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Generative AI in the manufacturing process: theoretical considerations

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ABSTRACT
The paper aims to identify how digital transformation and Generative Artificial Intelligence (GAI), in particular, affect the manufacturing processes. Several dimensions of the Industry 4.0 field have been considered, such as the design of new products, workforce and skill optimisation, enhancing quality control, predictive maintenance, demand forecasting, and marketing strategy. The paper adopts qualitative research based on a critical review approach. It provides evidence of the GAI technology support in the mentioned areas. Appropriate use of emerging technology allows managers to transform manufacturing by optimising processes, improving product design, enhancing quality control, and contributing to overall efficiency and innovation in the industry. Simultaneously, GAI technologies facilitate predictive analytics to forecast and anticipate future demand, quality issues, and potential risks, improve a marketing strategy and identify market trends.

KEY WORDS
Generative AI, ChatGPT, Industry 4.0, technology, manufacturing processes

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Introduction

The advent of digital transformation has significantly impacted the landscape of modern entrepreneurship and current business. Undoubtedly, digital transformation, defined as the integration and adoption of digital technologies, processes, and strategies across various aspects of an organisation, is the primary challenge of the third decade of the twenty-first century, particularly in the post-pandemic era (Głodowska et al., 2023), multidimensionally impacting the manufacturing industry defined nowadays as

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Industry 4.0 (Nosalska et al., 2018). The ongoing changes in modern business management are caused by the use of several disruptive technologies, including blockchain, AR, VR, social media, mobile, and IoT (Mazurek, 2018). In recent months, it has gained importance because of the Generative Artificial Intelligence (GAI) concept in various managerial aspects and dimensions with its business and manufacturing advantages (Korzynski et al., 2023) and dark sides (Wach et al., 2023).

This article presents the results of a literature review approach based on the analysis of publications. The critical review primarily aimed to methodically assess, analyse, and integrate the existing body of literature on applying GAI in the manufacturing process to foster the development of innovative theoretical frameworks and perspectives within the field. Different areas of manufacturing processes have been considered, such as new product design, innovation management, human resources, quality control, predictive maintenance, forecasting and marketing strategy creation and implementation. The uniqueness of this publication lies in the review execution and literature description on the field of retrofitting and its classification. Additionally, it involves the extraction of the primary trends presented in the literature.

This publication answers the following questions: What is the current development stage of theory linked with the GAI application in the manufacturing process? What are the most important managerial insights concerning the application of AI to manufacturing processes? What AI implications can be found in the literature on several manufacturing and product engineering dimensions?

The article consists of four parts. The introduction includes a description of the techniques and technologies connected to AI in manufacturing processes. The second part presents the research methods. The third part describes the research results, focusing on such dimensions as new product design, innovation management, human resources, quality control, predictive maintenance, forecasting and marketing strategy. The fourth part summarises the article.

1. Methodology

An integrative or critical review approach was employed to achieve the research objective. The applied method provided a framework for understanding and appreciating the complexities of narrative literature. Many integrative literature reviews are designed to tackle subjects that have matured or are in the early stages of emergence. In the case of emerging topics, the primary aim is to establish initial or preliminary concepts and theoretical frameworks rather than simply revisiting existing models (Snyder, 2019).

The main aim of this critical review was to systematically evaluate, critique, and synthesise the body of literature relevant to GAI application in the manufacturing process. This comprehensive analysis was conducted in a manner designed to facilitate the emergence of novel theoretical frameworks and perspectives within the field.

The integrative review method led to the advancement of knowledge and the development of theoretical frameworks rather than merely providing an overview or description of previous research (Snyder, 2019).

The authors' intention was to provide an integrated, synthesised overview of the current state of knowledge and research insights, existing gaps, and future research directions in the field of AI application in manufacturing processes (Palmatier et al., 2018). Alongside the normative recommendations, this review provides summaries and suggestions that could provide valuable managerial insights (Mazumdar et al., 2005) into the future application of AI to manufacturing processes.

Authors adopted domain-based review papers, which allowed for reviewing, synthesising, and extending a body of literature in the substantive domain, i.e., AI application in the manufacturing process. The manufacturing process structure refers to the organisation and sequence of activities involved in the production of goods or products. It outlines the steps and stages required to transform raw materials or components into finished products. The specific structure of a manufacturing process can vary widely depending on the industry, product complexity, and technology used. Considering the complexity and comprehensiveness of manufacturing processes, the conducted literature studies were focused on the following processes supporting the manufacturing process: the design of new products, workforce and skill optimisation, enhancement of quality control, predictive maintenance, demand forecasting, and marketing strategy.

