Role of An Effective Strategy In Ai-based Product Manufacturing Industries – A Systematic Literature Review

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ABSTRACT

The paper on the role of an effective strategy in Artificial Intelligence based product manufacturing delves into the evolving landscape of technology and its impact on modern product design and manufacturing processes.

With traditional manufacturing facing challenges in context of time- consuming processes and manual labour, the emergence of AI-based manufacturing processes utilizing machine learning algorithms and other AI technologies presents transformative potential. This research investigates various strategies employed in AI-based product manufacturing and analyses their effectiveness in terms of time, cost, and quality. The scope of the study focuses on six AI strategies, namely Machine Learning, Deep Learning, Internet of Things, Neural Networks, Big Data, and Robotics.

Keywords : AI Strategies, Strategic Decision Making, Product Design and Manufacturing Process.

Introduction

Considering the evolving landscape of technology and its profound impact on modern product design and manufacturing processes, the introduction sets the stage for understanding the need for effective strategies in AI-based product manufacturing by highlighting the challenges faced by traditional manufacturing processes and the transformative potential of AI technologies. Evolution of technology has had a dramatic effect on modern product design and manufacturing, resulting in shorter product life cycles, an increased preference for personalization, and a greater focus on producing smaller batches of varied items Traditional manufacturing processes are based on manual labour and limited automation. They involve a long and intricate series of steps to manufacture a product, including designing the product, procuring materials, manufacturing, and assembly. This process is time-consuming and often relies on human effort.

In contrast, AI-based manufacturing processes utilize machine learning algorithms and other AI technologies to automate and optimize production. The AI system can be trained to detect data patterns, identify potential issues, and take corrective actions. This can significantly reduce manufacturing overheads and improve product quality. Additionally, AI can be used to monitor product manufacturing in real-time, ensuring greater precision and efficiency.

have carried out research on application of AI in software engineering. Their research talks about application of AI in every part of Software development life cycle - planning, analysis, design, implementation, testing, integration and maintenance. It also talks about different AI strategies like big data analysis, machine learning and artificial neural networks that are applicable in each phase for managing complex tasks like computer vision or natural language processing. This research attempts to provide IT industry a lookout on possibilities that can be explored regarding application of AI in software development life cycle.

Similarly,) have carried out research wherein the researchers have created AI model based on nonlinear programming and have transformed it further in linear programming while solving for design and implementation process of RH alloying model. There are other researchers like who have researched on impact of artificial intelligence on future of marketing, who have researched on role of business intelligence on organisation's success and who have researched on application on nonlinear programming for creating telecommunication model. All the aforementioned researchers have thought-out and analysed the AI based technologies in several real life and engineering problems and found reasonable results. There work is a stepping stone in conceptualizing and analysing scope of usage of AI strategies.

The emergence of AI-based products has allowed companies to produce higher-quality items more quickly and economically. However, to make the most of this technology, effective strategies must be implemented to ensure that the manufacturing process is efficient, cost-effective, and meets customer needs. A well-thought-out strategy is essential as it provides detailed guidance for the creation and launch of the product. It defines the goals and objectives and outlines all the necessary steps required to achieve them. By having a clear strategy in place, all stakeholders can remain organized and focused on obtaining top-notch results. Moreover, a well-defined strategy can help anticipate potential issues and ensure that all necessary resources are accessible for the successful completion of the project.

An effective strategy in AI-based product manufacturing should incorporate a comprehensive understanding of customer requirements, a well-defined timeline, and an understanding of technology capabilities. Additionally, it is imperative to contemplate the costs associated with AI-based product development, the time it takes to develop the product, and any risks associated with using this technology. With an effective strategy in place, businesses can optimize the benefits from AI-based manufacturing and ensure the success of their products in today's market.

Section 2 Discusses about Literature Review, the theoretical base of the Paper. Section 3 elucidates about the methodology used followed by the characteristics of the Data in Section 4. Section 5 provides insights about the results and discussion of the study. The conclusion summarizes the findings and highlights implications for future research and limitations of the study.

