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Artificial Intelligence in Modern Manufacturing: Opportunities and Barriers

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ABSTRACT

The manufacturing sector is being transformed by Artificial Intelligence (AI) which brings in smart automation, data making decisions, and act as real time adapt. This review will dive into the fundamental technologies that give AI its foundation, including; machine learning, computer vision and robotics, and the role they play in predictive maintenance, quality control, process optimization and supply chain management. The implementation of AI has proved to be very effective in terms of improvement of efficiency, minimization of the downtime, quality of their products and flexibility. Manufacturers, however, suffer with respect to poor data quality, legacy infrastructure, cost of implementation, shortage of skills and cybersecurity risk problems. With the example of such industry leaders as GE, BMW, Siemens, and Tesla, the disruptive power of AI is visible in the different manufacturing settings. The indicators of the trends in the future indicate self-governing factories, edge AI, digital doubles, human-AI interaction, and environmentally responsible manufacturing processes. Although there are barriers, strategic adoption and maintenance innovation are key drivers that make AI one of the drivers of the next generation of smart, agile, and sustainable manufacturing systems.

INTRODUCTION

The process of the rapid adoption of the digital technologies, which are generally referred to as the Industry 4.0, is leading to a powerful change in the manufacturing industry at the moment. Among them, Artificial Intelligence (AI) is one of the most revolutionary powers that transform the traditional manufacturing process into the smart industry, data-driven process, and highly efficient systems [1].

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The opportunities provided by the application of AI technologies It is possible to create additional opportunities of increasing productivity, quality, customization, and flexibility of the manufacturing environment by using AI technologies, including machine learning, deep learning, computer vision, and natural language processing [2].

Traditionally, manufacturing was developed in industrial revolutions: the production was mechanized with the help of steam, and afterward, it became massively manufactured via electric power and analyzed with the help of electronic and information technologies. Fourth industrial revolution (Industry 4.0) is now combining cyber-physical systems, Internet-of-Things and artificial intelligence to build intelligent, self-monitoring, self-diagnosing, self-decisioning factories [3]. In this case, AI cannot be discussed as some auxiliary technology: it is a primary driver of intelligent automation and digital transformation throughout the whole manufacturing value chain.

Today manufacturers are under pressure to deliver products of a superior quality, speedier delivery, and highly customized to satisfy the requirements of the market, on a lower number of costs on minimizing the environmental implication [4]. Although to some degree, more traditional rule-based automation and lean practices are inadequate to keep pace with increasing complexity and variability in manufacturing systems. This has made there to be great urge of moving to AI driven solutions that are much more adaptable and data drenched smart [5].

The power of AI is in drawing insights out of so much and so complex data created throughout the production lifecycle including data in machine logs and sensors, customer feedbacks, and supply chain feeds. These can be used to generate predictive maintenance, defect detection, adaptive process control and real-time optimization, and in the end, make overall operations to be more efficient. Answering these questions, the review aims to become a resourceful tool that can be used by the researcher, engineers, decision-makers, and policymakers concerned with the development of smart manufacturing systems [6].

The results of this review use a critical perspective of peer-reviewed articles in journals, industry white papers, conference publications, and the publication of cases found in the decade-long period. Relevant literature was identified through databases like IEEE Xplore, ScienceDirect, SpringerLink and Google Scholar [7]. The novelty, quality, and relevance of the study as well as depth of discussion on practical challenges were used to select the articles. This review is organized in such a way that a brief description of the most important AI technologies in manufacturing should come first, and then a specific examination of areas of application. It subsequently talks about the opportunities and advantages of AI, explains the major hurdles encountered in implementation in the real world, and identifies future courses and lines of inquiry [8].

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MANUFACTURING AI TECHNOLOGIES DIGEST

Artificial Intelligence (AI) is a wide area that includes methods of computation, which enable machines to emulate the ability of humans to act intelligently, and learn through data, and make every choice in a minimal intervention of humans. In manufacturing terms, AI has become the technology core in developing smart, adaptive, and autonomous systems. This part gives a summary of the main technological AI that are currently transforming the realm of modern manufacturing [9].

One of the most popular AI-related areas in the manufacturing business is Machine Learning. It is a field of training algorithms with historical data and real-time data and identifying patterns, forecasting and streamlining processes. ML is applied in manufacturing in prediction maintenance, process control, demand prediction, and anomaly detection [10]. Classification tasks with supervised learning method (e.g., decision tree and support vector machines) are more popular; pattern recognition and fault identification can be carried out with unsupervised learning (ex., k-means clustering) [11].

Deep learning is a branch of machine learning that applies multi-layered neural networks to systematically plan intricate relationships of big datasets. Its advantage is the ability to process unstructured data in the form of pictures, sound, and text [12]. In manufacturing DL is mainly used in visual inspection where defects or irregularities on the surface of parts are detected through convolutional neural networks (CNNs) with high accuracy. The predictive analytics in high-dimensional data setting, as with monitoring many sensors along a production line, are also supported by DL models [13].

Computer Vision allows the machines to process and take decisions based on the visual information. It is used in automated quality inspection, assembly verification and robotic guidance systems to an important extent. Artificial intelligence-enabled vision systems have cameras, sensors and image processing algorithms that identify flaws in products, size of the components and make sure that they are in accordance to the design requirements [14]. These systems make use of less human inspectors and increases accuracy and speed a lot. NLP enables the machines to comprehend and recognize language that is used by human beings. NLP has been used in manufacturing applications in speech recognition in human machine conversation, automated report writing and knowledge management applications. As an example, maintenance logs or notes that are provided by operators can be analyzed using NLP and turned into useful pieces of information that can be used to make decisions [15].