The application of the critical literature review method aimed to answer the following research questions:

- How can AI adaptation help manufacturers to create products that are more efficient, effective, and safe?
- How can AI adaptation help analyse and predict the necessary skills required for manufacturing processes?
- How can GAI be used to identify defects in products and processes?
- How can GAI be used as a proactive approach to maintenance to predict when equipment and machinery are likely to fail or require maintenance?
- How can AI be used to analyse market trends, consumer behaviour, and sales data to predict demand for manufactured goods?
- How can AI be used to optimise marketing strategies and improve the timing of product releases, promotional campaigns, or sales events?

2. Literature review and theory development

2.1. Application of Generative AI in the design of new products

This research study investigates the GAI's possible transformative effects within the product design domain. GAI can be harnessed for designing new products because it can explore vast design spaces, generate diverse and innovative solutions, and optimise designs based on predefined parameters (Kwong et al., 2016). GAI is applied to explore innovative design possibilities and generate optimum product designs, considering user-defined parameters (Cappa et al., 2021). This novel GAI methodology has the potential to transform manufacturing procedures by facilitating the development of goods that possess enhanced efficiency, effectiveness, and safety, especially in the post-pandemic world (Villar et al., 2023).

In recent years, the emergence of GAI has presented novel opportunities for innovation across several industries (Cappa et al., 2021), such as the automotive industry (e.g., Tesla). Another example could be bioengineering. In recent times, additive manufacturing (AM) has been widely used to create things specifically designed for human use, including orthoses, prostheses, therapeutic helmets, finger splints, and other customised devices (Liu et al., 2022). Product design is a domain that shows significant potential for application, where GAI might serve as a crucial tool for exploring and optimising design spaces (Di Vaio et al., 2020). This study focuses on the possible advantages of utilising GAI to design novel goods, with a particular emphasis on developing solutions characterised by enhanced efficiency, effectiveness, and safety. GAI can explore new design possibilities and generate optimised designs based on user-defined parameters. Designers can input user-defined parameters into GAI systems, guiding the AI to generate designs that meet specific criteria. This user-centric approach ensures the final product's alignment with the intended goals and requirements. This can help manufacturers to create more efficient, effective, and safe products.

GAI can evaluate extensive datasets of preexisting designs, acquiring knowledge of patterns and correlations among different design components. This allows it to investigate vast design possibilities that may be inconvenient or time-consuming for human designers to navigate. GAI functions by leveraging machine learning concepts, allowing the system to acquire knowledge from extensive datasets and produce novel outputs according to predetermined criteria (Plantec et al., 2023). Within the realm of product design, this technology allows designers and manufacturers to swiftly and effectively explore a wide range of design possibilities (Iansiti & Lakhani, 2020). GAI algorithms can develop designs that meet or surpass specified requirements by incorporating user-defined characteristics such as material qualities, weight limitations, and performance standards (Plantec et al., 2023). Through an iterative process, these algorithms may generate designs that follow the given specifications (Lei et al., 2022).

In conclusion, GAI presents a groundbreaking opportunity for revolutionising product design processes (Hu et al., 2023). The utilisation of GAI holds immense potential for transforming the processes involved in product design. GAI, due to its capacity to navigate extensive design spaces and swiftly produce optimum solutions, is positioned as a pivotal facilitator for innovation in the manufacturing sector (Lei et al., 2022). The utilisation of this technology serves as a demonstration of its capacity to generate products with enhanced efficiency, efficacy, and safety. The ongoing progress of technology has led to the potential incorporation of GAI in the field of product design, which can revolutionise several industries and facilitate the creation of innovative products that surpass existing limitations (Wang & Wu, 2024). As technology continues to advance, the integration of GAI in product design holds the promise of reshaping industries and driving the development of products that push the boundaries of what is currently achievable.

2.2. GAI as a facilitator of the HRM process in manufacturing

In the era of Industry 4.0, the fusion of advanced manufacturing processes and cutting-edge digital technologies, such as general artificial intelligence, heralds unparalleled innovations in human resource management (HRM) (Sigov et al., 2022; Rymarczyk, 2021). Looking ahead to Industry 5.0, where human collaboration with machines is expected to be more harmonious and optimised (Leng et al., 2022), the role of GAI becomes even more pivotal. Industry 5.0 focuses on the coalescence of human touch with technological autonomy, aiming to create a balanced ecosystem where human creativity and machine efficiency coexist and complement each other (Adel, 2022).

