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Identifying the Dimensions and Components of Smart Manufacturing Systems in the Automotive Industry: Emphasizing the Application of Artificial Intelligence and the Internet of Things

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Alimohammad. Nasirian[1], Hossein. Adab[1*], Shahrzad. Tayaran[1]

1 Department of Industrial Management, CT.C., Islamic Azad University, Tehran, Iran

Corresponding author email address:
hos.adab@iauctb.ac.ir

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ABSTRACT

The present study aimed to identify the dimensions and components of smart manufacturing systems in the automotive industry with an emphasis on the application of Artificial Intelligence (AI) and the Internet of Things (IoT), and to develop a comprehensive implementation model based on the perspectives of industry and academic experts. This study was conducted using a qualitative exploratory approach. Participants consisted of 14 experts from the automotive industry and academia who were selected through purposive sampling based on their expertise in smart manufacturing, Industry 4.0 technologies, artificial intelligence, industrial automation, and digital transformation. Data were collected through semi-structured, in-depth interviews and analyzed using thematic analysis with the support of MAXQDA 2020 software. The coding process was performed in two iterative stages, including initial and secondary coding. Through continuous comparison, refinement, and integration of codes, 84 unique open codes were extracted and subsequently organized into axial categories and higher-order themes. To ensure rigor and trustworthiness, member checking, peer review, and audit trail procedures were employed throughout the analytical process. The findings revealed a comprehensive paradigm model for the implementation of smart manufacturing systems in automotive parts manufacturing. The model identified two major causal conditions, including domestic and international competitive pressure and infrastructural, functional, and technological challenges. Contextual conditions comprised human resources, skills and organizational culture, as well as economic and implementation considerations. Intervening conditions included cybersecurity and risk management, and system quality and reliability. Four major strategic dimensions were identified, namely advanced automation and robotics, artificial intelligence-driven data analytics, Industrial Internet of Things (IIoT) and connectivity development, and smart supply chain and logistics management. The implementation of these strategies was found to result in structural and functional improvements, economic efficiencies, enhanced customer orientation, production flexibility and personalization, and the development of management and technological knowledge. Collectively, the findings demonstrated that successful smart manufacturing implementation requires the integrated alignment of technological, organizational, strategic, and human-resource factors. The study provides a holistic framework for understanding and implementing smart manufacturing systems within the automotive industry. The proposed model demonstrates that artificial intelligence and Internet of Things technologies function as central enablers of intelligent production environments, but their effectiveness depends on organizational readiness, technological infrastructure, cybersecurity capabilities, and strategic management support.

Keywords: Smart Manufacturing Systems; Automotive Industry; Artificial Intelligence; Internet of Things; Industry 4.0; Industry 5.0; Industrial Internet of Things.

Introduction

The automotive industry has long been recognized as one of the most technologically intensive and strategically important industrial sectors in the global economy. In recent years, rapid technological advancements, increasing market competition, rising customer expectations, environmental sustainability requirements, and the growing complexity of production systems have compelled automotive manufacturers to pursue new approaches for enhancing operational efficiency, product quality, flexibility, and innovation. Among these developments, the emergence of smart manufacturing systems has fundamentally transformed traditional production paradigms by integrating advanced digital technologies into manufacturing environments. Smart manufacturing represents a new generation of industrial systems characterized by real-time connectivity, autonomous decision-making, intelligent process optimization, predictive capabilities, and seamless integration across organizational functions. These capabilities have become increasingly important for automotive manufacturers seeking to remain competitive in highly dynamic and technologically evolving markets [1-3].

The conceptual foundations of smart manufacturing are closely associated with the principles of Industry 4.0, which emphasize the integration of cyber-physical systems, advanced analytics, intelligent automation, cloud computing, and interconnected industrial networks. Industry 4.0 technologies enable manufacturing systems to move beyond traditional automation toward adaptive, data-driven, and self-optimizing production environments. More recently, discussions surrounding Industry 5.0 have further highlighted the importance of human-centric, resilient, and sustainable manufacturing ecosystems that combine technological intelligence with human expertise. These developments have expanded the strategic significance of intelligent manufacturing systems, particularly in industries characterized by high product complexity and stringent quality requirements, such as automotive manufacturing [1, 4, 5].

Among the technologies driving the smart manufacturing revolution, Artificial Intelligence (AI) occupies a central position. AI technologies enable machines and production systems to learn from historical data, identify patterns, make predictions, optimize operational decisions, and continuously improve performance. AI applications in industrial environments encompass machine learning, deep learning, computer vision, natural language processing, intelligent control systems, predictive analytics, and autonomous decision support. The increasing maturity of AI technologies has created unprecedented opportunities for manufacturers to automate complex cognitive tasks that were previously dependent upon human expertise. Consequently, AI has become a critical enabler of intelligent production systems, contributing to improvements in efficiency, quality control, maintenance planning, process optimization, and organizational decision-making [6-8].

The automotive industry has been particularly receptive to the adoption of artificial intelligence due to its complex manufacturing processes, extensive supply chains, high-volume production requirements, and strong emphasis on quality assurance. AI technologies are increasingly utilized throughout the automotive value chain, including design engineering, production planning, quality inspection, inventory management, predictive maintenance, logistics optimization, autonomous manufacturing operations, and customer-oriented product customization. Recent studies suggest that AI-driven systems enable manufacturers to reduce operational inefficiencies, improve production consistency, accelerate product development cycles, and enhance overall competitiveness in increasingly demanding markets [9-11].

