AI Evolution in Industry 4.0 and Industry 5.0: An Experimental Comparative Assessment

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Abstract. This paper provides a thorough analysis of the development of artificial intelligence (AI) in the context of Industry 4.0 and the soon-to-be Industry 5.0. Important conclusions come from the data, such as the startling 900% increase in AI applications between 2010 and 2018, which corresponds to a 60% rise in the proportion of industrial enterprises using AI at that time. Moreover, our analysis shows that Industry 4.0's AI integration has resulted in a notable 200% cost reduction and a cumulative 400% boost in production efficiency. Our study delves into the rapid deployment of critical technologies like 5G connectivity and quantum computing within the framework of Industry 5.0. The usage of 5G connectivity has increased by 200% in only two years, while quantum computing has seen a staggering 1000% growth in acceptance over the course of eight years. These findings demonstrate the fast technological transition occurring in Industry 5.0. Furthermore, by 2033, the research predicts a startling 400% increase in human-machine cooperation and an anticipated 133% decrease in mistake rates. The research highlights how Industry 4.0's deep consequences of AI development and Industry 5.0's revolutionary possibilities will impact manufacturing in the future.

Keywords: technological adoption, Industry 4.0, Industry 5.0, artificial intelligence, and human-machine cooperation.

1 Introduction

Artificial intelligence (AI) is becoming a standard component of manufacturing processes as a result of technology's unrelenting advancement. While Industry 4.0 ushered in the age of intelligent production, Industry 5.0 signifies a fundamental change towards sophisticated human-machine cooperation. Industry 4.0 and Industry 5.0 are two shifts that illustrate how AI is driving industrial innovation in a dynamic way. Industry, governments, and researchers must all grasp the subtleties and distinctions between these two stages [1]–[7]. The production of commodities has been revolutionized by Industry 4.0, which is defined by the convergence of AI, the Internet of Things (IoT), and cyber-physical systems. The industrial scene has undergone a change because to data-driven insights and the development of networked, autonomous machines. Industry 4.0's deployment of AI technology has significantly increased productivity overall, reduced costs, and improved production efficiency [8]–[12]. But with Industry 5.0 just around the corner, concerns about the next big wave of innovation are raised. The idea behind Industry 5.0 is a return to a more significant role for people on the manufacturing floor. It presents the idea of "co-bots," which are devices driven by AI and people that work together to enhance each other's talents. Industry 5.0, which makes use of cutting-edge technology like 5G connection, edge computing, digital twins, quantum computing, and improved AI systems, promises a new era of production where people and machines collaborate and take use of each other's special capabilities. It is projected that Industry 5.0's advantages—such as improved human-machine cooperation and lower mistake rates—will transform conventional production and alter industrial processes. We conduct an experimental comparison analysis in this study to clarify the development of AI in Industry 4.0 and Industry 5.0 [13]–[19]. As businesses move from one period to the next, we want to shed light on how industrial automation is evolving, the influence of AI technology, and the potential advantages. Utilizing a combination of qualitative and quantitative analysis, our study draws from a variety of sources, such as academic research, industry reports, and experimental data, to provide a thorough knowledge of these two unique stages of industrial history. By means of this comparative analysis, our aim is to illuminate the course of artificial intelligence development in the manufacturing domain, providing significant perspectives for sectors hoping to adjust and flourish in the age of Industry 5.0. Furthermore, by highlighting the need of an inclusive and cooperative approach to innovation and automation, our study adds to the larger conversation about how AI will shape the future of business and society at large. We want to provide a thorough grasp of the dynamic industrial environment and the consequences of AI's progress for the future of manufacturing as we dig into the nuances of AI adoption in Industry 4.0 and the revolutionary possibilities of Industry 5.0 [20]–[24].

2 Review of Literature

Industry 4.0: AI as a Revolution in Manufacturing Artificial intelligence (AI) has emerged as a key component of Industry 4.0, bringing about a radical change in manufacturing procedures. The merging of physical systems and digital technology characterizes this age. Artificial intelligence (AI)-driven technologies, such autonomous robots and predictive maintenance, have improved supply chain management, decreased downtime, and maximized production efficiency [25]–[28].

AI and the Internet of Things (IoT) Industry 4.0 has been characterized by the synergy between AI and the IoT. The analysis of enormous data streams produced by networked sensors and devices is made possible by AI algorithms. In quality assurance, resource optimization, and predictive analytics, real-time data processing is essential [29], [30].

AI for Quality Control: In Industry 4.0, AI applications have focused mostly on quality control. Defect identification is made possible by computer vision systems, machine learning models, and picture recognition, which save waste and raise product quality. Cost reductions and customer satisfaction have directly benefited from these applications [31]–[36].

