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Production system optimization in industry 4.0: A new organizational approach to intelligent automation

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Abstract

This study explores the contribution of digital artificial intelligence tools to productive systems within the industry 4.0 paradigm. It highlights how emerging intelligent technologies have transformed operational processes, leading to increased automation, efficiency, and sustainability. This research aims to analyze how digital technologies supported by artificial intelligence help to the optimization and productive of organizations. A qualitative and descriptive approach was used, based on a systematic literature review following the PRISMA method. Scientific articles published between 2020 and 2025 were analyzed. The information was gathered from internationally recognized academic, including Scopus, Web of Science, and Science Direct. The keywords used for the search were artificial intelligence, industry 4.0, automation, and digital transformation. Selected documents underwent both content and descriptive statistical analysis trends, predominant styles, and significant findings. A total of 20 articles were analyzed and categorized by theory. The most prominent technologies identified were: artificial intelligence, internet of things, big data, and cyber-physical systems. Additionally, 15 studies were examined to address the research questions posed. This study concludes that artificial intelligence enhances efficiency, sustainability, and innovation in the industrial sector. However, its effective implementation requires overcoming obstacles such as resistance to change and a lack of training. Success ultimately depends on mixing technology with qualified human factors who are committed to organizational transformation

Keywords: artificial intelligence, industry 4.0, automation, optimization, production systems.

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1. Introduction

Industry 4.0 has established a milestone in global production systems, driving a digital revolution that reinterprets industrial processes. This new phase, characterized by the incorporation of burgeoning digital technologies such as artificial intelligence AI, the internet of things IoT, cloud computing, and data analytics, has facilitated the automation and optimization of production systems with an unprecedented level of accuracy and efficacy. In this context, AI is solidified as a foundational pillar, providing cutting-edge solutions in fields like energy management, smart manufacturing (Chiang et al., 2024), and demand forecasting. The digitization and automation in the industry 4.0 era are enhancing the way corporations manage their production processes. Despite these technological advancements, many companies have not yet effectively adopted these tools to a lack of expertise, high implementation costs, and organizational resistance (Zong & Guan 2025; Choi, 2025).

The integration of AI into production processes enables not only smarter and more flexible manufacturing but also introduces novel opportunities and challenges in capital management, decision-making, and the establishment of sustainable practices. This technological revolution prompts transformations that are not just technological but also social, organizational, and labor-related. This perspective aligns with sociotechnical systems theory, which posits that the success of such changes depends on the balanced interaction between humans and technology. Within the industrial sector, industry 4.0 technologies represent a significant digital and automation investment that has redefined competition for small and medium-sized enterprises SMEs. The fourth industrial revolution has influenced and helped industrial processes across various sector, leading to optimized resource utilization and improved productivity within corporations (Anshari & Ordóñez, 2025).

In this context, it is crucial to analyze the impact of technological instruments of industry 4.0 on a company's productive outcomes, as their implementation can optimize resources, improve decision-making, and reduce downtime. The IoT, AI, and enhanced automation have down tangible benefits for operational efficiency, quality, and sustainability across various competitive sectors.

Authors such as Duran & Castillo (2023) in their research conducted within the Colombian context, note that among the 135 companies surveyed, approximately 50% of the entrepreneurs were unaware of these technologies, while the other half had only limited knowledge of them. This highlights a significant issue of a lack of awareness, which consequently hinders their application.

Given the lack of mindfulness and limited application of AI technologies within the Colombian context, the following research question is posed: in what ways do AI technological tools impact the productive performance of organizations within the framework of industry 4.0? To address this central question, several key sub-questions emerge: what are the most relevant technological tools employed in industry 4.0? How does the integration of AI impact the efficiency, planning, and maintenance of production processes within the framework of industry 4.0? What common patterns and best practices can be identified from the different approaches of industry 4.0?

To answer the questions, the general objective of this study is to analyze the contribution of AI technological tools to the productive performance of organizations in the paradigm of industry 4.0. This objective will be achieved through the following three specific objectives: 1. Identify the most relevant technological tools for industry 4.0 used in organizations and their application in production processes? 2. Determine the impact of AI on the optimization of productive processes in industry 4.0 organizations, and 3. Compare different approaches and case studies on the implementation of AI in industrial organizations to identify standards and best practices.

