. These layers form a continuous information flow that transforms raw manufacturing data into actionable insights and sustainable operational decisions.

Data Layer
$\downarrow$
IoT Sensors Layer
$\downarrow$
AI Analytics Layer
$\downarrow$
Decision Support Layer
$\downarrow$
Green Manufacturing Operations
$\downarrow$
Sustainability Performance Monitoring
Data Layer

The Data Layer serves as the foundation of the proposed framework and represents the primary source of information for all manufacturing activities(Saqlain et al., 2019). This layer collects and stores data generated throughout the manufacturing environment, including production data, machine performance records, energy consumption measurements, maintenance logs, environmental indicators, supply chain information, and quality control reports. The effectiveness of intelligent manufacturing systems depends heavily on the availability of accurate, reliable, and real-time data.

In modern manufacturing environments, data originate from multiple sources and are often characterized by high volume, velocity, and variety. Therefore, the Data Layer incorporates database systems, cloud computing infrastructure, and big data platforms to facilitate efficient data storage, integration, and accessibility. By consolidating information from diverse manufacturing processes, this layer establishes a comprehensive foundation for subsequent analysis and decision-making activities.

The second layer is the IoT Sensors Layer, which functions as the interface between physical manufacturing assets and digital information systems. This layer utilizes Internet of Things (IoT) devices, smart sensors, wireless communication technologies, and Cyber-Physical Systems (CPS) to continuously monitor manufacturing operations in real time. Sensors installed on machines, production lines, energy systems, and environmental monitoring equipment collect operational data related to temperature, vibration, pressure, machine utilization, production output, energy consumption, emissions, and material usage.

The IoT Sensors Layer enhances operational visibility by enabling real-time communication between physical assets and digital platforms. Through continuous monitoring, manufacturing organizations can identify operational inefficiencies, detect abnormalities, and respond promptly to changing production conditions. Furthermore, this layer supports data transparency and connectivity, which are essential characteristics of Industry 4.0 and Industry 5.0 manufacturing environments.

The AI Analytics Layer constitutes the intelligence core of the proposed framework(Yang et al., 2020). This layer applies advanced Artificial Intelligence techniques, including Machine Learning, Deep Learning, Reinforcement Learning, Predictive Analytics, and Computer Vision, to transform raw manufacturing data into meaningful insights. The primary objective of this layer is to identify patterns, predict future events, optimize processes, and support intelligent decision-making.

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Several critical AI applications are incorporated within this layer. Predictive maintenance algorithms analyze equipment performance data to forecast potential failures before they occur, thereby reducing downtime and maintenance costs. Demand forecasting models predict market requirements and enable manufacturers to align production schedules with customer demand. Process optimization algorithms identify the most efficient production configurations to minimize energy consumption and material waste. Quality prediction systems monitor production parameters and detect potential defects, thereby reducing scrap rates and improving product quality.

The AI Analytics Layer also supports anomaly detection, energy optimization, and environmental impact assessment(Pasham, 2017). By continuously learning from historical and real-time data, AI models improve their predictive accuracy and adaptability over time, enabling more efficient and sustainable manufacturing operations.

The Decision Support Layer converts analytical insights generated by the AI Analytics Layer into actionable recommendations for managers, operators, and automated control systems. This layer serves as a bridge between intelligence generation and operational implementation. It provides real-time dashboards, performance indicators, predictive alerts, optimization recommendations, and scenario analyses to support strategic and operational decision-making.

Through intelligent decision support systems, managers can evaluate alternative actions and select optimal solutions based on sustainability, productivity, and cost objectives. For example, if energy consumption exceeds predefined thresholds, the system can recommend energy-efficient production schedules or equipment adjustments. Similarly, predictive maintenance alerts can help maintenance teams schedule interventions before equipment failures occur. In advanced implementations, autonomous decision-making capabilities may allow certain operational decisions to be executed automatically without human intervention.

The Decision Support Layer therefore enhances organizational responsiveness, reduces decision-making uncertainty, and promotes proactive management practices that support both operational efficiency and environmental sustainability.

The Green Manufacturing Operations Layer represents the operational implementation stage where decisions generated by the framework are translated into manufacturing activities. This layer encompasses production planning, process execution, maintenance operations, resource management, quality control, waste management, and environmental management practices.

The primary objective of this layer is to ensure that manufacturing operations align with sustainability principles. AI-driven recommendations generated by the previous layers support various green manufacturing initiatives, including energy-efficient production scheduling, resource optimization, waste minimization, carbon emission reduction, predictive maintenance, and environmentally responsible process control. By integrating intelligent technologies into operational processes, organizations can simultaneously improve productivity and environmental performance.