Literature Review

Artificial Intelligence (AI) has revolutionized industries, including product manufacturing, with applications throughout the product lifecycle. It aims to explore the diverse applications and successful implementations of AI in product manufacturing, offering insights for organizations seeking to integrate AI into their operations.

AI has the potential to enhance product design through concept generation, virtual prototyping, and design optimization. However, the adoption of AI, big data analytics, IoT, and blockchain technologies varies across businesses, with predictive maintenance, inventory management, demand forecasting, customer analytics, data acquisition, and product provenance being the most implemented applications According to , the automotive manufacturing leads in implementing machine learning for risk assessment, demonstrating the industry's willingness to embrace AI in product and process development. AI offers the potential to improve product quality and reduce manufacturing costs, but selecting the appropriate AI framework for engineering and manufacturing processes poses challenges due to the wide range of theories, methods, and algorithms available However, this also provides opportunities to tailor AI frameworks to specific manufacturing or product development requirements, cost considerations, and production environments. In the manufacturing sector, AI is extensively utilized for tasks such as product assembly, packaging, and quality control, particularly in conjunction with methodologies like six sigma Further research is needed to explore effective strategies, safety considerations, and the application of AI in maintenance tasks in product manufacturing.

According to digital transformation (DT) involves the implementation of digital tools, techniques, and automation to revolutionize businesses, applications and services. In engineering, DT enables the replacement of manual processes with automation, addressing big data challenges and leveraging system information. This integration of digital tools and automation enhances system efficiency, promoting innovation and creative approaches. presented research on the implementation of Industrial Internet of Things (IIoT) and artificial intelligence (AI) in vehicular logistics and supply chain management. Their proposed IIoT integrated vehicle logistics system efficiently managed a logistic network with numerous nodes, ensuring security and achieving superior performance compared to similar models. Their model offers cost savings, reduced energy consumption, and improved output performance, enhancing efficiency and effectiveness in vehicle logistics operations. Their research highlights the potential of the model to optimize logistics processes and improve outcomes, emphasizing the usability of IoT in logistics and supply chain management. offered valuable insights into the transition from pre-scheduled preventive maintenance to predictive maintenance in cyber-physical production systems. By utilizing real-time operational data and employing a deep learning algorithm, their study aims to enhance maintenance efficiency and effectiveness. Their research emphasizes the potential of advanced technologies, such as deep learning, in optimizing maintenance strategies and maximizing operational performance. The findings contribute to the field of predictive maintenance and underscore the value of real-time data in decision-making processes. The approach has the potential to revolutionize maintenance practices by providing accurate and timely insights into machine health and performance.

demonstrated that Machine Learning, in conjunction with digital manufacturing techniques, creates a cyber-physical platform for additive manufacturing. Their study focuses on predicting deposition angles in Fused Deposition Modelling (FDM) using an ensemble-based machine learning classifier, outperforming existing methods. The potential for future work includes a web application utilizing deep neural networks to predict optimal deposition angles, highlighting opportunities for further research in digital manufacturing. highlighted the strengths and limitations of deep learning and proposes the integration of fuzzy systems to address uncertainty and imprecision. This fusion of fuzzy systems and deep learning offers promise in improving the robustness and adaptability of AI models, enabling better handling of real-world complexities. Both studies contribute to advancing the field of artificial intelligence by exploring complementary approaches to enhance accuracy and address challenges. emphasized on the growing importance of Big Data Analytics (BDA) in intelligent manufacturing systems. BDA enables forecasting and decision-making capabilities, unlocking insights and optimizing processes through analysis of large datasets. Integrating BDA in manufacturing empowers manufacturers to make informed decisions, improve efficiency, and drive innovation. By leveraging real-time data and predictive analytics, manufacturers can anticipate market demands, optimize production schedules, and enhance supply chain management. BDA also enables advanced quality control, defect detection, and predictive maintenance, minimizing downtime and maximizing productivity. The recognition of BDA's transformative impact underscores its significance in research and industry, driving value creation and sustainable growth in manufacturing.

