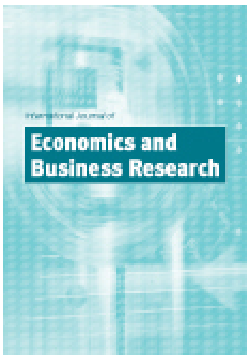

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The role of AI applications in production and operations management: complementing or replacing human labour

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The role of AI applications in production and operations management: complementing or replacing human labour

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Abstract: This study aims to assess the role of artificial intelligence (AI) within the production and operations management (POM) framework and its related fields. It explores AI applications in POM to determine whether they complement or replace human roles in the future. A literature-based content analysis was conducted, examining peer-reviewed publications from the past five years across key areas such as optimisation and automation, quality control, supply chain management, inventory management, and AI-driven robotics. The findings highlight AI applications and their benefits within POM, along with AI's academic progress across various industries. The study demonstrates how AI can either complement or replace human efforts. Additionally, it outlines best practices for organisations, emphasising change management strategies and supportive leadership when adopting AI-driven solutions. This study contributes to both academia and industry by summarising recent AI applications within a specific business function, serving as a foundational resource for scholars and professionals alike.

Keywords: artificial intelligence; AI; production and operations management; POM; human-AI collaboration; AI-driven automation and optimisation; AI-driven robotics; change management; leadership.

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1 Introduction

Artificial intelligence (AI) is transforming business intelligence, reshaping how companies operate and compete globally. As a subfield of computer science, AI enables machines to mimic human cognitive functions such as learning, pattern recognition, and decision-making (Dalzochio et al., 2020; Soori et al., 2023). Once confined to science fiction, AI is now an integral part of daily life and a critical tool across industries, including healthcare, education, retail, and finance (Agarwal et al., 2024; Paramesha et al., 2024). Its ability to analyse vast datasets, identify patterns, and facilitate autonomous decision-making has made it indispensable for organisations seeking to enhance efficiency, reduce costs, and improve customer satisfaction (Agarwal et al., 2024; Fosso Wamba et al., 2022; Lobo and Samaranayake, 2020). The growing adoption of AI underscores its role as a driving force for innovation, automating complex tasks and streamlining decision-making processes. According to Reilly et al. (2023), 84% of executives believe AI will fundamentally reshape their organisations within the next three to five years, particularly in production, marketing, and customer service.

In production and operations management (POM), AI-driven tools such as predictive maintenance and supply chain optimisation have significantly reduced downtime and increased productivity. Similarly, in marketing and sales, AI enhances personalisation and predictive analytics, enabling businesses to tailor strategies and engage customers more effectively (Kumar et al., 2024; Muthu, 2024; Paramesha et al., 2024; Yadav et al., 2024). AI applications span from automating routine tasks to facilitating complex, data-driven decision-making across various business functions (Agarwal et al., 2024). Looking ahead, AI is expected to play a crucial role in POM, marketing, human resources, and customer service. In POM specifically, AI automates repetitive tasks, streamlines supply chains, and enables managers to forecast outcomes, enhancing strategic planning and operational efficiency (George and George, 2023; Negoita and Borangiu, 2023; Zhang et al., 2022).

The growing integration of AI within organisational operations presents a compelling case for examining its role through the POM framework. On a broader scale, AI is projected to contribute trillions to the global economy, highlighting its immense value. However, concerns remain regarding AI's impact on the workforce, particularly its potential to complement or displace human labour. Organisations must adopt thoughtful strategies to navigate these disruptions. Effective leadership will be essential to managing this transformation and ensuring a sustainable, human-centred transition.

As part of a broader project examining AI's impact across key POM themes, this study focuses on three main objectives:

a Assess the extent to which AI applications are currently integrated within the POM framework.

b Evaluate AI's impact on human labour – specifically, whether it complements human work or poses a risk of job displacement within POM contexts.

c Explore the strategies and leadership models organisations must adopt to sustain effective POM practices amid disruptive workplace changes.

To achieve these objectives, this paper systematically reviews the effects of AI within the POM framework by analysing recent literature. It investigates how AI is reshaping industries, the benefits of AI-driven tools, and their implications for human labour. Additionally, this study examines trends in AI applications using academic databases to track their evolution and impact over time. Findings will be categorised according to the POM framework, followed by a comprehensive discussion on AI's future strategies and the leadership styles necessary for organisations to adapt to AI-driven transformations in POM.

2 POM framework

AI technologies – such as machine learning (ML), predictive analytics, and intelligent automation – are driving operational improvements across various industries. Their effectiveness within the POM framework varies by application, as highlighted in recent literature (Abhulimen and Ejike, 2024; Ali et al., 2024; Fosso Wamba et al., 2024).

For instance, AI-powered robotics have significantly improved assembly line operations in manufacturing, contributing to greater efficiency and effectiveness (Balasubramanian and Scholar, 2023; Dimény and Koltai, 2024). Beyond this, several broader drivers are fuelling the integration of AI into POM. These include the emergence of Industry 4.0, the growing availability of big data, the increasing complexity of global supply chains, persistent shortages of skilled labour in key operational areas, and substantial investments in research and development by governments aiming to accelerate innovation (Fosso Wamba et al., 2024; Gao et al., 2024; Samuels, 2025).

Together, these drivers underscore the importance of exploring AI applications within POM themes such as manufacturing process optimisation, intelligent automation, and robotics. They form the foundation for understanding how AI can support more resilient, agile, and efficient operational systems.

2.1 Optimisation and automation

AI is transforming the manufacturing sector by optimising processes and automating operations, leading to greater efficiency, accuracy, and cost reduction (Kasaraneni, 2021; Okuyelu and Adaji, 2024). AI-driven drilling advancements enhance performance across manufacturing by streamlining drilling and production applications (Biswal et al., 2020; Domínguez-Monferrer et al., 2022; Fosso Wamba et al., 2022). By automating repetitive tasks and optimising complex operations, AI increases output while ensuring accuracy and consistency (Zhang et al., 2022). Manufacturers leveraging AI achieve higher productivity and reliability (Bhatnagar, 2020; Chukwunweike et al., 2024; George and George, 2023; Ghelani, 2024).