The methodology employed in this research is qualitative-descriptive, grounded in a documentary review of current sources published within the last five years 2020 and 2025. Through the analysis of scientific and technical literature, the most frequently used data analysis tools were identified and systematized. This process allowed for the evaluation of their characteristics, levels of accessibility, and utility across different application scenarios.

This article is organized into distinct sections that progressively and coherently address the theoretical foundations of data analysis, the classification of existing technological tools, and a detailed description of the most representative ones. Finally, the conclusions and a discussion summarize the main findings and highlight the importance of the tools for optimizing productive processes in the new digital era of industry 4.0.

2. Theoretical framework

2.1 Artificial intelligence

The integration of AI has fundamentally revolutionized demand forecasting through the implementation of highly accurate and adaptative predictive models. These systems not only learn but also continuously improve over time. AI-driven demand forecasting leverages advanced techniques such as deep learning, reinforcement learning, and hybrid AI models to analyze huge amounts of both structured and unstructured data. This capability allows for the identification of hidden patterns and the generation of real-time forecasts (Paul & Longdet, 2025; Bin, 2024).

This transformation aligns with the progress of the fourth industrial revolution, which has significantly advanced AI and its daily application in the form of machine learning ML. ML plays a pivotal role in addressing inherent manufacturing challenges by enhancing and optimizing process quality (Rakholia et al., 2024; Culot et al., 2024). The adoption of AI and ML is becoming increasingly common in factory operations (Fahle et al., 2020). This is considered the fourth industrial revolution as it represents a comprehensive system that strengthens companies through innovative technologies. It signifies a new organizational and value chain management framework spanning a product's lifecycle and production systems, all enabled by information technologies (Yang & Gu, 2021). The core objective is to develop automation tools based on data collection from smart devices like software and sensors, which facilitate and optimize processes (Ghobakhloo et al., 2025; Bolton et al., 2018).

Mixing these technologies into manufacturing offers immense potential to increase productivity, efficiency, and safety. However, achieving these benefits requires a concerted effort to upskill the workforce and prepare them for the challenges of the digital era (Tsaramirsis et al., 2022). Furthermore, due to the exponential growth of industrial data during this revolution, deep learning solutions have gained popularity in predictive maintenance PM. This approach involves monitoring assets to anticipate their needs and optimize maintenance tasks (Serradilla et al., 2022).

2.2 Industry 4.0

Industry 4.0 has led to greater automation of industrial processes, which has enhanced operational efficiency. The integration of technologies like internet of things IoT and AI optimizes production, enables real-time monitoring and machinery and production systems, anticipates errors, and reduce downtime (Hughes et al., 2022; Rai et al., 2021).

The adoption and use of industry 4.0 technologies have grown rapidly in some nations while remaining a challenge in others. This divergence is attributed to technological progress and development, which has created new information to support the competitive advantages of valuable assets and foster innovative techniques that optimize organizational productivity (Javaid et al., 2023). According to Queiroz et al., (2025) the combination of digital skills is crucial for increasing productivity, innovation, and employment. Overcoming structural obstacles and promoting strategies for training and digitalization will enable employees and companies to adapt to the challenges of the digital age.

These technologies and their positive impact, along with their association with organizational management in the pursuit of sustainable alternatives for businesses, are widely discussed in scientific and commercial circles (Li, 2024; Gharibvand et al., 2024). There is no doubt that technological changes contribute to every industrial process. Moreover, the rapid entry of new technology has enabled the youth to spearhead a digital revolution across several sectors of the global economy, although this transformation is progressing more slowly in developing nations (Lim, 2019).

3. Method

3.1 Methodological design

This research was conducted under a qualitative perspective, employing a non-experimental descriptive design. The primary method utilized was a Systematic Literature Review SLR, which followed the rigorous guideline of the PRISMA method (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) statement. This approach was adopted to ensure the transparency, rigor, and reproducibility of the search and selection process across various databases.

3.2 Inclusion y exclusion criteria

Table 1 specifies the criteria that guided the inclusion and exclusion of the reviewed articles.

