International Journal of
Multidisciplinary Sciences and Arts

E-ISSN : 2962-1658
Volume 3, Number 4 ,October , 2024
https://doi.org/ 10.47709/ijmdsa.v3i4.4616

AI-Powered Innovations in Contemporary Manufacturing Procedures: An Extensive Analysis

Shahrukh Khan Lodhi[1], Ahmad Yousaf Gill[2], Ibrar Hussain[3*]
[1]Trine University Detroit, Michigan
[2]American National University, USA
[3]University of Punjab Lahore
[1]slodhi22@my.trine.edu, [2]gilla@students.an.edu, [3*]2021-pgcma-38@nca.edu.pk

open access

***Corresponding Author**

Article History:
Submitted: 31-08-2024
Accepted: 01-09-2024
Published: 02-09-2024

Key words: Supply chain optimization; artificial intelligence (AI); robots; automation; predictive maintenance; quality assurance; computer vision; machine learning; data analytics; manufacturing efficiency; operational flexibility; defect detection; inventory management; forecasting; and supplier performance.

ABSTRACT

The industrial sector is undergoing a transformation thanks to artificial intelligence (AI), which is bringing revolutionary changes to a number of areas like robots and automation, supply chain efficiency, predictive maintenance, and quality control and assurance. This thorough analysis investigates AI's significant influence on contemporary manufacturing procedures. Artificial Intelligence (AI) improves machine capabilities in robotics and automation, creating more intelligent and flexible systems. Robots can now complete complicated tasks with more flexibility and precision thanks to AI-driven developments, which boosts manufacturing efficiency and human-robot cooperation. Another crucial area where AI has a big impact is predictive maintenance. With the use of machine learning algorithms and real-time data analysis, artificial intelligence (AI) helps manufacturers anticipate equipment faults before they happen. By taking a proactive stance, unplanned downtime is decreased, resource usage is optimized, and machinery longevity is increased. AI has a significant positive impact on quality assurance and control because to cutting-edge technologies like data analytics and computer vision. Artificial intelligence (AI) solutions facilitate predictive quality management, improve fault identification, and offer real-time monitoring. Higher quality standards, less waste, and more customer happiness are the outcomes of this. Artificial Intelligence (AI) tackles issues related to supplier performance, accurate forecasting, and inventory management in supply chain optimization. Automation and analytics powered by AI simplify supply chain processes, increase transparency, and facilitate improved decision-making, which lowers costs and increases flexibility. All things considered, integrating AI into manufacturing processes offers a strategic advantage by promoting increased accuracy, flexibility, and efficiency. The continued developments in AI technology have the potential to significantly influence how manufacturing develops in the future by creating new avenues for creativity and excellence in the sector.

INTRODUCTION

Driving economic growth and societal development, the manufacturing sector has always been at the forefront of technical breakthroughs. But the industry has seen a revolutionary change recently, mostly due to the incorporation of artificial intelligence (AI). Artificial Intelligence (AI) is transforming manufacturing by enabling previously unheard-of levels of efficiency, precision, and customization in product design, production, and delivery [1]. An overview of the ways artificial intelligence (AI) is changing the manufacturing scene is given in this introduction, along with a discussion of the technology's importance, prospective uses, and future implications.

AI's Ascent in the Manufacturing Sector: Artificial intelligence (AI) has quickly developed from a theoretical concept into a useful tool that can solve challenging issues and streamline procedures across a range of industries [2]. AI can replicate human intelligence and learning processes. AI is not only an additional tool in manufacturing; rather, it is a key component of the upcoming Industrial 4.0 revolution. The convergence of digital technologies with physical production processes, or "smart manufacturing," is the defining feature of this revolution. The emergence of AI in manufacturing is a reaction to various issues that more conventional approaches have found difficulty solving. Increasing productivity, improving quality control, decreasing downtime, and quickly adapting to shifting market demands are some of these problems. In order to address these needs, AI technologies like computer vision, machine learning, deep learning, and natural language processing are now being used, giving manufacturers a competitive edge in a global market [3].

AI's Revolutionary Effect on Contemporary Manufacturing: Artificial intelligence is revolutionizing the manufacturing industry in a number of ways that affect every facet of the production process. Process optimization is

E-ISSN : 2962-1658
Volume 3, Number 4 ,October , 2024
https://doi.org/ 10.47709/ijmdsa.v3i4.4616

one of the areas where the effects are most noticeable. Large volumes of data produced by production lines and machines can be analyzed by AI algorithms to find patterns and connections that are impossible for humans to notice. With the use of this expertise, firms may optimize their processes, increasing productivity, cutting waste, and cutting expenses [4]. Predictive maintenance systems, for instance, are becoming used in contemporary manufacturing thanks to artificial intelligence. By using machine learning models, these systems may anticipate equipment faults before they happen, enabling prompt repair that saves expensive downtime. Artificial Intelligence (AI) can detect minute variations in operation that might point to a potential problem by evaluating data from sensors built into machines. This increases overall production dependability and prolongs the life of the equipment.

AI is also very important for quality control. Errors and inconsistencies might occur in traditional quality inspection systems since they mostly rely on human examination [5]. AI-powered computer vision systems, on the other hand, are able to examine products at a microscopic level and detect flaws with a speed and precision that far exceed human capabilities. Because these algorithms can learn continuously, as more data is processed over time, their accuracy increases. Supply chain management is a further field where AI is having a significant impact. Artificial intelligence (AI) can improve supply chains over conventional techniques by anticipating demand, controlling inventories, and arranging logistics more skillfully. For example, AI can estimate product demand by analyzing weather patterns, consumer behavior, and market trends. This information enables producers to modify their production plans. By guaranteeing prompt product delivery, this not only lowers the possibility of overproduction or stock outs but also improves customer satisfaction [6].

AI is also making it possible to create "smart factories," which are highly automated and integrated environments where humans, robots, and machines coexist. Artificial intelligence (AI) systems in these factories are able to monitor the whole manufacturing process and make decisions in real time to maximize output. AI is capable of dynamically allocating resources, including labor and supplies, adjusting machine settings for maximum productivity, and even scheduling maintenance tasks for times when demand is low. In addition to increasing production, this degree of automation gives manufacturers more flexibility, allowing them to react swiftly to shifting market conditions. There are difficulties in integrating AI in the production process [7]. Considerations including data security, the requirement for workers with specialized skills, and the substantial expenses linked to the integration of AI technologies are important. But these difficulties are greatly outweighed by the potential advantages, which is why AI is a crucial part of contemporary manufacturing methods [8].