AI-powered vehicles equipped with sensors monitor traffic and road conditions, enhancing delivery safety and manufacturing logistics (Huang et al., 2021). These advancements align logistics and production processes, improving overall operational efficiency (Gupta et al., 2023). A key achievement of AI in manufacturing is the automation of labour-intensive tasks that were once prone to human error (Bhatnagar, 2020; Chukwunweike et al., 2024; George and George, 2023). Deploying AI in areas with minimal human intervention allows organisations to reallocate human resources to high-value tasks, such as innovation, problem-solving, and strategic decision-making (Helo and Hao, 2022). Table 1 presents recent literature highlighting AI applications in Optimisation and Automation within the manufacturing sector.

Table 1 AI Applications in optimisation and automation for the manufacturing sector

AI application	*Tools used*	*Generated benefits*	*Article (s)*
Assembly line allocation for goods manufacturing	AI-powered robotics, automation, AI-driven inspection and testing	High accuracy, reduced waste, enhanced efficiency	Balasubramanian (2023), Dimény and Koltai (2024)
Automation in manufacturing processes	Robotic process automation (RPA), machine learning (ML)	Improved production speed, reduced human errors, real-time monitoring	Nayak et al. (2023), Moraes et al. (2022), Ribeiro et al. (2021)
AI integration in manufacturing	AI integration readiness factors	Enhanced data collection, IT investment, improved employee skills	Kinkel et al. (2022), Lerch et al. (2024)
AI-driven robotics in manufacturing	AI-driven robotics, collaborative robots	Automated repetitive tasks, increased precision, reduced human error, improved productivity	George and George (2023), Negoita and Borangiu (2023)
AI in drilling processes	AI algorithms	Facilitated drilling, predicted potential problems	Biswal et al. (2020), Domínguez-Monferrer et al. (2022), Fosso Wamba et al. (2022)

2.2 Predictive maintenance

Predictive maintenance is a key application of AI in POM, enabling proactive equipment maintenance to minimise disruptions and optimise efficiency. AI-powered predictive maintenance leverages simulation models to analyse supply chain scenarios and facilitate dynamic flow-shop scheduling (Azab et al., 2021; Dogru and Keskin, 2020; Jittawiriyanukoon and Srisarkun, 2022).

By utilising ML techniques, AI analyses equipment usage data, identifies patterns, and predicts potential failures before they occur (Abidi et al., 2022; Arena et al., 2024; Lobo and Samaranayake, 2020). This proactive approach ensures timely maintenance, reduces downtime, extends machinery lifespan, and enhances overall operational efficiency (Putha, 2022; Kurkute et al., 2023; Ucar et al., 2024). AI-powered predictive maintenance has been shown to reduce machine downtime by up to 30%, leading to increased productivity and streamlined operations (Zhang et al., 2021). By preventing overuse-related damage, AI enhances production continuity and maximises return on investment (ROI) in production assets (Chen et al., 2021; Smith et al., 2022).

Additionally, AI-driven maintenance aligns repair schedules with operational demands, ensuring efficient resource allocation (Dogru and Keskin, 2020).

AI-powered systems analyse real-time sensor data to detect anomalies that indicate potential equipment failures (Nunes et al., 2023; Pech et al., 2021). In industries such as automotive and aerospace, these systems monitor sensor data to identify wear-and-tear patterns and schedule maintenance before breakdowns occur (Baryannis et al., 2019a, 2019b). Furthermore, AI-driven maintenance scheduling optimises repair intervals, avoids unnecessary maintenance, and prevents major failures, leading to significant cost savings (Chukwunweike et al., 2024; Khurana, 2025; Papadopoulos et al., 2022; Yadav et al., 2024).

Table 2 AI applications in predictive maintenance

AI application	*Used tool*	*Generated benefits*	*Article (s)*
Predictive maintenance	AI-driven simulation models, dynamic flow-shop scheduling	Optimises supply chain scenarios, enhances operational efficiency	Azab et al. (2021), Dogru and Keskin (2020), Jittawiriyanukoon and Srisarkun (2022)
Failure prediction	Machine learning algorithms, real-time sensor analysis	Detects anomalies, predicts failures before occurrence, reduces downtime	Abidi et al. (2022), Arena et al. (2024), Lobo and Samaranayake (2020)
Maintenance optimisation	AI-powered predictive maintenance, real-time equipment monitoring	Reduces downtime by up to 30%, extends machinery lifespan, maximises ROI	Zhang et al. (2021), Chen et al. (2021), Smith et al. (2022)
Anomaly detection	Real-time sensor data analysis, AI-driven predictive tools	Identifies wear-and-tear patterns, prevents breakdowns in automotive and aerospace industries	Nunes et al. (2023), Pech et al. (2021), Baryannis et al. (2019a, 2019b)
Cost reduction and resource optimisation	AI-driven maintenance scheduling, predictive analytics	Optimises repair schedules, reduces unnecessary maintenance, minimises major failures	Chukwunweike et al. (2024), Khurana (2025), Papadopoulos et al. (2022), Yadav et al. (2024)
Proactive maintenance scheduling	Machine learning models, historical and real-time data integration	Detects deviations from normal cycles, eliminates reliance on reactive repairs, reduces costly downtime	Keleko et al. (2022), Papadopoulos et al. (2022), Dogru and Keskin (2020), Smith et al. (2022)

By integrating historical and real-time production data, AI detects deviations from normal operating cycles (Keleko et al., 2022; Papadopoulos et al., 2022). ML models forecast failures and schedule maintenance proactively, eliminating reliance on reactive repairs that often result in costly downtime (Chen et al., 2021; Dogru and Keskin, 2020; Papadopoulos et al., 2022; Smith et al., 2022). Table 2 presents recent literature highlighting AI applications in predictive maintenance.

2.3 *Quality control*

Quality control is a critical component of manufacturing, directly impacting customer satisfaction and a company's reputation. AI has revolutionised quality assurance by enabling automated inspection systems that are faster, more accurate, and more reliable than traditional methods (Chhetri, 2024; Oborski and Wysocki, 2022). By leveraging real-time analysis, AI enhances quality inspection, minimises human error, and ensures higher consistency in production standards (Bhosale et al., 2024).