The remarkable growth of the Internet of Things (IoT) market and its projected expansion by tenfold by 2025 , researchers highlight the need for advanced technologies to optimize wireless networks. AI, including machine learning and deep learning, offers potential solutions to address the challenges posed by diverse IoT devices. Integrated photonics in neural networks can accelerate processes and provide cost-effective manufacturing and assembly, revolutionizing the field of artificial intelligence. The speed and scalability of integrated photonics create opportunities for real-time applications and improved network performance. These advancements have the potential to shape a more connected and efficient IoT ecosystem.

The evolution of robots in manufacturing involves transitioning from nonprogrammable to programmable systems. The concept of program-free robots that can adapt to uncertainties through learning, particularly reinforcement learning, is gaining recognition in smart robotic manufacturing This learning ability mimics the reward-based mechanisms observed in living creatures and holds significant potential for enhancing robotic control. By integrating learning mechanisms, manufacturers can develop robots that exhibit adaptability, efficiency, and autonomy, contributing to the realization of intelligent manufacturing systems. Smart manufacturing (SM) integrates sensors, communication technology, computing platforms, simulating platforms, and data-intensive modelling to optimize manufacturing processes It represents an interconnected and intelligent approach that enables real-time data collection, informed decision-making, and advanced analysis through simulating platforms and data-intensive modelling. However, the wide range of available AI techniques and scattered literature pose challenges in selecting the most suitable AI technique for specific engineering or manufacturing processes and environments

The study has gathered most relevant literature considering scope and timelines of this research.

Conceptual framework

The conceptual framework for this study provides a comprehensive framework for understanding and implementing six key AI strategies in product manufacturing. Each component of the conceptual model plays an important role in enhancing different features of the manufacturing process. By examining and explaining each part of the model in detail, this work focuses on the potential benefits and implications of these AI strategies in product manufacturing.

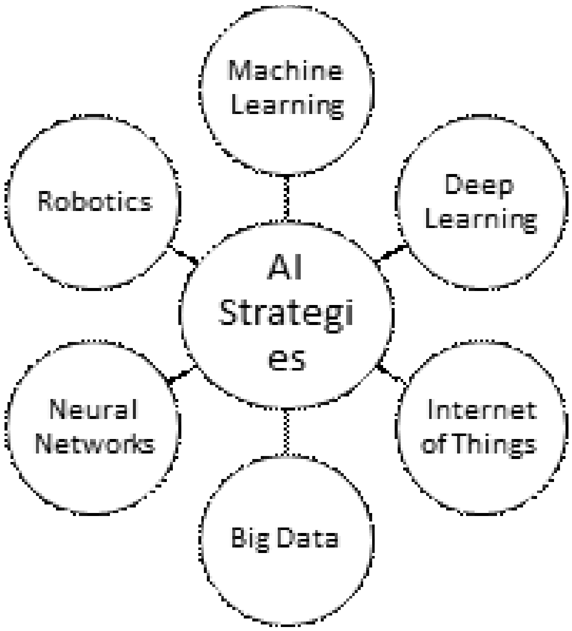

Figure 1: Conceptual Model for AI strategies

Machine Learning

It plays a significant role in AI-based manufacturing by enabling computers to learn from data and make predictions or decisions without explicit programming. In manufacturing, Machine Learning algorithms can analyse large datasets to understand patterns, optimize processes, predict equipment failure, and enhance product quality.

Deep Learning

Deep Learning, focuses on training deep neural networks with multiple layers to process complex data. In AI-based manufacturing, Deep Learning techniques excel in tasks that require pattern recognition, image and speech processing, and natural language understanding.

Internet of Things (IoT)

The Internet of Things plays a vital role in AI-based manufacturing by connecting physical devices, sensors, and machines to gather real-time data and enable intelligent decision-making.

Neural Networks

Neural Networks, inspired by the structure and function of the human brain, are computational models that process and transmit information. In AI-based manufacturing, Neural Networks are used for various applications such as fault diagnosis, process optimization, quality control, and anomaly detection.

Big Data

Big Data refers to large and complex datasets that are challenging to process using traditional data processing methods. In AI-based manufacturing, Big Data analytics enables the analysis of vast amounts of data collected from sensors, machines, and other sources to extract valuable insights.