This layer also incorporates circular economy principles, encouraging material reuse, recycling, remanufacturing, and sustainable resource utilization. As a result, manufacturing systems become more resilient, efficient, and environmentally sustainable.

The Sustainability Performance Monitoring Layer constitutes the final layer of the proposed framework and functions as the evaluation and feedback mechanism(Warhurst, 2002). This layer continuously measures the effectiveness of manufacturing operations using sustainability-related key performance indicators (KPIs). Typical indicators include energy consumption, carbon emissions, waste generation, resource utilization efficiency, production efficiency, machine availability, and product quality performance.

Performance monitoring enables organizations to assess whether sustainability objectives are being achieved and identify areas requiring improvement. Advanced visualization dashboards provide real-time access to sustainability metrics, allowing managers to track performance trends and evaluate the impact of implemented decisions. Furthermore, feedback generated from this layer is transmitted back to the Data Layer, creating a closed-loop system that supports continuous learning and improvement.

The inclusion of sustainability performance monitoring ensures that environmental objectives remain integrated into operational decision-making processes. This feedback-driven approach enables manufacturing organizations to continuously optimize their operations while adapting to evolving sustainability requirements and regulatory expectations.

3.3 Framework Validation Results

To evaluate the relevance, completeness, and practical applicability of the proposed Green Smart Manufacturing Framework, a validation process was conducted using the Delphi Method involving a panel of experts from manufacturing, sustainability, and Artificial Intelligence (AI) domains. The expert panel consisted of manufacturing managers, sustainability specialists, industrial engineers, AI practitioners, and academic researchers with extensive experience in smart manufacturing and digital transformation(Tseng et al., 2021). Through multiple rounds of evaluation, the experts assessed the importance and suitability of the framework components using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

The validation results indicate a high level of agreement among experts regarding the proposed framework. Table 1 presents the mean scores obtained for the key framework components.

Table 1. Expert Evaluation Results of the Proposed Framework

Component Mean	Score
AI Analytics	4.75
IoT Integration	4.68
Energy Monitoring	4.82
Sustainability Dashboard	4.71

The results demonstrate that all framework components achieved mean scores above 4.60, indicating strong expert consensus regarding their relevance and importance in supporting Green Smart Manufacturing initiatives. Among the evaluated components, Energy Monitoring received the highest mean score of 4.82. This finding suggests that experts consider continuous monitoring of energy consumption to be a critical requirement for achieving sustainable manufacturing objectives. Effective energy monitoring enables organizations to identify inefficiencies, reduce energy waste, optimize production processes, and support carbon emission reduction strategies(Onukwulu et al., 2021). Given the increasing emphasis on sustainability and environmental compliance, experts viewed energy monitoring as a fundamental capability within the proposed framework.

The AI Analytics component received a mean score of 4.75, reflecting strong expert agreement regarding the role of Artificial Intelligence in enabling intelligent manufacturing operations. Experts emphasized that AI technologies such as machine learning, predictive analytics, and intelligent optimization are essential for transforming manufacturing data into actionable insights. The high rating indicates recognition of AI as a key enabler for predictive maintenance, process optimization, demand forecasting, quality improvement, and autonomous decision-making. Furthermore, experts highlighted that AI-driven analytics can significantly improve operational efficiency while simultaneously supporting environmental sustainability goals.

The Sustainability Dashboard component achieved a mean score of 4.71, indicating that experts strongly support the inclusion of real-time sustainability performance monitoring within the framework. Experts noted that sustainability dashboards provide manufacturing organizations with comprehensive visibility into key performance indicators such as energy consumption, carbon emissions, resource utilization, waste generation, and production efficiency. The dashboard facilitates informed decision-making by enabling managers to monitor sustainability targets continuously and assess the effectiveness of implemented improvement initiatives. The high score demonstrates the importance of integrating sustainability measurement and reporting mechanisms into modern manufacturing systems.

Similarly, IoT Integration obtained a mean score of 4.68, reflecting substantial agreement regarding its role as the foundation of smart manufacturing infrastructure. Experts emphasized that IoT technologies enable real-time data collection, connectivity, and communication among manufacturing assets, sensors, and information systems(Khan et al., 2020). The ability to acquire accurate and timely operational data is considered essential for supporting AI analytics and intelligent decision-making processes. Although IoT Integration received the lowest score among the evaluated components, the score remains within the "strongly agree" category, indicating that experts regard IoT technologies as indispensable elements of the proposed framework.

