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Improving Manufacturing Processes through Artificial Intelligence - Example of Printed Circuit Board Manufacturing

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Abstract: The advent of Artificial Intelligence (AI) in manufacturing has heralded a new era of industrial revolution, characterised by unprecedented efficiency, productivity, and innovation. This critical review delves into the application of AI technologies in the manufacturing sector, scrutinising their impact on process enhancement and addressing the spectrum of opportunities and challenges they present. By thoroughly analysing recent studies, industry reports, and case examples, this paper outlines the transformative potential of AI in various manufacturing domains, including predictive maintenance, supply chain optimisation, quality control, and intelligent manufacturing. However, the paper does not shy away from discussing the critical challenges facing the deployment of AI in manufacturing. These include technical limitations, data privacy and security concerns, the need for substantial investment, and the socio-economic implications of workforce displacement and skill gaps. Concluding with a forward-looking perspective, the review suggests practical strategies for overcoming these hurdles, such as fostering public-private partnerships, investing in AI literacy and training, and adopting ethical guidelines for AI use.

Keywords: artificial intelligence; lean management; predictive maintenance; printed circuit board; process improvement; quality management

1 INTRODUCTION

Artificial Intelligence (AI) represents a significant technological opportunity in manufacturing, offering a wide range of applications that lead to increased efficiency, productivity, and innovation. By utilising AI in manufacturing, businesses can automate complex processes, optimise production lines, reduce manufacturing costs, and minimise the duration of manufacturing processes. AI, employing intelligent algorithms, allows machines to learn from data, predict production errors, conduct predictive maintenance, and enhance the overall quality of products. AI also enables the personalisation of products based on individual customer preferences and the flexible response to changing market conditions. With these capabilities, AI opens the door to significant innovations in the manufacturing sector, supports sustainability, and improves the competitiveness of companies in the global market.

On the other hand, applying AI in manufacturing can bring certain risks that may negatively impact manufacturing processes. Therefore, this article aims to critically summarise the advantages and disadvantages of using AI to improve manufacturing processes. Specifically, attention will be focused on these areas:

- Lean manufacturing
- Predictive maintenance
- Internal logistics and SCM
- Production planning
- Quality management.

Based on the previous introduction, the paper tries to answer this research question:

"How can artificial intelligence technologies be effectively integrated into existing manufacturing processes to enhance efficiency, reduce costs, and improve product quality while also addressing the challenges of implementation and workforce adaptation?"

This research question is designed to explore the potential benefits of AI in manufacturing (such as efficiency and quality improvements) and the practical aspects of integrating these technologies into current systems. It considers the economic (cost reduction) and human factors (workforce adaptation), ensuring a comprehensive review of AI's impact on manufacturing. This broad yet focused approach encourages an exploration of multiple dimensions - technological, economic, and human resource management - making it suitable for a critical review.

2 RESEARCH METHODOLOGY

The research is based on a combination of methods research framework, integrating both qualitative and quantitative analyses to critically review the role of Artificial Intelligence (AI) in manufacturing processes. This approach allows for a holistic understanding of AI's transformative potential in manufacturing, encompassing efficiency, productivity, innovation, and the challenges therein.

Data Collection: Data collection involved a comprehensive literature review, focusing on recent studies, industry reports, and case examples. The selection criteria emphasised relevance to AI applications in manufacturing, including predictive maintenance, supply chain optimisation, quality control, and intelligent manufacturing solutions. This approach ensured a robust foundation of evidence for analysis.

Analysis Method: The study utilised a thematic analysis to identify common themes and trends within the literature, facilitating an in-depth exploration of AI's contributions and challenges in manufacturing.

Pre-implementation Study Approach: This kind of study is essential in ensuring the successful adoption and integration of new technologies, methods, or processes within an organization. This study helps identify potential challenges, estimate benefits, and refine implementation strategies before full-scale deployment. A practical implementation of this study was conducted through Printed Circuit Board (PCB) manufacturing and assembly. This case study provided concrete example of AI's potential improvements in process efficiency, predictive maintenance, and quality management within a specific manufacturing domain.

SWOT Analysis: The research methodology incorporated a SWOT analysis as part of results pre-implementation study. The aim is too comprehensively critically evaluate the strengths, weaknesses, opportunities, and threats associated with AI integration in manufacturing. This analysis facilitated a balanced view of AI's potential benefits and the challenges needing strategic consideration.