Robotics

Robotics plays a crucial role in AI-based manufacturing by enabling automation and precision in various tasks. Robots can be programmed and controlled using AI techniques to perform complex operations, such as assembly, material handling, quality inspection, and packaging.

Methodology

The approach used in this study combines qualitative methods, trend analysis, and graphical data representation to examine the role of effective strategies in AI-based manufacturing. The findings and insights derived from this research aims to the advancement of knowledge and aids practical implications for the industry.

The research strategy employed in this study is an approach that emphasizes the analysis and synthesis of existing literature. It involves systematically reviewing and extracting relevant information from research papers to gain a better understanding of the topic. It allows for the identification of patterns, trends, and key insights regarding the role of effective strategies in AI-based product manufacturing. By utilizing this strategy, the research intents to provide a wideranging overview of the current state of knowledge in the field.

It also includes an extensive trend analysis of the manufacturing industry's adoption of AI-based manufacturing. This involves examining industry reports, market trends, and case studies to identify the increasing affinity towards AI strategies in product manufacturing. The aim is to gain insights into the current state of AI adoption, the specific strategies employed, and any emerging trends in the industry.

Followed by an extensive literature review, which is conducted to explore the rationale behind the manufacturing industry's selection of specific AI strategies. This involves reviewing academic research papers, industry publications, and relevant literature to understand the advantages, limitations, and risks associated with each AI strategy. The literature review helps to identify the key factors influencing the choice of AI strategies, such as cost-effectiveness, scalability, compatibility with existing systems, or the ability to improve product quality and efficiency.

Followed by a data representation technique, which is used to analyse and present information about the preferences of the manufacturing industry regarding AI strategies. This may involve collecting data from various sources such as industry surveys, interviews with industry professionals, or analysis of relevant datasets. The data representation technique helps identify which AI strategies are most sought after by the industry and provides a quantitative or qualitative understanding of their adoption.

By employing this research strategy, the paper aims to contribute to the existing knowledge in the research field by conducting trend analysis, visually representing data, and critically reviewing relevant literature. The strategy ensures a rigorous and systematic approach to the research, enhancing the validity and reliability of the study's findings and insights.

Characteristics of Data

Data Collection

Data collection for this research is conducted through the collection of research papers. The papers are selected based on their relevance to the topic of AI-based product manufacturing and the inclusion of effective strategies. Online paper publishing platform Scopus is used as primary source of information. The choice of Scopus as the primary source for literature search holds several advantages. Scopus is a widely recognized and respected platform within the academic community, providing access to a vast collection of peer-reviewed articles. Its extensive database encompasses publications from various disciplines, making it suitable for interdisciplinary research such as the study of AI-based product manufacturing. Additionally, Scopus employs rigorous selection criteria for indexing publications, ensuring that the retrieved literature is of high quality and relevance to initiate the literature search, a set of carefully chosen keywords were utilized to ensure the retrieval of pertinent articles. The selected keywords include "artificial intelligence," and "manufacturing." These keywords were specifically chosen to capture the major AI strategies relevant to the field of product manufacturing. By employing these keywords, the research aimed to encompass a broad spectrum of literature, ensuring the inclusion of various perspectives and approaches. The collection spans the period from 2015 to 2023 to ensure the inclusion of recent and up-to-date research for trend analysis and graphical data representation and most relevant papers from 2020 to 2023 for literature review. The selected research papers serve as the primary data source for the analysis and synthesis conducted in this study.

A trend analysis is a statistical technique used to identify and analyse patterns in a set of data. It involves observing data over a period of time to identify trends and patterns that may develop and to forecast future trends. Trend analysis can be used to measure various aspects of a business, including sales, profitability, competition, and customer behaviour. The researcher has used this research methodology to analyse the state of AI-based manufacturing and to derive and highlight its growing popularity amongst researchers and the engineering industry.

Statistics of the Reviewed Articles

A total of 574 papers were published from the year 2015 to 2022 and 85 papers were published in 2023 till June 27th. The table below provides more information on year-wise papers published.