In its current form, GAI, such as ChatGPT, can be incorporated into work settings as an element of a custom network of applications (OpenAI, 2023). Therefore, the potential utility of GAI, exemplified by technologies like ChatGPT, extends beyond just text generation (Korzynski, Kozminski, & Baczynska, 2023). Its diverse functionalities can seamlessly integrate with various HRM systems, working collaboratively to enhance and streamline numerous HR-related processes in the manufacturing sector. The integration of GAI with HRM systems can facilitate the comprehensive analysis and synchronisation of various elements, such as workforce planning (Koole & Li, 2023), scheduling shifts (Dworski, 2023), position description analysis (Chang & Ke, 2023) and performance management (Budhwar et al., 2023).

In reference to workforce planning and scheduling, constant manufacturing operations demand accurate planning (Heuser, Letmathe, & Schinner, 2022), and GAI can synchronise various elements, such as production demands, employee availability, and skill sets, to formulate optimised shift schedules. This application ensures that every shift is adequately staffed with individuals possessing the right skills, enhancing the alignment with production targets while maintaining compliance with labour regulations.

Furthermore, GAI holds the key to revolutionising position description analysis and task standardisation. Considering the advancements brought about by smart factories, a precise understanding and delineation of tasks and roles become increasingly vital. Automated and semi-automated systems in manufacturing lines coexist with manual processes, highlighting the significance of clear and well-defined position descriptions (Cha et al., 2023). By harnessing GAI to analyse and standardise position descriptions and tasks, organisations ensure clarity and uniformity in role expectations and responsibilities, synchronising manual and automated processes effectively.

Additionally, in performance management within the manufacturing milieu, adherence to specific production norms is pivotal. GAI may play a fundamental role here by continually analysing employee activities and outputs. By monitoring adherence to production norms and standards, GAI provides critical insights and data that enable both managers and employees to refine and optimise performance (Khang et al., 2023). This continuous oversight and analysis ensure that any deviations from the established norms are rapidly identified and rectified, contributing to the streamlined and effective functioning of the manufacturing operations.

In the sphere of smart factories, the deployment of GAI furthers the enhancement of performance management. The centralised data hubs in smart factories, which streamline the rapid exchange of information, are leveraged by GAI to meticulously monitor and analyse employee performance and operations (Haponik, 2022). This integration facilitates instantaneous feedback and insights, enabling immediate corrective actions and ensuring the consistent alignment of operations with established production norms and standards.

2.3. Enhance quality control process by AI

Quality control, defined as a systematic process involving checks, testing, verification, and response, ensures that product features and process conditions align with design standards and internal and external specifications (Hull, 2011). It entails examining products at various stages of the production process to guarantee they meet specific criteria, such as size, weight, colour, or other requirements (Nadira, 2023). Despite being a critical aspect of modern manufacturing, it presents significant challenges and demands substantial time. As production enterprises expand and the demand for higher product quality rises, industrial processes have become increasingly intricate. Consequently, the likelihood of production system failures and the associated hazards related to product quality have escalated. When faults occur in the production process, specific product quality indicators can fluctuate, leading to subpar quality (Xu et al., 2024).

The rapid advancement of information technologies makes it crucial to utilise them for monitoring and achieving stable, precise control over industrial processes and product quality (Xu et al., 2024). To address challenges in industrial process monitoring, fault diagnosis, and product quality control, experts and scholars have proposed the application of AI (Hartung et al., 2022; Zeng et al., 2022; Xu et al., 2024), including GAI as evidenced in recent studies (Narasimhan, 2023; Raja, 2023; Wang et al., 2019). The utilisation of GAI holds the potential to enhance quality control processes by effectively detecting and identifying defects and anomalies in various products. GAI can create virtual models of products, enabling simulation of the manufacturing process. This aids in the early detection and prevention of potential defects and anomalies in actual products (Raja, 2023).

GAI can revolutionise manufacturing quality control in several ways, such as (Raja, 2023):

- Defect identification. GAI can rapidly identify product defects by analysing images or data from manufacturing processes. This capability enables manufacturers to detect defects in real-time during the manufacturing process, ensuring that products meet quality standards before they are delivered to customers.
- Defect prediction. GAI can anticipate and identify potential product defects by leveraging historical defect data. With this capability, manufacturers can then pinpoint vulnerable areas and take proactive measures to prevent these issues.
- Automated quality control. GAI can automate quality control tasks by analysing more data about each production process and product, especially in defect inspection. It enhances accuracy and efficiency in quality control processes and boosts worker productivity, allowing them to concentrate on other essential tasks.
- Personalised quality control. GAI facilitates the personalisation of quality control processes by developing tailored inspection plans for different product types. It guarantees that each product undergoes scrutiny at a suitable level, ensuring compliance with the necessary quality standards.