Conclusions and Recommendations: Findings from the literature review, case study, and analyses conducted, the study concludes with actionable recommendations for industry practitioners.

This methodology establishes a comprehensive framework for exploring AI's role in improving manufacturing processes, providing a robust basis for the paper's critical review.

3 LITERATURE REVIEW

Lean management and AI are two important concepts in the manufacturing industry nowadays. Lean manufacturing reduces waste and improves productivity [1]. It has been shown to increase plant efficiency and decrease processing times in major manufacturing operations [2]. On the other hand, AI has the potential to improve manufacturing efficiency, productivity, and sustainability. It can be used in predictive maintenance, quality assurance, and process optimisation [3]. Combining lean management and AI can lead to significant cost and efficiency benefits in manufacturing [4].

AI technologies can be used as additional tools in the lean manufacturing toolkit, enhancing the effect. By using AI, manufacturing enterprises can collect, analyse, and structure production information, improve the quality of products, and increase overall efficiency. Implementing AI in lean manufacturing can help optimise production, reduce losses, and increase working productivity.

Predictive maintenance (PdM) is a key strategy in manufacturing, aiming to reduce costs and improve product quality. The integration of AI into the maintenance process has achieved the most significant progress in predicting the condition of rotating machinery based on the monitoring of vibration parameters such as vibration, acceleration, and displacement. On the other hand technological advancements such as Big Data and the Internet of Things have made PdM more effective. Machine learning models, such as Gradient Boosting (GB) and Support Vector Machine (SVM), have been implemented for PdM [5]. These models have achieved high recall and accuracy, demonstrating their effectiveness [6].

Integrating AI and machine learning in manufacturing can improve efficiency, productivity, and sustainability [3]. Challenges in using AI in manufacturing include data acquisition, security risks, and lack of trust or understanding [7]. However, AI has the potential to be extremely helpful in applications such as predictive maintenance, quality assurance, and process optimisation [7]. Innovative technologies, such as Unsupervised Learning (UL) algorithms, can automate specific parts of industrial processes, reducing costs and human error. Combining AI and predictive maintenance can enhance manufacturing performance and reduce downtime [8, 9].

For instance, AI has been utilised to develop a distributed system for predictive maintenance across manufacturing plants, significantly enhancing the response time of monitoring systems by processing data near sensors and reducing the need for central data transmission [10]. This approach aligns with the broader vision of IoT-based predictive maintenance, leveraging Big Data Analytics and Machine Learning to foster intelligent manufacturing practices that are more efficient and cost-effective [11].

In the context of Industry 4.0, machine learning, a subset of AI, plays a crucial role in predictive maintenance strategies to monitor industrial equipment's health status. These strategies are designed to minimise downtime, enhance utilisation rates, and prolong the useful life of machinery components [12]. Furthermore, AI and IoT technologies have been combined in low-cost frameworks for anomaly detection, offering a pragmatic solution to predictive maintenance challenges in real-world industrial settings, thereby improving maintenance efficiency and equipment lifespan [13].

Predictive maintenance powered by AI aims to enable real-time maintenance interventions and strives to lower operational costs, diminish downtime, and enhance production quality, contributing to manufacturing excellence [14]. This excellence is further bolstered by adopting cyber-physical systems in manufacturing, which utilise big data to enable a cost-oriented dynamic predictive maintenance strategy, offering a more economical alternative to conventional preventive maintenance methods [15].

The application of AI in predictive maintenance extends to developing business models in manufacturing, focusing on case studies that highlight the practical benefits of predictive maintenance technologies. Integrating deep learning and augmented reality into predictive maintenance further exemplifies AI's capability to enhance maintenance operations, making them smarter and more efficient, thereby paving the way for the future of IoT-enabled manufacturing [16].

In summary, AI's integration into predictive maintenance revolutionises manufacturing by offering smarter, more efficient, and cost-effective solutions. This technological advancement supports the broader goals of Industry 4.0 by enhancing production quality, reducing downtime, and ultimately leading to more sustainable manufacturing practices.