AI IN MANUFACTURING MARKET

This graph showing AI in manufacturing market

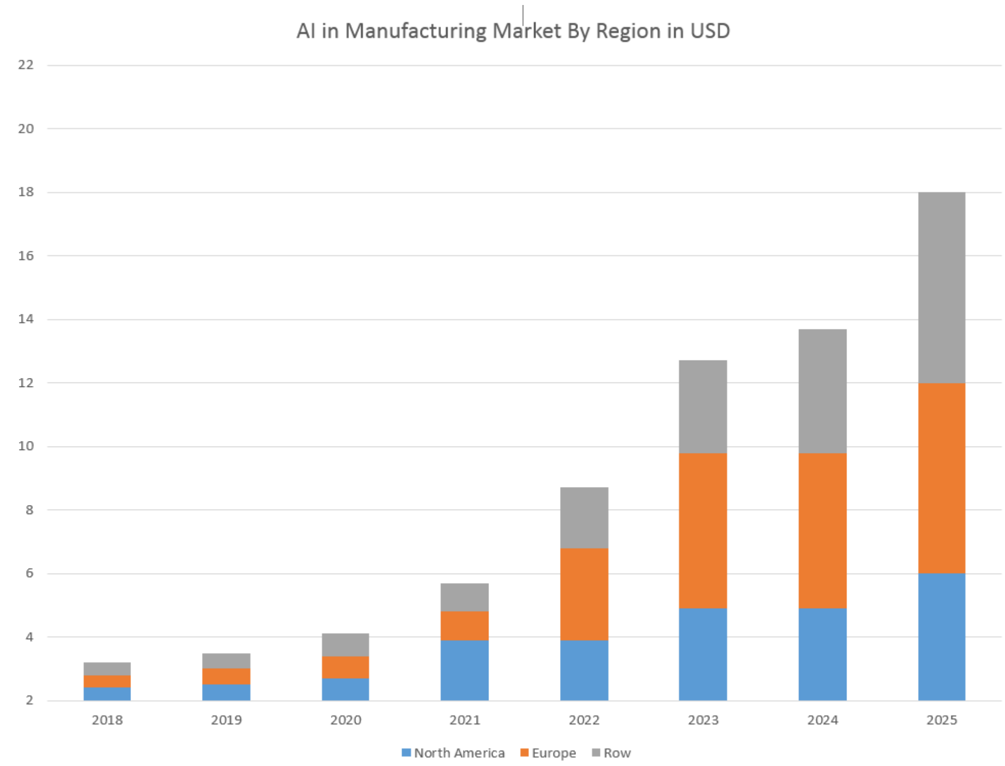

Figure 1. Graph showing AI in manufacturing market

International Journal of Multidisciplinary Sciences and Arts
E-ISSN : 2962-1658
Volume 3, Number 4 ,October , 2024
https://doi.org/ 10.47709/ijmdsa.v3i4.4616

ADDITIVE MANUFACTURING ENHANCED BY AI (3D PRINTING)

Additive Manufacturing (AM), also referred to as 3D printing, is a significant development in the design, prototyping, and production of goods. In contrast to conventional subtractive manufacturing, which makes products by removing material, additive manufacturing constructs objects directly from digital models, layer by layer. The manufacturing industry has witnessed a revolution thanks to this technology, which provides unparalleled customization, material efficiency, and creative freedom [9]. Nonetheless, the incorporation of Artificial Intelligence (AI) into additive manufacturing is elevating this technology to unprecedented levels, augmenting its potential and mitigating certain innate constraints. In order to fully realize the potential of additive manufacturing, this section examines how artificial intelligence (AI) is being used to enhance quality control, forecast maintenance requirements, and optimize 3D printing processes.

AI-Driven 3D Printing Design and Optimization: The field of design optimization is where artificial intelligence has made one of the biggest contributions to additive manufacturing. For traditional design processes to get the appropriate product specifications, a number of iterations and thorough testing are frequently necessary [10]. On the other hand, AI-driven design tools can quickly produce and assess a large number of design alternatives depending on particular requirements like weight, strength, material utilization, and cost. AI algorithms may produce highly optimized structures that are both lightweight and strong, hence decreasing material consumption and production time, through approaches such as generative design and topology optimization. Engineers can input precise design goals, limitations, and material attributes using AI-powered generative design. After then, the AI investigates every scenario in order to produce a wide range of design possibilities that satisfy the predetermined standards [11].

AI Monitoring in Real Time for Quality Assurance: A crucial component of additive manufacturing is quality control, particularly in sectors like aerospace and healthcare where accuracy and dependability are vital. Conventional quality control techniques can be labor-intensive and may not identify flaws until an item is finished. They frequently entail post-production inspection. On the other hand, AI is providing real-time monitoring and inspection during the printing process, which is revolutionizing quality control in 3D printing. 3D printers can be equipped with computer vision systems driven by artificial intelligence (AI) to track each layer as it prints. These devices identify anomalies or flaws like warping, delamination, or voids as soon as they appear using sophisticated image recognition algorithms [12].

Predictive Analytics for Additive Manufacturing Maintenance: AI is also having a big impact on additive manufacturing in the field of maintenance. To function effectively and generate high-quality parts, 3D printers need routine maintenance, just like any other piece of complex production equipment. Traditional maintenance schedules, on the other hand, might result in needless downtime and decreased production because they are frequently based on fixed intervals or reactive responses to equipment faults. By anticipating when maintenance is required and tracking the state of 3D printers in real-time, AI-driven predictive maintenance systems provide a more effective solution. These systems track important variables like temperature, vibration, and component wear using data from sensors built into the printers [13]. Then, using machine learning techniques, these data are analyzed to find patterns that point to possible problems, such an impending printer head failure or a misaligning build platform. AI enables manufacturers to schedule maintenance tasks at the most convenient periods, minimizing unscheduled downtime and increasing equipment lifespan by anticipating maintenance requirements before a malfunction occurs. This proactive technique raises overall production efficiency and strengthens the dependability of 3D printers.

AI FOR SOPHISTICATED MACHINING PROCEDURES

Manufacturing has always relied heavily on advanced machining techniques to produce intricate, highly precise parts for sectors like aerospace, automotive, and healthcare. To get the necessary outcomes, these processes—laser cutting, electrical discharge machining (EDM), and ultrasonic machining—require the highest levels of control and precision. But the execution, optimization, and monitoring of these machining processes are being revolutionized by the introduction of Artificial Intelligence (AI) [14]. AI is improving advanced machining's productivity, precision, and adaptability, enabling producers to satisfy the ever-tougher requirements of contemporary manufacturing. This section examines how artificial intelligence (AI) is influencing innovation in three crucial areas: ultrasonic machining, EDM, and laser cutting.

AI Systems for Laser Machining and Cutting: A powerful laser is used in the commonly used machining method known as "laser cutting" to precisely cut materials. The method is highly appreciated for its capacity to generate complex patterns and minute details, notably in composites, metals, and polymers. However, precise control over a number of variables, including laser power, cutting speed, and focus, is necessary to achieve the best possible outcomes when using laser cutting [15]. These parameters have typically been changed manually or using preset values, which might not always take into consideration changes in the material's characteristics or the surrounding environment that occur in real time.