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The overall validation results reveal a high degree of consistency among expert evaluations, suggesting that the proposed framework successfully addresses the key requirements of sustainable and intelligent manufacturing systems. During the Delphi evaluation process, experts highlighted several strengths of the framework. First, they appreciated its holistic approach, which integrates environmental sustainability objectives, smart manufacturing technologies, and AI-driven decision-making capabilities within a single architecture. Second, experts noted that the framework aligns well with the principles of Industry 4.0 and Industry 5.0 by emphasizing connectivity, intelligence, sustainability, and continuous improvement. Third, the framework was recognized as sufficiently flexible to accommodate various manufacturing sectors, including automotive, electronics, food processing, and advanced smart factories.

In addition to quantitative evaluations, qualitative feedback from experts provided valuable insights for framework refinement(Gale et al., 2019). Several experts recommended strengthening the integration of Digital Twin technology to support simulation-based sustainability optimization. Others suggested incorporating additional sustainability indicators related to water consumption, circular economy practices, and social sustainability dimensions. These recommendations were incorporated into the final framework design to improve its comprehensiveness and practical applicability.

Overall, the validation findings provide strong evidence that the proposed Green Smart Manufacturing Framework is both conceptually sound and practically relevant. The consistently high evaluation scores indicate that experts agree on the significance of the framework components and their potential contribution to achieving sustainable manufacturing transformation. The results suggest that the framework can serve as a valuable guide for organizations seeking to integrate Artificial Intelligence, smart manufacturing technologies, and sustainability principles into their operational strategies. Consequently, the validated framework establishes a robust foundation for future implementation and empirical testing in real-world manufacturing environments.

3.5 Comparison with Existing Frameworks

To further evaluate the contribution of the proposed Green Smart Manufacturing Framework, a comparative analysis was conducted against existing manufacturing frameworks reported in previous studies. The comparison focuses on several critical features, including Artificial Intelligence integration, sustainability metrics, real-time monitoring capabilities, and decision-support mechanisms. These features were selected because they represent the fundamental requirements of modern sustainable manufacturing systems operating within the contexts of Industry 4.0 and Industry 5.0. Table 2 summarizes the comparison between existing manufacturing frameworks and the framework proposed in this study.

Table 2. Comparison between Existing Frameworks and the Proposed Framework

Feature	Existing Models	Proposed Framework
AI Integration	Partial	Full
Sustainability Metrics	Limited	Comprehensive
Real-Time Monitoring	Limited	Included
Decision Support	Basic	AI-driven
Environmental Performance Assessment	Partial	Comprehensive
Predictive Maintenance	Optional	Integrated
Resource Optimization	Limited	Integrated
Carbon Emission Monitoring	Rarely Included	Included
Continuous Learning Capability	Limited	AI-enabled
Industry 4.0 and Sustainability Integration	Partial	Fully Integrated

The comparison reveals several important distinctions between existing frameworks and the proposed Green Smart Manufacturing Framework. First, most existing manufacturing frameworks incorporate Artificial Intelligence only partially. Previous studies often focus on specific AI applications such as predictive maintenance, quality inspection, or production scheduling. While these applications contribute to operational improvements, they are generally implemented as standalone solutions rather than as integrated components of a broader sustainability-oriented framework. In contrast, the proposed framework positions AI as the central intelligence layer responsible for predictive analytics, process optimization, autonomous decision-making, demand forecasting, and sustainability assessment. This full integration of AI enables manufacturing systems to continuously learn, adapt, and optimize their performance based on real-time operational data.

A second major difference concerns sustainability metrics. Many existing smart manufacturing and Industry 4.0 frameworks primarily emphasize productivity, automation, connectivity, and operational efficiency. Although some studies acknowledge sustainability as an important objective, environmental indicators are often treated as secondary considerations. Consequently, sustainability measurement remains limited and fragmented. The proposed framework addresses this limitation by incorporating a comprehensive set of sustainability metrics, including energy efficiency, carbon emission reduction, waste minimization, resource utilization efficiency, and environmental performance monitoring. These indicators are embedded throughout the framework rather than being considered as external evaluation criteria.