Table 1. Inclusion y exclusion criteria

Inclusion criteria	Exclusion criteria
Publications from 2020 to 2025 were considered	Duplicated works or those not verifiable in reliable academic sources, or with restricted access
Studies written in English	Studies of an exclusively theoretical nature, documents without empirical or statistical support, opinion articles, and reviewers without methodological analysis (essays, opinions, editorials)
Peer-reviewed publications indexed in Scopus, Web of Science, and Science Direct	Research focused on sectors other than the productive sector
Studies that show the use of AI in productive contexts and present quantifiable results about its impact	
Documents with applied cases in industrial sectors that provide empirical data to support their conclusions	

Source: authors

3.3 Information sources and search strategies

A robust search strategy was developed based on a technical search query. This query systematically combined key descriptors related to the study's central topic: AI, industry 4.0, automation, and digital transformation. The structure of the search was established by logical combining the terms using Boolean operators to ensure comprehensive and relevant results.

3.3.1 Technical criteria of the search equation

The search methodology was defined by the following technical criteria:

- Primary descriptors: Three main groups of descriptors were selected to represent the core topics of the research: *AI, industry 4.0, and automation*.
- Booleans operators: to effectively combine the descriptors and refine search, the following Boolean operators were used: *And* to link different groups of descriptors, ensuring that all concepts were present in the search results, and *Or* to include synonyms or closely related terms within the same descriptor group.
- Search constraints: The study was limited by the following criteria to ensure the relevance and quality of the sources: *publication date*: documents published between 2020 and 2025, *language:* articles written in English, and *Document type*: the search was focused on peer-reviewed academic works, such as journal articles and conference papers.

Table 2 shows the structure of the search equation in the SLR process.

Table 2. Structure of the search equation

Component	Description	Boolean operator	Final equation
Artificial intelligence (AI)	Terms related to AI, sucha as "artificial	OR	("artificial intelligence" OR "AI")

	intelligence"		
Industry 4.0	Terms related to "industry 4.0"	OR	("industry 4.0 " OR "production")
Automation	Terms related to "automation"	OR	("automation" OR "mechanization")
Final combination of descriptors	Relationship between the main descriptors	AND	("artificial intelligence" OR "AI") AND ("industry 4.0" OR "production") AND ("automation" OR "mechanization")

Source: authors

3.3.2 Implementation of the equation in databases

The search equation was implemented in the Scopus, Web of Science, and Science Direct databases. This process, which was conducted for the period between 2020 and 2025, yielded relevant and peer- reviewed articles.

3.4 Selection and analysis of studies

The selection process was carried out in two stages: First, a review of titles and abstracts was performed to filter studies with the highest potential. This was followed by a comprehensive and in-depth evaluation of the full content of the selected studies to determine their relevance, applying the previously defined inclusion and exclusion criteria.

4. Results

4.1 The most important technological tools for industry 4.0 used in organizations and their use in production processes

The studies featured in Table 3 analyze the technological and conceptual advancements related to industry 4.0. These works focus on key tools such as Cyber-Physical Systems (CPS), the IoT, digitalization, and cloud computing.

The research highlights how these technologies enable a deep transformation of industrial procedures, introducing significant efficiency, automation, and intelligent capabilities that redefine production and resource management. Furthermore, the investigations consider both the technological developments and their social and economic implications, with a particular emphasis on the Latin American context.

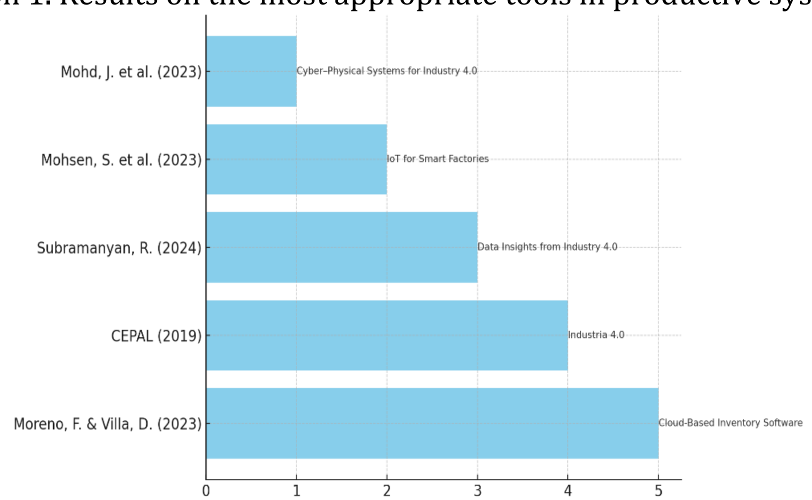
Table 3. Results on relevant technological tools for industry 4.0 used in production processes in organizations