Artificial Intelligence for Optimizing Electrical Discharge Machining (EDM) Processes: Electrical discharge machining (EDM) is a very accurate machining technique that removes material from a workpiece by means of electrical sparks. EDM is very helpful for creating intricate features and complicated patterns in hard materials that are challenging to process with conventional techniques. To get the intended effects, EDM is a complicated process that necessitates precise control over variables including electrode wear, pulse duration, and spark energy. AI's superior

E-ISSN : 2962-1658
Volume 3, Number 4 ,October , 2024
https://doi.org/ 10.47709/ijmdsa.v3i4.4616

control and monitoring skills are essential to the optimization of EDM processes. In order to continuously improve the spark parameters, machine learning models may assess data from the EDM process in real-time, including current, voltage, and discharge frequency. By ensuring that the material is removed effectively and consistently, this real-time optimization lowers the likelihood of flaws like over- or undercutting [16].

Applications of Machine Learning in Ultrasonic Machining: High-frequency vibrations are used in the specialized process of ultrasonic machining to remove material from a workpiece. This material is usually fragile and includes metals, ceramics, and glass. Because the procedure is non-thermal and non-chemical, it is perfect for uses where the material's integrity needs to be maintained. To get the intended effects, ultrasonic machining necessitates exact control over the ultrasonic frequency, amplitude, and tool feed rate [17]. By offering sophisticated process control and optimization capabilities, artificial intelligence and machine learning are augmenting ultrasonic machining. The relationship between different process parameters and the material removal rates, surface finish, and tool wear that are produced can be analyzed by machine learning algorithms. AI systems can improve productivity and quality by using this data to learn the best set of settings for a particular material and machining activity.

AI IN AUTOMATION AND ROBOTICS

For many years, automation and robotics have formed the backbone of contemporary production, resulting in notable gains in productivity, consistency, and scalability. Thanks to these technologies, firms can now make items at a never-before-seen size and speed, all while saving money on labor and minimizing human error. However, the sector is undergoing a transformation as Artificial Intelligence (AI) is incorporated into robots and automation, elevating these technologies to new heights of sophistication and potential. Robots and automated systems driven by artificial intelligence (AI) are become more sophisticated, adaptable, and able to carry out difficult tasks that were previously unachievable for them. This section examines how artificial intelligence (AI) is changing robotics and automation in the manufacturing sector, with a particular emphasis on autonomous manufacturing systems, robotic process automation (RPA), and improving human-robot collaboration [18].

Robotic Process Automation (RPA) using AI in: The term "robotic process automation" (RPA) describes the use of software "bots" to automate rule-based, repetitive processes that were previously completed by human labor. RPA has mostly been utilized in manufacturing for jobs like order processing, inventory control, and data entry. Even though RPA has been successful in increasing productivity and decreasing errors in many areas, the addition of AI is greatly expanding its possibilities. AI-driven RPA systems can incorporate cognitive functions like decision-making, picture recognition, and natural language processing in addition to basic task automation. For instance, unstructured data, like emails from customers or product specs, can be analyzed by AI-powered bots to extract pertinent information and start the production process in the right way [19].

This makes it possible for manufacturers to automate more complicated jobs that require real-time information interpretation and processing, like handling supply chain interruptions, answering consumer inquiries, and modifying production plans in response to demand projections. RPA systems with AI capabilities can grow and change over time. These systems can recognize patterns and adjust their operations on their own thanks to machine learning, which results in ongoing gains in accuracy and efficiency [20]. To maintain maximum performance, an AI-driven RPA system in a manufacturing plant should be able to identify patterns in production data that point to possible bottlenecks or inefficiencies. This would enable the system to proactively modify workflows.

AI-Powered Autonomous Manufacturing Systems

The future of industrial automation is autonomous manufacturing systems, in which whole production lines run with little or no human involvement. These systems use artificial intelligence (AI) to plan and manage every aspect of the production process, from packing and quality assurance to material handling and assembly. The idea is to build fully automated factories, sometimes called "lights-out" manufacturing facilities, where automated systems and robots collaborate to make items continuously. AI is essential to the efficient operation of these autonomous systems. Making decisions and adapting quickly is one of the main issues with autonomous manufacturing. Large volumes of data from sensors and equipment throughout the production line may be processed by AI-powered systems, giving them the ability to instantly make decisions that maximize output and quality [21]. For instance, in order to dynamically modify production parameters and preserve ideal operating circumstances, AI algorithms can track production metrics like throughput, defect rates, and machine performance.

Improving AI-Assisted Human-Robot Collaboration: Even while AI-driven automation is developing quickly, human-robot collaboration is still vital, particularly for activities that call for both robotic precision and human dexterity. In production settings, this cooperative approach—also known as "cobots" or collaborative robots—is becoming more and more common. Cobots are made to complement human laborers, enhancing their abilities and allowing them to complete tasks more quickly and securely. By enabling robots to comprehend and react to human actions and intentions, artificial intelligence (AI) is essential to improving human-robot collaboration [22]. AI-powered cobots are able to comprehend both visual and audio cues from human workers, including spoken commands, hand gestures, and body language, thanks to machine learning and computer vision. Because of this, the robots may help workers in real-time by giving them equipment, changing their force and pace to suit the task at hand, or even

International Journal of
Multidisciplinary Sciences and Arts
E-ISSN : 2962-1658
Volume 3, Number 4 ,October , 2024
https://doi.org/ 10.47709/ijmdsa.v3i4.4616

predicting their needs based on past interactions.

AI and Predictive Maintenance in the Manufacturing Sector

Artificial intelligence (AI)-driven predictive maintenance is completely changing how manufacturers operate their machinery and workflows. In the past, manufacturing maintenance techniques have either been preventive, based on planned intervals, or reactive, addressing equipment breakdowns after they occur. Although these techniques have shown some degree of efficacy, they frequently result in needless downtime, higher expenses, and possible production disruptions. AI-enabled predictive maintenance provides a more effective and proactive strategy, enabling manufacturers to extend the life of machinery, optimize maintenance schedules, and foresee equipment breakdowns before they occur [23]. This section explores the benefits, operation, and revolutionary potential of AI-driven predictive maintenance in contemporary industry.

The Development of Manufacturing Maintenance Techniques: Upkeep has long been a vital component of manufacturing, keeping production lines running smoothly and continuously. Reactive maintenance and preventive maintenance are the two basic categories into which traditional maintenance techniques can be divided. Also referred to as "run-to-failure," reactive maintenance is replacing or fixing machinery only after it has malfunctioned. Although this method saves money up front, it frequently leads to unplanned downtime, lost output, and more expensive repairs because of catastrophic failures [24]. In contrast, preventive maintenance entails carrying out maintenance tasks on a regular basis in accordance with the equipment's age, usage, or manufacturer guidelines. This strategy seeks to stop unplanned breakdowns by swapping out components or fixing issues before they arise.

The Operation of AI-Driven Predictive Maintenance: A number of critical technologies, like as sensors, data analytics, machine learning, and the Industrial Internet of Things (IIoT), are necessary for AI-driven predictive maintenance. The first step in the process is gathering data from sensors built into production machinery. These sensors provide a constant stream of real-time data about the state of the machinery by monitoring a variety of factors, including temperature, vibration, pressure, and lubrication levels. AI algorithms are then used to evaluate this data in order to find patterns and correlations that could indicate future problems. With their ability to analyze historical data and draw lessons from previous accidents, machine learning models in particular are essential to predictive maintenance [25].