A particularly important application of artificial intelligence in automotive manufacturing relates to quality management and defect detection. Traditional quality inspection methods often rely on manual observation or rule-based systems that may fail to identify subtle defects in complex production environments. In contrast, AI-powered computer vision and machine learning systems can analyze vast quantities of production data in real time, detect anomalies with high accuracy, and facilitate proactive quality improvement. These capabilities support the transition toward zero-defect manufacturing and significantly enhance production reliability and customer satisfaction. Research has consistently demonstrated the effectiveness of AI-based quality assurance systems in improving defect detection, reducing waste, and supporting continuous process improvement within automotive production systems [12-14].

Another transformative technology shaping smart manufacturing is the Internet of Things (IoT), particularly its industrial variant known as the Industrial Internet of Things (IIoT). IoT refers to interconnected networks of sensors, devices, machines, and systems capable of collecting, transmitting, and exchanging data across manufacturing environments. Through continuous monitoring and communication, IoT technologies provide unprecedented visibility into operational activities, enabling real-time control, performance monitoring, predictive maintenance, and adaptive decision-making. In manufacturing contexts, IoT facilitates the creation of connected production ecosystems where machines, products, and stakeholders communicate seamlessly to support intelligent operations and process optimization [5, 15, 16].

The convergence of artificial intelligence and IoT has given rise to the concept of Artificial Intelligence of Things (AIoT), which combines the sensing and connectivity capabilities of IoT with the analytical and predictive capabilities of AI. AIoT technologies enable manufacturing systems to move beyond data collection toward intelligent interpretation and autonomous response. In automotive production environments, AIoT supports predictive maintenance, equipment health monitoring, process optimization, anomaly detection, inventory control, and energy management. The integration of AI and IoT has therefore become a cornerstone of modern smart manufacturing strategies and a critical driver of industrial digital transformation [15, 17, 18].

Predictive maintenance represents one of the most widely recognized applications of AIoT technologies in manufacturing systems. Traditional maintenance approaches are often reactive or schedule-based, resulting in unnecessary downtime, excessive maintenance costs, and suboptimal asset utilization. By leveraging sensor data, machine learning algorithms, and real-time analytics, predictive maintenance systems can forecast equipment failures before they occur, allowing organizations to optimize maintenance schedules and reduce operational disruptions. These capabilities are particularly valuable in automotive manufacturing, where production interruptions can generate substantial financial losses and negatively affect supply chain performance [17, 19, 20].

The growing adoption of robotics and intelligent automation further reinforces the strategic importance of smart manufacturing systems. Advanced robotic systems increasingly collaborate with human operators in flexible manufacturing environments, performing repetitive, hazardous, and precision-intensive tasks while allowing human workers to focus on higher-value activities. Human-robot collaboration enhances productivity, safety, and operational efficiency while supporting more agile manufacturing processes. As automotive manufacturers continue to automate production activities, intelligent robotics are expected to become increasingly integrated with AI and IoT infrastructures, creating highly adaptive and autonomous production ecosystems [21-23].

Beyond operational benefits, smart manufacturing systems contribute significantly to organizational sustainability objectives. Automotive manufacturers face increasing pressure to reduce environmental impacts, optimize energy consumption, minimize waste generation, and improve resource utilization. AI and IoT technologies facilitate more sustainable production by enabling intelligent energy management, resource optimization, predictive resource allocation, and environmentally conscious decision-making. These capabilities align closely with global sustainability agendas and support the development of carbon-neutral manufacturing strategies within the automotive sector [8, 10, 18].

Despite their considerable potential, the implementation of smart manufacturing systems presents numerous organizational, technological, and managerial challenges. One major challenge involves the integration of legacy manufacturing systems with emerging digital technologies. Many automotive manufacturers continue to operate production infrastructures that were not originally designed for interoperability with AI-driven applications or IoT platforms. Achieving seamless integration often requires substantial investments in technological upgrades, infrastructure modernization, and workforce development. Furthermore, the complexity of digital transformation initiatives may generate organizational resistance and implementation risks that hinder successful adoption [2, 3, 5].

Cybersecurity has emerged as another critical concern in smart manufacturing environments. The increasing connectivity of production systems expands the potential attack surface for cyber threats, creating new vulnerabilities related to data breaches, system disruptions, and operational sabotage. Consequently, cybersecurity must be considered an integral component of smart manufacturing system design. Recent research highlights the growing importance of AI-driven cybersecurity solutions, privacy-preserving technologies, explainable AI frameworks, and risk management strategies in protecting industrial cyber-physical systems from evolving security threats [24-26].

In addition to cybersecurity concerns, organizations must address issues related to trust, transparency, and explainability in AI-based decision-making systems. As manufacturing processes become increasingly dependent on autonomous algorithms, stakeholders require greater visibility into how decisions are generated and validated. Explainable AI approaches have therefore gained prominence as mechanisms for improving accountability, transparency, and confidence in intelligent manufacturing systems. These considerations are particularly important in safety-critical industries such as automotive manufacturing, where production decisions may directly affect product quality, operational safety, and regulatory compliance [4, 25, 26].