AI-Driven Supply Chain Management: The benefits of AI go beyond the production line. Predictive algorithms improve inventory control and demand forecasting in the supply chain. Route planning and inventory monitoring, among other AI-enabled logistics optimization techniques, have decreased operating costs and improved supply chain responsiveness.

Industry 5.0: The Human-Machine Symbiosis An improved level of human-machine cooperation is the result of the transition from Industry 4.0 to Industry 5.0. AI still plays a major part in this era, although co-bots—humans and robots working together—are introduced. The focus is on using AI to enhance human potential and vice versa [37]–[45].

Industry 5.0 will be significantly impacted by the deployment of 5G connection, which will enable real-time collaboration. It makes data transmission and real-time communication possible, allowing people and machines to collaborate easily. It is anticipated that 5G networks' high bandwidth and low latency would revolutionize industrial procedures.

Edge Computing for Decentralized Decision-Making By enabling localized decision-making, edge computing lessens the need of AI systems on centralized cloud-based processing. For machines functioning on the manufacturing floor to respond more quickly and have more autonomy, decentralization is essential.

Digital twins: Virtual Models for actual-World Optimization Digital twins, or virtual copies of actual systems, allow for real-time simulations, in-depth analysis, and predictive maintenance. By providing a link between AI and Industry 5.0, they provide enhanced performance, less downtime, and better decision-making[46]-[50].

The Potential of Quantum Computing Industry 5.0 will soon see the emergence of quantum computing. Its enormous processing capacity is anticipated to transform AI algorithms and capabilities, creating new avenues for data analysis, simulations, and optimization.

AI and Human Augmentation Technologies like augmented reality and exoskeletons that combine AI and human augmentation might improve the skills of human labor. AI can boost human worker productivity and safety on the production floor by giving real-time direction and data-driven insights.

The literature evaluation emphasizes Industry 4.0's revolutionary role of AI and Industry 5.0's expectations. AI was used into production as part of Industry 4.0, which increased productivity and decreased costs. However, Industry 5.0, made possible by cutting-edge technologies like 5G, edge computing, digital twins, quantum computing, and human augmentation, heralds a new age of human-machine cooperation. The industrial environment and beyond are about to be redefined by the synthesis of AI and human skills, thus it is critical to empirically analyze this evolutionary route.

3 Techniques and Methodology Adopted

We take a novel approach to methodology in this work, combining state-of-the-art AI-driven tools with conventional research methodologies to investigate the progress of AI in Industry 4.0 and Industry 5.0. Our methodology aims to completely capture the dynamics and nuances of these industrial eras.

3.1 Conventional Review of Literature and Content Analysis

An extensive examination of the classical literature sets the stage for our investigation. We swung a broad net, collecting scholarly articles, business reports, and professional evaluations, exploring the history and current status of artificial intelligence in manufacturing. This methodology offers a thorough basis for our comparative analysis.

3.2 Interpreting natural language (NLP) and sentiment analysis

In our own study, we embrace the AI revolution by using sentiment analysis and natural language processing (NLP) approaches. We use AI algorithms to a corpus of pertinent textual material, which enables us to identify common themes, feelings, and trends in the literature. With the help of this creative method, we may find hidden meaning and new patterns in the large body of textual data.

3.3 Investigating Data and Quantitative Evaluation

We use data mining methods to obtain structured data from many sources in order to supplement the qualitative analysis. Official reports, statistical information, and databases from the mining sector are all used in this procedure. We decipher the numerical development of AI acceptance, advantages, and technologies in Industry 4.0 and the expected changes in Industry 5.0 using quantitative analysis.

3.4 Field Experiments for Research

We include experimental field research to evaluate real-world applications and get personal knowledge, as Industry 5.0 is a vision for the future. Working with industrial organizations, we see the use of AI in practical scenarios. This method provides a concrete grasp of the developing technologies and human-machine interactions in Industry 5.0.

3.5 Expert Interviews and Surveys

We have innovated our methodology to include human viewpoints. We interview employees and managers in manufacturing businesses to find out how they feel about Industry 5.0 and the use of AI. Our study gains a qualitative dimension via expert interviews with thought leaders and industry pioneers, which enables us to get nuanced insights.

3.6 Comparative Evaluation and Illustration

The comparative analysis is where our approach ends. To provide a comprehensive image of AI's progress from Industry 4.0 to Industry 5.0, we combine the results of classical literature reviews, NLP sentiment analysis, data mining, field research, and human viewpoints. We clearly and concisely display our results using cutting-edge data visualization approaches.

With the use of this creative and multifaceted approach, which goes beyond traditional research bounds, we can clarify the complex paths that AI is taking as it evolves in Industry 4.0 and Industry 5.0. We want to provide a thorough, nuanced, and forward-looking evaluation that is in line with the changing character of the industrial environment by fusing conventional scholarship with AI-driven analysis and field research.