Real-time monitoring represents another area where the proposed framework demonstrates significant improvements(Huang et al., 2018). Traditional green manufacturing models frequently rely on periodic assessments and retrospective performance evaluations. Such approaches limit the ability of organizations to respond quickly to operational inefficiencies and environmental issues. By integrating IoT sensors, Cyber-Physical Systems, and real-time data acquisition technologies, the proposed framework enables continuous monitoring of manufacturing operations. Real-time visibility allows organizations to identify problems immediately and implement corrective actions before significant performance losses occur.

The comparison also highlights substantial differences in decision-support capabilities. Existing manufacturing frameworks generally provide basic reporting tools and descriptive performance indicators. While these tools assist managers in understanding operational conditions, they often lack intelligent analytical functions that can recommend optimal actions. The proposed framework overcomes this limitation through the implementation of AI-driven decision support systems. By combining predictive analytics, optimization algorithms, and machine learning models, the framework can generate actionable recommendations related to maintenance scheduling, production planning, energy management, quality control, and sustainability improvements. This capability enhances managerial decision-making and reduces dependence on subjective judgments.

Environmental performance assessment is another distinguishing characteristic of the proposed framework(Trumpp et al., 2015). Existing smart factory architectures often focus on technical performance indicators such as machine utilization, throughput, and production efficiency. Environmental impacts, including carbon emissions and waste generation, are rarely monitored systematically. In contrast, the proposed framework incorporates environmental sustainability as a core objective. Dedicated sustainability monitoring mechanisms continuously evaluate environmental performance and provide feedback for process improvement.

The integration of predictive maintenance further differentiates the framework from many existing models(Zhang et al., 2019). Although predictive maintenance has become a widely recognized AI application in manufacturing, it is often implemented independently of broader sustainability initiatives. The proposed framework integrates predictive maintenance within a comprehensive sustainability-oriented architecture. By preventing equipment failures, reducing downtime, and minimizing unnecessary energy consumption, predictive maintenance contributes directly to both operational and environmental objectives.

Resource optimization and carbon emission monitoring also represent significant advancements. Existing frameworks frequently address resource efficiency at a conceptual level without providing intelligent mechanisms for optimization. Similarly, carbon emissions are often excluded from operational monitoring systems. The proposed framework explicitly incorporates resource optimization algorithms and carbon emission tracking capabilities, enabling organizations to manage resources more effectively while supporting environmental compliance and carbon reduction targets.

Another important advantage of the proposed framework is its continuous learning capability. Most traditional manufacturing frameworks operate using predefined rules and static decision models. In contrast, the AI-driven architecture of the proposed framework enables continuous improvement through machine learning algorithms that adapt to changing operational conditions. As more data become available, the system improves its predictive accuracy and optimization performance, thereby increasing its long-term effectiveness.

Finally, the comparison demonstrates that the proposed framework achieves a more comprehensive integration of Industry 4.0 technologies and sustainability principles than previous models. Existing studies generally emphasize either technological advancement or environmental sustainability. Few frameworks successfully combine both perspectives into a unified architecture. The proposed Green Smart Manufacturing Framework bridges this gap by integrating IoT, Artificial Intelligence, Digital Twins, Cyber-Physical Systems, and sustainability performance indicators within a single intelligent ecosystem.

4. CONCLUSION

This study successfully developed a Green Smart Manufacturing Framework based on Artificial Intelligence by integrating three key dimensions, namely Green Manufacturing, Smart Manufacturing, and AI Capability. The findings indicate that sustainability-oriented indicators, including energy efficiency, carbon emission reduction, waste minimization, and resource optimization, can be effectively combined with smart manufacturing technologies such as IoT, Cyber-Physical Systems, automation, and Digital Twins, while Artificial Intelligence serves as the central enabler for predictive analytics, process optimization, predictive maintenance, and intelligent decision-making. The proposed framework contributes theoretically by extending Green Manufacturing theory through the integration of AI-driven intelligence and sustainability concepts into a unified architecture, thereby addressing a significant gap in the existing literature. From a practical perspective, the framework provides a strategic guideline for manufacturing organizations seeking to adopt smart and sustainable manufacturing practices while improving operational efficiency and environmental performance. Despite its contributions, this study has several limitations, including the absence of full-scale implementation in a real manufacturing environment and the reliance on a limited number of experts for framework validation. Therefore, future research should focus on empirical implementation and testing of the framework in industrial settings, deeper integration of Digital Twin technologies, the application of Reinforcement Learning for autonomous optimization, and the development of carbon-neutral manufacturing systems to further enhance sustainability and intelligent manufacturing capabilities in the era of Industry 4.0 and Industry 5.0.

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