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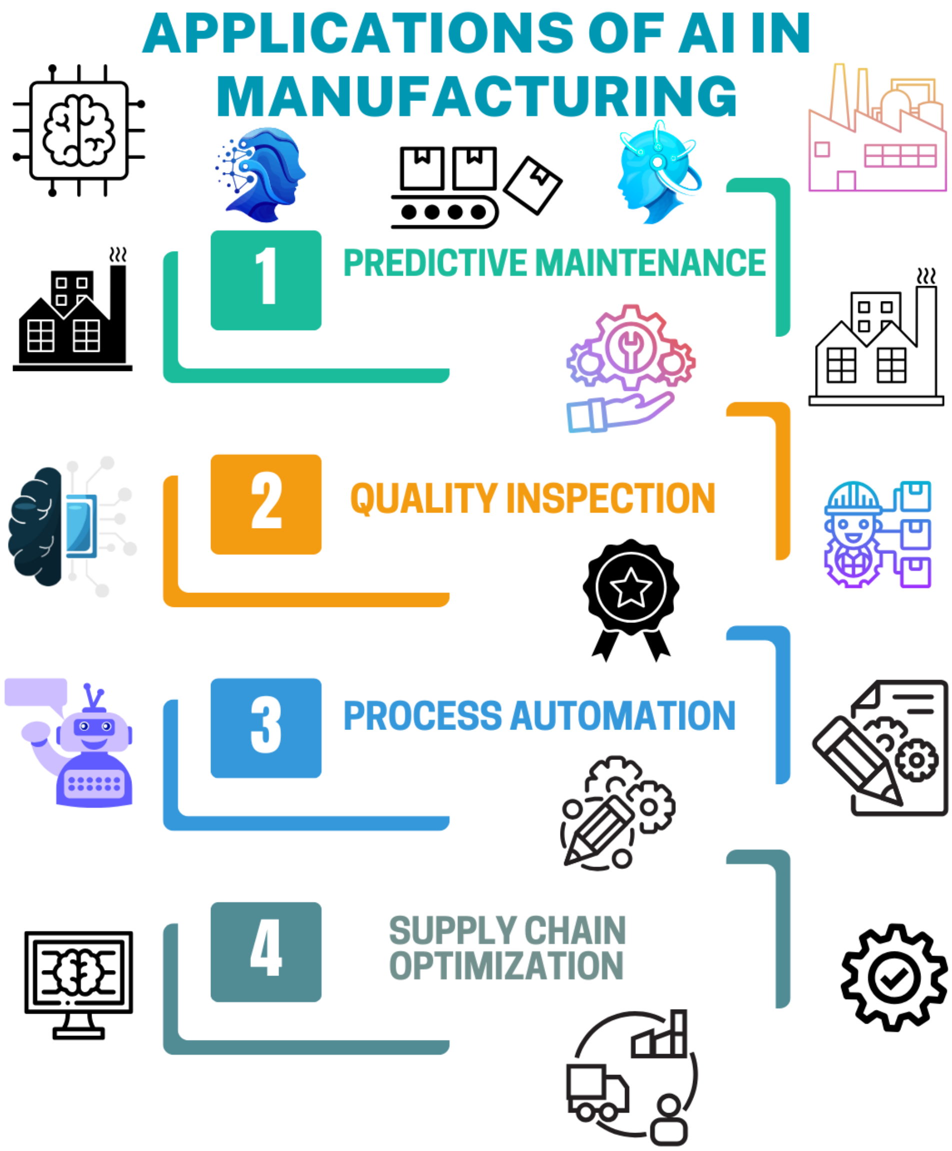

Figure: 1 showing applications of AI in manufacturing

Reinforcement Learning (RL) is a trial and error method in which learning occurs as algorithms are rewarded or penalized. The use of RL is being considered increasingly in robotics, automated process control and the use of resources in manufacturing systems. Its versatility to suit changing environments renders it applicable in complex and real time decision making activities [16]. Digital twins are virtual copies of existing physical systems that allow simulation, monitoring, and on-the-fly optimisation provided by the powerful AI. Predictive maintenance, design validation, and performance forecasting largely employ them. Digital twins coupled with AI models have the potential to give valuable insights to manufacturers and help them gain foresight and control of the operations with reduced downtimes and offer increased resilience of the system [17].

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USES OF AI IN THE MANUFACTURING INDUSTRY

Artificial Intelligence (AI) is also changing almost all the factors in manufacturing lifecycle, such as design, production, quality control, and supply chain management. Through incorporation of AI-based systems, manufacturers will have increased efficiencies, flexibility, and precision. Some of the crucial domains of application where AI can be seen to have a significant influence in the current manufacturing processes have been highlighted in this section [18]. Predictive maintenance is one of the most obvious and cost-efficient areas of manufacturing health care where AI is used. AI systems review sensor readings, machine logs and past failure trends to determine when equipment's are likely to break [19]. This enables manufacturers to effect maintenance right before a break-down and thereby reduces unscheduled downtime and prolong lifetime of equipment. In this endeavor regression analysis, decision trees and deep learning networks are the most common machine learning models [20].

Quality inspection AI-based system involves computer vision and deep learning to identify surface flaws, dimensional defects and inconsistencies in the material of products. Such systems can in many cases replace human inspectors because they are more consistent and speedier to perform evaluations than people [21]. The ability to detect defects in real time does not only enhance the quality of the product but also eliminates waste and rework. Inspection systems based on vision became a standard in electronics, automotive and aerospace industries. The variables that are used to produce manufacturing products are usually complex and they require constant tuning so as to ensure that production is maximised and the quality of products is enhanced [22]. Using operational data of production in real-time, AI algorithms can be trained to locate bottlenecks, optimize process conditions and increase throughput. The use of reinforcement learning and adaptive control systems are especially handy in the dynamic operation adjustment and this results in more responsive and competent production environments [23].

AI plays an important part in generating smart production plans and scheduling, particularly in high-mix, low-quantity production environments. AI models can assess the limit of resources, delivery dates, machine capacity, etc so as to produce the best production schedules. The result is superior resource application, a shorter lead time and more flexibility to respond to fluctuation in demand [24]. AI can be used to improve the supply chain making it offer real-time visibility, demand forecasting, and risk management. Machine learning frameworks can forecast the disruption in the supply, propose an additional sourcing method, and integrate an inventory. These are essential features of enabling the company to remain resistant to the changing nature of the global market, as well as the unpredictable supply status [25].