AI-Driven Predictive Maintenance's Advantages: Manufacturers can profit greatly from the application of AI-driven predictive maintenance, which can lead to increased reliability, cost savings, and operational efficiency.

- **Decreased Downtime:** Reducing unscheduled downtime is one of predictive maintenance's most important benefits. Manufacturers can minimize the impact on production schedules by doing maintenance at opportune times by anticipating equipment problems before they occur. Higher manufacturing output and an increase in overall equipment effectiveness (OEE) result from this [26].
- **Cost savings:** By preventing emergency repairs, extra labor, and lost output, predictive maintenance helps manufacturers avoid the hefty costs that come with unplanned equipment breakdowns [27]. Additionally, manufacturers can save money on labor, parts, and materials by reducing the frequency of maintenance activities and only executing maintenance when necessary.
- **Extended Equipment Lifespan:** Predictive maintenance can help manufacturing equipment last longer by addressing possible problems before they become serious ones. By doing this, manufacturers are able to maximize the return on investment (ROI) from their current assets and lessen the need to invest resources in new machinery [28].
- **Enhanced Safety:** Equipment malfunctions can provide serious dangers to people's safety, particularly in sectors of the economy that use heavy machinery or dangerous materials. By preventing these malfunctions, predictive maintenance makes the workplace safer for workers.
- **Enhanced Decision-Making:** Predictive maintenance solutions powered by AI give firms important information about the condition and functionality of their machinery [29]. Manufacturers are better able to plan for future investments in equipment and technology, prioritize maintenance tasks, and allocate resources efficiently thanks to this data-driven strategy.
- **Sustainability:** Predictive maintenance helps to create more environmentally friendly industrial processes by streamlining maintenance schedules and cutting waste. This entails lessening the environmental effect of production processes, using fewer spare parts, and consuming less energy [30].

PREDICTIVE MAINTENANCE'S EFFECT ON CONTEMPORARY MANUFACTURING

Manufacturing is changing as a result of the use of AI-driven predictive maintenance, which enables more accuracy, efficiency, and dependability in operations. As more firms put these technologies into place, the industry will be significantly impacted overall. In addition to making individual firms more competitive, predictive maintenance also makes the manufacturing industry more resilient and sustainable as a whole [31]. Predictive maintenance integration with other sophisticated manufacturing technologies, such smart factories and Industry 4.0 projects, is also opening up new avenues for growth and innovation. Artificial intelligence (AI) systems are expected to advance in accuracy and

E-ISSN : 2962-1658
Volume 3, Number 4 ,October , 2024
https://doi.org/ 10.47709/ijmdsa.v3i4.4616

sophistication as they develop, which will boost predictive maintenance's efficacy and open up new manufacturing applications. To sum up, AI-driven predictive maintenance is a significant advancement in the way manufacturers oversee their machinery and manufacturing procedures [32]. Predictive maintenance is assisting firms in reaching new heights of productivity, dependability, and sustainability by anticipating and averting equipment breakdowns, streamlining maintenance plans, and cutting expenses. With new opportunities for creativity and productivity, the technology is predicted to become more and more significant in determining the direction of manufacturing in the future [33].

AI-Powered Manufacturing Quality Assurance and Control

A crucial part of manufacturing is quality assurance and control, which guarantees that goods fulfill the necessary requirements for excellence and perform as intended. To find flaws and confirm product quality, quality control has historically depended on human inspectors and standardized testing procedures. These techniques, however, are frequently insufficient to fulfill the exacting standards and intricate needs of contemporary manufacturing. They can also be labor-intensive and prone to human mistake [34]. Artificial Intelligence (AI) is changing quality assurance and control by providing producers with new tools to improve consistency, efficiency, and accuracy. AI-driven quality control makes use of data analytics, computer vision, and machine learning to predict quality problems, find flaws, and streamline manufacturing procedures. This section examines the main uses, advantages, and ways AI is transforming manufacturing quality assurance and control [35].

The Development of Manufacturing Quality Control: Traditionally, manual testing and inspection of products at different stages of the production process was part of quality control in manufacturing. Employees would use gauges to measure important measurements, visually inspect goods for flaws, or run tests to make sure they adhered to requirements. Although these techniques were labor-intensive, subjective, and often ineffective at identifying minute flaws or inconsistencies—particularly in high-volume or extremely complicated production environments—they were nevertheless useful to some extent [36]. Traditional quality control methods got more and more limited as production processes became more automated and advanced.

Artificial Intelligence for Quality Control and Assurance: Machine learning, computer vision, and data analytics are three essential technologies for AI-driven quality control and assurance. Together, these technologies provide producers a dynamic and all-encompassing approach to quality control. AI-driven quality control systems rely heavily on machine learning techniques for defect detection [37]. These algorithms can identify patterns linked to flaws because they have been trained on massive databases of sensor readings, product photos, and historical quality data. For instance, a machine learning model might be trained to recognize soldering flaws like cold joints or bridges by examining pictures taken by high-resolution cameras in a production line that makes electrical components. After being trained, the AI system can identify these flaws far more accurately in real time than human inspectors could. As fresh data becomes available, machine learning models can also be updated and improved over time [38]. This flexibility is essential in production settings where processes and goods are continuously changing. The AI system can learn from these events and enhance its detection capabilities over time when it comes across new kinds of errors or adjustments in production [39].

AI-driven quality control systems can employ data analytics to anticipate possible quality problems before they occur, in addition to detecting defects. AI systems can find patterns and correlations that might point to a higher likelihood of faults by examining production data, environmental factors, and past quality records. Manufacturers can prevent problems by proactively modifying production parameters, servicing equipment, or changing material inputs thanks to predictive quality assurance [40]. For instance, an AI system might notify operators to carry out extra checks or adjust the production process if it determines, based on historical performance, that a particular batch of raw materials is likely to result in quality difficulties. This predictive ability contributes to more economical and efficient manufacturing processes by lowering waste, rework, and downtime in addition to increasing product quality [41].

AI-driven quality control systems have a high degree of precision in identifying even the slightest flaws, which lowers the possibility that faulty goods will be sold. AI systems maintain a consistent level of performance, guaranteeing that quality requirements are met consistently across all manufacturing batches, in contrast to human inspectors who may grow weary or unreliable over time. AI systems give producers immediate input on the quality of their products, enabling them to take quick action in response to problems. As a result, post-production inspections and rework take less time and money [42]. Manufacturers can also keep a closer eye on their manufacturing processes thanks to real-time monitoring, which produces results that are more dependable and predictable. AI-driven quality control helps manufacturers cut waste and the need for rework by identifying errors early in the production process and forecasting possible quality problems. This reduces the cost of production while also promoting more environmentally friendly manufacturing techniques by using less energy and raw resources [43].