Supply Chain Management (SCM) in manufacturing is being transformed by integrating artificial intelligence (AI) technologies. AI, including machine learning (ML), is being used to improve various aspects of the supply chain, such as risk identification and management, material planning and forecasting, and optimisation of production processes [17, 18].

However, there are challenges to successfully integrating AI into supply chain management, including understanding and implementing responsible and ethical AI practices. Organisations must make an economic case for AI adoption, develop an implementation plan, and manage the coordination between humans and AI systems [19]. The use of AI in supply chain management offers the potential for increased efficiency and improved decision-making, but careful consideration must be given to the challenges and implications of its integration [20, 21].

Internal logistics in manufacturing can be improved by applying Lean Management tools, such as supermarkets and electric logistic trains [22]. These tools help eliminate waste and improve the flow of materials within a company, ultimately enhancing production processes [23]. Additionally, computer simulation and routing plans can optimise the transportation of goods and raw materials within a production plant [24].

Analysing and adjusting the internal logistics system increases factory efficiency and productivity [25]. Furthermore, artificial intelligence (AI) is playing an increasing role in the automotive industry's logistical aspects of production sites [26]. AI can assess disruption risks caused by natural disasters or social actions and propose countermeasures to ensure material availability. Overall, combining Lean Management tools and AI can significantly improve internal logistics in manufacturing [27].

Manufacturing planning is a crucial process in the manufacturing industry. It involves production planning, scheduling, and coordination among different locations. Artificial intelligence (AI) has been applied to improve manufacturing efficiency and productivity. AI can be used for intelligent production scheduling, considering project constraints, temporal and spatial characteristics, and production part distribution [28].

AI can also be used to design and operate manufacturing systems, including system layout, capacity planning, and control of material and information flows [29]. Additionally, AI planning approaches have been employed to simplify the process of production planning and scheduling, providing valuable guidance for real production manufacture [10, 3]. Despite challenges such as data acquisition, security risks, and trust issues, AI has the potential to bring significant cost and efficiency benefits to manufacturing, especially when combined with the ability to capture large amounts of data [30, 10].

The area of ***quality management*** can be enhanced by integrating artificial intelligence (AI) and machine learning (ML) techniques. These technologies can improve quality assurance processes by detecting and analysing deviations from quality specifications, as well as predicting and preventing problems at an early stage [30-33]. The application of AI and ML in quality control is part of the emerging field of Quality 4.0, which aims to drive innovation in the manufacturing industry [34].

Traditional quality control tools, such as the Six Sigma methodology, may have limitations in handling the complexity and dynamics of modern manufacturing processes, making AI and ML valuable tools for addressing these challenges [35]. AI-driven data science methods, such as machine learning, can identify complex relationships in large amounts of data, contributing to process improvement and failure management [36]. Overall, the integration of AI into quality management systems can lead to more efficient and effective manufacturing processes.

4 PRE-IMPLEMENTATION STUDY

This study focus on PCB manufacturing and assembly. A pre-implementation study is an essential step in ensuring the successful adoption and integration of new technologies, methods, or processes within an organization. This type of study helps identify potential challenges, estimate benefits, and refine implementation strategies before full-scale deployment. The results of the study are

The aim of the study is to evaluate and demonstrate the possibilities of using AI tools in a model example of printed circuit board (PCB) manufacturing. The reason is that this sector can be used as an excellent example in terms of the maturity of automation and robotics, including possible improvements. At the same time, this market is poised for future growth according to Mordor Intelligence's report and market analysis [37]. Printed Circuit Board (PCB) market highlights its projected growth and the current trends shaping the industry from 2019 to 2029.

The estimated market size is expected to increase from USD 76.12 billion in 2024 to USD 93.87 billion by 2029, demonstrating a growth rate of 4.28% CAGR (Compound Annual Growth Rate). This growth can be attributed to the indispensable role played by PCBs in the contemporary electronics sector, which is driven by advancements in technologies such as 5G, IoT, and AI, despite a temporary decline in consumer electronics demand by the end of FY 2023. The report underscores the significance of PCBs in the miniaturisation of electronic components, thereby facilitating the development of portable, wearable, and more resilient consumer electronics devices.

