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Review Article

Artificial Intelligence for Adaptive Safety and Task Allocation in Smart Manufacturing: A Comprehensive Review

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Abstract

Artificial intelligence (AI) is transforming smart manufacturing by enabling intelligent automation, data-driven decisions, and stronger collaboration between humans and manufacturing systems. The widespread adoption of collaborative robots, the industrial internet of things, and cyber-physical systems is driving demand for manufacturing environments that are safer, more flexible, and more efficient. Despite AI's broad application in manufacturing, few studies have combined adaptive safety and intelligent task allocation within a single human-centered framework. This review offers a comprehensive look at AI applications that support these two complementary functions. Literature from Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink, and the ACM Digital Library was systematically reviewed following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses guidelines and analysed thematically. The findings show that machine learning, deep learning, computer vision, reinforcement learning, knowledge-driven approaches, digital twins, and explainable AI contribute to improvements in predictive maintenance, quality inspection, production scheduling, adaptive safety, and collaborative decision-making. That said, challenges remain - such as interoperability, explainability, limited access to high-quality manufacturing data, industrial validation, and integrating multiple AI technologies. This review gives researchers and practitioners a holistic perspective and highlights integrated, human-centered AI frameworks as key enablers of resilient, efficient, and sustainable Industry 5.0 manufacturing systems.

Categories: AI applications, AI Ethics and Fairness, Machine Learning (ML)

Keywords: artificial intelligence, smart manufacturing, adaptive safety, intelligent task allocation, human–robot collaboration, digital twins, industry 5.0

Introduction And Background

Digital technologies, automation and decision-making based on data are driving a significant change in the manufacturing industry. With the advent of artificial intelligence (AI), the industrial internet of things (IIoT), cyber-physical systems (CPS), cloud computing and advanced robotics, the traditional manufacturing process has been increasingly transformed into smart manufacturing, in which production systems are increasingly connected and adaptive with autonomous decision-making capabilities. The progress has resulted in greater productivity and flexibility, higher product quality and better use of resources, and the ability of manufacturers to meet evolving market needs. One of these enabling technologies is AI, which is able to analyse huge volumes of industrial data, detect complex patterns, predict future events in real time, and help with real-time decision-making - all of which contribute to intelligent manufacturing [1,2]. In the field of manufacturing systems, predictive maintenance, quality inspection, process optimisation, production scheduling and collaborative robotics are areas in which the use of machine learning (ML), deep learning, computer vision and reinforcement learning (RL) is gaining ground to enable increasingly autonomous and responsive manufacturing systems [3-6]. Collaborative robots are a part of the manufacturing environment where

humans and robots are placed in the same workspace and interact and collaborate with each other. The partnership offers several benefits in terms of flexibility and productivity but also presents some challenges in terms of worker safety, dynamic decision-making and effective task coordination. In highly dynamic collaborative work environments, traditional safety systems using fixed barriers and predetermined operating rules are sometimes not enough, and intelligent safety systems that can continuously adapt to the changing production conditions are needed. Meanwhile, manufacturing systems need to adapt their task allocation to the capabilities of their workers, the performance of their robots, and operational constraints within the system in real-time to execute the manufacturing tasks effectively [7-11]. Research in recent years has demonstrated the potential of AI technologies in making adaptive safety decisions [12,13], intelligent task allocation [14-16], the use of digital twins [17-19], and explainable AI [20], to assist with decision-making. Current literature mainly focuses on adaptive safety and intelligent task allocation separately, and few studies focus on the combination of the two aspects for human-centred smart manufacturing. Furthermore, challenges like explainability, real-time deployment, scalability, interoperability, and implementation in industry remain and continue to impede the industry use of AI-based manufacturing systems [21-24]. This review aims to provide a comprehensive understanding of the use of AI in adaptive safety, smart manufacturing and intelligent task allocation. This review is a summary of recent research which provides an overall perspective for researchers, engineers and industrial practitioners of the opportunities for AI to enable safer, efficient and human-centred manufacturing systems. The review combines adaptive safety and intelligent task allocation under a human-centred manufacturing perspective, whereas most previous reviews focused on specific AI techniques or individual manufacturing applications. It also explores how new technologies, such as digital twins, explainable AI, trustworthy AI and knowledge-driven technologies, can be combined to improve intelligent manufacturing systems and identify research priorities for future industrial deployment. The evolution from Industry 4.0 towards Industry 5.0 highlights the increasing integration of AI, collaborative robotics, and adaptive safety to achieve human-centred manufacturing, as illustrated in Figure *1*.