Year of Publication	Papers Published on AI -based Manufacturing
2015	14
2016	21
2017	32
2018	50
2019	51
2020	90
2021	121
2022	195
2023 (Till June 27, 2023)	85

Table 1: Year-wise papers published on AI based manufacturing.

From 2015 to 2016 there was an increase of 7 papers, from 2016 to 2017 there was an increase of 11 papers, from 2017 to 2018 there was an increase of 18 papers, from 2018 to 2019 there was an increase of 1 paper, from 2019 to 2020 there was an increase of 39 papers, from 2020 to 2021 there was an increase of 31 papers, and from 2021 to 2022 there was a massive increase of 74 papers.

By analysing the data, the researcher observed a robust growth rate in the number of papers being published on AI-based manufacturing over the years. Visualization of the data will aid to better understanding of the trends.

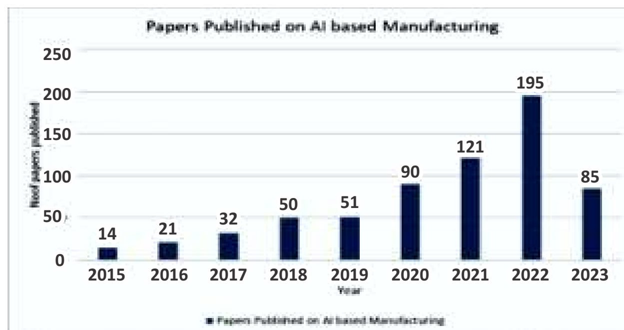

Figure 2: Year-wise trend of papers published on AI based manufacturing.

From the chart, it is visible that the number of papers published on AI-based manufacturing has been steadily increasing since 2015. However, there are also noticeable fluctuations in the growth rate. To gain a deeper understanding, the annual growth rate (AGR) for the years 2016 to 2022 can be calculated.

Annual Growth Rate (AGR) Calculation

To further analyse the trends, it is imperative to calculate the annual growth rate (AGR) for the years 2016 to 2022.

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AGR = [(Pn / Pn - 1) (1/n) - 1] * 100

Where:

Pn = the number of papers published in year n.

Pn-1 = the number of papers published in year n-1.

n = the number of years.

The AGR for the period from 2016 to 2022 is computed as follows:

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n = the number of years.
The AGR for the period from 2016 to 2022 is computed as follows.

Based on the calculated AGR, it is possible to estimate the average annual growth rate of papers published on AI-based manufacturing. It is essential to acknowledge that past trends do not guarantee future outcomes, as various factors can influence publication trends. Subsequently, the prediction for 2023 can be further explored.

Prediction for 2023

To predict the number of papers expected to be published on AI-based manufacturing in 2023, both the historical growth rate and the data available for the period until June 27, 2023, will be considered.

Average Annual Growth Rate (AAGR)

The calculation of the average annual growth rate (AAGR) for the 2016-2022 period is crucial in estimating the average growth rate of papers published each year. The AAGR is determined as follows:

AAGR (2016-2022) = (AGR (2016-2022)) / (n-1)

Where:

AGR (2016-2022) = previously calculated annual growth rate.

n = number of years.

AAGR (2016-2022) = 3.21%

Extrapolation for the Remaining Months of 2023

Extrapolation is employed to estimate the growth rate for the remaining months of 2023, encompassing the period from July to December. The extrapolation process is outlined as:

Predicted Papers (2023)

= Papers Published until June 27, 2023 +

(AAGR (2016) - 2022)

* Number of months remaining in 2023)

Predicted Papers (2023) = 85 + (3.21% * 6)

Predicted Papers (2023) $\simeq$ 85 + 0.1926

Predicted Papers (2023) ~ 85193

Consequently, based on the trend analysis and extrapolation, it is predicted that approximately 85 additional papers will be published on AI-based manufacturing in 2023

Data Distribution

To conduct this study, an extensive review of the literature on AI-based manufacturing was done. The identified papers were categorized based on their primary AI strategies. The distribution of papers across the identified AI strategies were then analysed to determine the proportionate representation of each strategy. Other AI strategies such as computer vision, natural language processing, expert systems are placed in 'Other AI technologies' category as those are out of scope of this study.