Author and year	Title	Contribution
Mohd et al., (2023)	An integrated outlook of Cyber–Physical Systems for Industry 4.0: Topical practices, architecture, and applications	This presents a comprehensive view of Cyber-Physical Systems (CPS) in industry 4.0, focusing on current practices, technological

		architectures, and key applications in industrial sectors.
Mohsen et al., (2023)	Internet of Things for Smart Factories in Industry 4.0: A Review	Review of the use of the internet of things (IoT) in smart factories, highlighting its role in automation, operational efficiency, and device connectivity in industry 4.0.
Subramanyan et al., (2021)	Evaluation of enablers of cloud technology to boost industry 4.0 adoption in the manufacturing micro, small and medium enterprises	Analyze how data generated by industry 4.0 technologies can be translated into practical knowledge for effective decision-making in manufacturing processes
CEPAL (2019)	Industry 4.0	Study the economic and social impacts of industry 4.0 in Latin America, emphasizing challenges such as the technological gap and the need for inclusive public policies.
Moreno & Villa (2023).	Cloud based manufacturing: A review of recent developments in architectures, technologies, infrastructures, platforms and associated challenges.	This research examined cloud technologies proposed for implementation of Cloud manufacturing such as architectures, models, frameworks, infrastructure, interoperability, virtualization, optimal service selection

Source: authors

Graph 1. Results on the most appropriate tools in productive systems



Source: own elaboration

Graph 1 shows the number of publications pertaining to industry 4.0, encompassing thematic areas such as cyber-physical systems, smart factories, and cloud-based inventory management.

Within the framework of industry 4.0, digital transformation has catalyzed the adoption of advanced technological tools designed to optimize production systems, enhance operational efficiency, and promote sustainability (Mohsen et al., 2023). Among the most salient technologies are AI, the IoT, Cyber-Physical Systems (CPS), cloud computing, and big data analytics. It last, in particular, serves as a critical tool by converting vast volumes of both structured and unstructured data into valuable information for strategic decision-making. Within production processes, this capability facilitates improved planning, early problem detection, performance evaluation, and the customization of products and services (Mohd et al., 2023).

AI is one of the most influential technologies. It is deployed in process automation, energy management, and demand forecasting. Through machine learning algorithms, organizations can identify hidden patterns into large datasets, make real-time decisions, and anticipate potential operational failures, thereby reducing downtime and increasing productivity (Moreno & Villa, 2024). Concurrently, the IoT enables the interconnection of devices, sensors, and machinery into manufacturing facilities, generating real-time data that is essential for informed decision-making and the continuous monitoring of production processes. CPS integrate physical and digital components, enabling seamless interaction between the physical and virtual realms. These systems underpin the development of smart factories, where processes can autonomously adapt to changing conditions (CEPAL, 2019). Through CPS, machines can communicate with each other (machine-to- machine) and with human operators (human-machine, interface), resulting in more flexible and customizable production processes. Cloud computing complements these technologies by providing a scalable and secure infrastructure for the storage and processing of data generated by connected devices (Moreno & Villa, 2023). Organizations can access digital platforms any location, facilitating remote collaboration, seamless software updates, and the integration of new services without significant capital investment in local hardware.

4.2 Influence of artificial intelligence on the optimization of production processes in industry 4.0 organizations

Table 4 consolidates research examining the role of AI and machine learning within the context of industry 4.0. The studies illustrate how these technologies enhance decision-making, optimize processes, reduce cost, and improve adaptability to evolving business demands. Through applications such as predictive analytics and intelligent automation, the potential of AI to generate sustainable competitive advantages in both manufacturing and commercial sectors is emphasized.