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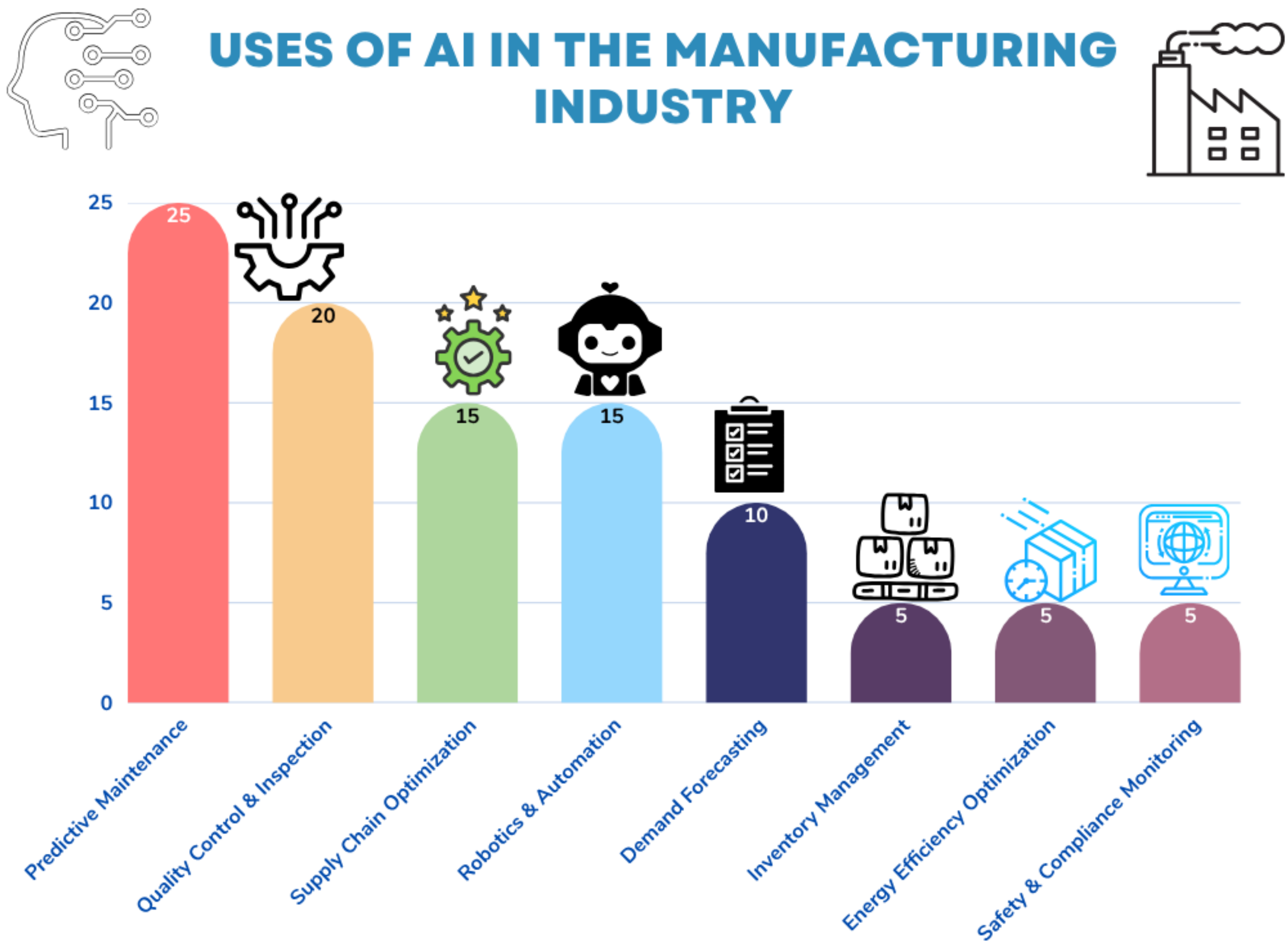

Figure: 2 showing uses of AI in the manufacturing industry

AI facilitates intelligent robotics that can sense their surroundings, learn as they interact and come up with their decisions. AI In the form of collaborative robots (cobots) that assist human operators to carry out assembly, welding, and packaging. Such robots ensure that the workers are safe and can also respond to various task allocated within the factory floor. AI enables control of stock levels and stock in the warehouse, as well as flow of materials. There are automated guided vehicles (AGVs), robotic picking systems, and AI-based analytics tools which facilitate effective storage, pick and replace [26].

THE ADVANTAGES AND OPPORTUNITIES OF INCLUSION OF AI.

Artificial Intelligence (AI) integration in manufacturing provides enough opportunities that amount across a broad category of conventional automation. With the application of improved data analytics, machine learning, and smart systems, manufacturers have a chance to develop responsive, efficient, and nimble operations. In this section, the researcher describes the key advantages and new opportunities artificial intelligence introduces into modern manufacturing. Among the greatest opportunities of AI integration, an improvement in the efficiency of the operations should be placed

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first [27]. The AI systems are able to examine large amounts of production information in real time, recognize what is inefficient, and advise, or even execute a solution. It allows making decisions quicker and allows optimizing such processes as the energy costs, equipment use, and manufacturing schedule, and end up reducing the expenses and increasing production [28].

Quality control systems which are inspired by AI are able to use computer vision and deep learning algorithms to identify anomalies and defects with a high degree of accuracy. Compared to the conventional methods of inspection, AI-based systems can work 24 hours per day without getting tired, and their assessment will be fair and steady [29]. When the issues of quality have been raised early in the manufacturing process, the manufacturing companies have the ability to rework it reduce the rate of scrap and also ensure a high adherence to the product quality. AI enables the shift in thinking among manufactures, where their decision-making can be proactive, and in some cases, prescriptive [30]. Real-time analysis of machine production line streaming data can be done by AI instruments by identifying patterns and ignoring anomalies. This is because there will be the ability of making quick changes to operations enhancing responsiveness and lower downtimes that are caused by sudden or unforeseen interruptions [31].

The contemporary consumers are more individualized and customizable. AI allows manufacturers to change fast according to the preferences of customers and variations of the products. Smart systems have the ability to optimize the machinery, the supply chain logistics and the production plans automatically according to the incoming data. The result is mass customization that does not sacrifice efficiency and opens up new markets that make them more competitive [32]. The use of AI-based predictive maintenance systems has demonstrated the ability to detect something wrong with the equipment before it stops working, which decreases unplanned downtimes dramatically.