It underscores the substantial market share held by consumer electronics, which leverage PCBs to achieve compactness and efficiency. The analysis also delves into the environmental concerns associated with PCB disposal and the impact of the COVID-19 pandemic on the semiconductor market. With Asia-Pacific expected to witness noteworthy growth, the report provides detailed information about the dominance of Chinese manufacturers, who hold a 54.76% market share in the region. Furthermore, it outlines the strategic positions of Taiwan and South Korea in the global PCB industry. [37]

4. 1 PCB Manufacturing Process and Optimisation

The manufacturing and assembly of PCBs involve processes that determine the functionality and reliability of the final product. This part deals with PCB manufacturing and assembly processes [38].

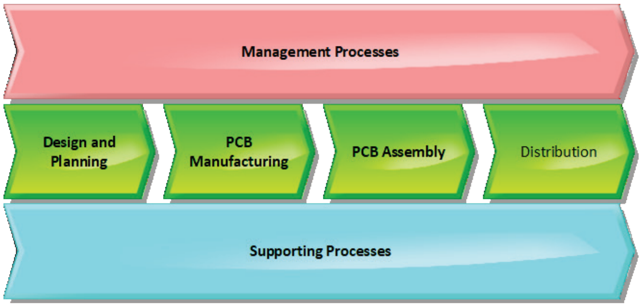

Figure 1 Process model of PCB Manufacturing and Assembly

Design and Planning: The PCB manufacturing process begins with design and layout, typically using CAD (Computer-Aided Design) software. The results are important for production planning.

This step is also crucial for determining the circuit functionality component layout and ensuring electrical efficiency and reliability.

Photolithography: Photolithography involves transferring the circuit design onto the PCB using a photosensitive film. This step is pivotal for pattern definition and precision.

Etching: The etching removes unwanted copper from the board, leaving the circuit pattern behind. Chemical or plasma etching techniques are commonly employed.

Drilling: Drilling creates vias and mounting holes for through-hole components. Precision is key to ensuring the functionality of multi-layer boards.

Plating and Copper Deposition: Plating enhances the electrical connectivity between layers through vias. Copper deposition adds a thin copper layer on the surface and within the drilled holes.

Solder Mask Application: The solder mask, usually green, protects the circuit from oxidation and prevents solder bridging during component soldering.

Silkscreen Printing: Silkscreen printing adds labels and component identifiers, facilitating manual assembly and inspection.

4.1.1 PCB Assembly Process

Solder Paste Stencilling: Solder paste is applied to the board in areas designated for component attachment. This step requires precision to ensure proper soldering and electrical connection.

Components Picking: Components are placed on the board using automated equipment, aligning with the solder paste deposits.

Reflow Soldering: The board passes through a reflow oven, where controlled heating melts the solder, securely attaching components to the board.

Inspection and Quality Control: Various inspection techniques, including AOI (Automated Optical Inspection), are employed to ensure the accuracy and quality of the assembly.

Through-Hole Component Insertion (if applicable): For boards requiring through-hole components, this manual or automated process inserts and solders components to the board.

Final Inspection and Functional Testing: The completed board undergoes final inspection and functional testing to ensure it meets all specifications and functional requirements.

4.2 Opportunities for Implementing AI tools for Improving Processes in Manufacturing and PCB Assembly

Fig. 2 presents a designed model of AI tools in the context of potential improvements in PCB manufacturing and assembly. The design and structure is based on a process mapping approach, dividing processes into control, primary and support processes. The management processes consist mainly of processes that are implemented by the management of the company, and AI tools can be an important support for decision-making here, especially in the creation of analyses and predictions of future developments.

The core processes are the actual process of designing, manufacturing, and assembling the PCBs, including the provision of lo. Within these processes, sub-processes are shown where AI tools can be implemented to improve the processes themselves. The last level consists of support processes, in particular, processes related to predictive maintenance and product planning.