Table 3 AI applications in quality control

AI application	*Used tool*	*Generated benefits*	*Article (s)*
Automated inspection	AI-powered machine vision, real-time analysis	Enhances accuracy, minimises human error, improves consistency	Chhetri (2024), Oborski and Wysocki (2022), Bhosale et al. (2024)
Defect detection	Machine vision systems, image comparison, predefined quality standards	Detects deviations in real-time, ensures quick corrective actions, reduces defective output	Arrabiyeh et al. (2024), Benbarrad et al. (2021), Sioma (2023), Sun et al. (202)3
Production line optimisation	AI-driven computer vision, robotic inspection systems	Reduces inspection time, elevates quality standards, decreases product waste	Ettalibi et al. (2024), Islam et al. (2024), Nascimento et al. (2023)
Robotic quality control	AI-powered robotic defect detection	Ensures consistent quality across production lines, eliminates manual inspection bottlenecks	Azamfirei et al. (2023), Ghelani (2024), Papavasileiou et al. (2025)
Process optimisation	Machine learning algorithms, production data analysis	Identifies inefficiencies, detects process deviations, enhances operational performance	Chhetri (2024), Lekan et al. (2023), Nimmagadda (2024)
Self-automated quality control	AI-driven predictive analytics, real-time abnormality detection	Ensures flawless product delivery, minimises defects	Sony et al. (2020), Qureshi et al. 2020)

AI-powered machine vision systems utilise cameras to capture images, compare them against predefined quality standards, and detect deviations or defects in real-time (Arrabiyeh et al., 2024; Benbarrad et al., 2021; Sioma, 2023; Sun et al., 2023). This precision improves consistency, reduces defective output, and enables swift corrective actions (Ghelani, 2024). As a result, businesses minimise resource waste and operational losses while delivering higher-quality products to customers.

AI-driven computer vision systems further enhance defect detection during production, reducing inspection time and elevating quality standards (Ettalibi et al., 2024; Hegedić et al., 2023; Islam et al., 2024; Nascimento et al., 2023). These systems decrease product waste and optimise assembly line operations by identifying defects more efficiently than human inspectors (Xiong et al., 2024; Zhang, 2020). Additionally, AI-powered robotic systems streamline defect identification, ensuring consistent quality across production lines and eliminating bottlenecks caused by manual inspections (Azamfirei et al., 2023; Ghelani, 2024; Papavasileiou et al., 2025).

Beyond real-time inspection, ML algorithms analyse production data to uncover inefficiencies and identify process deviations (Chhetri, 2024; Lekan et al., 2023; Nimmagadda, 2024). By providing actionable insights, AI helps organisations proactively address quality challenges and enhance overall operational performance (Lekan et al., 2023; Nimmagadda, 2024). Furthermore, self-automated AI-driven quality control systems detect abnormalities during production, ensuring that only flawless products reach the market (Sony et al., 2020; Qureshi et al., 2020). Table 3 presents recent literature highlighting AI applications in quality control.

2.4 Supply chain management

AI is transforming supply chain management (SCM) by enhancing real-time monitoring, demand forecasting, inventory control, and operational efficiency (Dogru and Keskin, 2020; Ransbotham et al., 2021; Zhang et al., 2022). By integrating data analytics, ML, and predictive tools, AI enables more efficient, reliable, and cost-effective supply chain networks (Nzeako et al., 2024).

AI-driven systems analyse historical and real-time data to accurately predict demand and align production levels accordingly (Raji et al., 2024). This capability minimises excess inventory, reduces costs, and ensures timely product delivery (Rege, 2023a). AI models account for key variables such as product demand, transportation costs, and inventory levels to optimise supply chain operations (Dogru and Keskin, 2020). By improving material flow and logistics, AI enhances overall performance while reducing costs and delivery times.

AI-powered demand forecasting significantly improves accuracy by 20–50%, allowing businesses to minimise overstocking, cut unnecessary expenses, and enhance customer satisfaction (Rege, 2023b). ML algorithms and big data analytics identify historical trends and generate reliable forecasts, improving resource allocation and operational efficiency (Aamer et al., 2020; Kabashkin et al., 2023; Rashid et al., 2025; Seyedan and Mafakheri, 2020).

AI is also revolutionising transportation and logistics. For instance, in the airline industry, AI algorithms optimise flight schedules and resource allocation by analysing traffic density and passenger information, ensuring streamlined operations (Garcia et al., 2021; Balasubramanian and Scholar, 2023).

In supply chain optimisation, AI processes large datasets to predict machine failures, enabling proactive maintenance, reducing costs, and ensuring uninterrupted operations (Fosso Wamba et al., 2022; Lobo and Samaranayake, 2020). AI's predictive analytics is reshaping industries such as IT, manufacturing, and retail by integrating with IoT systems for real-time tracking, improving inventory visibility and control (Gupta et al., 2023; Nzeako et al., 2024). Additionally, AI tools detect inefficiencies in supply chain processes and recommend adjustments, leading to smoother production flows, reduced downtime, and lower operational costs (Gupta et al., 2023; Lobo and Samaranayake, 2020). Table 4 presents recent literature highlighting AI applications in supply chain.

Table 4 AI applications in supply chain.

AI application	*Used tool*	*Generated benefits*	*Article (s)*
Supply chain optimisation	AI-driven data analytics, machine learning, predictive tools	Enhanced efficiency, reliability, and cost-effectiveness in supply chain networks	Nzeako et al. (2024), Rege (2023a), Zhang et al. (2022)
Demand forecasting	AI-powered predictive models, machine learning, big data analytics	Accurate demand prediction, minimised excess inventory, reduced costs, improved customer satisfaction	Rege (2023b), Aamer et al. (2020), Kabashkin et al. (2023)
Logistics and transportation	AI algorithms for scheduling optimisation, real-time analysis	Optimised flight schedules, improved resource allocation, reduced operational disruptions. Early fault detection, minimised downtime, cost savings	Garcia et al. (2021), Balasubramanian and Scholar (2023)
Supply chain efficiency	AI-driven predictive analytics, IoT integration	Improved inventory visibility, reduced inefficiencies, smoother production flow, cost reduction	Gupta et al. (2023), Nzeako et al. (2024), Lobo and Samaranayake (2020)

2.5 Inventory management

AI is transforming inventory management by enhancing demand forecasting, optimising stock levels, and automating warehouse operations (Albayrak Ünal et al., 2023; Eldred et al., 2023; Kumar et al., 2024). AI's predictive capabilities help businesses maintain optimal inventory levels, reduce storage costs, and minimise the risks of overstocking or stockouts (Kaul and Khurana, 2022; Rege, 2023a). Companies integrating AI into supply chain operations have reduced inventory costs by up to 30% due to improved demand forecasting (Rege, 2023b).