Human factors also remain central to the successful implementation of intelligent production systems. While automation and AI can replace certain repetitive tasks, the transition toward smart manufacturing requires a highly skilled workforce capable of managing, maintaining, and optimizing advanced technological infrastructures. Organizational culture, employee competencies, leadership commitment, and continuous learning play crucial roles in facilitating successful digital transformation. Moreover, emerging concepts such as human-centric digital twins emphasize the importance of integrating human expertise into intelligent manufacturing ecosystems rather than replacing human involvement entirely [1, 21, 27].

Within the automotive sector, additional contextual challenges may arise from supply chain complexity, geopolitical uncertainties, and external economic constraints. In countries operating under economic sanctions or trade restrictions, technology acquisition, supplier integration, and infrastructure development may face additional barriers. Recent evidence from the automotive sector suggests that supply chain resilience, supplier performance management, and risk assessment mechanisms are becoming increasingly important determinants of successful technological transformation and sustainable competitive advantage [28, 29].

Although previous studies have extensively examined individual aspects of artificial intelligence, IoT technologies, predictive maintenance, robotics, cybersecurity, quality management, and smart manufacturing architectures, the literature reveals a lack of comprehensive models that systematically identify and integrate the dimensions and components required for implementing smart manufacturing systems in automotive parts manufacturing. Existing research often focuses on specific technologies or isolated applications, while limited attention has been given to developing a holistic framework that captures the causal conditions, contextual factors, intervening variables, strategic mechanisms, and expected outcomes associated with smart manufacturing implementation in the automotive industry [2, 3, 17, 30].

Therefore, the aim of the present study was to identify the dimensions and components of smart manufacturing systems in the automotive industry with a particular emphasis on the application of Artificial Intelligence and the Internet of Things and to develop a comprehensive implementation model based on the perspectives of industry and academic experts.

Methodology

This study was conducted using a qualitative exploratory research design with the aim of identifying the dimensions and components of smart manufacturing systems in the automotive industry, with a particular emphasis on the applications of Artificial Intelligence (AI) and the Internet of Things (IoT). Given the emerging nature of smart manufacturing technologies and the need to develop a comprehensive conceptual understanding of their organizational, technological, and operational implications, a qualitative approach was considered the most appropriate methodology. The study sought to capture the experiences, insights, and expert knowledge of specialists actively involved in the design, implementation, management, and evaluation of intelligent manufacturing systems within the automotive sector.

Participants were selected through purposive sampling, a widely accepted strategy in qualitative inquiry that enables researchers to identify information-rich cases capable of providing deep and relevant insights into the phenomenon under investigation. The inclusion criteria required participants to possess substantial expertise in at least one of the following domains: automotive manufacturing, industrial engineering, smart factory technologies, artificial intelligence applications in production systems, Industrial Internet of Things (IIoT), digital transformation, Industry 4.0 implementation, manufacturing strategy, or academic research related to intelligent production systems. Sampling continued until theoretical saturation was achieved, meaning that no new concepts, categories, or insights emerged from additional interviews. A total of fourteen experts participated in the study.

Data were collected through semi-structured, in-depth interviews, which are particularly suitable for exploratory qualitative studies seeking to uncover complex concepts, perceptions, and experiences. Semi-structured interviews provide a balance between consistency across participants and flexibility to explore emerging themes in greater depth. An interview protocol was developed based on an extensive review of the literature related to Industry 4.0, smart manufacturing systems, artificial intelligence applications, cyber-physical systems, industrial automation, and Internet of Things technologies in manufacturing environments.

The interview guide included a series of open-ended questions designed to encourage participants to discuss the key dimensions, enabling factors, technological infrastructures, organizational requirements, strategic implications, and operational outcomes associated with smart manufacturing systems in the automotive industry. Participants were also asked to elaborate on the roles of artificial intelligence and IoT technologies in production planning, predictive maintenance, quality management, supply chain integration, real-time decision-making, autonomous operations, data analytics, workforce transformation, and digital ecosystem development. Follow-up questions and probing techniques were employed whenever necessary to clarify responses and gain deeper insights into emerging concepts.

Each interview was conducted individually and lasted approximately 45 to 90 minutes. Interviews were conducted either face-to-face or through secure online communication platforms depending on participants' availability and geographic location. Prior to data collection, participants were informed about the purpose of the study, confidentiality procedures, voluntary participation, and their right to withdraw at any stage of the research process. Informed consent was obtained from all participants before the interviews commenced.

To ensure trustworthiness and rigor, several validation procedures were implemented throughout the data collection process. Credibility was enhanced through prolonged engagement with the data, member checking, and iterative questioning. Following preliminary coding, selected participants were invited to review summaries of the findings to verify the accuracy of interpretations and ensure that the extracted themes adequately reflected their perspectives. Transferability was strengthened through the provision of rich descriptions of the research context, participant characteristics, and data collection procedures. Dependability was established through maintaining a detailed audit trail documenting methodological decisions, coding procedures, and analytical processes. Confirmability was supported through researcher reflexivity, peer debriefing, and systematic documentation of analytical decisions to minimize subjective bias and enhance transparency.

The collected data were analyzed using Thematic Analysis, a rigorous and flexible qualitative analytical method that facilitates the identification, organization, interpretation, and reporting of patterns within textual data. The analysis followed a systematic process inspired by established thematic analysis procedures. Immediately after each interview, audio recordings were transcribed verbatim to preserve the richness and authenticity of participants’ responses. The resulting transcripts were carefully reviewed multiple times to achieve familiarity with the data and gain a comprehensive understanding of the emerging concepts.