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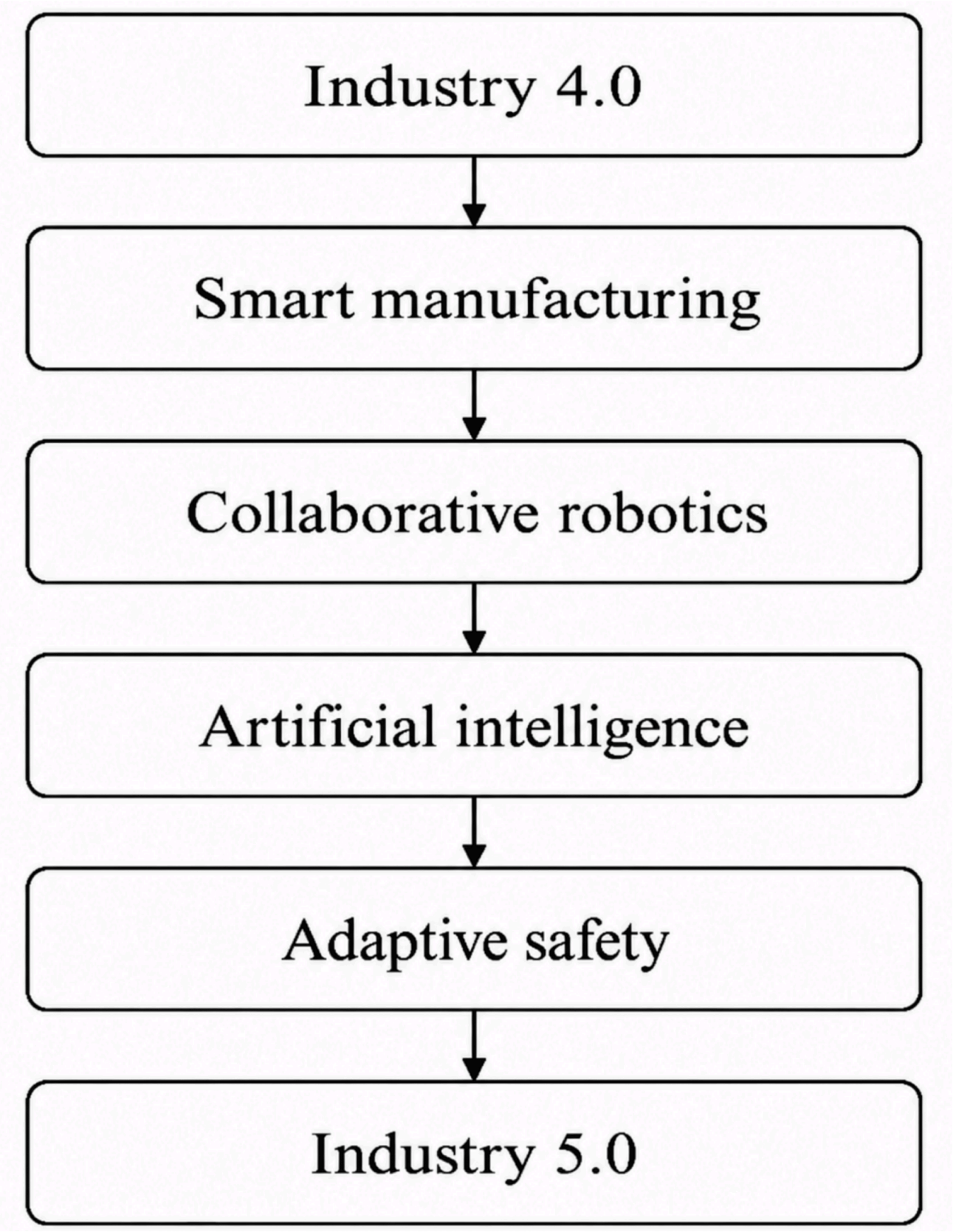


FIGURE 1: Evolution on manufacturing from industry 4.0 to industry 5.0 (developed by the authors)

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Review

Review methodology

Review Design

This review followed a structured narrative to discuss recent advances related to adaptive safety and intelligent task allocation for smart manufacturing using AI. The review was conducted using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) principles to ensure a transparent and reproducible literature selection. The main difference from a systematic review was that the aim was not to undertake a statistical meta-analysis, but rather to synthesise existing knowledge, uncover emerging trends in research and critically reflect on the use of AI in human-centred manufacturing environments [25].

Literature Search Strategy

The literature search was reported in accordance with the PRISMA 2020 statement to maximise transparency and reproducibility. Six electronic databases were searched independently: Scopus, Web of Science Core Collection, IEEE Xplore, ScienceDirect, SpringerLink, and the ACM Digital Library. Database searches were performed between 28 and 31 May 2026, with all searches completed on 31 May 2026. Only publications available before the final search date were considered. Searches were performed within the Title, Abstract, and Keywords fields whenever supported by the database. Equivalent topic-search fields were used for databases employing different indexing structures. Search strategies combined controlled vocabulary and free-text keywords using Boolean operators.