Also, AI will be able to minimize material utilization, identify excessive production, and propose methods of minimizing scrap and energy wastes. These will enhance more sustainable and cost-efficient operations in manufacturing. AI enhances transparency of every process in manufacturing, supply chain, customer responses [33]. AI enables companies to make strategic decisions based on data, plan demand and reveal new revenue streams by discovering missing trends and correlations. Those companies which can embrace AI properly and early enough stand higher chances of developing a sustainable competitive advantage in a world that continues to embrace digitalization [34].

BARRIERS AND CHALLENGES TO AI ADOPTION

Although Artificial Intelligence (AI) is massive in terms of changing manufacturing, its popularization is not without barriers. Although technology moves fast, the problems of AI integration

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into complicated industrial settings are of technical, economic, organizational and ethical nature. In this part, the authors look into the key obstacles that prevent the smooth introduction of AI into manufacturing. AI technologies rely substantially on the high quality and high amount of data to use during training and precise decisions [35]. Nevertheless, quite a number of production plants do not have clean, organized, and accessible datasets. Legacy equipment might not generate the necessary data or the data could not be complete, accurate, or siloed among systems. AI models are only effective upon having effective data pipelines as models without them are ineffective and therefore have limited application [36].

Legacy systems and conventional control systems continue to be used in a lot of manufacturing plants and are not meant to be integrated with AI. The process of retrofitting these systems to accept AI tools is both expensive, time-consuming, and technical in nature. The inability of the new AI platforms to integrate with the already operational technologies (OT) forms a major adoption cadre [37]. The one-time expense of implementing AI solutions, such as hardware, software, and infrastructure improvement, as well as qualified human employees, may be quite big. In particular, SMEs might not be able to rationalize or sustain such an investment without an immediate and evident pleasure of a return on investment (ROI). In most instances, failure to implement AI initiative becomes a financial risk, which puts off organizations [38].

Effective AI adoption means having an employee base, competent in data science and machine learning, narrowing down how they will deploy the AI model and assured digital infrastructure. Nevertheless, the manufacturing industry lacks qualified specialists with such abilities significantly. There can also be the unwillingness of employees who fear that they will lose their job or will be reluctant to use new technologies. Change management or up skilling programmes are very important yet not given much emphasis [39]. The greater digitation and connectivity necessitated by the AI systems subject them to cybersecurity threats. Artificial intelligence systems, especially the ones connected to cloud services or industrial Internet of Things systems are prone to cyber-attacks. The security of the data, safeguarding of intellectual properties and adherence to privacy laws are big issues that the manufacturers are concerned about [40].

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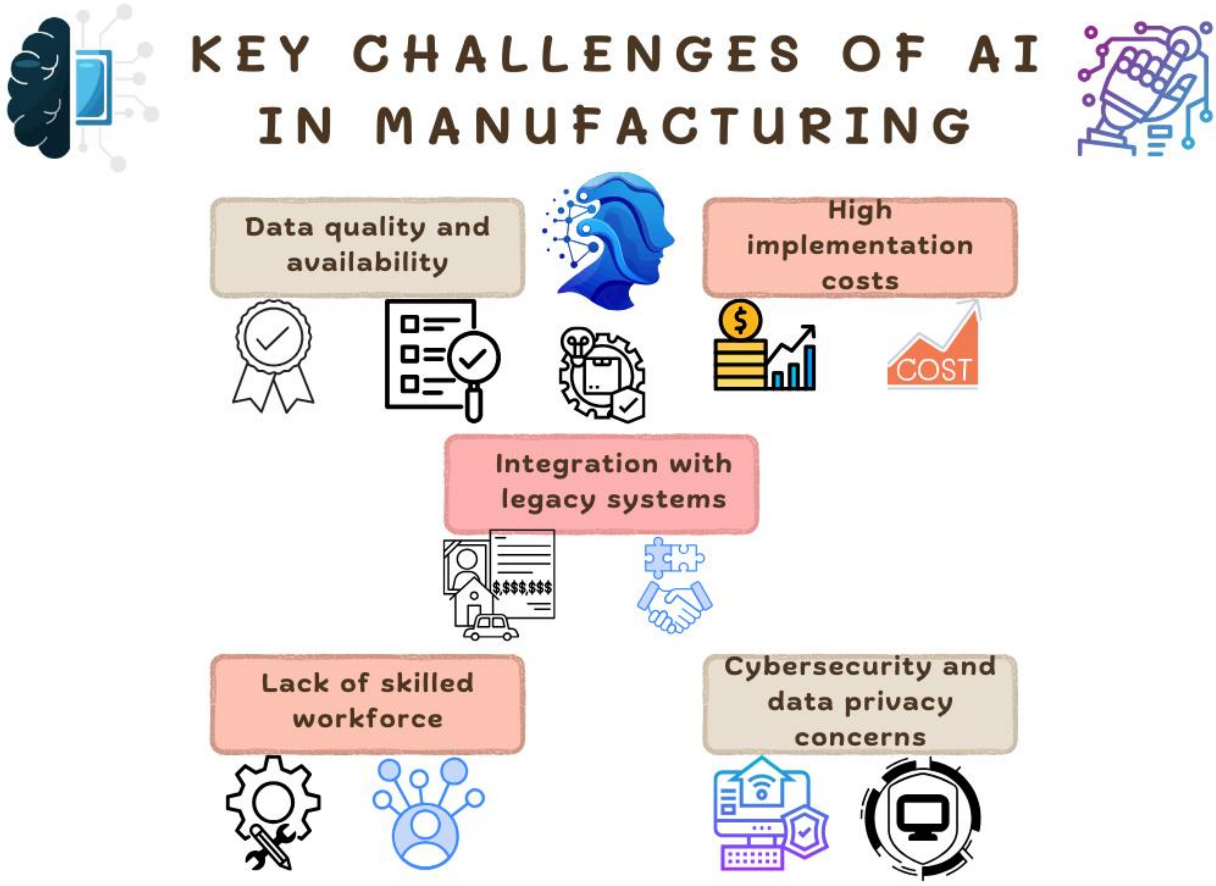

Figure: 3 showing key challenges of AI in manufacturing

The use of AI in manufacturing suggests concerns in the regulatory compliance, algorithmic transparency, and accountability issues as well. Ethical AI applications in industry also lack the standardized frameworks of using AI in the industrial environment. The development of biased algorithms, decision-making in the dark, and a lack of legal responsibility in case of failures is an issue that hinders trust and acceptability on a larger level [41].