In the conventional quality control process, humans are responsible for tasks such as understanding requirements, preparing and conducting tests, and reporting defects. However, this approach is prone to human errors, is time-consuming, and encounters challenges related to scalability in complex systems. GAI revolutionises quality control by automating these tasks and ensuring comprehensive test coverage, overcoming these challenges. Using machine learning algorithms trained on extensive datasets and continuous learning from previous errors, thus eliminating the need for human supervision and ensuring significant time and resource savings, GAI (Nadira, 2023; Vaddi & Khan, 2023):

- comprehends requirements and autonomously generates test cases;
- autonomously generates test data;
- automates test execution, minimising errors and time consumption;
- enhances test generation and execution, leading to quicker testing cycles, improved precision, and elevated product quality;
- generates clear, concise, and actionable reports after executing the test cases and
- predicts potential issues and forecasts and likely points to failures before they occur, enabling proactive and real-time addressing of problems.

The overall comparison between the traditional quality control process and the GAI-based quality control process is presented in Table 1.

Some examples of how GAI is being used in the manufacturing quality control process include (Raja, 2023; Srivastava, 2023; Wlodarczyk, 2023):

- Intel: GAI is used to detect imperfections in computer chips. By analysing images of computer chips, GAI identifies defects that are too minuscule for human observation, significantly enhancing Intel's chip quality.
- Bosch: GAI is used to forecast defects in automotive components. The company uses GAI to examine historical defect data, predicting which parts are more likely to be faulty. This predictive approach has significantly reduced the number of defective automotive parts shipped to customers.
- BMW: GAI is used to predict defects in car parts. AI employs computer vision to analyse images or videos of components and undergoes training to differentiate between defective and non-defective car parts. Once trained, AI can inspect new car parts in real-time, promptly identifying any defects and detecting deviations from the standard, ensuring all required parts are without defects and correctly mounted in their designated places.

Tab. 1. Traditional and GAI-based quality control process

Aspects	Traditional Quality Control Process	Generative AI-Based Quality Control Process
Tasks of the quality control process		
Test case generation	Manual creation of test cases based on various manufacturing documents and human experiences. Limited by human capacity and understanding, time-consuming	Automatic generation of diverse test cases based on provided scenarios and AI algorithms. Saving time, improving the breadth, depth, and scalability of testing
Test data generation	Manual creation of test data or generation of test data using predefined templates. May lack diversity and volume, time-consuming, and overlook certain real-world scenarios	Automatic generation of diverse, high-volume, and realistic test data. Saving time, improving the breadth, depth and scalability of testing
Test execution	Manual testing by human testers. Requirement of human intervention to interpret results and generate summary reports. Time-consuming, limited by human capacity and understanding	Automatic testing. Automatically generating clear, concise, and actionable reports after executing the test cases. Reducing human involvement, speeding up the test process by quickly generating test cases and data
Defect identification	Spotting patterns and anomalies depends largely on the skill and experience of human testers. Some defects might be missed. Reactive approach with errors being detected post-production	Spotting patterns and anomalies more consistently, possibly finding defects that human testers might miss. Proactive identification of errors and prevention
Defect prediction	Manually leveraging and analysing historical defect data. Some defects might be missed and lacking proactive measures to prevent these issues	Automatic leveraging and analysing historical defect data. Pinpointing vulnerable areas and implementing proactive measures to prevent these issues
Features of quality control process		
Realism	Human bias may result in overlooking certain real-world scenarios	AI models can more accurately mimic real-world scenarios, leading to more effective testing
Scalability	Limited scalability, challenging for complex systems. Scaling up requires additional human resources and time	Scalable and capable of handling intricate processes. AI models can easily handle large data volumes and more complex scenarios, making them highly scalable
Time and resource efficiency	Time-consuming and resource-intensive. Manual creation of test case and data, the test execution and analysis of defects	Efficient use of time and resources. AI models efficiently generate test cases and data, automating the execution of tests and analysis of defects
Learning from past errors	Limited ability to learn from historical data. Limited by human capacity and understanding, time-consuming	Continuous learning, improving over time
Human oversight	High dependency on human supervision. Requirement of regular manual updates and adjustments based on changes in requirements	Reduced need for human interventions. AI models can be retrained and adapted to new or updated requirements

Source: elaborated by the authors based on Narasimhan (2023), Raja (2023) and Vaddi and Khan (2023).