AI Strategy	Papers published on different AI Strategies
Big Data	8%
Deep Learning	13%
Internet of Things	13%
Machine Learning	34%
Neural Networks	5%
Robotics	12%
Other AI technologies	15%

Further visualization of data in graphical format shall help in understanding the data distribution concisely. Figure below graphically represents table above.

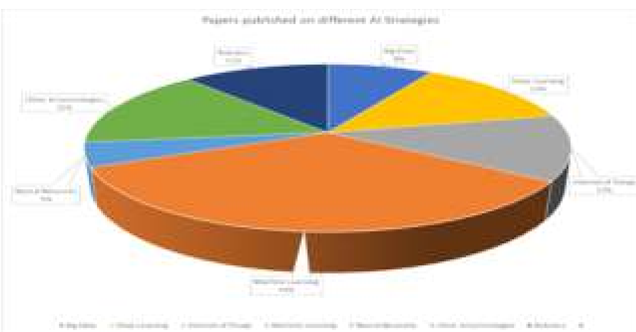

Figure 3: Graphical representation of AI strategy-wise distribution of papers

Results and Discussion

The role of effective strategy in AI-based manufacturing was explored by conducting a trend analysis of research papers published over a nine-year period, from 2015 to 2023. The trend analysis of papers published on AI-based manufacturing from 2015 to 2023 (June) highlights a consistent growth pattern. However, there appears to be a slight decline in the number of papers in 2023 (until June 27) compared to the previous year. By calculating the average annual growth rate (AAGR) and extrapolating it to the remaining months of 2023, it is predicted that approximately 85 more papers will be published on AI-based manufacturing in 2023. It is vital to note that these predictions are based on historical trends and underlying assumptions, and actual publication rates may vary due to various influencing factors. Also, the papers published in every month will not be same, there are high chances that the number will surpass 85 for the rest of the months in 2023. However, the outcomes indicate a substantial increase in the number of papers published. This upward trend suggests a rising interest towards the importance of effective strategies in AI-based manufacturing.

Which AI-based product manufacturing strategy/strategies are best suited for organizations?

Based on the literature review and the distribution of papers published on different AI strategies in the field of product manufacturing, the research question, "Which AI-based product manufacturing strategy/strategies are best suited for organizations?" can be addressed.

- Machine Learning (34% of papers published) is the most prevalent AI strategy in academic research related to product manufacturing. Its popularity can be attributed to its versatility, ability to handle large datasets, and effectiveness in learning from historical data to make data-driven decisions.
- Deep Learning (13% of papers published) is another prominent AI strategy in manufacturing research. Its application in manufacturing ranges from image recognition for defect detection to process optimization through reinforcement learning.
- Internet of Things (IoT) (13% of papers published) is also gaining traction in manufacturing. It plays a crucial role in data-driven decision-making and predictive maintenance in manufacturing processes.

- Big Data (8% of papers published) is closely related to machine learning and IoT. The abundance of data generated in modern manufacturing processes necessitates effective big data analytics to extract meaningful insights and facilitate data-driven decision-making.

- Other AI technologies (15% of papers published) encompass a diverse range of AI techniques, including robotics, hybrid models, and explainable AI. These technologies are employed in specific applications, such as quality control, fault diagnosis, process optimization, and human-robot interactions in smart manufacturing environments.

Considering the distribution of published papers, organizations should primarily focus on adopting Machine Learning and Deep Learning strategies in their product manufacturing processes. Machine Learning's versatility and Deep Learning's ability to learn intricate patterns from complex data make them well-suited for a wide range of manufacturing applications. Additionally, organizations can benefit from incorporating IoT and Big Data analytics to enhance real-time data collection, analysis, and predictive maintenance in manufacturing operations. Organizations should also keep an eye on emerging AI technologies falling under the "Other AI technologies" category, as they may offer innovative solutions for specific manufacturing challenges. These technologies can provide opportunities for enhanced quality control, fault diagnosis, and human-robot interactions in smart manufacturing environments.