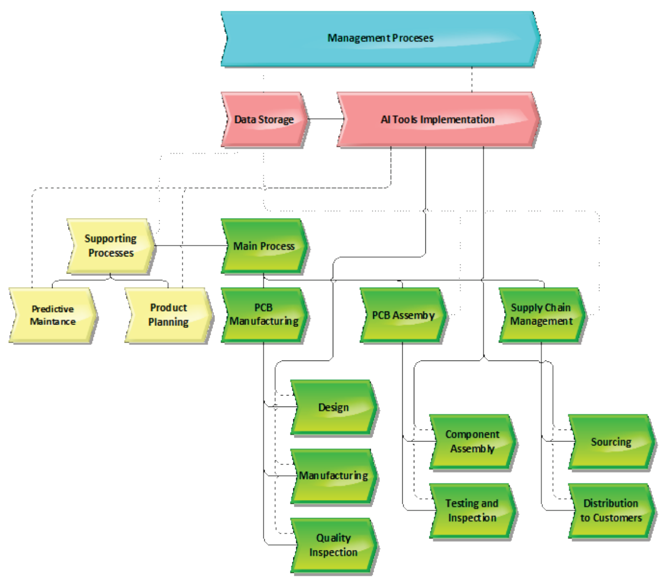

Figure 2 PCB Designed Manufacturing and Assembly with AI Tools

Specifically, the following tools can be used within these processes:

Machine Learning and Deep Learning: Machine learning algorithms can analyse data from previous designs and production cycles to identify the most efficient configurations and material use. Furthermore, deep learning models can predict equipment failures and maintenance needs by analysing patterns in operational data.

AI-driven Robotics: Robots equipped with AI can place components on PCBs with high precision and speed, adapting to different sizes and types of PCBs. At the same time, advanced robotic systems allowing for visual inspection using convolutional neural networks can detect defects and inconsistencies on PCBs during and after manufacturing.

Natural Language Processing (NLP): AI tools utilising NLP can analyse large volumes of textual data from internal reports, emails, and documents to provide management with summaries and decision-making materials. Simultaneously, AI tools can automate management's communication with suppliers, simplify ordering, and track inventory.

Predictive Analytics and Simulation: AI can simulate the entire manufacturing process, identify bottlenecks, and predict the impact of changes in the process. This also relates to possible process improvements, where algorithms can analyse historical data and demand forecasts to optimise production planning, improve inventory management, and minimise delivery times.

Image Recognition and Computer Vision: Computer vision systems can continuously monitor and analyse products on the production line, instantly identifying defects and ensuring that all PCBs meet the required quality standards.

Manufacturing Data Management Systems; AI tools can aggregate and analyse data from various parts of the manufacturing process, allowing for quick adjustments and process optimisation.

These are just a few examples of selected AI tools that can be implemented in the manufacturing and PCB assembly process. Integrating these technologies requires careful planning and consideration of each manufacturing operation's specific needs and goals.

A key element is the development of a suitable data storage. Data storage is crucial for AI tools for several reasons:

Source for learning and training: AI and machine learning (ML) models "learn" from vast volumes of data. The more quality data available for training, the more accurate and reliable they can be in their predictions and decisions. Data storage provides a base for storing these data, allows easy access for learning processes, and enables iterative improvement of models.

Support for real-time analysis: Many AI applications, such as decision support, real-time monitoring, and automation, require immediate access to data. Powerful data storage enables fast analysis and real-time data processing, essential for applications requiring immediate responses or updates.

Availability and scalability: AI systems often work with exponentially growing data volumes. Data storage must be able to scale to accommodate growing needs without losing performance or availability. Efficient storage ensures that AI systems have constant access to data regardless of their volume.

Data security and protection: Data used by AI systems may contain sensitive information. Secure data storage ensures protection against unauthorised access and attacks, which is key for complying with legal and ethical standards. In addition, data security mechanisms such as encryption and tokenisation play an important role in protecting data during storage and transmission.

Integration and interoperability: AI applications often work with data from various sources and must integrate data from different systems and technologies. Flexible and interoperable data storage allows easy integration and processing of data from various sources, which is key for comprehensive analyses and full utilisation of available data.

In the context of the demanding requirements of AI and ML, choosing the right data storage solution becomes a critical decision. An effective solution must support fast analysis of large data volumes, scalability for future growth, and provide advanced data security and protection features.

4.3 Discussion of Results

These tools can be introduced to improve the processes mentioned above. However, they are very costly technologies, and their implementation may bring certain negatives on the other side. Although the benefits of AI are undeniable, there are potential negatives that may arise from its use in this area. This text will examine in detail what these negatives may be and their impact on the industry, workforce, and society. The negatives detected in the literature mentioned in Chapter 3 are detailed below.