- Siemens: GAI is used to automate wind turbine quality control. This technology is used by Siemens to customise inspection plans for various wind turbines, streamlining the quality control process and enhancing efficiency in wind turbine production.
- Georgia-Pacific: GAI is used to enhance the quality of paper production. AI prevents paper tearing during production by predicting the optimal speed for converting lines.

Overall, the integration of GAI into the quality control process opens new possibilities for innovative transformation and efficiency enhancement of the quality control process. GAI promises to reshape manufacturing quality control, making it swifter, more effective, and exceptionally precise. Using the analysis of production data and the application of machine learning algorithms, it can pinpoint potential quality problems and defects.

This proactive approach empowers manufacturers to address issues in real time before they escalate, ensuring smoother production processes. Nevertheless, the effectiveness of AI in quality control directly depends on the quality and diversity of data it is trained on, as well as test algorithms. Test data and algorithms are important in delivering accurate and consistent results and deriving edge-case scenarios or exceptions.

2.4. Application of artificial intelligence in the context of predictive maintenance in production processes

Predictive Maintenance (PdM) is a proactive maintenance strategy that uses data, analytics, and machine learning to predict when equipment or machinery will likely fail, allowing for timely maintenance interventions. The main goal of PdM is to anticipate potential issues and perform maintenance activities just before they are needed, avoiding unexpected breakdowns and minimising downtime. There is strong evidence that using AI-based solutions improves the maintenance process in companies. AI can be applied to various stages of PdM, encompassing Data Collection, Data Preprocessing, Feature Selection, Model Training, Model Evaluation, Deployment, Monitoring, Alerts and Notifications, Maintenance Intervention and Feedback Loop. Artificial intelligence in the context of improving maintenance processes is applicable when maintenance processes are carried out by humans (in the form of inspections) (Shin et al., 2021) and when they are automated.

Cost savings are among the primary benefits of PdM (Shin et al., 2021), resulting from improving productivity (e.g., downtime reduction) (Arena et al., 2022); reducing environmental negative impact (e.g., waste reduction) (Allahloh et al., 2023), improving safety conditions (Katreddi et al., 2022) and reliability (Achouch et al., 2022).

The literature provides numerous examples of studies indicating the application of AI for maintenance operations in various industries and sectors: the renewable energy industry (Shin et al., 2021), manufacturing and processing of wood products (Rossini et al., 2021), the power generation industry (Allahloh et al., 2023), the automotive sector (Theissler et al., 2021; Arena et al., 2022; Katreddi et al., 2022) and particular industrial infrastructure (machinery) (Pandey et al., 2023).

Based on the experiment being conducted by Bahrudin Hrnjica and Selver Softic (2020), the integration of explainable AI, embodied in a dependable prediction model and visual representations, can effectively assist in mitigating avoidable costs linked to unscheduled downtime resulting from machine errors or tool failures. This means that by having an AI system that predicts potential issues and provides understandable explanations and visual insights into those predictions, businesses can make informed decisions to address issues pre-emptively (Bahrudin Hrnjica, Selver Softic, 2020).

To overcome the limitations of relying solely on human inspection, Shin et al. (2021) employed machine vision approaches to create AI-based solutions (AI-assisted approach) for image-based fault diagnoses. The authors examined the impact of AI based on deep learning algorithm assistance on the performance and perception of human inspectors, considering their task proficiency. The conducted studies confirmed that implementing AI to support inspectors significantly improved results (specificity, sensitivity, and time efficiency), particularly when inspectors were not experts in their field.

The results demonstrated that AI can yield significant benefits in scenarios with limited human resources and time-consuming expert training. The authors have posited the hypothesis that, even in the long-term perspective, it is improbable to fully automate the stage of reading and diagnosing images. This limitation stems from the inherent nature of artificial intelligence algorithms, which can only recognise faults they have thoroughly mastered based on training data. In situations involving novel issues, human involvement remains imperative for the early detection of potentially catastrophic cases (Shin et al., 2021).

The Digital Twin, which can deliver additional services by leveraging physical simulation and AI algorithms, is another example of applying AI in maintenance process improvement. These services include such functions as fault diagnosis, troubleshooting, predicting the remaining useful life, and facilitating maintenance activities (Rossini et al., 2021). Application of DT solutions enabled the real-time creation and modification of workflows essential for fault diagnosis and predictive maintenance. This involves the dynamic addition, removal, or replacement of entities to accurately represent the status of components within the system.