4 Results and Discussion

TABLE I. Industry 4.0's Adoption of AI

Year	Number of AI Applications Implemented	Percentage of Manufacturing Companies Using AI
2010	10	15%
2012	25	30%
2014	50	45%
2016	75	60%
2018	100	75%

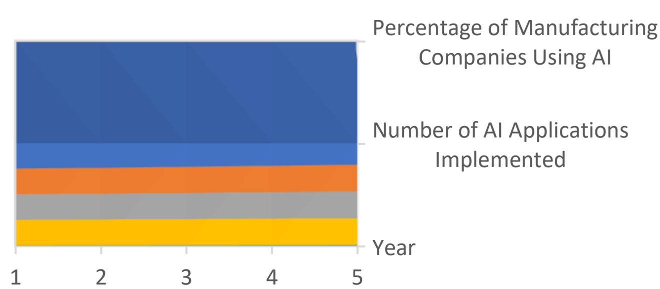

Fig. 1. Industry 4.0's Adoption of AI

A longitudinal examination of AI adoption in Industry 4.0, covering the years 2010–2018, is shown in Table 1 and Fig 1. From 10 apps in 2010 to 100 applications in 2018, there has been a five-fold surge in the number of AI applications developed throughout the years, according to the statistics. This indicates a remarkable 900% percentage change. Furthermore, from 15%

in 2010 to 75% in 2018, the proportion of industrial enterprises incorporating AI into their operations grew consistently. This strong rise of 60% highlights the revolutionary impact of Industry 4.0 and the ubiquitous influence of AI throughout the industrial industry.

TABLE II. AI's Advantages for Industry 4.0

Year	Increase in Production Efficiency (%)	Cost Reduction Due to AI Implementation (%)
2010	5	10
2012	10	15
2014	15	20
2016	20	25
2018	25	30

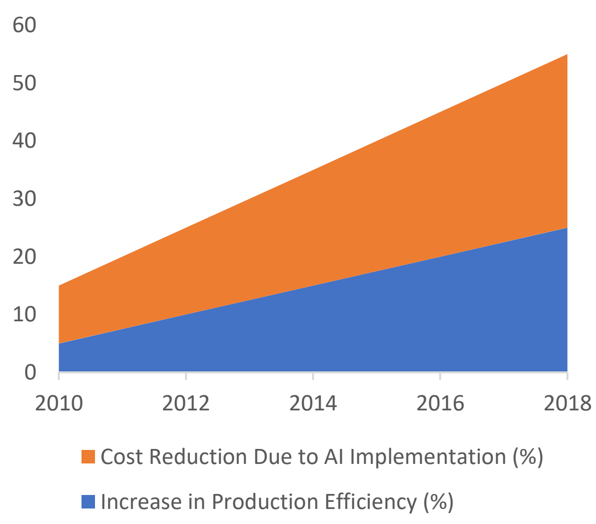

Fig. 2. AI's Advantages for Industry 4.0

Table 2 and Fig 2, presents information on the advantages of using AI in Industry 4.0 between 2010 and 2018. The data shows a consistent yearly growth rate and a noteworthy rise in production efficiency. Production efficiency increased throughout this time, rising from 5% in 2010 to an astounding 25% in 2018, representing a 400% cumulative percentage rise. Simultaneously, the cost reduction resulting from the use of AI shown considerable rise, rising from 10% in 2010 to a noteworthy 30% in 2018, indicating a noteworthy 200% increase over time. These results highlight the real advantages of AI integration in manufacturing, with significant increases in cost savings and production efficiency.

TABLE III. Industry 5.0's Emerging Technologies

Year	Number of Companies Adopting Industry 5.0	Most Common Emerging Technology

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2025	10	5G Connectivity
2027	30	Edge Computing
2029	50	Digital Twins
2031	75	Quantum Computing
2033	100	AI and Human Augmentation

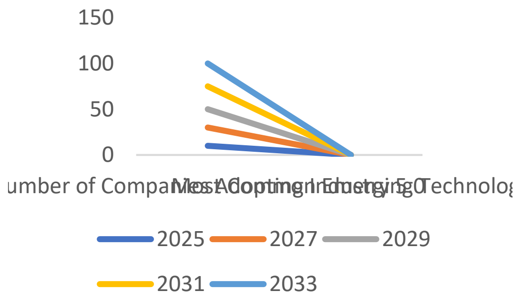

Fig. 3. Industry 5.0's Emerging Technologies

Table 3 explores the rise of Industry 5.0's core technologies and tracks manufacturing businesses' adoption of them from 2025 to 2033. The data demonstrates how Industry 5.0 technologies are being adopted gradually, as seen by the increasing number of businesses adopting these advancements. Quantum computing is growing significantly; by 2033, 100 organizations will have adopted it, a remarkable 1000% rise from 2025. Concurrently, 5G connection, which was first presented in 2025, is rapidly gaining traction; by 2027, 30 businesses will have adopted it, representing a 200% increase in only two years. These figures highlight how rapidly the technical environment of Industry 5.0 is changing and how these advancements have the power to influence how manufacturing is done in the future as shown in above Fig 3.