INDUSTRY EXAMPLES AND CASE STUDIES

Practical use of Artificial Intelligence (AI) in processing industry shows its effective role in productivity and efficiency increase as well as in decision-making. Major players in various industries have already started to deploy AI-based technologies to streamline their operations, lower the costs and create a competitive edge. Incredible case studies and examples in the industry where AI has been effectively adopted in manufacturing settings are illuminated in this section [42]. General Electric (GE) has also been a leader in terms of using AI in machinery by using their Predix platform that is an industrial IoT and analytics system to do predictive maintenance. Based on the data obtained about turbines, compressors, and other strategic equipment, AI algorithms can determine equipment failure before the failure takes place. Such a strategy has lowered the unplanned downtime, has saved

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millions in maintenance expenses as well as enhanced asset utilization. The experience of GE indicates how AI can help to control large-scale and complex equipment networks [43].

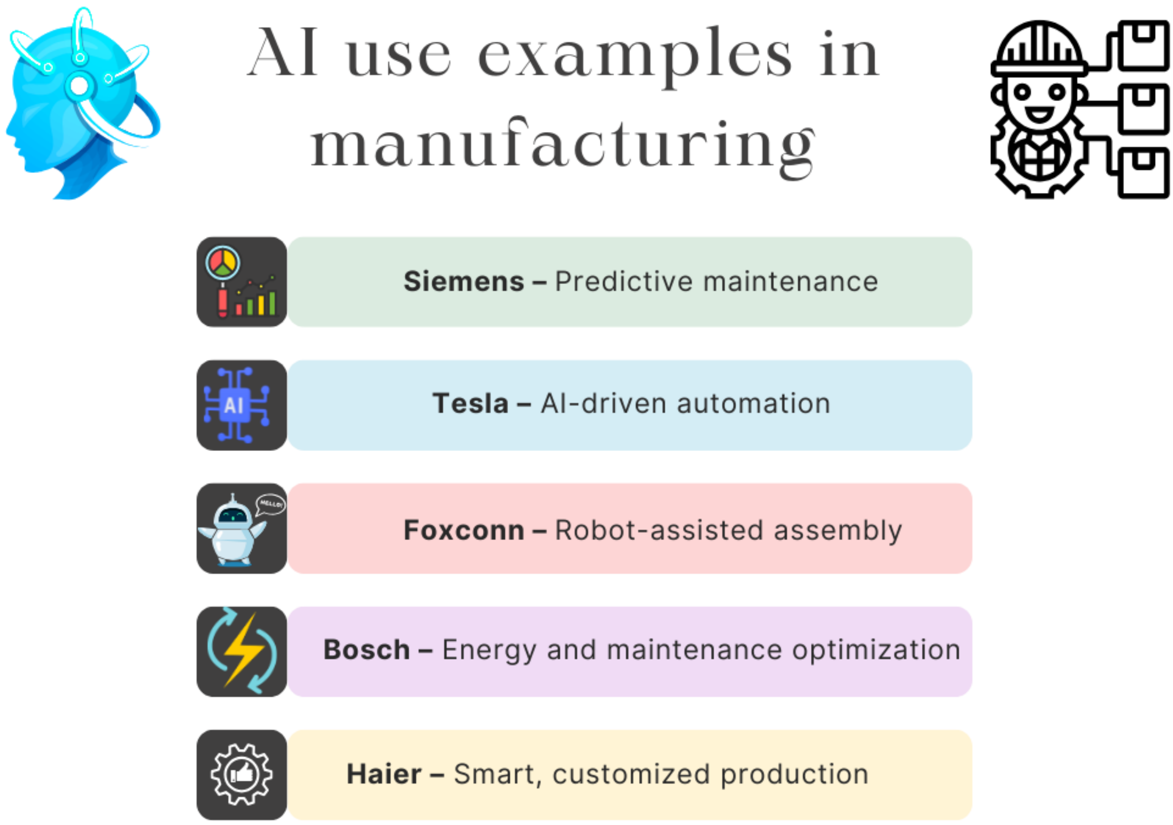

Figure: 4 showing the AI use examples in manufacturing

BMW applies AI-enhanced computer vision technology to automate inspection of quality in their assembly lines. Deep learning algorithms are implemented by cameras to detect defects on the surfaces, scratches, or wrongful parts in real time. At AI-equipped facilities, vehicle assembly is verified, and the right place of components in it is checked. This increases quality assurance and also minimizes the use of human inspectors and manual rework [44]. In Germany, Siemens applies AI in Amberg Electronics Plant to handle more than 1,000 various variants of products. Artificial intelligence systems are useful in real-time monitoring and streamlining of the entire process so that the machine can dynamically supply itself where necessary. Because of this, the quality level of the products of the factory is above 99.99%. The inclusion of AI has decreased production cycles and enabled less waste production and increased productivity [45].

Tesla is already deeply reliant on robotics especially in their production plants for something as far reaching as robotics coordination, welding automation and real time decision making. Robots learn to adjust their actions and tasks using Deep learning and reinforcement learning algorithms which are more precise and efficient dependent on the sensor signals [46]. Tesla is also using AI in the supply

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chain forecasting and production scheduling that make the company responsive and quick in responding to changes in the market. A large-scale manufacturer of electronics, Foxconn, has invested so much in AI in order to diminish the need to rely on labor forces and enhance the effectiveness of the assembly line. The firm has rolled out thousands of AI-installed robotic arms also known as the Foxbots that automate the likes of screwing, welding, and component fixing. Such activities have led to more accuracy and throughput speeds, particularly, in those processes that involve large amounts of products assembled [47].

FUTURE RESEARCH AND POSSIBLE FUTURE DIRECTIONS

Future opportunities with Artificial Intelligence (AI) manufacturing can be defined as the further development of AI, encompassing more emphasis and restructuring the old paradigms of industrial means. The forthcoming decade will see appearances of new AI-based capabilities, systems, frames, and cooperative systems that will render producing more independent, flexible, and smart. The section discusses some of the core future trends and current research areas that define the future of AI in manufacturing [48]. One huge trend in smart manufacturing is emergence of completely autonomous production facilities i.e. lights out factories. Such production systems will be in a position of running 24/7 without the input of humans. Future factories will be capable of self-monitoring, self-cure, and self-improvement because they use AI, real- time data analytics, and robotics. Fields such as reinforcement learning, edge computing and adaptive control systems are under research so that graphs of learning and improvement with each production cycle can be stored by the machine autonomously [49].