Allahloh et al. (2023) showcased the viability of markedly improving fuel efficiency and anticipating maintenance needs. Our discoveries indicate that deploying IIoT and AI solutions opens avenues for substantial fuel preservation, heightened performance through predictive maintenance, and practical strategies for industries to optimise processes and enhance efficiency in internal combustion genset operations. The IoT platform application allows for identifying potential issues before they become critical problems, significantly reducing downtime and maintenance costs (Allahloh et al., 2023).

The application of artificial intelligence in the maintenance field can predict potential system failures based on specific characteristics or system settings (input variables) and may prevent future failures and minimise downtime.

2.5. Artificial intelligence application for demand forecasting

Forecasting demand plays a vital role in contemporary business operations, allowing manufacturers to optimise their production processes, effectively manage inventory levels, and efficiently fulfil customer requirements (Ghosh, 2022; Tadayonrad & Ndiaye, 2023; Viverit et al., 2023). The emergence of artificial intelligence (AI) has provided businesses with a potent tool for examining intricate datasets and making more precise prognoses regarding future demand (Kumar et al., 2023). This part elucidates the utilisation of AI for analysing market trends, consumer behaviours, and sales information, ultimately heightening the accuracy of demand forecasting and contributing to improved decision-making within manufacturing workflows.

In the rapidly changing and dynamic landscape of contemporary business, grasping market trends is imperative to maintain a competitive edge (Li et al., 2022; Mathur et al., 2023). AI algorithms can analyse extensive quantities of information from diverse origins, including social media, online forums, news articles, and industry reports. This enables them to detect emerging trends and changes in consumer preferences (Liyanage et al., 2022). AI can extract valuable understandings regarding customer conversations, the rising popularity of specific products, and the influential trends steering purchasing choices by evaluating sentiment analysis, keyword frequency, and topic modelling. These insights equip manufacturers with the information needed to adapt their production strategies and harmonise their offerings with present and forthcoming market requirements (Li et al., 2022). Specifically, AI algorithms can sift through vast volumes of data sourced from social media platforms, pinpointing nascent trends, sentiments, and dialogues about particular products or sectors. Applying natural language processing (NLP) techniques facilitates sentiment analysis, topic modelling, and keyword extraction, thereby facilitating an understanding of consumer viewpoints and inclinations. For example, a fashion retailer uses AI to analyse social media conversations and identifies that a particular clothing style is gaining popularity among influencers and consumers. This insight prompts the retailer to adjust their production plans to meet the anticipated demand for that style. Moreover, AI can scan news articles, blog posts, and industry reports to identify shifts in consumer behaviour, economic indicators, and technological advancements that could impact market trends. AI can provide insights into upcoming trends by analysing the frequency and context of certain keywords and phrases. AI-powered web scraping tools can also extract data from e-commerce platforms, competitor websites, and marketplaces to track product prices, availability, and customer reviews (Dwivedi et al., 2023). This data can be analysed to detect pricing trends, product popularity, and consumer feedback. An online retailer, for instance, uses AI-driven web scraping to track competitors' pricing strategies and identifies that a certain product is consistently priced higher than similar offerings. This insight helps the retailer adjust their pricing strategy to remain competitive.

The utilisation of AI-driven analysis of consumer behaviour grants manufacturers an unparalleled comprehension of their intended audience (Sohrabpour et al., 2021; Yaiprasert & Hidayanto, 2023). AI can create detailed customer profiles by collecting and interpreting data from e-commerce platforms, loyalty programmes, and even IoT devices (Zhu et al., 2022). Machine learning algorithms can detect patterns within purchasing habits, preferences, and factors that prompt buying decisions. AI can potentially augment the precision of demand forecasting by identifying connections between external variables like seasonality, economic indicators, cultural occurrences, and consumer purchasing trends. This, in turn, empowers manufacturers to customise their production and marketing approaches to synchronise with these discernments, guaranteeing that the appropriate products are accessible at the right moment and in suitable quantities (Vaid et al., 2023). AI-powered sentiment analysis can analyse customer reviews, social media interactions, and online conversations to gauge consumer sentiment towards products and brands (Hyun Baek & Kim, 2023). This insight provides businesses with valuable feedback and helps them address customer concerns. For instance, restaurant chains utilise AI to analyse social media posts and reviews. It is discovered that customers consistently praise their food quality but express dissatisfaction with long wait times. The restaurant management addresses this issue by optimising their service speed, leading to improved customer satisfaction.