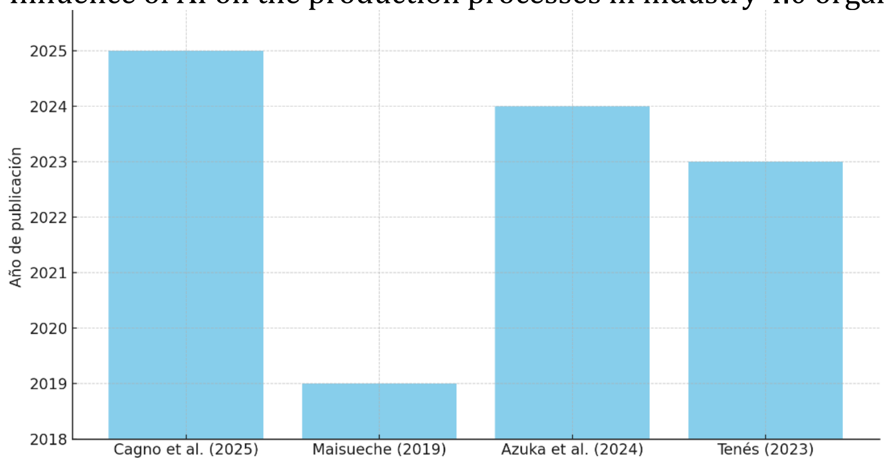
Table 4. Results on the influence AI on the optimization of production processes in industry 4.0 organizations

Author and year	Title	Contribution
Cagno et al., (2025)	Energy management and Industry 4.0: Analysis of the enabling effects of digitalization on the implementation of energy management practices	Examine how digitalization into the framework of industry 4.0 facilitates the implementation of energy management practices in industrial companies
Maisueche, (2019)	Machine learning in manufacturing and industry 4.0 applications	ML techniques have been used in a variety of manufacturing applications in the past, many open questions and challenges remain, from big data curation, storage, and understanding, data reasoning to enable real-time actionable intelligence to topics such as edge computing and cybersecurity aspects of smart manufacturing
Azuka et al., (2024)	Predictive Analytics for Market Trends Using AI: A Study in	Explore how AI and predictive analytics enable anticipating market trends through

	Consumer Behavior	the analysis of consumer behavior
Tenes, (2023)	Impact of artificial intelligence on businesses	Investigate the impact of AI on organizational dynamics, with a focus on its role in strengthening business competitiveness

Source: authors

Graph 2. Influence of AI on the production processes in industry 4.0 organizations



Source: own elaboration

An analysis of the literature a consistent and growing interest in research concerning AI and industry 4.0 in recent years, with studies ranging from the seminal work of Maisueche (2019) to the most recent investigation by Cagno et al., (2025). This trend underscores the increasing relevance of digital and energy transformation into industrial sectors over the past decade. Within this framework, AI has emerged as a transformative pillar of the industry 4.0 paradigm, playing a fundamental role in the optimization of production processes (Cagno et al., 2025). Its synergistic integration with technologies such as IoT, CPS, and big data analytics has driven significant evolution in organizational management, control, and the execution of industrial operations.

A primary contribution of AI lies in intelligent automation, which transcends mere task repetition. Through machine learning algorithms, systems can derive knowledge from data and autonomously and continuously optimize to their performance. This result in more efficient, flexible, and market-responsive processes, substantially reducing production times, and waste (Maisueche, 2019).

Furthermore, AI enables technologies tools, and application in industry 4.0 environments. Utilizing sensors and real-time analytics, it is possible to anticipate equipment failures before they occur, thereby preventing unplanned production downtime and extending asset lifespan. This practice not only increases operational availability but also optimizes maintenance by avoiding unnecessary corrective interventions. AI also exerts a positive influence on demand forecasting and production planning. By employing advanced predictive models, organizations can analyze market behavior patterns, consumer preferences, and external variables, enabling the dynamic adjustment of production levels (Azuka et al., 2024). Consequently, this enhances inventory management efficiency, minimizes losses from obsolescence or overstock, and improves responsiveness to environmental fluctuations.

Additionally, AI strengthens strategic decision-making by providing executives with deep, real-time analytics on operational status. This capacity to transform complex data into actionable insight allows organizations to anticipate problems, evaluate multiple scenarios, and make evidence-based decision, thereby enhancing corporate competitiveness (Tenes, 2023).

4.3 Comparison of approaches and case studies on the use of artificial intelligence in industrial organizations: patterns and best practices in industry 4.0