AI will be used more and more in large-scale data processing on the factory floor, making use of hybrid architecture that incorporates both edge and cloud computing. Although the completion of complex computations and storage will be achieved using the cloud platforms, real-time processing of data at the machine-level will be possible through edge devices. In future, research efforts are aimed at designing lightweight AI models capable of being deployed on resource-constrained edge devices without compromising the performance or accuracy of AI models. Use of artificial intelligence and digital twin is also an emerging important field of research [50]. Digital twins - computerized representations of physical systems provide the opportunity to simulate, monitor, and optimize the process of production by manufacturers. Digital twins are enhanced through AI, improving behavioral data analysis, failure predictions, and design alternatives testing without changing a design. The science is developing towards more dynamic real-time synchronized models that change dynamically with the physical models [51].

Instead of becoming a substitute, AI in the future will actually serve as a working partner. Machine

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assistance in the form of cobots (collaborative robots) and AI based decision support systems will allow human workers to concentrate on higher-level roles. AR and AI interfaces will help with training, diagnostics and maintenance. Studies are underway to provide explainable AI (XAI) to make AI solutions transparent, trustworthy, and intelligible to human operators [52]. Sufficient energy efficiency, wastage, and circular economy may also help sustainability grow in manufacturing, and artificial intelligence is likely to play a leading role in it. It will involve AI to maximize material consumption, minimize emissions, and track the environment [53]. The research for the future aims at developing green AI algorithms which consume low energy and goals and objectives of long term sustainability.

CONCLUSION

Artificial Intelligence (AI) is the new revolution in the manufacturing industry and revolutionized the process of product designing, manufacturing, testing, as well as delivery. AI takes the center stage as the potential solution to many problems by being not just smart but flexible, multi-purposed, and accurate, as industries strive to be able to handle the challenges of ever-more customization, effective operations and sustainability. The concept of AI integration is no longer a dream-come-true idea because it has already become a reality that continuously reinvents the manufacturing industry. Origins of the effects The basis of the effects of AI lies in getting a hold of its principle technologies. Machines are now able to simulate human thoughts and decision-making with the use of machine learning, deep learning, computer vision, natural language processing and robotics. With the assistance of cloud computing and Internet of Things connectivity these technologies tend to enable the manufacturing systems to become predictive and autonomous rather than reactive. Since manufacturers are increasingly turning into a data-driven organization, these AI tools play a crucial role in uncovering the information that lies buried in huge stores of data.

The scope of AI used in manufacturing is enormous and has been on the rise. Artificial intelligence is integrated into the life cycle of production, starting with predictive maintenance, which will reduce unplanned shutdowns, and inspections through computer vision. On one hand, in operations, AI allows dynamically optimizing the process, and on the other hand, in the logistics field, it enhances supply chain management by means of forecasting and timely adjustments. There is robotics, which run on AI to collaborate with humans in increasing precision and safety. Such smart systems provide producers with an opportunity to produce more, minimize erring, and personalize at the large scale.

The advantages of integrating AI are also very convincing. Other than operation efficiency and cost savings, AI enables quicker decision making, enhanced product and services quality, less wastage and enhanced flexibility in adapting to new market dynamics. The early adopters of AI can improve their

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competitiveness in regard to innovation, customer satisfaction, and sustainability. Nonetheless, these advantages are not gained without a as a one-sided affair. The route to adopting AI is tricky. Some of the barriers that manufacturers encounter are; poor quality data, legacy systems, expensive implementation and skills gap among the workforce. Integration is also complicated by the security and ethical issues. Though such are indeed challenging, they are not imposable. By considering planning in advance, investing in the development of the workforce and treating deployment to scale, manufacturers can resolve these challenges and begin to move toward AI-powered operations.

The usefulness of AI is corroborated in real-world case study. GE, BMW, Siemens, Tesla and Falcon and other companies are showing how AI can be used in a production environment, including intelligent maintenance, to robot automation. These examples of success stories offer a guideline to other institutions, which may want to harness the use of AI technologies to their advantage. In the longer term, there is an optimistic future of AI in manufacturing. The studies are still exploring the limits in such spheres as self-governing factories, digital twins powered by AI, edge AI, and green manufacturing technologies. The cooperation between human and AI will become more active because AI will not take away jobs from people but make them better. Even small and medium-sized manufactures will benefit from the use of AI technologies, as their application will no longer require any special tools or skills. AI is not only making manufacturing better, but it is revolutionizing it. As long as it is continuously innovated, strategically used, and sufficiently implemented, AI will lead to the next wave of smart, sustainable, and resilient manufacturing systems.

REFERENCES

[1]. Qian F, Zhong W, Du W. Fundamental theories and key technologies for smart and optimal manufacturing in the process industry. Engineering 2017; 3 (2):154–60.

[2]. Soni K, Kumar N, Nair AS, Chourey P, Singh NJ, Agarwal R. Artificial Intelligence: Implementation and obstacles in industry 4.0. InHandbook of metrology and applications 2022 Aug 28 (pp. 1-23). Singapore: Springer Nature Singapore.

[3]. Giffi CA, Rodriguez MD, Gangula B, Roth AV, Hanley T. Global manufacturing competitiveness index. London: Deloitte Touche Tohmatsu Limited Global Consumer & Industrial Products Industry Group and the Council on Competitiveness; 2016.

[4]. Godinho Filho M, de Almeida SV, Lage Junior M, Osiro L, Lima B, Callefi MH. A path to follow to overcome foundational barriers to the adoption of artificial intelligence within the manufacturing industry: a conceptual framework. Enterprise Information Systems. 2025 Feb 1; 19(1-2):2458685.

ISSN : 3079-5761
Volume 1, Number 3, 2025
https://doi.org/10.70445/gtst.1.3.2025.83-100

[5]. Williams E. Environmental effects of information and communications technologies. Nature 2011; 479(7373):354–8.

[6]. Smart Manufacturing Leadership Coalition. Implementing 21st century smart manufacturing: workshop summary report. Washington: Smart Manufacturing Leadership Coalition; 2011.