AI-driven systems analyse historical sales data, cyclical trends, and market fluctuations to predict demand and determine appropriate stock levels accurately (Eldred et al., 2023; Kaul and Khurana, 2022). This ensures efficient inventory management by maintaining optimal stock quantities while avoiding unnecessary storage expenses and shortages. ML algorithms, a key component of AI, process vast datasets – including historical sales data and market trends – to optimise inventory levels effectively (Ransbotham et al., 2021; Helo and Hao, 2022). This technology reduces waste while ensuring businesses consistently meet customer demand (Kumar et al., 2024; Ma et al., 2024; Pasupuleti et al., 2024).

AI also automates logistics and inventory control by tracking stock levels, recommending efficient delivery routes, and facilitating faster, more reliable deliveries (Preil and Krapp, 2022). In warehouses, AI-powered robots handle tasks such as sorting, picking, packing, and inventory management, improving efficiency and minimising human errors (Gupta et al., 2023; Helo and Hao, 2022).

In the retail sector, AI-based predictive analytics provide significant advantages. Ajiga et al. (2024) highlight how AI tools, including natural language processing (NLP) and big data analytics, analyse customer trends, social media behaviour, and market data to refine inventory decisions. Walmart, for instance, leverages AI for demand forecasting, inventory optimisation, and timely restocking, leading to improved delivery efficiency and enhanced customer service (Gupta et al., 2023). These advancements enable retailers to make precise inventory adjustments, minimise unnecessary stock procurement, and reduce overstocking costs. Table 5 presents recent literature highlighting AI applications in inventory management.

Table 5 AI applications in inventory management

AI application	*Used tool*	*Generated benefits*	*Article (s)*
Inventory optimisation	AI-driven predictive analytics, demand forecasting tools	Maintains optimal inventory levels, reduces storage costs, minimises overstocking and stockouts	Agarwal et al. (2024), Kaul and Khurana (2022), Rege (2023a), Eldred et al. (2023)
Demand forecasting	Machine learning algorithms, big data analytics	Accurately predicts demand, optimises stock levels, reduces waste, improves customer satisfaction	Ransbotham et al. (2021), Helo and Hao (2022), Kumar et al. (2024), Ma et al. (2024), Pasupuleti et al. (2024)
Logistics and inventory control	AI-driven tracking systems, delivery route optimisation tools	Enhances logistics efficiency, ensures timely deliveries, minimises errors	Gupta et al. (2023), Preil and Krapp (2022)
Warehouse automation	AI-powered robots for sorting, picking, packing, inventory management	Improves efficiency, reduces manual errors, enhances operational speed	Gupta et al. (2023), Helo and Hao (2022)
Retail sector inventory management	AI-based predictive analytics, NLP, big data analytics	Enhances demand forecasting, refines inventory decisions, reduces overstocking costs	Ajiga et al. (2024), Gupta et al. (2023).

2.6 AI-driven robotics in POM fields

AI-driven robotics play a crucial role in the POM framework by enhancing efficiency across manufacturing, quality control, inventory management, and supply chain operations (Bhatnagar, 2020; Chakraborti et al., 2020; Moraes et al., 2022; Ransbotham et al., 2021). By reducing manual intervention, eliminating production bottlenecks, and accelerating output, AI-integrated robotics significantly optimise industrial processes (Kumar, 2024; Irawan and Biyanto, 2024). Key areas where AI-driven robotics contribute to the POM framework include:

1 Robotic process automation (RPA): RPA optimises inventory management, order processing, and assembly line operations (Bhatnagar, 2020; Chakraborti et al., 2020; Moraes et al., 2022). AI-driven automation increases manufacturing speed by 25–35%, minimises human errors, and enables real-time production monitoring, improving both quality and performance (Nayak et al., 2023; Ribeiro et al., 2021). This automation enhances production capacity, reduces delays, and ensures process consistency (Helo and Hao, 2022).

2 Robotic assembly: AI-driven robotic assembly improves production scalability, maintains consistency, adapts to changing conditions, and collaborates with human operators to enhance efficiency (Dimény and Koltai, 2024; Soori et al., 2023). Integrated with deep learning, robotic assembly systems adapt to variations in parts and materials, ensuring accuracy (Chukwunweike et al., 2024). Additionally, vision-guided assembly systems utilise computer vision to verify correct part placement and alignment (Ramachandran, 2024).

3 Autonomous mobile robots (AMRs): AMRs automate warehouse operations, manage inventory, and fulfill orders, contributing to the Industry 5.0 landscape (Cognominal et al., 2021; Gouthaman et al., 2024; Ramachandran, 2024). These robots transport materials between production areas, warehouses, and distribution centres, streamlining operations, enhancing productivity, and improving workplace safety (Cognominal et al., 2021).

4 AI-driven robotic quality control: AI-driven robotics revolutionise quality control through real-time monitoring, defect detection, waste reduction, and improved inspection speed (Chhetri, 2024; Ettalibi et al., 2024; Papavasileiou et al., 2025; Xiong et al., 2024). Equipped with computer vision systems, these robots enhance accuracy and reliability in quality assessment (Ramachandran, 2024; Sadiku et al., 2023; Sioma, 2023). In some applications, human-robot collaboration further refines the inspection process (Ghelani, 2024; Papavasileiou et al., 2025).

5 Collaborative robots (Cobots) for human-robot interaction: Cobots assist human workers by automating repetitive, labour-intensive tasks, allowing employees to focus on complex and strategic activities (Rahman et al., 2024; Vemuri and Thaneeru, 2023). These AI-driven robots improve precision and quality in assembly line operations.

6 Industrial robot predictive maintenance: AI-driven predictive maintenance enables continuous monitoring of industrial equipment, preventing failures and reducing unplanned downtime (Ucar et al., 2024; Soori et al., 2023; Channi and Chowdhary, 2025; Izagirre et al., 2022; Soori et al., 2024). This proactive approach extends machinery lifespan and enhances operational efficiency (Soori et al., 2024; Ucar et al., 2024).

7 Exoskeletons for workforce enhancement: wearable robotic exoskeletons enhance worker mobility, reduce fatigue, and improve workplace safety, particularly in lifting and physically demanding tasks (Gouthaman et al., 2024; Nair, 2024; Rahman et al., 2024). These robotic suits, powered by active or passive actuation, support human ergonomics and efficiency.