The first stage of analysis involved open coding, during which meaningful segments of text were identified and assigned descriptive labels. These initial codes represented key ideas, experiences, perceptions, challenges, opportunities, technological requirements, and strategic considerations associated with smart manufacturing systems. Coding was conducted iteratively, allowing new codes to emerge naturally from the data while simultaneously comparing and refining existing codes.

In the subsequent stage, related codes were grouped into broader categories based on conceptual similarities and relationships. Through constant comparison and repeated examination of the data, higher-order themes and subthemes gradually emerged. These themes represented the fundamental dimensions and components of smart manufacturing systems within the automotive industry. Particular attention was given to identifying the interactions among technological infrastructures, intelligent decision-making mechanisms, data management systems, organizational capabilities, digital integration processes, and innovation-oriented practices enabled by AI and IoT technologies.

As analysis progressed, thematic maps were developed to illustrate the relationships among categories and to facilitate the construction of an integrated conceptual framework. The emerging themes were continuously reviewed against the original transcripts to ensure consistency, coherence, and representativeness. Any discrepancies or ambiguities were resolved through iterative discussions among the research team and repeated consultation of the source data.

The final stage involved defining, refining, and naming the major themes and subthemes to develop a comprehensive model of smart manufacturing systems in the automotive industry. The resulting framework reflects the collective expertise of industry and academic specialists and provides a systematic representation of the technological, organizational, strategic, and operational dimensions underlying intelligent manufacturing environments. The qualitative findings generated through thematic analysis subsequently provide the foundation for future quantitative validation studies involving larger samples and advanced statistical techniques to assess the empirical robustness and generalizability of the proposed model.

Findings and Results

The demographic profile of the 14 experts showed that the expert panel was predominantly male, with 12 men (85.71%) and 2 women (14.29%). In terms of age, 5 participants (35.71%) were between 36 and 45 years old, 5 participants (35.71%) were between 46 and 55 years old, and 4 participants (28.57%) were 56 years old or above. Regarding educational level, 4 participants (28.57%) held a master’s degree and 10 participants (71.43%) held a doctoral degree. In terms of relevant professional experience, 6 participants (42.86%) had 6 to 10 years of experience and 8 participants (57.14%) had 11 years or more of relevant experience. Overall, the participants had an appropriate combination of academic expertise, industrial background, and professional experience in automotive manufacturing, smart production systems, artificial intelligence, the Internet of Things, automation, and digital transformation.

Table 1

Open Coding Process of the Sixth Interview as a Sample

Open Code	Statement Attributed to the Open Code in the Interview
Use of robotics in assembly	Smart manufacturing means maximum use of robots...
Automation of control processes	Automation systems
Analysis of production data using artificial intelligence	Artificial intelligence is used to perform repetitive, precise, dangerous, and exhausting tasks.
Reduction of production line downtime	In this way, the production line is always active.
Automation of control processes	Factors such as the need to increase production, maintain quality at high volume, and protect worker safety push us toward automation and smart manufacturing.
Use of robotics in assembly	Priority should be given to automating assembly, painting, and welding sections using industrial robots.
Challenges of integrating old and new systems	Integration means that robots and automation systems can communicate with each other and with factory management systems such as MES. The main challenge is programming and configuring these robots to perform different tasks...
Need for strong network infrastructure	A fast and stable communication network is needed for robots.
Integrated software platforms	Software for robot planning and simulation is needed.
High initial investment costs	Management must be prepared for long-term investment in this field.
Training and development of human resource skills	There must be a plan for training technical staff. We need to train specialists who can program, maintain, and repair these robots.
Increasing production line productivity	This reduces labor costs and increases production volume.
Maintenance and technical support challenges	Shortage of specialized personnel for programming and maintenance
Effect of sanctions on technology supply	External barriers include sanctions affecting access to advanced robots and spare parts, as well as exchange-rate fluctuations.
Gradual implementation strategies	In my opinion, implementation should be gradual. First, automation should be applied to repetitive and high-risk sections.
Cooperation with knowledge-based companies	Robot and automation manufacturing companies can provide the required systems and training.
Cooperation with universities	Universities can contribute to designing new robots, optimizing robot movements, and developing intelligent control systems.
Increasing production line productivity	First of all, the speed and volume of production increase significantly.
Improving final product quality	Product quality becomes uniform and excellent.
Reduction of production line downtime	Delays in the production line decrease because robots do not get tired.
Production flexibility	Flexibility also increases because robots can be programmed for different tasks.
Improving worker safety	Finally, workshop safety increases because risks are removed from human labor.

Table 1 presents a sample of the open coding process conducted on the sixth interview, which was selected randomly as an illustrative case. The coding process was carried out simultaneously with the qualitative data analysis in MAXQDA 2020. Each initial code was assigned to a meaningful segment of the interview text, including a paragraph, sentence, clause, or phrase. Although equivalent and conceptually similar codes were organized during the first phase of coding, secondary coding was also performed through an iterative process of reviewing, merging, refining, and reorganizing the initial codes. This procedure was consistent with the exploratory logic of qualitative thematic analysis and was used to maximize conceptual discovery from the expert interviews. As a result, 84 unique open codes were finally extracted from the 14 interviews. The sample presented in Table 1 indicates that the sixth interview contained several recurring concepts related to smart manufacturing, including robotics, automation, artificial intelligence-based data analysis, network infrastructure, human resource training, investment requirements, university-industry cooperation, production flexibility, quality improvement, and worker safety.