[7]. Mao S, Wang B, Tang Y, Qian F. Opportunities and challenges of artificial intelligence for green manufacturing in the process industry. Engineering. 2019 Dec 1; 5(6):995-1002.

[8]. Kar AK, Kushwaha AK. Facilitators and barriers of artificial intelligence adoption in business–insights from opinions using big data analytics. Information Systems Frontiers. 2023 Aug; 25(4):1351-74.

[9]. Lopez-Garcia J, Rojas EM. Barriers to AI adoption and their influence on technological advancement in the manufacturing and finance and insurance industries. In2024 IEEE Colombian Conference on Communications and Computing (COLCOM) 2024 Aug 21 (pp. 1-6). IEEE.

[10]. Von Dewall J. Mitigating Barriers on Artificial Intelligence Pre-adoption in Forecasting: A case Study in a Manufacturing Firm.

[11]. Zavodna LS, Überwimmer M, Frankus E. Barriers to the implementation of artificial intelligence in small and medium-sized enterprises: Pilot study. Journal of Economics and Management. 2024; 46:331-52.

[12]. Bagherian A, Srivastav AL, Mukherjee S. Exploring barriers and strategic approaches in smart factory adoption: A real-world case study in a German manufacturing company. The International Journal of Advanced Manufacturing Technology. 2024 Oct; 134(11):5191-224.

[13]. Grünbichler R, Salimbeni S. Artificial Intelligence in Small and Medium-Sized Enterprises: Requirements and Barriers. InInternational Symposium on Industrial Engineering and Automation 2024 Jun 19 (pp. 173-184). Cham: Springer Nature Switzerland.

[14]. Yuan Z, Qin W, Zhao J. Smart manufacturing for the oil refining and petrochemical industry. Engineering 2017; 3(2):179–82

[15]. Mahbub MB, Ayman A. Utilising artificial intelligence-prospects and obstacles for modern businesses. Malaysian E Commerce Journal. 2024; 8(1):23-8.

[16]. Zhou J, Li P, Zhou Y, Wang B, Zang J, Meng L. Toward new-generation intelligent manufacturing. Engineering 2018; 4(1):11–20.

[17]. Müller B, Roth D, Kreimeyer M. Barriers to the use of artificial intelligence in the product development–a survey of dimensions involved. Proceedings of the Design Society. 2023 Jul; 3:757-66.

ISSN : 3079-5761
Volume 1, Number 3, 2025
https://doi.org/10.70445/gtst.1.3.2025.83-100

[18]. Mukhamediev RI, Popova Y, Kuchin Y, Zaitseva E, Kalimoldayev A, Symagulov A, Levashenko V, Abdoldina F, Gopejenko V, Yakunin K, Muhamedijeva E. Review of artificial intelligence and machine learning technologies: classification, restrictions, opportunities and challenges. Mathematics. 2022 Jul 22; 10(15):2552.

[19]. Gabsi AE. Integrating artificial intelligence in industry 4.0: insights, challenges, and future prospects–a literature review. Annals of Operations Research. 2024 May 8:1-28.

[20]. Abbasi N, Nizamullah FN, Zeb S, Fardous MD. Generative AI in healthcare: revolutionizing disease diagnosis, expanding treatment options, and enhancing patient care. Journal of Knowledge Learning and Science Technology ISSN: 2959-6386 (online). 2024 Aug 15;3(3):127-38.

[21]. Hall A, Agarwal V. Barriers to adopting artificial intelligence and machine learning technologies in nuclear power. Progress in Nuclear Energy. 2024 Oct 1; 175:105295.

[22]. Peres RS, Jia X, Lee J, Sun K, Colombo AW, Barata J. Industrial artificial intelligence in industry 4.0-systematic review, challenges and outlook. IEEE access. 2020 Dec 7; 8:220121-39.

[23]. Zulfiqar M, Sony M, Bhat S, Antony J, Salentijn W, McDermott O. Unlocking the potential: empirical analysis of enablers, barriers, benefits and technologies for integrating Industry 4.0 and Lean Six Sigma in manufacturing organisations. The TQM Journal. 2024 Nov 26; 36(8):2360-82.

[24]. Gupta A, Kumar R. Modelling the Barriers of Artificial Intelligence Adoption in the Organisations: An Interpretive Structural Modelling and MICMAC Analysis. InSmart Analytics, Artificial Intelligence and Sustainable Performance Management in a Global Digitalised Economy 2023 May 29 (pp. 45-66). Emerald Publishing Limited.

[25]. Zemplényi A, Tachkov K, Balkanyi L, Németh B, Petykó ZI, Petrova G, Czech M, Dawoud D, Goettsch W, Gutierrez Ibarluzea I, Hren R. Recommendations to overcome barriers to the use of artificial intelligence-driven evidence in health technology assessment. Frontiers in public health. 2023 Apr 26; 11:1088121.

[26]. Tachkov K, Zemplenyi A, Kamusheva M, Dimitrova M, Siirtola P, Pontén J, Nemeth B, Kalo Z, Petrova G. Barriers to use artificial intelligence methodologies in health technology assessment in central and east European countries. Frontiers in Public Health. 2022 Jul 14; 10:921226.

[27]. Gupta A, Kumar R. Modelling the Barriers of Artificial Intelligence Adoption in the Organisations: An Interpretive Structural Modelling and MICMAC Analysis. InSmart

ISSN : 3079-5761
Volume 1, Number 3, 2025
https://doi.org/10.70445/gtst.1.3.2025.83-100

Analytics, Artificial Intelligence and Sustainable Performance Management in a Global Digitalised Economy 2023 May 29 (pp. 45-66). Emerald Publishing Limited.

[28]. Zeb S, Lodhi SK. AI and Cybersecurity in Smart Manufacturing: Protecting Industrial Systems. American Journal of Artificial Intelligence and Computing. 2025 Apr 7;1(1):1-23.

[29]. Bagherian A, Srivastav AL, Mukherjee S. Exploring barriers and strategic approaches in smart factory adoption: A real-world case study in a German manufacturing company. The International Journal of Advanced Manufacturing Technology. 2024 Oct; 134(11):5191-224.

[30]. Verevka T, Mirolyubov A, Makio J. Opportunities and barriers to using big data technologies in the metallurgical industry. InInternational Scientific Conference on Innovations in Digital Economy 2020 Oct 22 (pp. 86-102). Cham: Springer International Publishing.