8 AI-driven autonomous drones: AI-integrated drones streamline operations by enabling faster delivery services, inventory audits, and remote inspections, reducing time and labour costs (Cao, 2021; Soori et al., 2023; Yadav et al., 2024; Chen et al., 2024; Rahaman et al., 2025). Their applications enhance safety, efficiency, and logistical accuracy across industries.

Through these advancements, AI-driven robotics transform production, logistics, and quality control within the POM framework, driving efficiency, accuracy, and innovation across industrial processes.

3 Evaluation of AI-based POM

Qualitative data for this study was extracted from articles indexed in the Scopus academic research database. Scopus was selected due to its broad and reputable coverage of top journals in both POM and AI, as well as its extensive repository of peer-reviewed publications – many of which are not always available through other indexes such as Google Scholar or IEEE Xplore. The focus was placed on publications from the last five years (2020–2024) to capture the most recent advancements in AI applications.

To identify the most commonly used AI applications within the POM framework, content analysis was employed as the primary research tool. This method allowed for a systematic evaluation of the presence of AI technologies across different POM fields. While numerous definitions of content analysis exist (Roller, 2019), this study adopts the definition by Roller and Lavrakas (2015), who describe it as "the systematic reduction of content, analysed with special attention to the context in which it was created, to identify themes and extract meaningful interpretations of the data" (p.232). Here, context refers to the idea that 'useful claims in content analysis require contextual understanding' [Krippendorff and Bock, (2009), p.40], recognising that 'textual units are rarely ever entirely independent of each other' and that 'words may have many meanings' [rippendorff and Bock, (2009), p.44].

In this study, *context* is defined as "the juxtaposition of words, substance, and the 'broader environment' of the content" [Roller and Lavrakas, (2015), p.4]. For instance, during the Scopus search process, phrases such as 'AI application used' and 'ML' were examined within the context of POM themes like 'optimisation' and 'automation.' All in all, the search yielded 2,951 articles published between 2020 and 2025, which were compiled into an excel spreadsheet. These articles were then categorised by year under each specific POM theme, as summarised in Table 6. Finally, the dataset was analysed using ChatGPT-4.0 to aggregate and classify AI applications across various POM domains. Leveraging its advanced language processing capabilities, ChatGPT-4.0 facilitated knowledge-intensive tasks by generating new content and extracting meaningful insights from structured data (Alto, 2023; Amini et al., 2025; Bogireddy and Dasari, 2024).

3.1 Classification of AI applications by POM field

POM is undergoing a significant transformation with the integration of AI. Based on our study, AI applications have been systematically categorised across various POM fields, as summarised in Tables 1 to 5. These tables provide a classification of AI applications, their benefits, and supporting research articles demonstrating real-world implementations, as indexed in Scopus.

With advancements in AI, studies highlight increasingly sophisticated applications in POM, developed to complement or, in some cases, replace human involvement. This progress is also reflected in the growing number of research papers published over the past five years, showcasing the expanding role of AI in POM fields.

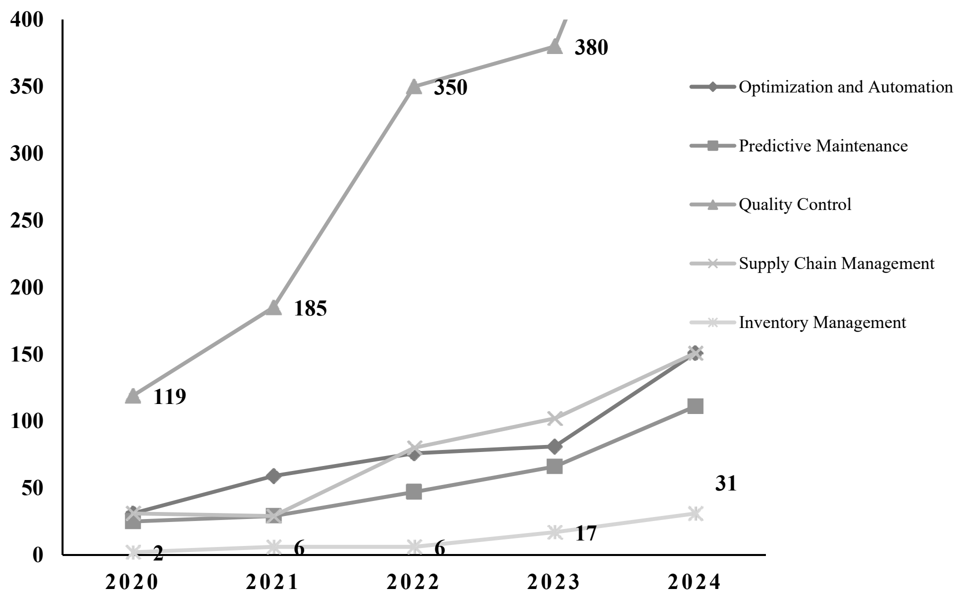
To illustrate these trends, Table 6 presents the changes in the number of research papers across different fields. Notably, quality control is the most frequent area of AI application, incorporating technologies such as ML, computer vision, deep learning, defect detection, and intelligent inspection.

Table 6 Number of research papers in various POM fields based on AI applications, as indexed in Scopus

POM fields	*2020*	*2021*	*2022*	*2023*	*2024*	*2025*	*Total*
Optimisation and automation	31	59	76	81	151	18	416
Predictive maintenance	25	29	47	66	111	24	302
Quality control	119	185	350	380	640	74	1748
Supply chain management	31	29	80	102	151	26	419
Inventory management	2	6	6	17	31	4	66
Total							2951

Figure 1 provides a comparative analysis of the number of AI-driven POM research papers published annually across five key fields. Quantitative analysis of qualitative research serves as a comparative measure. For instance, quality control has shown significant growth since 2024 compared to 2020, with the number of related publications increasing from 119 to 330 per interval. Overall, the past five years have seen a dramatic rise in research on AI-driven POM applications, reflecting the rapid adoption and increasing availability of AI technologies. These advancements continue to bring substantial benefits, driving progress and innovation across POM fields.

Figure 1 Distribution of research papers across various POM fields utilising ai applications



There is a significant difference in the number of research papers across various POM fields related to AI applications; not all areas within the POM framework have received equal attention. For example, the quality control theme appears to have a disproportionately high number of articles compared to other themes. This can be attributed to several factors: the availability of high volumes of real-time data, the effectiveness of inspection processes using computer vision and related technologies, and the substantial cost implications of product defects. These advantages make quality control a particularly rich and attractive area for AI integration within the POM framework.