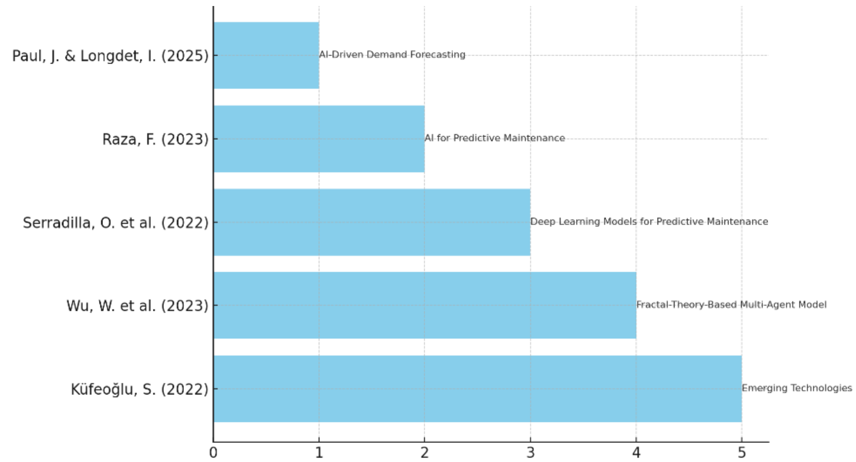
Table 5 compiles studies that examine specific applications of AI- particularly deep learning models and multi-agent systems- for optimizing industrial processes. A prominent thematic focus is predictive maintenance, which enables the anticipation of systems and equipment failures, thereby enhancing operational continuity. Furthermore, the Table 5 reviews innovative proposals, such as customized cyber-physical production systems and the impact of emerging technologies within modern industry. Collectively, these investigations reflect the growing integration of intelligent models, operational efficiency, and industrial personalization.

Table 5. A comparison of approaches to the use of AI in organizations: patterns and best practices in industry 4.0

Author and year	Title	Contribution
Paul & Longdet, I. (2025)	AI-Driven Demand Forecasting: Enhancing Accuracy in Supply Chain Planning	This research analyzes the mechanisms by which AI algorithms increase the precision of need-based forecasting, resulting in more robust and efficient supply chain planning
Raza, (2023)	AI for Predictive Maintenance in Industrial Systems	This study analyzes the implementation of AI in predictive maintenance systems, which facilitates the early detection of incipient faults and optimizes operational efficiency
Serradilla et al., (2022)	Deep Learning Models for Predictive Maintenance: A Survey, Comparison, Challenges and Prospects	A Comprehensive review of deep learning models for predictive maintenance, highlighting their advantages, limitations, and future challenges
Wu et al., (2023)	A Fractal-Theory-Based Multi-Agent Model of the Cyber Physical Production System for Customized Products	It proposes a cyber-physical production system model based on fractal theory and multi-agent systems for personalized manufacturing
Küfeoğlu, (2022)	Emerging Technologies	It reflects on the implications of modern technologies, including AI and digitalization, for the transformation of industrial and societal sectors

Source: authors

Graph 3. A comparison of approaches to the use of AI in organizations: patterns and best practices in industry 4.0



Source: own elaboration

Graph 3 shows the authors, titles, and contributions of their publications on topics such as AI and emerging technologies.

Within the context of industry 4.0, AI has been deployed across various industrial organizations through multiple approaches, yielding significant improvements in operational efficiency, product customization and energy management. A comparative analysis of these approaches facilitates the identification of common patterns and best practices, which can serve as a guideline for other organizations seeking to integrate AI into their production processes.

One prominent slant involves the use of autonomous learning-based predictive models to forecast demand and manage supply chains. For instance, according to Paul & Longdet (2025), companies have substantially enhanced their foretelling accuracy by integrating deep learning models with historical data analysis. This methodology not only improves production planning but also mitigates losses associated with inventory surplus or shortfalls.

Another significant application is technology predictive maintenance. Research by Raza (2023) and Serradilla et al., (2022) highlights how AI, by analyzing real-time sensor data, enables the anticipation of machinery failures and a drastic reduction in unplanned downtime. This practice has emerged as one of the most cost-effective AI applications in manufacturing, with its success being directly contingent upon the proper integration of sensors, robust algorithms, and high-quality data.

Regarding energy optimization, studies such as that by Keramati et al., (2025) demonstrate that AI can identify patterns of energy consumption and propose real-time adjustments, thereby enhancing economic efficiency and environmental sustainability. This is particularly valuable in energy industries, where even marginal efficiency gains can translate into substantial cost savings.

An emerging approach is that of intelligent mass customization, as noted by Wu et al., (2023) and Küfeoğlu (2022). Leveraging AI, industries such as automotive and electronics have developed production systems capable of adapting to specific customer requirements without compromising efficiency or significantly increasing costs. This strategy relies on big data analytics, 3D printing, and collaborative robotics.