The principal search concepts included:

AI, ML, deep learning, smart manufacturing, industry 4.0, industry 5.0, human-robot collaboration, adaptive safety, intelligent task allocation, digital twins, XAI, collaborative robotics.

The complete database-specific search strategies are provided to facilitate replication. Only peer-reviewed journal articles and conference papers published in English between 1 January 2015, and 31 May 2026 were considered. Earlier publications were excluded from study selection because the review focuses on the rapid evolution of AI-enabled smart manufacturing associated with industry 4.0 and industry 5.0. Earlier landmark publications cited in the Introduction are included only as background literature and were not part of the systematic review dataset.

Database-specific Search Strategy

The search strategies were adapted for each database according to the available search syntax while maintaining the same core concepts related to AI, smart manufacturing, human-robot collaboration, adaptive safety, task allocation, and digitalisation technologies.

Scopus: TITLE-ABS-KEY (("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Reinforcement Learning") AND ("Smart Manufacturing" OR "Industry 4.0" OR "Industry 5.0") AND ("Human-Robot Collaboration" OR "Human-Robot Interaction" OR "Collaborative Robot*" OR "Cobot*") AND ("Adaptive Safety" OR "Safety" OR "Risk Assessment") AND ("Task Allocation" OR "Task Scheduling" OR "Production Scheduling") AND ("Digital Twin*" OR "Digital Twins")). Web of Science Core Collection: TS= (("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Reinforcement Learning") AND ("Smart Manufacturing" OR "Industry 4.0" OR "Industry 5.0") AND ("Human-Robot Collaboration" OR "Human-Robot Interaction" OR "Collaborative Robot*" OR "Cobot*") AND ("Adaptive Safety" OR Safety OR "Risk Assessment") AND ("Task Allocation" OR "Task Scheduling" OR "Production Scheduling") AND ("Digital Twin*" OR "Digital Twins")). IEEE Xplore: ("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning") AND ("Smart Manufacturing" OR "Industry 4.0" OR "Industry 5.0") AND ("Human-Robot Collaboration" OR "Human-Robot Interaction" OR "Collaborative Robot" OR "Cobot") AND ("Adaptive Safety" OR "Safety" OR "Risk Assessment") AND ("Task Allocation" OR "Task Scheduling" OR "Decision Making") AND ("Digital Twin" OR "Digital Twins"). ScienceDirect: ("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning") AND ("Smart Manufacturing" OR "Industry 4.0" OR "Industry 5.0") AND ("Human-Robot Collaboration" OR "Human-Robot Interaction" OR "Collaborative Robot") AND ("Adaptive Safety" OR Safety OR "Risk Assessment") AND ("Task Allocation" OR "Task Scheduling" OR "Production Scheduling") AND ("Digital Twin" OR "Digital

Twins"). SpringerLink: ("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning") AND ("Smart Manufacturing" OR "Industry 4.0" OR "Industry 5.0") AND ("Human-Robot Collaboration" OR "Human-Robot Interaction" OR "Collaborative Robot*" OR "Cobot*") AND ("Adaptive Safety" OR "Industrial Safety" OR "Risk Assessment") AND ("Task Allocation" OR "Task Scheduling" OR "Production Scheduling") AND ("Digital Twin*" OR "Digital Twins"). ACM Digital Library: ("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Reinforcement Learning" OR "Explainable Artificial Intelligence") AND ("Smart Manufacturing" OR "Industry 4.0" OR "Industry 5.0") AND ("Human-Robot Collaboration" OR "Human-Robot Interaction" OR "Collaborative Robot*" OR "Cobot*") AND ("Adaptive Safety" OR Safety OR "Risk Assessment") AND ("Task Allocation" OR "Task Scheduling" OR "Production Scheduling" OR "Decision Making") AND ("Digital Twin*" OR "Digital Twins"). Although minor variations were introduced to accommodate database-specific search functions and indexing structures, all searches were based on the same conceptual framework. The complete search strings, database platforms, search dates, and retrieved records are documented to support reproducibility. Table *1* summarises the database-specific search characteristics, including search periods, principal keywords, and eligibility criteria applied during the literature retrieval process. Although database syntax was adapted according to platform requirements, the searches followed a common conceptual framework covering AI, smart manufacturing, human-robot collaboration, adaptive safety, task allocation, and digital twin technologies.