Sustaining brand reputation and customer satisfaction depend heavily on producing high-quality items. By ensuring that products satisfy the highest standards of quality, AI-driven quality control lowers the possibility of customer complaints, returns, or recalls. Consequently, this enhances client loyalty and may result in a larger portion of the market [44]. AI-driven QC systems are very flexible and scalable, making them suitable for a variety of production settings and product kinds. AI systems can be customized to satisfy the unique quality requirements of various

E-ISSN : 2962-1658
Volume 3, Number 4 ,October , 2024
https://doi.org/ 10.47709/ijmdsa.v3i4.4616

industries, whether they are creating huge, complicated assemblies or small, intricate components. Furthermore, AI systems can manage bigger datasets and more difficult inspection jobs without sacrificing performance as production quantities rise. AI-driven quality assurance and control are revolutionizing the manufacturing sector by giving producers access to sophisticated instruments for fault finding, quality issue forecasting, and process optimization [45].

AI technologies provide previously unheard-of levels of precision, consistency, and efficiency in quality control by utilizing machine learning, computer vision, and data analytics. Beyond only producing higher-quality products, AI-driven quality control also saves money, minimizes waste, increases customer happiness, and allows for greater scalability. AI technology is expected to play a bigger part in quality assurance and control as it develops, opening up new avenues for manufacturing innovation and excellence [46]. The integration of artificial intelligence (AI) into quality management not only makes manufacturers more competitive, but it also advances the industrial sector as a whole by establishing new benchmarks for productivity and quality.

MANUFACTURING SUPPLY CHAIN OPTIMIZATION DRIVEN BY AI

Maintaining responsive, economical, and efficient manufacturing processes requires supply chain optimization. Effective management is difficult due to the complexity of current supply chains, which can span international networks of manufacturers, distributors, suppliers, and retailers. Conventional supply chain management techniques frequently depend on manual forecasting, historical data, and static models, which may not adequately reflect the dynamic and interconnected character of modern supply networks. Supply chain optimization is undergoing a transformation thanks to artificial intelligence (AI), which offers sophisticated tools for forecasting, data analysis, and decision-making [47]. Manufacturers can improve visibility, optimize processes, and respond more quickly to changing circumstances thanks to AI technologies. This section examines the main uses of AI in industrial supply chain optimization, as well as the advantages it presents.

Traditional Supply Chain Management's Challenges: Coordination of a broad range of tasks, including as distribution, logistics, inventory control, production scheduling, and procurement, is a requirement of traditional supply chain management. Spreadsheets and other antiquated technologies, such as enterprise resource planning (ERP) systems, have historically been used to handle these tasks [48]. Although these approaches have given rise to supply chain management, they frequently encounter many obstacles: It may be challenging to keep an eye on the progress of orders, inventory levels, and supplier performance with traditional systems since they may not provide real-time visibility into supply chain activity. Delays, stock outs, and supply chain inefficiencies may result from this [49].

Predicting demand and supply requirements based solely on past data and static models may prove to be imprecise, particularly when confronted with abrupt shifts in market dynamics, consumer inclinations, or interruptions in supply. This may lead to either an overstocking or an understocking situation, which would raise expenses and lower consumer satisfaction. Manual decision-making procedures, which can be cumbersome and prone to mistakes, are frequently used in traditional supply chain management. It could be difficult for decision-makers to assess several possibilities or react swiftly to new problems [50]. Because supply chains are dynamic, static supply chain models may fail to take this into consideration, making it difficult to adjust for shifts in demand, interruptions in the supply chain, or other unanticipated circumstances. AI uses cutting-edge technology like automation, data analytics, and machine learning to solve many of the problems with traditional supply chain management. With the use of these technologies, manufacturers may increase visibility, boost forecasting accuracy, and streamline decision-making procedures [51].

AI-driven supply chain solutions leverage real-time data from several sources, such as external data feeds, ERP systems, and Internet of Things sensors, to give a thorough picture of supply chain operations. This data can be analyzed by machine learning algorithms to find patterns, trends, and anomalies, providing information on the state of shipments, inventories, and supplier performance at any given time [52]. AI, for instance, may evaluate information from RFID tags and GPS trackers to offer real-time visibility into the location and state of shipments. Manufacturers can track any delays, keep tabs on order progress, and take proactive measures to resolve problems before they affect production with the use of this information. Artificial Intelligence (AI) improves demand forecasting by analyzing past sales data, market trends, and outside variables like weather patterns or economic indicators using machine learning models. More accurate demand forecasts can result from these models' ability to spot intricate patterns and connections that conventional forecasting techniques would overlook [53]. AI helps firms control inventory levels, minimize stock outs and overstocking, and match production schedules with actual demand by increasing forecast accuracy. This leads to a more effective supply chain, lower costs, and higher customer satisfaction [54].

Predictive analytics is used by AI-driven inventory management systems to determine the ideal stock levels and reorder points. The ideal inventory levels for every product can be found by using machine learning algorithms to examine data on lead times, sales trends, and supplier performance. AI can also assist firms in more efficiently managing buffer inventories and safety stock by anticipating any disruptions in the supply chain or variations in demand. By lowering the possibility of stockouts and excess inventory, this improves cash flow and lowers carrying costs. By evaluating data on supplier performance, dependability, and risk factors, artificial intelligence (AI) enhances supplier management [55]. To find the most dependable and economical suppliers, machine learning models can assess supplier indicators including quality flaws, on-time delivery rates, and pricing patterns. Manufacturers can evaluate the possible effects of supplier disruptions on their supply chain with the aid of AI. AI has the ability to identify alternate

E-ISSN : 2962-1658
Volume 3, Number 4 ,October , 2024
https://doi.org/ 10.47709/ijmdsa.v3i4.4616

sourcing options and issue early warnings of possible supply chain hazards by evaluating data on natural catastrophes, geopolitical events, and other external factors [56].

ADVANTAGES OF SUPPLY CHAIN OPTIMIZATION DRIVEN BY AI

Manufacturers can gain a great deal from the incorporation of AI into supply chain management, including:

Enhanced Efficiency: AI improves operational efficiency by automating repetitive processes, optimizing inventory levels, and offering real-time visibility [57]. This results in shorter lead times, quicker reaction times, and less operating expenses.

Increased Accuracy: Demand forecasts and inventory management are more accurate thanks to AI-driven forecasting and analytics. By doing this, the likelihood of stockouts, overstocking, and production delays is decreased, improving supply and demand alignment.

Increased Flexibility: AI helps producers respond swiftly to fluctuations in demand, interruptions in the supply chain, and other unanticipated circumstances [58]. AI supports proactive response and supply chain resilience by giving manufacturers access to sophisticated scenario planning and decision-making tools.

Savings: Artificial intelligence (AI)-driven optimization lowers the price of excess inventory, production hold-ups, and supply interruptions [59]. Manufacturers may save a lot of money and boost their profits by increasing the accuracy of their forecasts and optimizing their operations.

Improved Supplier Relationships: By offering insights into supplier performance and risk variables, artificial intelligence (AI) enhances supplier management. By doing this, manufacturers can improve their rapport with dependable suppliers, bargain for better terms, and lessen the impact of supply chain risks [60].

Improved Customer Satisfaction: AI assists manufacturers in providing clients with products more promptly and dependably by streamlining inventory levels, production schedules, and order fulfillment [61]. Higher customer satisfaction and a more formidable competitive position in the market result from this.