3.2 AI applications' intervention in POM fields

The primary objective of this analysis was to identify the most widely applied AI technologies within the POM framework. The findings indicate that ML and AI-driven Analysis are among the most prevalent AI applications, demonstrating significant advancements and impact across POM fields. The detailed results are presented in Table 7.

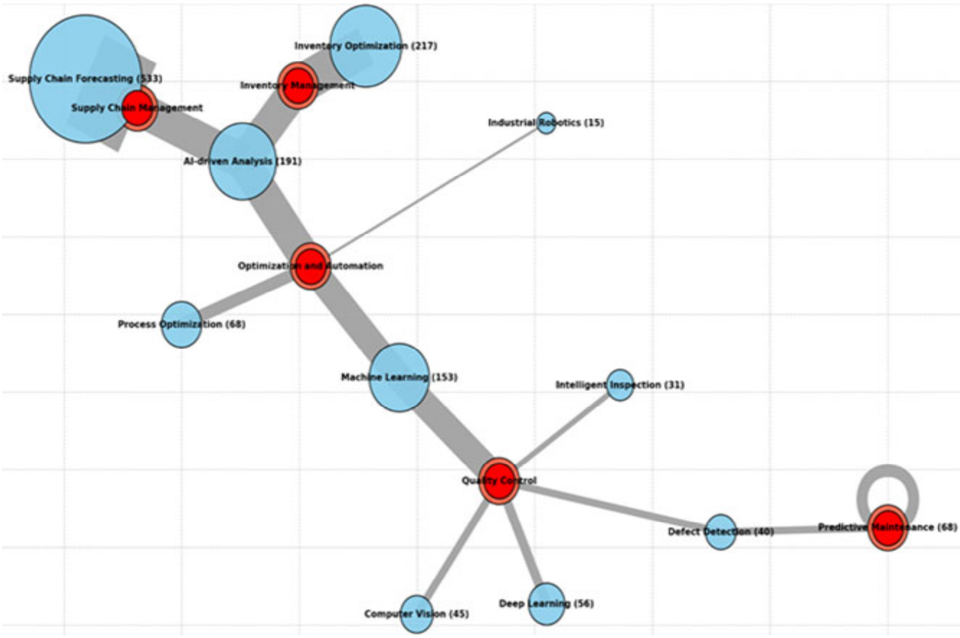
Table 7 POM fields based on AI applications, as indexed in Scopus (years and number of papers)

Central theme	*AI application*	*# of research articles*
Optimisation and automation	Machine learning	153
	Industrial robotics	15
	Process optimisation	68
	AI-driven analysis	191
Predictive maintenance	Predictive maintenance	68
	Defect detection	40
Quality control	Machine learning	153
	Computer vision	45
	Deep learning	56
	Defect detection	40
	Intelligent inspection	31
Supply chain management	Supply chain forecasting	533
	AI-driven analysis	191
Inventory management	Inventory optimisation	217
	AI-driven analysis	191

The aggregation and classification of AI applications across different POM fields reveal significant interventions and advancements in AI integration. The findings indicate that AI-driven analysis, ML, and robotics (including sensors and computer vision) are widely implemented across all POM fields.

To illustrate these interventions, Figure 2 presents a sample of articles classified according to Table 7, highlighting the most commonly used AI applications in various POM fields. All applications operate within the same dataset under the POM framework, demonstrating their ability to assist and complement human efforts in the workplace in diverse ways.

Figure 2 The intervention of AI applications across various POM fields (see online version for colours)



3.3 *AI robotics in POM fields*

The practical applications and benefits of eight distinct AI-driven robotic systems in POM have been well-documented in the literature, as outlined in Section 2.6. Using the same content analysis approach to assess their presence, each type was examined in the Scopus database over a five-year period. Notably, each AI robotic system was referenced in at least seven research papers, highlighting its real-world implementation, as detailed in Table 8.

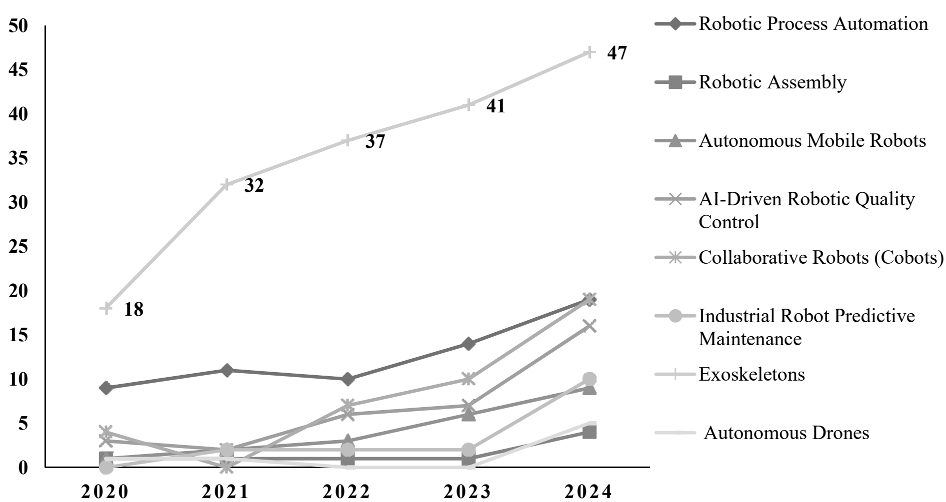
Thus, different types of AI robotics demonstrate varying levels of effectiveness across specific POM fields. This suggests that AI robotics should be strategically integrated not only within multiple areas of the POM framework but also across broader business functions. As shown in Figure 3, Exoskeletons for Workforce Enhancement and RPA are the two most widely adopted AI robotics types in POM. Together, they have exhibited consistent growth from 2020 to 2024, accounting for more than half of the total research papers and surpassing other AI robotics in terms of adoption and application.

Moreover, there is a noticeable disparity in the number of research publications across different types and applications of AI robotics. For instance, exoskeletons for workforce enhancement have a significantly higher representation in academic literature. This trend can be attributed to their interdisciplinary relevance and human-centric focus, which bring forward key regulatory and ethical considerations. These characteristics have attracted extensive academic attention, resulting in increased research output from diverse scholarly communities.