To successfully implement AI-based strategies, organizations should consider the specific needs and challenges of their manufacturing processes, invest in robust data infrastructure, prioritize data privacy and security, and continuously update and improve their AI models to stay at the forefront of technological advancements.

Effective Strategy in AI-based Manufacturing

The results of this study provide valuable insights for articulating an effective strategy in AI-based manufacturing. The increasing trend of research papers indicates the growing importance of AI in manufacturing, making it imperative for industries to invest in AI technologies and strategies to stay competitive. The successful applications of ML in process optimization, predictive maintenance, defect recognition, and quality maintenance highlight the significant potential of ML techniques in enhancing manufacturing operations. Industries should prioritize incorporating ML technologies into their engineering processes to progress efficiency, reduce expenses, and enhance product quality. Furthermore, the advancements in Deep Learning and its successful applications in various manufacturing domains indicate the need for industries to explore and adopt deep learning techniques for complex problem-solving and optimization tasks. Integrating Deep Learning with existing manufacturing processes can lead to significant performance improvements and better decision-making. Industries should invest in IoT infrastructure and data analytics capabilities to harness the potential of IoT and Big Data in optimizing manufacturing operations and ensuring smooth production processes. Collaborative robotics and human-robot interactions have shown promise in enhancing manufacturing capabilities, improving safety, and increasing efficiency. Manufacturers should explore the integration of collaborative robotic systems in their production lines to leverage their benefits and enhance overall manufacturing performance. Addressing environmental and sustainability challenges is crucial for the manufacturing industry's long-term growth and viability. The application of AI, IoT, and Big Data in promoting circular economies, reducing carbon footprints, and implementing environmentally friendly design parameters can contribute to a more sustainable manufacturing ecosystem.

Conclusion

The study highlights the role of effective strategy in AI-based manufacturing. The literature review revealed that Machine Learning is the most prominent AI strategy in manufacturing, accounting for 34% of the published research papers. The diverse applications of Machine Learning in manufacturing include laser surface texturing optimization, predictive maintenance, defect detection, surface roughness prediction, and quality assessment of biomedical implants. Additionally, the trend analysis of research papers on AI-based manufacturing showed a significant upward trajectory, with a remarkable growth in publications from 2015 to 2023. The role

of Deep Learning in manufacturing was also explored in the literature review, highlighting its significant advancements and successful applications in wind turbine diagnostics, steel surface defect identification, predictive maintenance in Laser Metal Deposition (LMD), visual inspection in the semiconductor industry, and robotic scheduling in changeable workshop environments. The Internet of Things (IoT) and Big Data were identified as key enablers in AI-based manufacturing, facilitating real-time monitoring, data-driven decision-making, and predictive maintenance. The integration of IoT and AI also addressed challenges related to circular economy and sustainability in manufacturing. Robotics, particularly collaborative robots (cobots) and unmanned aerial vehicles (UAVs), showed promise in enhancing manufacturing capabilities and human-robot interactions in Industry 5.0. The integration of AI and Robotics has the potential to revolutionize manufacturing processes and improve safety and efficiency.

As per the findings from the literature review and trend analysis, it is evident that AI technologies, especially Machine Learning and Deep Learning, are likely to transform manufacturing operations by enhancing productivity, reducing costs, and refining product quality. Moreover, the integration of IoT, Big Data, and Robotics further enhances the effectiveness of AI-based strategies in manufacturing.

The study can help in the identification of best practices for creating AI-based product manufacturing strategies and can serve as ready reference for the organizations globally who want to define best AI based product manufacturing strategy tailored to their needs. The outcome of the study can contribute to a better understanding of the impact of role of strategy on AI based product manufacturing and Improved understanding of how to use AI effectively to optimize product manufacturing processes.

A prominent limitation of the study is that the field of Artificial Intelligence and manufacturing is speedily developing with new technologies, strategies and practices evolving constantly. The literature review and trend analysis may not fully capture the most recent advancements and trends in the field due to the time lag between data collection and publication. The study focuses on the role of effective strategy in AI-based manufacturing, and the conclusion may be specific to this context. Therefore, broader implications for other industries or AI applications may require further research and analysis.

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