Table 2

Axial Codes and Their Related Open Codes

Dimension	Axial Code	Related Open Codes
Causal Conditions	Domestic and international competitive pressure	Need to improve final product quality; development of international standards for smart manufacturing; necessity of demand forecasting; need for continuous improvement; acceleration of new product development
Causal Conditions	Infrastructural, functional, and technological challenges	Need for strong network infrastructure; challenges of integrating old and new systems; problems in technical knowledge transfer; maintenance and technical support challenges; time-consuming implementation process
Contextual Conditions	Human resources, skills, and organizational culture	Necessity of specialized training for technical teams; innovation-supportive organizational culture; need for training and development of human resource skills; resistance to technological change
Contextual Conditions	Economic and implementation considerations	High initial investment costs; gradual implementation strategies; evaluation of return on investment; cooperation with knowledge-based companies; effect of sanctions on technology transfer; cooperation with universities; assessment of organizational readiness for digital transformation; role of government in supporting smart manufacturing
Intervening Conditions	Cybersecurity and risk management	Use of advanced simulators; supply chain risk management; production risk management; cybersecurity in smart manufacturing systems; role of organizational leadership in implementation
Intervening Conditions	System quality and reliability	Data mining for process optimization; reliability of smart systems
Core Phenomenon	Designing a model for implementing smart manufacturing systems in automotive parts manufacturing with emphasis on artificial intelligence and the Internet of Things	All open codes are related to this core phenomenon in different ways
Strategies	Advanced automation and robotics	Use of robotics in assembly; automation of control processes; use of augmented reality for operator training; automation of internal factory logistics
Strategies	Employing artificial intelligence for data analysis	Analysis of production data using artificial intelligence; use of big data; use of artificial intelligence in visual quality control; advanced production planning systems; open data platforms
Strategies	Development of Industrial Internet of Things and connectivity	Implementation of the Internet of Things in the factory; production flexibility; connection of vehicles to production systems; development of the automotive technology ecosystem
Strategies	Smart supply chain and logistics management	Smart supply chain management; real-time monitoring of equipment performance; automation of internal factory logistics; smart inventory management; connection to external suppliers
Consequences	Structural and functional improvement	Increasing production line productivity; reducing raw material waste; predictive maintenance systems; increasing accuracy in quality inspection; integrated software platforms; improving worker safety; effect of smart manufacturing on product innovation; standardization of production data; monitoring environmental pollution in the production line; product traceability throughout the whole process; layout optimization; development of cloud platforms for manufacturing; scalability of smart solutions; reliability in mass production; monitoring individual and team performance; standardization of production processes; increasing the speed of new product development; flexibility in changing production plans; reducing dependence on human labor in repetitive tasks; positive effect of digital transformation on organizational structure
Consequences	Economic efficiencies	Reduction of production line downtime; optimization of energy consumption; factory-level energy management; reduction of operational costs; energy management in production
Consequences	Enhancement of customer orientation	Improving customer experience through customized production; improving final customer satisfaction
Consequences	Flexibility and personalization of production	Mass customization of products; improving customer experience through customized production
Consequences	Development of management and technology knowledge	Data-driven decision-making; recommender systems for production managers; standardization of communication protocols; simulation of production processes; development of native software; organizational knowledge management

Table 2 shows the results of axial coding and the organization of the extracted open codes into higher-level axial categories. The findings indicate that smart manufacturing systems in the automotive industry are not limited to the adoption of isolated technologies; rather, they emerge from the interaction of causal conditions, contextual conditions, intervening conditions, implementation strategies, and expected consequences. The causal conditions mainly include competitive pressure, the need to improve quality, the necessity of continuous improvement, demand forecasting, and the acceleration of new product development. These conditions show that the movement toward smart manufacturing is driven by both market pressure and technological necessity.

The contextual conditions emphasize the importance of organizational readiness, human capital, technical skills, cultural acceptance, economic feasibility, and institutional support. The findings show that even when advanced technologies such as artificial intelligence, IoT, robotics, and automation are available, successful implementation depends on skilled human resources, innovation-oriented organizational culture, gradual implementation, cooperation with universities and knowledge-based companies, and the ability to manage high initial investment costs. Therefore, smart manufacturing should be understood as a socio-technical transformation rather than a purely technological change.

The intervening conditions refer to factors that may facilitate or restrict the implementation process. Cybersecurity, risk management, system reliability, leadership support, and the ability to manage supply chain uncertainty were identified as important intervening factors. These findings indicate that the deployment of connected and intelligent systems increases the need for secure data exchange, reliable digital infrastructure, and risk-aware management practices. In smart manufacturing environments, the integration of physical production assets with digital platforms increases efficiency, but it also creates new vulnerabilities related to cyber threats, system failure, data quality, and operational continuity.