The manufacturing sector is undergoing a transformation because to AI-powered supply chain optimization, which offers sophisticated tools for forecasting, data analysis, and decision-making. Manufacturers may increase visibility, improve accuracy, and expedite processes by utilizing automation, machine learning, and real-time analytics. AI-driven supply chain optimization offers several advantages, such as improved customer satisfaction, lower costs, stronger supplier connections, and increased efficiency [62]. AI technology is predicted to play a bigger part in supply chain management as it develops, opening up new avenues for manufacturing innovation and excellence. AI's incorporation into supply chain optimization boosts the manufacturing industry's resilience and overall progress while also making individual enterprises more competitive.

CONCLUSION

Artificial Intelligence (AI) is radically changing the industrial sector by propelling progress in a number of vital domains, such as supply chain optimization, robotics and automation, predictive maintenance, and quality control and assurance. Artificial Intelligence (AI) becomes a key factor in changing industry norms and practices as production adapts to meet growing demands for accuracy, flexibility, and efficiency. Artificial Intelligence is augmenting machine and automated system capabilities in robotics and automation, enabling them to execute intricate tasks with increased precision and flexibility. Increased human-robot collaboration, autonomous manufacturing systems, and more intelligent robotic process automation (RPA) are made possible by the integration of AI, which raises operational flexibility and production efficiency.

Artificial intelligence (AI)-driven predictive maintenance is transforming how manufacturers maintain equipment and stop malfunctions. Manufacturers may reduce unexpected downtime, extend the life of their machinery, and anticipate maintenance needs with the help of artificial intelligence (AI) by utilizing real-time data, machine learning, and predictive analytics. This proactive strategy lowers expenses, maximizes resource utilization, and avoids disruptions. AI greatly improves quality assurance and control by utilizing cutting-edge technologies like data analytics, computer vision, and machine learning. Artificial intelligence (AI) technologies ensure that goods meet the highest standards while cutting waste and rework by providing more accurate defect detection, real-time monitoring, and predictive quality management. Customer satisfaction rises as a result, and competitive positioning is reinforced.

Artificial Intelligence (AI) enhances supply chain optimization by improving visibility, forecasting accuracy, and decision-making capabilities. Automation, predictive models, and AI-driven data analytics improve flexibility, cut costs, and streamline supply chain processes. AI helps create more robust and effective supply chains by tackling issues like inventory control, supplier performance, and changeable market conditions. All things considered, incorporating AI into manufacturing processes is not only a technological achievement but also a critical strategic move. It gives producers the ability to handle challenging situations, adjust to changing customer needs, and spur innovation. AI will have a greater influence on production as it develops, presenting fresh possibilities for quality, efficiency, and optimization. The role artificial intelligence plays in boosting output, guaranteeing quality, and streamlining processes will increasingly shape the manufacturing industry in the future. Manufacturers may achieve improved operational effectiveness, maintain competitiveness in a continuously changing market, and provide customers with superior products by embracing AI-driven solutions. AI has enormous potential to revolutionize the manufacturing sector, and as

E-ISSN : 2962-1658
Volume 3, Number 4 ,October , 2024
https://doi.org/ 10.47709/ijmdsa.v3i4.4616

it develops further, it should open up even more opportunities.s

REFERENCES

1. Abdallah, Ali, Yogesh K Dwivedi, and Nripendra P Rana. 2017. "International Journal of Information Management Factors Influencing Adoption of Mobile Banking by Jordanian Bank Customers : Extending UTAUT2 with Trust." International Journal of Information Management 37 (3): 99–110. doi:10.1016/j.ijinfomgt.2017.01.002.
2. Aboelmaged, Mohamed Gamal. 2014. "Predicting E-Readiness at Firm-Level: An Analysis of Technological, Organizational and Environmental (TOE) Effects on e-Maintenance Readiness in Manufacturing Firms." International Journal of Information Management 34 (5): 639–51. doi:10.1016/j.ijinfomgt.2014.05.002.
3. ACMA. 2019. "Indian Auto Component Industry Performance Review-FY 18." ACMC. file:///C:/Users/Admin/Downloads/ACMA-Presentation_press-conference_2019.pdf.
4. Al-Qirim, Nabeel. 2006. "The Role of the Government and E-Commerce Adoption in Small Businesses in New Zealand." International Journal of Internet and Enterprise Management 4 (4): 293. doi:10.1504/ijiem.2006.011042. ———. 2007.
5. "The Adoption of ECommerce Communications and Applications Technologies in Small Businesses in New Zealand." Electronic Commerce Research and Applications 6 (4): 462–73. doi:10.1016/j.elerap.2007.02.012.
6. Alaiad, Ahmad, and Lina Zhou. 2014. "The Determinants of Home Healthcare Robots Adoption: An Empirical Investigation." International Journal of Medical Informatics 83 (11): 825–40. doi:10.1016/j.ijmedinf.2014.07.003.
7. Alshamaila, Yazn, Savvas Papagiannidis, and Feng Li. 2013. "Cloud Computing Adoption by SMEs in the North East of England: A Multi-Perspective Framework." Journal of Enterprise Information Management 26 (3): 250–75. Doi: 10.1108/17410391311325225.
8. Bibby, Lee, and Benjamin Dehe. 2018. "Defining and Assessing Industry 4.0 Maturity Levels– Case of the Defence Sector." Production Planning and Control 29 (12): 1030–43. doi:10.1080/09537287.2018.1503355.
9. Chau, Patrick Y K, Kar Yan Tam, and Kar Yan Tam. 1991. "Factors Affecting the Adoption of Open Systems : An Exploratory." MIS Quarterly 21 (1): 1–24. doi:10.2307/249740.
10. Cheng, Hong, Ruixue Jia, Dandan Li, and Hongbin Li. 2019. "The Rise of Robots in China." Journal of Economic Perspectives 33 (2): 71–88. doi:10.1257/jep.33.2.71.
11. Chin, Wynne W., Robert A. Peterson, and Steven P. Brown. 2008. "Structural Equation Modeling in Marketing: Some Practical Reminders." Journal of Marketing Theory and Practice 16 (4): 287–98. doi:10.2753/MTP1069-6679160402.
12. Chiu, Chui-Yu, Shi Chen, and Chun-Liang Chen. 2017. "An Integrated Perspective of TOE Framework and Innovation Diffusion in Broadband Mobile Applications Adoption by Enterprises." International Journal of Management, Economics and Social Sciences (IJMESS) 6 (1): 14–39. doi:http://hdl.handle.net/10419/157921.
13. Choi, Moon Jong, Sanghyun Kim, and Hyunsun Park. 2018. "Empirical Study on the Factors Influencing Process Innovation When Adopting Intelligent Robots at Small- and MediumSized Enterprises-The Role of Organizational Supports." Information (Switzerland) 9 (12). Doi: 10.3390/info9120315. Chong, Alain Yee Loong, and Felix T.S.
14. Chan. 2012. "Structural Equation Modeling for MultiStage Analysis on Radio Frequency Identification (RFID) Diffusion in the Health Care Industry." Expert Systems with Applications 39 (10): 8645–54. doi:10.1016/j.eswa.2012.01.201.
15. Chouhan, Swarnima, Priyanka Mehra, and Ankita Daso. 2017. "India's Readiness for Industry 4.0 – A Focus on Automotive Sector." http://www.grantthornton.in/insights/articles/indias-readiness-for-industry-4.0--a-focuson-automotive-sector/.
16. Gursoy, Dogan, Oscar Hengxuan Chi, Lu Lu, and Robin Nunkoo. 2019. "Consumers Acceptance of Artificially Intelligent (AI) Device Use in Service Delivery." International Journal of Information Management 49 (March): 157–69. doi:10.1016/j.ijinfomgt.2019.03.008.
17. Hair, J. F., Jr., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. 2017. A Primer on Partial Least Squares Structural Equation Modeling (2nd Ed.). Long Range Planning. Landon, UK: Sage Publication.
18. Hair, Joe F., Christian Ringle, and Marko Sarstedt. 2011. "PLS-SEM: Indeed a Silver Bullet." Journal of Marketing Theory and Practice 19 (2): 139–51. Doi: 10.2753/MTP1069- 6679190202.
19. Hair, Joe F., Marko Sarstedt, Lucas Hopkins, and Volker G. Kuppelwieser. 2014. "Partial Least Squares Structural Equation Modeling (PLS-SEM): An Emerging Tool in Business Research." European Business Review 26 (2): 106–21. Doi: 10.1108/EBR-10-2013-0128.
20. Hassan, Haslinda, Alexei Tretiakov, and Dick Whiddett. 2017. "Factors Affecting the Breadth and Depth of E-Procurement Use in Small and Medium Enterprises." Journal of Organizational Computing and Electronic Commerce 27 (4). Taylor & Francis: 304–24. doi:10.1080/10919392.2017.1363584.