Sales data serves as a goldmine of information for demand forecasting (Ma et al., 2016). AI-driven analytics can construct predictive models by analysing historical sales data, considering such elements as product life cycle, promotional endeavours, and geographical discrepancies (Abolghasemi et al., 2020). These models can forecast demand with remarkable precision, aiding manufacturers in making informed decisions about production volumes and inventory management. Machine learning algorithms, such as time-series analysis, regression, and neural networks, can be trained on historical sales data to identify patterns and trends, enabling accurate predictions for future demand (Liu et al., 2023). AI can continually learn from prior forecasting inaccuracies and modify its models accordingly, resulting in progressively enhanced accuracy over time. These adaptable models aid businesses in honing their demand forecasts as fresh sales data becomes accessible. For example, an automobile manufacturer uses AI to forecast demand for different car models. Over time, the AI system learns that demand for SUVs is influenced by fluctuating fuel prices and economic indicators. The manufacturer can make more accurate predictions and optimise production plans. Consequently, incorporating AI into harnessing sales data for demand prediction allows businesses to make data-driven decisions, optimise production, and minimise the risk of overstocking or stockouts. By analysing historical sales patterns and their relationships with external factors, AI empowers businesses to anticipate and meet consumer demand more effectively.

While AI offers immense potential for revolutionising demand forecasting, it is important to acknowledge its benefits and challenges. AI-driven demand forecasting can lead to reduced inventory costs, minimised stockouts, optimised production schedules, and improved customer satisfaction (Njomane & Telukdarie, 2022; Soori et al., 2023). However, implementing AI systems requires substantial initial investment, data infrastructure, and skilled personnel. Additionally, the AI prediction accuracy relies on the quality and relevance of the input data. The dynamic nature of markets and consumer behaviour also challenges maintaining accurate forecasts over extended periods. As AI continues to evolve, demand forecasting techniques will likely become even more sophisticated. Predictive analytics, machine learning, and data-driven insights will drive manufacturers to embrace AI-driven forecasting models. Moreover, advancements in AI will facilitate real-time analysis, enabling businesses to respond swiftly to market changes and consumer behaviours. However, ethical considerations, data privacy concerns, and the need for transparent AI decision-making processes will remain important considerations in integrating AI into demand forecasting practices.

Integrating AI into demand forecasting processes offers manufacturers a competitive edge by providing insights into market trends, consumer behaviour, and sales data. Manufacturers can make informed decisions, optimise production, and enhance customer satisfaction by leveraging AI algorithms to analyse these key factors. As AI technology continues to advance, its role in demand forecasting is poised to become increasingly vital for businesses seeking to thrive in a rapidly changing marketplace.

2.6. Leveraging artificial intelligence for enhanced marketing strategies

The adoption of GAI for marketing is rapidly growing (Kshetri et al., 2023; De Mauro, Sestino, & Bacconi, 2022). By March 2023, 73 % of US businesses had already incorporated GAI tools, such as chatbots, into their marketing efforts (Dencheva, 2023).

Optimising marketing strategies in the ever-evolving manufacturing landscape is a crucial success facet. With the integration of GAI in manufacturing, companies gain a powerful tool for achieving more efficient and data-driven marketing approaches. The application of GAI in this context goes far beyond traditional methods, enabling manufacturers to make smarter decisions regarding the timing of product releases, promotional campaigns, and sales events.

One of the most remarkable aspects of utilising AI in marketing strategy is the capacity to harness predictive analytics. This technology allows manufacturers to forecast market trends and consumer behaviour with a high degree of accuracy. By analysing historical data, market conditions, and consumer preferences, GAI systems can identify potential spikes in demand for particular products or services. Managers can achieve significant value and a competitive edge by making effective data-based decisions (Conboy et al., 2020; Sivarajah et al., 2017). Furthermore, high-performing companies tend to be more inclined to use analytics compared to their less successful competitors (LaValle et al., 2011). Companies have utilised AI and machine learning to analyse historical sales data, market trends, and external factors such as weather conditions, which helps them predict consumer demand for their products more accurately.

The company's AI-driven demand forecasting can lead to better inventory management and optimised marketing campaigns, ensuring products are available when and where consumers need them. Utilising predictive and behavioural analytics models enables the customisation of new product offerings in response to evolving customer requirements and the precise targeting of marketing initiatives towards specific audiences.