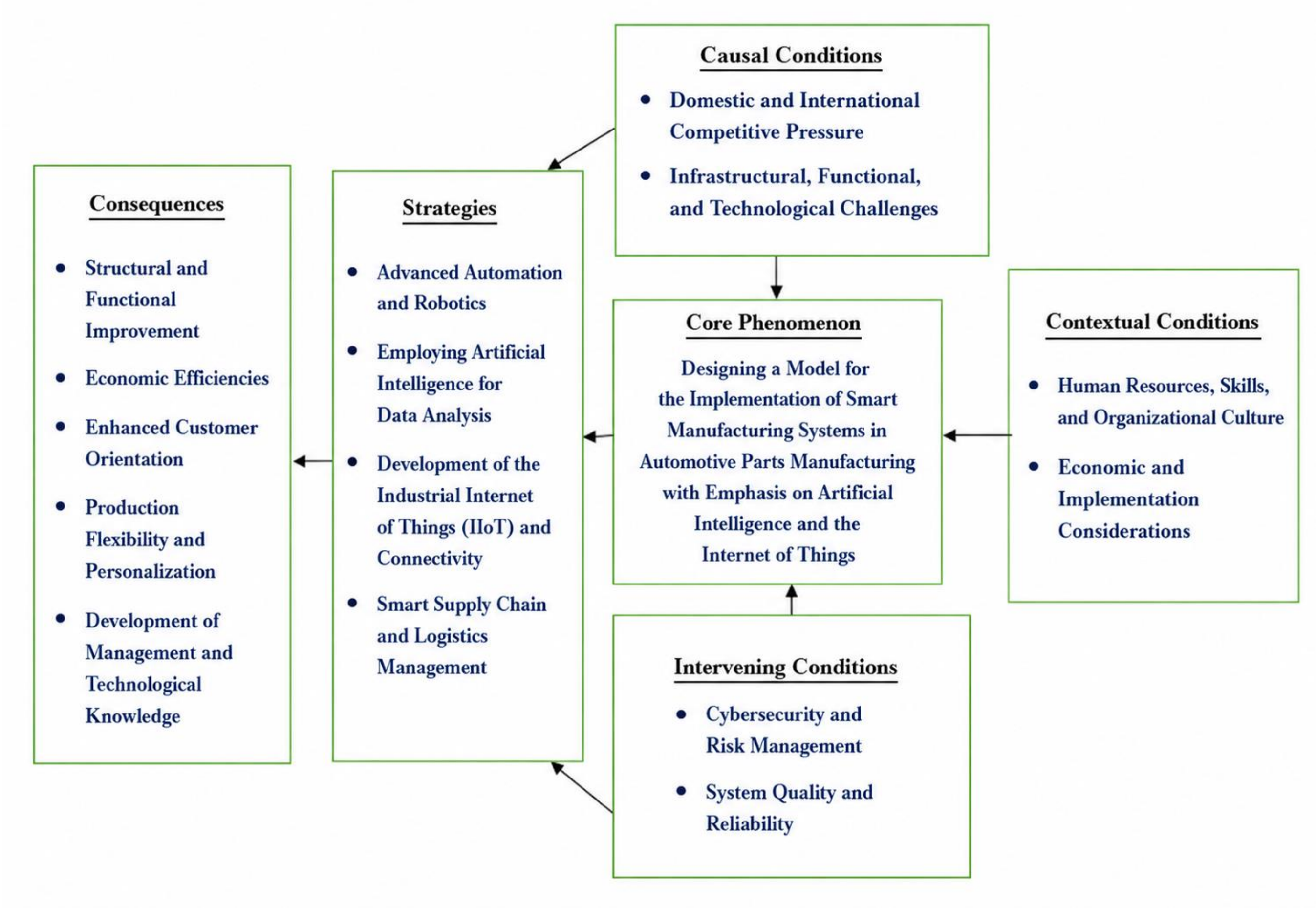
The strategic dimension of the model includes four major groups of actions: advanced automation and robotics, artificial intelligence-based data analysis, Industrial Internet of Things and connectivity, and smart supply chain and logistics management. These strategies represent the operational path through which automotive manufacturers can move from traditional production systems toward intelligent and adaptive production systems. The use of robotics in assembly, automation of control processes, AI-based visual quality control, big data analytics, real-time equipment monitoring, smart inventory management, and connectivity with suppliers are among the most important strategic components identified by the experts.

The consequences of implementing smart manufacturing systems were classified into structural and functional improvement, economic efficiencies, customer orientation, production flexibility and personalization, and development of management and technology knowledge. The results suggest that smart manufacturing can improve production line productivity, reduce downtime, decrease raw material waste, optimize energy consumption, improve quality inspection accuracy, enhance worker safety, support product innovation, and enable mass customization. In addition, the model shows that smart manufacturing contributes to data-driven decision-making, standardization of communication protocols, simulation-based production planning, development of native software, and organizational knowledge management.

Overall, the axial coding results indicate that the implementation of smart manufacturing systems in automotive parts manufacturing requires a comprehensive and integrated model. The core phenomenon of the study is the design of a model for implementing smart manufacturing systems with emphasis on artificial intelligence and the Internet of Things. This model is shaped by competitive and technological pressures, enabled by organizational and infrastructural readiness, influenced by cybersecurity and reliability concerns, operationalized through automation, AI, IoT, and smart logistics strategies, and finally reflected in productivity, flexibility, quality, economic efficiency, customer satisfaction, and technological knowledge development.

Figure 1

Proposed Model for Implementing Smart Manufacturing Systems in Automotive Parts Manufacturing with Emphasis on Artificial Intelligence and the Internet of Things



Discussion and Conclusion

The present study sought to identify the dimensions and components of smart manufacturing systems in the automotive industry with an emphasis on the application of Artificial Intelligence (AI) and the Internet of Things (IoT), and to develop a comprehensive implementation model based on the perspectives of industry and academic experts. The findings revealed that the implementation of smart manufacturing systems is a multidimensional phenomenon influenced by a combination of causal conditions, contextual conditions, intervening conditions, strategic actions, and organizational consequences. More specifically, the proposed model demonstrated that competitive pressures, technological challenges, organizational readiness, cybersecurity considerations, advanced automation, artificial intelligence, industrial internet of things technologies, and smart supply chain management collectively shape the successful deployment of intelligent manufacturing systems in automotive parts production.