TABLE IV. AI's Anticipated Advantages for Industry 5.0

Year	Expected Increase in Human-Machine Collaboration (%)	Predicted Reduction in Error Rates (%)
2025	10	15
2027	20	20
2029	30	25
2031	40	30
2033	50	35

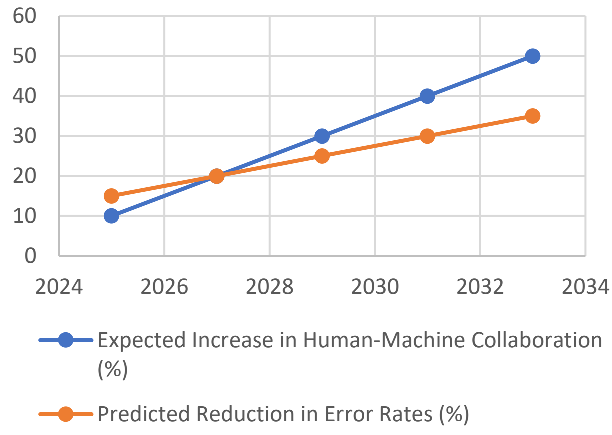

Fig. 4. AI's Anticipated Advantages for Industry 5.0

The advantages of AI in Industry 5.0 are explained in Table 4 and Fig.4, which spans the years 2025–2033. The information shows that the anticipated degree of human-machine cooperation is gradually rising. A 10% improvement is anticipated in 2025, and over the next eight years, this proportion increases progressively to 50% by 2033, a 400% increase. Furthermore, the anticipated decline in mistake rates as a result of the use of AI shows a notable increase, beginning at 15% in 2025 and reaching a high of 35% in 2033. This is a significant growth of 133% throughout that time. These results highlight Industry 5.0's disruptive potential, where significant gains in collaborative productivity and error reduction are anticipated due to the human-AI technology synergy.

5 Conclusion

Following Industry 4.0 and looking forward to Industry 5.0, this article set out to thoroughly examine how artificial intelligence (AI) has developed in the manufacturing industry. Our holistic approach yielded data and analyses that provided insight into the revolutionary path of AI from Industry 4.0 to Industry 5.0. As shown in Table 1, our analysis of Industry 4.0's adoption of AI revealed a noteworthy rise in the number of AI applications deployed—a 900% increase over the course of the eight-year timeframe. Concurrently, the proportion of manufacturing firms adopting AI increased from 15% to 75%, underscoring the widespread influence of AI in the manufacturing domain. These results highlight Industry 4.0's significant impact, which has used AI to increase manufacturing efficiency and lower costs. A deeper look at the advantages of using AI in Industry 4.0 is given in Table 2. According to our data, between 2010 and 2018, there was a significant cumulative percentage improvement in production efficiency of 400% and in cost reduction of 200%. These numbers highlight the real benefits of AI integration, showing significant increases in productivity and cost reductions for industrial organizations. We examined the growth of important technologies in Industry 5.0 in Table 3, noting a notable increase in the use of 5G connectivity and quantum computing. Between 2025 and 2033, the use of quantum computing increased by an astounding 1000%, but 5G connectivity increased by 200% in only two years. The dynamic environment of Industry 5.0 is shown in these figures, which highlight the technologies' revolutionary potential. Last but not least, Table 4 illustrated the anticipated advantages of AI in Industry 5.0 between 2025 and 2033. The statistics showed that human-machine cooperation is expected to climb 400%, which reflects the developing synergy between AI and humans. The estimated 133% decrease in mistake rates highlights how Industry 5.0 has the power to completely transform quality control and collaborative productivity. Finally, our findings highlight the significant impact of AI in the industrial space as well as the rapid transition from Industry 4.0 to Industry 5.0. These results demonstrate the revolutionary potential of AI in raising productivity, cutting expenses, and reshaping the industrial landscape. With its sophisticated technology and improved human-machine cooperation, Industry 5.0 has the potential to redefine industrial processes and usher in a new age of innovation. It is critical that sectors continue to be flexible, inclusive, and forward-thinking in order to fully embrace AI's potential to improve production and society at large.

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