Table 8 Types and usage of ai robotics in academic articles, as indexed in Scopus (years and number of papers)

	Types and usage of AI robotics	*2020*	*2021*	*2022*	*2023*	*2024*	*2025*	*Total*
1	Robotic process automation (RPA)	9	11	10	14	19	3	66
2	Robotic assembly	1	1	1	1	4	1	9
3	Autonomous mobile robots (AMRs)	1	2	3	6	9	0	21
4	AI-driven robotic quality control	3	2	6	7	16	2	34
5	Collaborative robots (Cobots)	4	0	7	10	19	1	41
6	Industrial robot predictive maintenance	0	2	2	2	10	1	17
7	Exoskeletons for workforce enhancement	18	32	37	41	47	3	178
8	AI-driven autonomous drones	1	1	0	0	5	0	7
Total								*373*

Figure 3 Types and usage of AI robotics in academic articles



On the other hand, some studies suggest that certain industrial robotics applications in specific POM fields have the potential to replace human roles, highlighting the need for further investigation. This observation aligns with the second objective of the present study, which seeks to examine the impact of robotics and automation on workforce dynamics within the POM framework, particularly in terms of complementing versus replacing human roles.

Table 9 Human complementary and replacement potential of AI robotics in POM fields

	AI robotics	*Example*	*Complementary role*	*Replacement potential*	*Supporting literature*
1	Robotic process automation (RPA)	Tesla gigafactories	Low	High	Biradar et al. (2023), Chakraborti et al. (2020), Lievano-Martínez et al. (2022), Moraes et al. (2022), Ribeiro et al. (2025), Soori et al. (2023), Ugbebor et al. (2024)
2	Robotic assembly	Foxconn AI-powered smartphone assembly	Low	High	Chukwunweike et al. (2024), Dimény and Koltai (2024), Ramachandran (2024), Soori et al. (2023)
3	Autonomous mobile robots (AMRs)	Amazon Kiva system	Moderate	Moderate to high	Cognominal et al. (2021), Gouthaman et al. (2024), Nair (2024), Ramachandran (2024)
4	AI-driven robotic quality control	BMW AI-powered camera systems	Moderate	High	Cao (2021), Chhetri (2024), Ettalibi et al. (2024), George and George (2023), Ghelani (2024), Papavasileiou et al. (2025), Nair (2024)
5	Collaborative robots (Cobots)	Universal robots' Cobots	High	Low	Biradar et al. (2023), George and George (2023), Rahman et al. (2024), Vemuri and Thaneeru (2023)
6	Industrial robot predictive maintenance	General electric (GE) AI-powered aircraft engine inspections	High	Low	Ucar et al. (2024), Soori et al. (2023), Channi and Chowdhary (2025), Irawan and Biyanto (2024), Izagirre et al. (2022), Rahman et al. (2025), Soori et al. (2024)
7	Exoskeletons for workforce enhancement	Hyundai robotics' exoskeletons	Very high	Very low	Gouthaman et al. (2024), Nair (2024), Rahman et al. (2024)
8	AI-driven autonomous drones	Walmart AI-powered inventory drones	High	Moderate	Cao (2021), Chen et al. (2024), Irawan and Biyanto (2024), Nair (2024), Yadav et al. (2024), Rahaman et al. (2025), Soori et al. (2023)

Using content analysis, the human complementarity and replacement potential were assessed on a scale from low to high based on keywords related to different types of AI robotics found in the supporting literature. Then, the ranking for each type was validated using ChatGPT-4.0, as evidenced by numerous sources. The results indicate that RPA, robotic assembly, AMRs, and AI-driven robotic quality control have a high potential to replace human roles in their respective industries. In contrast, collaborative robots (cobots), industrial robot predictive maintenance, exoskeletons for workforce enhancement, and AI-driven autonomous drones demonstrate a strong potential to complement human efforts, enhancing productivity and efficiency rather than replacing workers, as shown in Table 9.

4 Discussion and implications

This study highlights the numerous benefits of AI applications in POM fields, as demonstrated in recent literature. AI presents significant opportunities to enhance decision-making, improve efficiency, and drive business innovation. However, its implementation also comes with notable challenges, particularly in terms of cost, workforce impact, and integration barriers.

One major challenge is the high cost of implementation, requiring substantial investments in software, hardware, and specialised skill sets (Perifanis and Kitsios, 2023; Smith et al., 2022). Additionally, workforce displacement is a critical concern, as AI-driven automation raises uncertainties about job security and compensation.

A major challenge in AI integration is its complexity for decision-makers. Key barriers to adoption include resistance to change, insufficient technical expertise, skills gaps, and inadequate infrastructure (Helo and Hao, 2022; Khogali and Mekid, 2023). AI impacts leadership across various business functions, including the POM, in four key areas: strategic change, professionalisation, organisational culture, and the human-AI relationship (Peifer et al., 2022).

To overcome these challenges and address the final objective, we believe that organisations must develop strategic AI implementation plans and align them with an appropriate leadership approach. Therefore, the upcoming subsections will explore these issues on two levels that POM leaders must consider in order to manage disruptive workplace changes and cultivate the benefits of AI integration in daily operational routines – without fear of workforce replacement.

4.1 AI at the strategic level

For successful AI adoption, organisations must cultivate a culture that embraces change and prepares employees for transformation. Resistance to change, often driven by concerns about job displacement, can hinder AI integration (Khogali and Mekid, 2023). Therefore, AI implementation must be supported by effective change management strategies to ensure a smooth transition. AI change management is increasingly embedded in business and functional strategies, positioning AI as a catalyst for organisational transformation (Perifanis and Kitsios, 2023). Organisations with dynamic capabilities can leverage AI to enhance decision-making, improve efficiency, and unlock new opportunities (Kerzel, 2021; Wamba, 2022). However, significant challenges persist, including skill gaps, data management issues, and integration complexities (Hamadaqa et al., 2024).

AI is poised to revolutionise business operations by complementing human employees rather than replacing them (Hamadaqa et al., 2024). Research shows that 83% of business leaders prioritise talent acquisition, underscoring the need for AI-driven hiring and workforce development (Kadirov et al., 2024). Beyond automation, companies must invest in digital transformation, upskilling, and reskilling initiatives to facilitate employees' transition into AI-enhanced roles (Kim and Kim, 2022; Morandini et al., 2023). While some fear AI will replace human intelligence, this view often disregards AI's collaborative potential. Rather than substituting human expertise, AI should be seen as a strategic tool that enhances decision-making, innovation, and problem-solving (Rachmad, 2022). AI can assist with complex, ambiguous problems while humans provide context, ethical oversight, and strategic direction (Dukes, 2023; Johnson et al., 2022; Usama et al., 2024). To mitigate resistance, organisations must foster an environment where employees perceive AI as a complement rather than a threat.