Loss of Jobs and Impact on Employees: One of the most discussed negatives of using AI is the potential loss of jobs. In the PCB manufacturing area, automation could mean that many traditional manual operations will be replaced by machines, which could significantly reduce the need for human labour. This trend could negatively impact individuals who may lose their jobs and entire communities where the manufacturing sector constitutes a considerable part of the economy.

Ethical Issues: The use of AI in PCB manufacturing processes also raises ethical issues, particularly concerning algorithm bias. AI systems are created and trained by humans to include human biases unconsciously. This bias can lead to inefficient decisions or discriminatory practices within the manufacturing process, negatively impacting the quality of production.

Loss of Personal Skills and Practical Experience: Automation and the integration of AI into PCB manufacturing could lead to the loss of human skills and practical experience. While AI can streamline processes, it can also cause us to lose valuable manual skills and practical experiences passed down and improved upon for generations. This loss can have long-term consequences for innovation and the ability to solve unexpected problems that may arise in the manufacturing process.

Increase in Social and Economic Inequality: Automation and the use of AI can also contribute to increasing social and economic disparities. Companies with access to the latest AI technologies can gain a significant competitive advantage, while smaller businesses may fall behind. This division can lead to a concentration of power and wealth in the hands of a few, while small and medium-sized companies may struggle to maintain competitiveness.

Improving manufacturing processes is also associated with introducing various methods and tools based on finding new or innovative solutions. These methods and tools also help address problems in the manufacturing cycle.

A key element here is people - individual teams who initiate these changes. Even though artificial intelligence tools can significantly assist in improving processes, it must be pointed out that the focus must always be on individuals. People provide creative thinking, empathy, and the ability to adapt, which AI and automation cannot fully replace. While AI can provide recommendations based on data analysis, final decisions often require human judgment that considers context, ethics, and long-term impact.

Effective implementation of changes also requires coordination between different departments and levels of management, which depends on human interactions, communication, and collaboration. While technology can provide tools and methods for improvement, the human factor plays an irreplaceable role in innovation and implementing changes in manufacturing processes. The engagement, experience, and creativity of people form the pillars for the successful improvement of manufacturing processes.

4.4 Summary

Through SWOT analysis, the conclusions and findings of the pre-implementation study are summarised. The SWOT analysis was chosen because it enables the identification of the Strengths, Weaknesses, Opportunities, and Threats associated with implementing AI in a manufacturing environment.

Strengths:

- Increased efficiency and productivity
- Potential for predictive maintenance
- Supply chain optimisation
- Quality control improvements.

Weaknesses:

- High investment and operational costs
- Acceptance of new technologies by workers
- Low initial knowledge of workers
- Complexity of implementation
- Dependence on data.

Opportunities:

- Innovation in products and services
- Personalisation of customer requirements
- Expansion into new markets
- Improvement in sustainability.

Threats:

- Risk of technology obsolescence
- Cybersecurity
- Regulatory and ethical challenges
- Dependence on technology suppliers.

In conclusion, introducing AI tools into manufacturing processes offers many significant opportunities for improving efficiency, quality, and innovation. However, it is also accompanied by challenges that require careful consideration and strategic planning.

5 CONCLUSION

This paper comprehensively examines the integration of Artificial Intelligence (AI) for process improvement in the manufacturing sector. It explores the potential and challenges of deploying AI technologies for process improvement in the manufacturing area. The authors analyse recent literature to emphasise AI's contributions to enhancing operational efficiency, productivity, and innovation in manufacturing. However, they also address critical challenges industries face when adopting AI.

The core of the paper is dedicated to an extensive literature review, which highlights the synergy between lean manufacturing and AI, the role of AI in predictive maintenance, the impact of AI on supply chain management, advancements in manufacturing planning through AI, and the enhancement of quality management with AI technologies.

A pre-implementation study on the production and optimisation of Printed Circuit Boards (PCBs) showcases the practical application and potential improvements AI tools can be implemented to manufacturing processes.

This paper critically supports the role AI should play in manufacturing and rallies for a future whereby AI and human expertise shall conjoin, driving the next industrial revolution.

As part of further research, we believe it is appropriate to look at the interaction between AI and human resource development. The reason is that human resources play, and will continue to play, an important role in improving productive processes.

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