A comparison of these cases reveals several common success factors: the efficient acquisition of real-time data, system interoperability, the continuous training of AI algorithms, and the development of human expertise to interpret and act upon the generated insights. Best practices include progressive implementation, cross-functional integration between technical and strategic units, and the continuous evaluation of outcomes for dynamic recalibration.

5. Discussion

Technological tools based on AI have had a decisive impact on strengthening the productive sector by enhancing efficiency, sustainability, and innovation within the framework of industry 4.0. Technologies such as the IoT, big data, CPS, and cloud computing have enabled the automation of processes, reduction of errors, and continuous optimization of decision-making. These solutions have not only improved energy management but have also facilitated mass customization and human-machine collaboration, thereby redefining existing production models. Collectively, these tools act as catalysts for transformation in industrial environments, enabling more agile, interconnected, and resilient processes in response to the demands of the global market.

Despite its relevant contributions, this research focused exclusively on the manufacturing sector, which constitutes a significant limitation. This narrow scope prevents the extrapolation of findings to other strategic sectors- such as agriculture, healthcare, or logistics- where advanced digital solutions are also being integrated. By concentrating solely on manufacturing, the study does not account for the specific particularities, challenges, and opportunities that other productive contexts might present in terms of technological adoption and digital transformation. Consequently, the results and conclusions presented here must be interpreted within this specific context and should not be automatically generalized to other sectors.

The analyzed technological tools were predominantly studied into manufacturing industry organizations, with particular emphasis on the use of technologies such as AI, IoT, CPS, and data analytics. Most of the reviewed literature corresponds to experiences implemented in countries with high levels of industrial digitalization, such as Germany, the United States, China, and South Korea. However, relevant applications were also identified in emerging contexts, such as Colombia, where a low level of familiarity with these technologies was observed, highlighting challenges related to knowledge dissemination and implementation. These technologies were deployed at various levels of the productive system, from process automation to energy management and product customization, demonstrating a versatility that facilitates their adaptation to companies of different sizes, especially small and medium-sized enterprises (SMEs) seeking to enhance their competitiveness in the new industrial landscape.

Furthermore, it is essential to expand the analysis to other economic sectors to fully understand the impact of AI and industry 4.0 technologies in non-manufacturing contexts. Further research is also required to study the dynamics of technological adoption in regions with lower levels of digital development, particularly in Latin America, Africa, and Southeast Asia, where significant technological gaps keep it up. Another relevant avenue of inquiry is the assessment of the social and ethical implications arising from the integration of AI in the workplace, considering aspects such as the reconfiguration of professional roles, vocational training, and the interaction between humans and intelligent systems. Finally, we suggest the exploration of interdisciplinary approaches that integrate technical, organizational, and cultural elements to design more inclusive, sustainable, and contextually adapted implementation processes.

6. Conclusions

The findings of this research lead to the conclusion that AI- based technological tools, in conjunction with other emerging technologies such as the IoT, CPS, and big data, have significantly transformed production systems within the manufacturing industry. These technologies have demonstrated a capacity to automate processes, optimize resources, and enhance decision-making, thereby generating positive impacts on operational efficiency, sustainability, and corporate competitiveness.

Among the most relevant findings, the implementation of mass customization, and intelligent automation stand out as key applications of AI contexts. These approaches enable the anticipation of failures, reduction of downtime, adaptation of production to specific customer demands, and minimization of material waste. It is important to note that their success is largely contingent upon the adequate integration of technological and human factors, as proposed by sociotechnical theory, which emphasizes the necessity of balancing technical capabilities with organizational and workforce competencies.

Furthermore, common success patterns in technology adoption were identified, including the efficient acquisition of real-time information, system interoperability, continuous training of human talent, and a strategy of progressive implementation. Despite these advancements, significant challenges persist in regions with lower levels of industrial digitalization, particularly in emerging economies, where a lack of knowledge, resistance to change, and insufficient in technological infrastructure remain prevalent.

Finally, this research confirms that industry 4.0 technological tools constitute an essential driver for innovation and the improvement of productive performance in the manufacturing sector. However, their effective implementation demands a strategic vision that encompasses both technological and human aspects. Firms that successfully coherently integrate these elements will be better positioned to navigate the complexities of digital transformation and capitalize on the opportunities to steer the complexities of digital transformation and capitalize on the opportunities presented by the fourth industrial revolution.

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