Therefore, Successful AI implementation requires a structured approach to behavioural change. The transtheoretical model of change (Prochaska and DiClemente, 1980) outlines six stages of behavioural transformation: precontemplation, contemplation, preparation, action, maintenance, and termination. This model highlights that change is a continuous process rather than a singular event. Employees in POM fields may progress through these stages at different rates before fully adopting AI-driven methodologies.

For AI integration at the POM level, organisations should implement key change strategies. First, developing a comprehensive AI continuum strategy. Aligning AI initiatives with long-term business objectives ensures that AI supports the organisation's vision, enhances efficiency, and drives innovation (Davenport and Ronanki, 2018; Kitsios and Kamariotou, 2021). Effective communication and a supportive organisational culture are crucial for the successful adoption of AI in POM functions, alongside robust infrastructure. Second, investing in workforce training and development. Equipping employees with the necessary skills to interact effectively with AI tools is essential. Continuous education and upskilling programs help employees adapt to AI-driven environments, reducing resistance and enhancing productivity (Kaplan and Haenlein, 2020). Third, implementing robust data security and governance. Ensuring data security, minimising algorithmic biases, and maintaining transparency in AI decision-making are critical. Strong data governance frameworks help protect sensitive information and build trust in AI systems. Finally, prioritising ethical AI deployment (Usama et al., 2024). Leadership plays a pivotal role in ensuring AI is implemented ethically. Organisations must maintain algorithmic transparency, eliminate biases, and comply with regulatory standards. Establishing ethical AI guidelines helps prevent unintended consequences and supports responsible innovation (Usama et al., 2024).

4.2 Leadership in an AI-driven organisations

Leadership is essential in aligning AI applications within POM fields with an organisation's key change strategies (Schmitt, 2024; Quaquebeke and Gerpott, 2023). Research highlights AI's impact on leadership flexibility and behavioural patterns (Cortellazzo et al., 2019; Fullan et al., 2024; Peifer et al., 2022; Strich et al., 2021). The increasing adoption of AI-driven automation has reshaped leadership by reducing time spent on routine tasks, enabling leaders to focus on higher-order functions such as innovation, planning, and strategic thinking (Peifer et al., 2022; Strich et al., 2021).

This transformation necessitates continuous adaptation, requiring leaders to integrate AI tools into their leadership approaches (Randriamiary, 2024; Strich et al., 2021). Those resistant to change risk obsolescence in industries embracing AI-driven innovation (Randriamiary, 2024; Strich et al., 2021). However, excessive reliance on AI for employee interactions may weaken workplace relationships, as AI lacks human emotions, empathy, and interpersonal communication skills (Coronado-Maldonado and Benítez-Márquez, 2023; Sejera and Bocarnea, 2022).

The Transtheoretical Model of Change suggests that leadership competencies must evolve in response to AI integration. Leaders must acquire new skills, including AI literacy, to effectively leverage AI for operations and decision-making – not necessarily through coding expertise, but by understanding AI's capabilities and limitations (Judijanto et al., 2022).

Beyond AI literacy, leaders must develop competencies related to human-AI collaboration (Peifer et al., 2022; Quaquebeke and Gerpott, 2023). Social competencies, such as communication, emotional intelligence, and adaptability, are essential, as leaders now oversee interactions between AI systems and human employees (Peifer et al., 2022; Quaquebeke and Gerpott, 2023). In the AI era, leaders must mediate between people and machines while fostering collaboration.

While AI enhances technical decision-making, it cannot replace human qualities such as morality, empathy, and creativity. Future leaders must prioritise soft skills such as interpersonal communication, ethical reasoning, and team management to ensure AI is implemented ethically and effectively within organisations (Usama et al., 2024; Xiong, 2022).

AI is also transforming leadership behaviours, requiring leaders to adopt cooperative, adaptable, and flexible approaches. As AI assumes routine administrative tasks, leaders must shift their focus from task management to relational leadership, fostering stronger team connections (Xiong, 2022). This transformation redefines AI from a mere tool to a collaborative partner in decision-making. Leaders must determine which tasks are best suited for AI and which require human judgment and creativity to create a balanced human-AI collaboration (Peifer et al., 2022).

Behavioural modifications are also necessary to address the ethical implications of AI in leadership. Leaders must establish ethical guidelines to ensure AI is applied responsibly in business settings (Judijanto et al., 2022; Usama et al., 2024). This includes addressing concerns related to data privacy, algorithmic bias, and AI's potential impact on employment.

By addressing these challenges and implementing strategic change management, leaders can facilitate AI integration while minimising workforce disruptions. A strong leadership framework ensures that AI serves as a valuable tool for business growth and innovation, fostering a balanced and sustainable digital transformation.

5 Conclusions

This study explored the impact of AI on the POM framework through an extensive literature review and a quantitative analysis of research articles published between 2020 and 2024. The findings highlight AI's significant role in enhancing efficiency, reducing costs, and improving product quality across various POM themes. This transformation underscores the importance of a balanced human-AI collaboration, where strategic change models and strong leadership are essential to address workforce concerns and ensure successful AI integration.

Despite its contributions as foundational research within the literature – offering valuable insights into AI's benefits and real-world applications for academia and decision-makers – the study is subject to two main limitations. First, it focuses solely on POM, excluding other key business functions such as finance, accounting, and human resources. Broader analysis across multiple domains would offer a more holistic understanding of AI's organisational value. Second, the research relied exclusively on the Scopus database, which, while comprehensive, may omit relevant studies available in other academic sources. Future research should consider databases like Web of Science, IEEE Xplore, or Google Scholar for more inclusive coverage.

Additionally, there remains a gap in AI-focused research on underrepresented POM areas such as inventory management, predictive maintenance, and the use of AI robotics. Addressing these gaps can reveal the readiness of these areas for AI integration and identify opportunities for innovation, paving the way for more effective and human-centred applications of AI in operations.

Declarations

During the preparation of this work, the author(s) used the ChatGPT to correct English grammar in some paragraphs. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

All authors declare that they have no conflicts of interest.

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