[31]. Rashid H. Investigating Barriers and Challenges to Artificial Intelligence (AI) Implementation in Logistic Operations: A Systematic Review of Literature. InProceedings of the International Conference on Industrial Engineering and Operations Management 2023.

[32]. Uwagaba J, Omotosho TD, George GO. Exploring the barriers to artificial intelligence adoption in Sub-Saharan Africa’s Small and Medium Enterprises and the potential for increased productivity. World Wide Journal of Multidisciplinary Research and Development. 2023; 9(6):4-10.

[33]. Singh AV, Chandrasekar V, Janapareddy P, Mathews DE, Laux P, Luch A, Yang Y, Garcia-Canibano B, Balakrishnan S, Abinahed J, Al Ansari A. Emerging application of nanorobotics and artificial intelligence to cross the BBB: advances in design, controlled maneuvering, and targeting of the barriers. ACS chemical neuroscience. 2021 May 19; 12(11):1835-53.

[34]. Omar AF, Zainordin N, Khoo SL, Peng JO. Barriers in implementing artificial intelligence (AI) and Internet of things (IoTs) among Malaysian construction industry. InAIP Conference Proceedings 2022 Nov 7 (Vol. 2644, No. 1, p. 030002). AIP Publishing LLC.

[35]. Lodhi SK, Zeb S. Ai-Driven Robotics and Automation: The Evolution of Human-Machine Collaboration. Journal of World Science. 2025 May 13;4(4):422-37.

[36]. Taribagil P, Hogg HJ, Balaskas K, Keane PA. Integrating artificial intelligence into an ophthalmologist’s workflow: obstacles and opportunities. Expert Review of Ophthalmology. 2023 Jan 2; 18(1):45-56.

[37]. Kumar G, Singh RK, Arya V, Mishra SK. Analyzing barriers in adoption of artificial intelligence for resilient health care services to society. Global Journal of Flexible Systems Management. 2024 Mar; 25(1):179-97.

ISSN : 3079-5761
Volume 1, Number 3, 2025
https://doi.org/10.70445/gtst.1.3.2025.83-100

[38]. Okwudiri NO, Nwafor AE, Umetiti CB. Harnessing Artificial Intelligence for Improved Quality Assurance in the Pharmaceutical Sector: Opportunities and Barriers. African Journal of Advances in Science and Technology Research. 2025 Jun 12; 19(1):201-12.

[39]. Hatani F. Artificial Intelligence in Japan: Policy, prospects, and obstacles in the automotive industry. InTransforming Japanese business: Rising to the digital challenge 2019 Dec 7 (pp. 211-226). Singapore: Springer Singapore.\

[40]. Deo RC. Artificial intelligence and health equity: opportunities and obstacles. JACC: Advances. 2024 Sep 1; 3(9_Part_2):101045.

[41]. Bodea CN, Mitea C, Stanciu O. Artificial intelligence adoption in project management: main drivers, barriers and estimated impact. InProceedings of the 3rd International Conference on Economics and Social Sciences 2020 Oct 15 (pp. 758-767).

[42]. Perifanis NA, Kitsios F. Investigating the influence of artificial intelligence on business value in the digital era of strategy: A literature review. Information. 2023 Feb 2;14(2):85.

[43]. Vrontis D, Christofi M, Pereira V, Tarba S, Makrides A, Trichina E. Artificial intelligence, robotics, advanced technologies and human resource management: a systematic review. Artificial intelligence and international HRM. 2023 May 22:172-201.

[44]. Ivanišević A, Tadin A. Artificial intelligence and modern technology in dentistry: attitudes, knowledge, use, and barriers among dentists in Croatia—A Survey-Based study. Clinics and practice. 2024 Dec 5; 14(6):2623-36.

[45]. Zare L, Benedini B, Ali MB, Rauch E, Salimbeni S. Opportunities and Barriers for Implementing Human-Centric Manufacturing in SMEs: Results from Focus Group Workshops in Argentina. Procedia Computer Science. 2025 Jan 1; 253:1452-61.

[46]. Zeb S, Lodhi SK. AI for predictive maintenance: Reducing downtime and enhancing efficiency. Enrichment: Journal of Multidisciplinary Research and Development. 2025 May 13;3(1):135-50.

[47]. Borboni A, Reddy KV, Elamvazuthi I, AL-Quraishi MS, Natarajan E, Azhar Ali SS. The expanding role of artificial intelligence in collaborative robots for industrial applications: a systematic review of recent works. Machines. 2023 Jan 13; 11(1):111.

[48]. Tavares ED, Leardini M, Pessoa MS. How do the barriers that prevent or hinder the applicability of artificial intelligence impact its use in an insurance company? Innovation & Management Review. 2025 Mar 18;22(1):13-46.

ISSN : 3079-5761
Volume 1, Number 3, 2025
https://doi.org/10.70445/gtst.1.3.2025.83-100

[49]. Singh SK, Mahapatra P. Artificial Intelligence in the Agri-Business Sector: Prioritizing the Barriers through Application of Analytical Hierarchy Process (AHP). InAdvanced Computational Methods for Agri-Business Sustainability 2024 (pp. 95-116). IGI Global.

[50]. Rababah A, Al-Shahi B, Al-Zeadi B, Al-Saadi A, Al-Senani R, Al-Washahi A. Barriers to Artificial Intelligence in Accounting Implementation in Oman. InEurasia Business and Economics Society Conference 2022 Jul 6 (pp. 301-315). Cham: Springer Nature Switzerland.

[51]. Ahmad I. The Strategic Role of Artificial Intelligence in Overcoming Intercultural Barriers for SME Internationalization: A Systematic Literature Review. Journal of Intercultural Communication. 2025 Jun 3; 25(2):148-63.

[52]. Ishengoma FR, Shao D, Alexopoulos C, Saxena S, Nikiforova A. Integration of artificial intelligence of things (AIoT) in the public sector: drivers, barriers and future research agenda. Digital Policy, Regulation and Governance. 2022 Nov 9;24(5):44

[53]. Hassan M, Kushniruk A, Borycki E. Barriers to and facilitators of artificial intelligence adoption in health care: scoping review. JMIR Human Factors. 2024 Aug 29; 11:e48633.