E-ISSN : 2962-1658
Volume 3, Number 4 ,October , 2024
https://doi.org/ 10.47709/ijmdsa.v3i4.4616

21. Hassan, Mayadah, Maged Ali, Emel Aktas, and Kholoud Alkayid. 2015. "Factors Affecting Selection Decision of Auto-Identification Technology in Warehouse Management: An International Delphi Study." Production Planning and Control 26 (12): 1025–49. doi:10.1080/09537287.2015.1011726.
22. Henderson, Dave, Steven D Sheetz, and Brad S Trinkle. 2012. "International Journal of Accounting Information Systems the Determinants of Inter-Organizational and Internal in-House Adoption of XBRL : A Structural Equation Model." International Journal of Accounting Information Systems 13 (2). Elsevier Inc.: 109–40. doi:10.1016/j.accinf.2012.02.001.
23. Henseler, Jörg, and Wynne W. Chin. 2010. "A Comparison of Approaches for the Analysis of Interaction Effects between Latent Variables Using Partial Least Squares Path Modeling." Structural Equation Modeling 17 (1): 82–109. Doi: 10.1080/10705510903439003.
24. Hossain, Mohammad Alamgir, Craig Standing, and Caroline Chan. 2017. "The Development and Validation of a Two-Staged Adoption Model of RFID Technology in Livestock Businesses." Information Technology and People 30 (4): 785–808. Doi: 10.1108/ITP-06- 2016-0133.
25. Hsu, Ching Wen, and Ching Chiang Yeh. 2017. "Understanding the Factors Affecting the Adoption of the Internet of Things." Technology Analysis and Strategic Management 29 (9). Taylor & Francis: 1089–1102. doi:10.1080/09537325.2016.1269160.
26. Huang, Ming Hui, and Roland T. Rust. 2018. "Artificial Intelligence in Service." Journal of Service Research 21 (2): 155–72. Doi: 10.1177/1094670517752459.
27. Lin, Hsiu Fen. 2014. "Understanding the Determinants of Electronic Supply Chain Management System Adoption: Using the Technology-Organization-Environment Framework." Technological Forecasting and Social Change 86. Elsevier Inc.: 80–92. doi:10.1016/j.techfore.2013.09.001.
28. Maduku, Daniel K., Mercy Mpinganjira, and Helen Duh. 2016. "Understanding Mobile Marketing Adoption Intention by South African SMEs: A Multi-Perspective Framework." International Journal of Information Management 36 (5). Elsevier Ltd: 711–23. doi:10.1016/j.ijinfomgt.2016.04.018.
29. Mani, Sunil. 2018. "Robot Apocalypse: Does It Matter for Indiaas Manufacturing Industry?" SSRN Electronic Journal. Tokyo. doi:10.2139/ssrn.3182255.
30. Mariani, Marcello M., Matteo Borghi, and Sergey Kazakov. 2019. "The Role of Language in the Online Evaluation of Hospitality Service Encounters: An Empirical Study." International Journal of Hospitality Management 78 (October 2018). Elsevier: 50–58. doi:10.1016/j.ijhm.2018.11.012.
31. Masood, Tariq, and Johannes Egger. 2019. "Augmented Reality in Support of Industry 4.0— Implementation Challenges and Success Factors." Robotics and Computer-Integrated Manufacturing 58: 181–95. doi:10.1016/j.rcim.2019.02.003.
32. Mathews, Sam. 2017. "India Ready to Accelerate Industrial Robotics Adoption." Systemantics.Com. http://www.systemantics.com/2017/04/24/india-ready-to-accelerateindustrial-robotics-adoption/.
33. Menifestias. 2020. "Robotics in India." Manifestias.Com. https://www.manifestias.com/2020/02/28/robotics-in-india/.
34. Mittal, Sameer, Muztoba Ahmad Khan, Jayant Kishor Purohit, Karan Menon, David Romero, and Thorsten Wuest. 2019. "A Smart Manufacturing Adoption Framework for SMEs." International Journal of Production Research 0 (0). Taylor & Francis: 1–19. doi:10.1080/00207543.2019.1661540.
35. Barmada, S., Dionigi, M., Mezzanotte, P., Tucci, M. (2017). Design and Experimental Characterization of a Combined WPT-PLC System. Wireless Power Transfer, 4(2), 160- 170. https://doi.org/10.1017/wpt.2017.11
36. Dhameliya, N. (2022). Power Electronics Innovations: Improving Efficiency and Sustainability in Energy Systems. Asia Pacific Journal of Energy and Environment, 9(2), 71-80. https://doi.org/10.18034/apjee.v9i2.752
37. Dhameliya, N., Mullangi, K., Shajahan, M. A., Sandu, A. K., & Khair, M. A. (2020). BlockchainIntegrated HR Analytics for Improved Employee Management. ABC Journal of Advanced Research, 9(2), 127-140. https://doi.org/10.18034/abcjar.v9i2.738
38. Dhameliya, N., Sai Sirisha Maddula, Kishore Mullangi, & Bhavik Patel. (2021). Neural Networks for Autonomous Drone Navigation in Urban Environments. Technology & Management Review, 6, 20-35. https://upright.pub/index.php/tmr/article/view/141
39. Ju, M. L., Zhai, X. Q., Zhang, Q. (2014). Application of Siemens S7-300 PLC in the Thermal Power Plant Flue Gas Desulfurization Control System. Applied Mechanics and Materials, 511-512, 1123-1127. https://doi.org/10.4028/www.scientific.net/AMM.511-512.1123
40. Jun-Ho, H. (2018). PLC-Integrated Sensing Technology in Mountain Regions for Drone Landing Sites: Focusing on Software Technology. Sensors, 18(8), 2693. https://doi.org/10.3390/s18082693
41. Koehler, S., Dhameliya, N., Patel, B., & Anumandla, S. K. R. (2018). AI-Enhanced Cryptocurrency Trading Algorithm for Optimal Investment Strategies. Asian Accounting and Auditing Advancement, 9(1), 101–114. https://4ajournal.com/article/view/91
42. Liu, X., Liu, H., Liu, J., Xu, D. (2017). An Automatic Networking and Routing Algorithm for Mesh Network in PLC System. IOP Conference Series. Materials Science and Engineering, 199(1). https://doi.org/10.1088/1757-899X/199/1/012092