One of the most significant findings of the study was the identification of domestic and international competitive pressure as a major causal condition influencing the adoption of smart manufacturing systems. Experts emphasized that increasing demands for quality improvement, faster product development cycles, demand forecasting, and compliance with international manufacturing standards are forcing automotive firms to embrace intelligent production technologies. This finding is consistent with previous research suggesting that global competition and rapidly changing customer expectations have become major drivers of Industry 4.0 adoption and manufacturing digitalization. Studies have shown that organizations increasingly utilize AI-driven production systems to improve responsiveness, quality performance, and operational agility in highly competitive markets [1-3]. Similarly, research on automotive transformation highlights that intelligent manufacturing technologies provide firms with strategic advantages through enhanced efficiency, innovation, and market responsiveness [9, 11].

Another important result concerned the role of infrastructural, functional, and technological challenges as causal conditions affecting smart manufacturing implementation. The participants highlighted issues such as network infrastructure requirements, system integration difficulties, technical knowledge transfer, maintenance complexity, and implementation duration. These findings indicate that technological readiness remains a prerequisite for digital transformation. Similar conclusions have been reported in previous studies emphasizing that successful smart manufacturing initiatives require robust digital infrastructures, interoperable systems, and effective integration of legacy manufacturing technologies with emerging AI and IoT platforms [3, 5]. Furthermore, Dini et al. noted that embedded Industrial Internet of Things applications often face implementation challenges associated with data interoperability, communication protocols, and system integration, supporting the present findings [15].

The findings also identified human resources, skills, and organizational culture as critical contextual conditions. Experts consistently emphasized the importance of specialized training, workforce development, organizational learning, and innovation-supportive cultures. Resistance to technological change was identified as a major barrier to implementation. This finding supports the growing body of literature suggesting that digital transformation is not merely a technological process but a socio-technical transition requiring substantial organizational adaptation. Previous studies have demonstrated that human-centric manufacturing systems perform more effectively when employees possess the competencies necessary to interact with intelligent technologies and when organizations foster cultures that encourage innovation and continuous learning [21, 27]. Likewise, Industry 5.0 perspectives emphasize balancing technological advancement with human expertise, underscoring the importance of workforce readiness and organizational culture in intelligent manufacturing environments [1, 4].

Economic and implementation considerations emerged as another important contextual dimension. The experts highlighted high initial investment costs, uncertainty regarding return on investment, organizational readiness, government support, cooperation with universities, and collaboration with knowledge-based firms. These findings suggest that financial and institutional support mechanisms are essential for accelerating smart manufacturing adoption. Previous studies similarly report that implementation costs and investment uncertainty remain among the most significant barriers to Industry 4.0 deployment, particularly in developing economies and technologically constrained environments [2, 18]. The importance of university-industry collaboration identified in the present study is also supported by research indicating that innovation ecosystems and knowledge-sharing networks facilitate technological diffusion and accelerate industrial digitalization [3, 5].

A particularly noteworthy finding was the identification of cybersecurity and risk management as a major intervening condition influencing implementation success. Experts recognized cybersecurity as an essential component of smart manufacturing due to increasing system connectivity and data exchange. As production systems become increasingly dependent upon IoT devices, cloud platforms, and AI-based analytics, vulnerabilities associated with cyberattacks, data breaches, and operational disruptions become more significant. This finding strongly aligns with recent studies emphasizing cybersecurity as one of the most critical challenges facing Industry 4.0 and Industry 5.0 environments [24, 25]. Research has demonstrated that AI-driven cybersecurity solutions, risk management frameworks, and explainable security mechanisms are increasingly necessary for protecting industrial cyber-physical systems from sophisticated threats [20, 26]. The findings therefore reinforce the argument that cybersecurity should not be treated as a secondary consideration but rather as an integral component of intelligent manufacturing architectures.

System quality and reliability also emerged as important intervening factors. The experts emphasized the need for reliable intelligent systems capable of supporting continuous production and data-driven decision-making. This finding is consistent with studies indicating that the value of AI-enabled manufacturing depends heavily on the reliability, accuracy, and robustness of technological infrastructures. Intelligent systems must provide trustworthy information and maintain stable performance under varying operational conditions to achieve their intended benefits [7, 23]. Furthermore, explainable and transparent AI models have been identified as critical mechanisms for increasing trust in automated decision-making processes within manufacturing environments [4, 26].

Regarding implementation strategies, the findings revealed four principal strategic domains: advanced automation and robotics, artificial intelligence-driven data analytics, Industrial Internet of Things development, and smart supply chain management. The prominence of automation and robotics reflects the increasing role of intelligent machines in enhancing manufacturing productivity, consistency, and safety. The experts identified robotics applications in assembly, logistics, and process control as key components of future manufacturing systems. These findings are consistent with studies demonstrating that intelligent automation and robotics significantly improve operational efficiency while reducing human exposure to hazardous environments [21, 22]. Research further indicates that AI-enhanced robotics contribute to adaptive manufacturing systems capable of responding dynamically to changing production requirements [23].