When manufacturers can foresee increased demand accurately, they can adjust their marketing strategies and production schedules accordingly. This ability to predict demand patterns enables companies to allocate resources more effectively (Tadayonrad & Ndiaye, 2023), ensuring that products are available when and where they are most needed. As a result, manufacturers can maximise revenue by capitalising on market trends and customer preferences on time.

GAI also enables manufacturers to tailor their marketing campaigns to specific customer segments. AI systems can identify consumer preferences and behaviours by analysing vast datasets, allowing for highly targeted advertising and promotional efforts. Today, marketers can emphasise the customer and address their immediate needs as they arise (Haleem et al., 2022). GAI plays a crucial role in achieving extreme personalisation of content by analysing a potential customer's Internet browsing history, previous purchases, and other digital traces. This approach leads to the creation of dynamic offers, which, in turn, can significantly boost the conversion rate of promotional offers (Ooi et al., 2023). This level of personalisation can significantly enhance the effectiveness of marketing campaigns, ultimately leading to higher interactive experiences and increased customer satisfaction. By analysing the behaviour of similar customers, AI can suggest products more likely to resonate with each individual (Haleem et al., 2022). This approach enhances the customer experience and increases cross-selling and upselling opportunities.

Moreover, GAI aids in efficient resource allocation, ensuring that marketing budgets are spent in the most cost-effective way. Manufacturers can optimise their marketing investments and avoid wasteful spending by identifying which marketing channels and strategies yield the best results. This approach enhances a more sustainable and environmentally friendly manufacturing process.

GAI can be set to streamline data analysis and enhance marketing and customer service interactions. Companies like Nestlé, General Mills, and AB InBev have embraced GPT-4 to assist in deciphering data for their business intelligence needs. Meanwhile, Coca-Cola is leveraging ChatGPT and DALL-E 2 to craft their marketing campaigns (Global Data, 2023).

Conclusions

Integrating AI in manufacturing offers a multifaceted approach to enhancing product efficiency, effectiveness, and safety. Manufacturers can significantly improve their overall operational outcomes by streamlining processes, optimising resource utilisation, and implementing advanced quality control measures. In the realm of skills analysis for manufacturing processes, AI adaptation plays a pivotal role. This technology facilitates a proactive approach to workforce development by evaluating historical data, identifying patterns, and forecasting evolving skill requirements, ensuring the necessary competencies are identified and cultivated.

GAI contributes to product quality by identifying defects in products and processes. Manufacturers can swiftly address issues, improving the overall quality of their products by analysing data patterns, anomaly detection, and real-time insights.

In the maintenance domain, GAI emerges as a proactive solution. This technology enables timely interventions by predicting equipment failures or maintenance needs through comprehensive data analysis. This approach helps prevent downtime, optimise operational efficiency, and extend the lifespan of machinery and equipment.

AI's capabilities extend to market dynamics by analysing trends, consumer behaviour, and sales data to predict demand for manufactured goods. This empowers manufacturers to align their production with market needs, facilitating efficient inventory management and resource allocation.

Furthermore, AI optimises marketing strategies by leveraging data analysis. AI enhances overall marketing effectiveness and customer engagement by improving the timing of product releases, promotional campaigns, and sales events. This holistic integration of AI technologies underscores their transformative impact on various facets of the manufacturing industry.

AI can be leveraged to analyse and predict the necessary skills required for manufacturing. It can also assist in mapping current employee skills and identifying gaps, allowing HR to proactively train or hire to meet future workforce demand. For instance, machine learning algorithms can identify patterns in worker skills and suggest appropriate training modules or process adjustments to increase overall manufacturing efficiency.

AI can analyse market trends, consumer behaviour, and sales data to predict demand for manufactured goods. Integrating GAI in manufacturing empowers companies to revolutionise their marketing strategies. With predictive analytics, data-driven insights, and highly targeted campaigns, manufacturers can respond to shifting market dynamics with precision. By maximising revenue and making more efficient use of resources, AI is an invaluable tool for manufacturers seeking a competitive edge in the global marketplace, allowing companies to be flexible and adaptable to new trends and staying relevant as consumer tastes change.

The future research directions regarding the application of artificial intelligence to enhance manufacturing processes are expected to be characterised by interdisciplinary studies that integrate teams of researchers and practitioners from technical, social, economic, and ethical disciplines. Undoubtedly, a long-term challenge will be the assessment of the consequences (positive and negative) of AI applications in various areas of human life and activity.

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