E-ISSN : 2962-1658
Volume 3, Number 4 ,October , 2024
https://doi.org/ 10.47709/ijmdsa.v3i4.4616

43. Maddula, S. S. (2018). The Impact of AI and Reciprocal Symmetry on Organizational Culture and Leadership in the Digital Economy. Engineering International, 6(2), 201–210. https://doi.org/10.18034/ei.v6i2.703
44. Maddula, S. S., Shajahan, M. A., & Sandu, A. K. (2019). From Data to Insights: Leveraging AI and Reciprocal Symmetry for Business Intelligence. Asian Journal of Applied Science and Engineering, 8(1), 73–84. https://doi.org/10.18034/ajase.v8i1.86 Mohammed, M. A.,
45. Kothapalli, K. R. V., Mohammed, R., Pasam, P., Sachani, D. K., & Richardson, N. (2017). Machine Learning-Based Real-Time Fraud Detection in Financial Transactions. Asian Accounting and Auditing Advancement, 8(1), 67–76. https://4ajournal.com/article/view/93
46. Mohammed, R., Addimulam, S., Mohammed, M. A., Karanam, R. K., Maddula, S. S., Pasam, P., & Natakam, V. M. (2017). Optimizing Web Performance: Front End Development Strategies for the Aviation Sector. International Journal of Reciprocal Symmetry and Theoretical Physics, 4, 38-45. https://upright.pub/index.php/ijrstp/article/view/142
47. Mullangi, K. (2017). Enhancing Financial Performance through AI-driven Predictive Analytics and Reciprocal Symmetry. Asian Accounting and Auditing Advancement, 8(1), 57–66. https://4ajournal.com/article/view/89
48. Mullangi, K. (2022). Transforming Business Operations: The Role of Information Systems in Enterprise Architecture. Digitalization & Sustainability Review, 2(1), 15-29. https://upright.pub/index.php/dsr/article/view/143
49. Mullangi, K., Anumandla, S. K. R., Maddula, S. S., Vennapusa, S. C. R., & Mohammed, M. A. (2018). Accelerated Testing Methods for Ensuring Secure and Efficient Payment Processing Systems. ABC Research Alert, 6(3), 202–213. https://doi.org/10.18034/ra.v6i3.662
50. Mullangi, K., Maddula, S. S., Shajahan, M. A., & Sandu, A. K. (2018). Artificial Intelligence, Reciprocal Symmetry, and Customer Relationship Management: A Paradigm Shift in Business. Asian Business Review, 8(3), 183–190. https://doi.org/10.18034/abr.v8i3.704
51. Mullangi, K., Yarlagadda, V. K., Dhameliya, N., & Rodriguez, M. (2018). Integrating AI and Reciprocal Symmetry in Financial Management: A Pathway to Enhanced Decision-Making. International Journal of Reciprocal Symmetry and Theoretical Physics, 5, 42-52. https://upright.pub/index.php/ijrstp/article/view/134
52. Nizamuddin, M., Natakam, V. M., Sachani, D. K., Vennapusa, S. C. R., Addimulam, S., & Mullangi, K. (2019). The Paradox of Retail Automation: How Self-Checkout Convenience Contrasts with Loyalty to Human Cashiers. Asian Journal of Humanity, Art and Literature, 6(2), 219-232. https://doi.org/10.18034/ajhal.v6i2.751
53. Patel, B., Mullangi, K., Roberts, C., Dhameliya, N., & Maddula, S. S. (2019). Blockchain-Based Auditing Platform for Transparent Financial Transactions. Asian Accounting and Auditing Advancement, 10(1), 65–80. https://4ajournal.com/article/view/92
54. Patel, B., Yarlagadda, V. K., Dhameliya, N., Mullangi, K., & Vennapusa, S. C. R. (2022). Advancements in 5G Technology: Enhancing Connectivity and Performance in Communication Engineering. Engineering International, 10(2), 117–130. https://doi.org/10.18034/ei.v10i2.715
55. Pinter, J. M., Trohak, A. (2013). System Integration Methods for Voice-Commanded PLC Controlled Systems. Applied Mechanics and Materials, 309, 280. https://doi.org/10.4028/www.scientific.net/AMM.309.280
56. Rabah, N. B., Saddem, R., Hmida, F. B., Carre-Menetrier, V., Tagina, M. (2017). Intelligent Case Based Decision Support System for Online Diagnosis of Automated Production System. Journal of Physics: Conference Series, 783(1). https://doi.org/10.1088/1742- 6596/783/1/012009
57. Rodriguez, M., Shajahan, M. A., Sandu, A. K., Maddula, S. S., & Mullangi, K. (2021). Emergence of Reciprocal Symmetry in String Theory: Towards a Unified Framework of Fundamental Forces. International Journal of Reciprocal Symmetry and Theoretical Physics, 8, 33-40. https://upright.pub/index.php/ijrstp/article/view/136
58. Sachani, D. K., & Vennapusa, S. C. R. (2017). Destination Marketing Strategies: Promoting Southeast Asia as a Premier Tourism Hub. ABC Journal of Advanced Research, 6(2), 127- 138. https://doi.org/10.18034/abcjar.v6i2.746
59. Kumar, V. M., Vijayaraghavan, P., Meshram, V. V., Sharma, M. K., Nithya, M. S., & Kumar, R. (2023, November). Transforming Data Analysis through AI-Powered Data Science. In *2023 2nd International Conference on Futuristic Technologies (INCOFT)* (pp. 1-5). IEEE.
60. AR, E. I. APioneering RESEARCH ON AUGMENTED REALITY REDEFINED: AI-POWERED.
61. Sharma, M., Shail, H., Painuly, P. K., & Kumar, A. S. (2023). AIPowered Technologies Used in Online Fashion Retail for Sustainable Business: AI-Powered Technologies Impacting Consumer Buying Behavior. In Sustainable Marketing, Branding, and Reputation Management: Strategies for a Greener Future (pp. 538-561). IGI Global.
62. Limna, P. (2022). Artificial Intelligence (AI) in the hospitality industry: A review article. Int. J. Comput. Sci. Res, 6, 1-12.