The importance of artificial intelligence for data analysis represents another significant finding. Participants highlighted the role of AI in quality control, production planning, process optimization, and predictive decision-making. These results support previous literature showing that AI technologies are transforming manufacturing by enabling predictive analytics, machine learning-driven optimization, defect detection, and intelligent decision support systems [6, 8]. In particular, studies focused on the automotive sector have demonstrated that AI-based systems significantly improve quality assurance, production efficiency, and operational visibility [9, 12]. The identification of big data analytics and advanced planning systems in the present study further reinforces the growing importance of data-driven manufacturing ecosystems [7, 23].

The development of Industrial Internet of Things capabilities was identified as another essential strategic component. Experts emphasized real-time connectivity, equipment monitoring, system integration, production flexibility, and ecosystem development. These findings align with the literature describing IoT as the technological backbone of smart manufacturing systems. IoT technologies enable continuous data collection, machine-to-machine communication, and intelligent process coordination, creating highly connected production environments capable of supporting autonomous decision-making and adaptive control mechanisms [15, 16]. Furthermore, the convergence of AI and IoT has been recognized as a key driver of next-generation intelligent manufacturing systems, enabling predictive maintenance, energy optimization, and enhanced operational intelligence [17, 18].

Smart supply chain and logistics management also emerged as a major strategic dimension. Participants emphasized intelligent inventory management, supplier integration, logistics automation, and real-time monitoring. This finding is particularly relevant in automotive manufacturing, where supply chain complexity significantly influences operational performance. Previous studies indicate that intelligent supply chain systems improve visibility, resilience, and decision quality through advanced analytics and interconnected digital infrastructures [29]. Furthermore, research focusing on risk assessment in automotive supply chains demonstrates that uncertainty, supplier performance variability, and geopolitical constraints necessitate more intelligent and adaptive supply chain management approaches [28].

The consequences identified in the proposed model further validate the strategic importance of smart manufacturing systems. The findings showed that implementation contributes to structural and functional improvements, economic efficiencies, customer orientation, production flexibility, and technological knowledge development. Increased productivity, reduced waste, predictive maintenance, enhanced quality inspection, and improved worker safety were among the most frequently cited outcomes. These results closely align with previous studies reporting substantial operational benefits from AI and IoT adoption in industrial settings [8, 18]. Predictive maintenance, for example, has consistently been associated with reduced downtime, lower maintenance costs, and increased equipment availability [17, 19]. Similarly, intelligent quality control systems have demonstrated significant improvements in defect detection and process reliability [12, 13].

The findings additionally suggest that smart manufacturing supports customer-oriented production through mass customization and enhanced responsiveness to changing market demands. These capabilities are increasingly important in the automotive sector, where consumers expect greater personalization and shorter product development cycles. Previous studies have similarly highlighted the role of AI and intelligent automation in enabling flexible and customer-centric manufacturing systems capable of delivering customized products without sacrificing efficiency [10, 11]. Furthermore, the identified outcomes related to organizational knowledge development, simulation capabilities, and data-driven decision-making support broader arguments regarding the transformative impact of AI on managerial effectiveness and strategic planning [6, 31].

Overall, the proposed model demonstrates that smart manufacturing implementation in automotive parts manufacturing is a complex and multidimensional process requiring the simultaneous alignment of technological infrastructures, organizational capabilities, human resources, cybersecurity mechanisms, and strategic management practices. The findings contribute to the existing literature by integrating these diverse dimensions into a comprehensive framework specifically tailored to the automotive manufacturing context and emphasizing the synergistic role of artificial intelligence and the Internet of Things in enabling intelligent industrial transformation.

This study has several limitations that should be considered when interpreting the findings. First, the study employed a qualitative research design based on a relatively small sample of experts, which may limit the generalizability of the findings to all segments of the automotive industry. Second, the perspectives collected were primarily based on expert experiences and perceptions rather than direct measurement of organizational performance outcomes. Third, the rapidly evolving nature of artificial intelligence and Internet of Things technologies means that some identified dimensions and components may change as new technologies emerge. Finally, contextual factors specific to the automotive sector and the regional industrial environment may influence the applicability of the proposed model in different countries or industries.

Future studies should quantitatively validate the proposed model using large-scale samples from automotive manufacturing organizations. Researchers may also investigate the causal relationships among the identified dimensions through structural equation modeling and other advanced analytical techniques. Comparative studies across different industrial sectors could provide insights into the transferability of the model beyond automotive manufacturing. In addition, future research may explore the role of emerging technologies such as generative artificial intelligence, digital twins, edge computing, blockchain, and autonomous industrial agents in expanding the capabilities of smart manufacturing systems. Longitudinal studies would also be valuable for examining how smart manufacturing maturity evolves over time and influences organizational performance.

Automotive manufacturers should adopt a holistic approach to smart manufacturing implementation that simultaneously addresses technological, organizational, and human-resource requirements. Organizations should invest in workforce development programs to ensure employees possess the skills necessary to operate and manage intelligent production systems. Managers should prioritize cybersecurity planning and risk management from the earliest stages of implementation. Establishing strong collaborations with universities, research institutions, and technology providers can facilitate knowledge transfer and innovation. Furthermore, organizations should pursue phased implementation strategies that allow gradual technological integration while minimizing operational disruption. Continuous monitoring, data-driven decision-making, and the development of flexible digital infrastructures will be essential for achieving sustainable competitive advantages through smart manufacturing transformation.

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Authors’ Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants. Written consent was obtained from all participants in the study.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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