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Database	Search period	Main search terms	Inclusion criteria	Exclusion criteria
Scopus	2015–31 May 2026	Artificial Intelligence; Machine Learning; Deep Learning; Smart Manufacturing; Industry 4.0; Industry 5.0; Human–Robot Collaboration; Collaborative Robots; Adaptive Safety; Risk Assessment; Task Allocation; Task Scheduling; Digital Twins	Peer-reviewed journal articles and conference papers published in English between 2015 and 31 May 2026 addressing AI-enabled smart manufacturing, human–robot collaboration, adaptive safety, intelligent task allocation, or related Industry 4.0/5.0 applications.	Duplicate records, non-English publications, editorials, reviews without original contributions, publications without full text, and studies unrelated to AI-based manufacturing systems.
Web of Science Core Collection	2015–31 May 2026	Artificial Intelligence; Machine Learning; Deep Learning; Smart Manufacturing; Industry 4.0; Industry 5.0; Human–Robot Collaboration; Human–Robot Interaction; Adaptive Safety; Task Allocation; Digital Twins	Peer-reviewed English-language journal articles and conference proceedings investigating AI-driven manufacturing systems, collaborative robotics, intelligent automation, safety, or production optimisation.	Conference abstracts, editorial material, opinion articles, duplicate records, non-peer-reviewed studies, and research outside manufacturing applications.
IEEE Xplore	2015–31 May 2026	Artificial Intelligence; Machine Learning; Deep Learning; Smart Manufacturing; Industry 4.0; Industry 5.0; Human–Robot Collaboration; Collaborative Robots; Adaptive Safety; Risk Assessment; Task Allocation; Digital Twins	Peer-reviewed engineering publications addressing AI algorithms, robotics, automation, collaborative manufacturing, intelligent decision-making, and smart factory technologies.	Duplicate publications, non-English studies, papers without accessible full text, and studies unrelated to AI-enabled manufacturing or robotics.

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ScienceDirect	2015–31 May 2026	Artificial Intelligence; Machine Learning; Deep Learning; Smart Manufacturing; Industry 4.0; Industry 5.0; Human–Robot Collaboration; Adaptive Safety; Task Allocation; Production Scheduling; Digital Twins	Peer-reviewed research articles examining AI techniques, intelligent production systems, manufacturing optimisation, collaborative robotics, and Industry 4.0/5.0 technologies.	Editorials, book reviews, conference summaries, duplicate records, non-English articles, and studies lacking relevance to AI-based manufacturing.
SpringerLink	2015–31 May 2026	Artificial Intelligence; Machine Learning; Deep Learning; Smart Manufacturing; Industry 4.0; Industry 5.0; Human–Robot Collaboration; Human–Robot Interaction; Collaborative Robots; Adaptive Safety; Task Scheduling; Digital Twins	Peer-reviewed journal articles and conference papers presenting AI-enabled manufacturing methods, intelligent production systems, adaptive safety approaches, or human-centred manufacturing solutions.	Book chapters, duplicate publications, opinion articles, publications without full text, non-English studies, and research unrelated to manufacturing applications.
ACM Digital Library	2015–31 May 2026	Artificial Intelligence; Machine Learning; Deep Learning; Reinforcement Learning; Explainable Artificial Intelligence; Smart Manufacturing; Human–Robot Interaction; Collaborative Robots; Adaptive Safety; Risk Assessment; Task Allocation; Digital Twins	Peer-reviewed publications addressing AI algorithms, intelligent decision-making, collaborative robotics, human–computer interaction, and smart manufacturing applications.	Duplicate records, workshop summaries, editorials, non-English publications, and studies not directly related to AI-enabled manufacturing systems.

TABLE 1: Database-specific search characteristics and eligibility criteria (compiled by the authors)

AI, Artificial Intelligence

Study Screening and Selection

All retrieved references were exported into a reference-management database, where duplicate records were identified and removed automatically and verified manually. The remaining studies underwent a two-stage screening. During the first stage, titles and abstracts were independently evaluated against the predefined eligibility criteria. Studies considered potentially relevant progressed to full-text assessment. During the second stage, full-text articles were

reviewed to determine final eligibility. Two reviewers independently screened all studies. Disagreements were resolved through discussion until consensus was reached. Where necessary, a third evaluation of the publication was undertaken before a final decision was made. Although the initial database search identified a substantially larger number of publications, many records were excluded during screening because they addressed general AI, robotics, or Industry 4.0 technologies without specifically investigating adaptive safety or intelligent task allocation in smart manufacturing. Additional exclusions resulted from duplicate records, non-English publications, review eligibility criteria, and studies lacking sufficient methodological relevance. Consequently, 40 publications met all inclusion criteria and formed the evidence base for the qualitative synthesis. The complete study-selection workflow is summarised in the PRISMA flow diagram Figure *2*.

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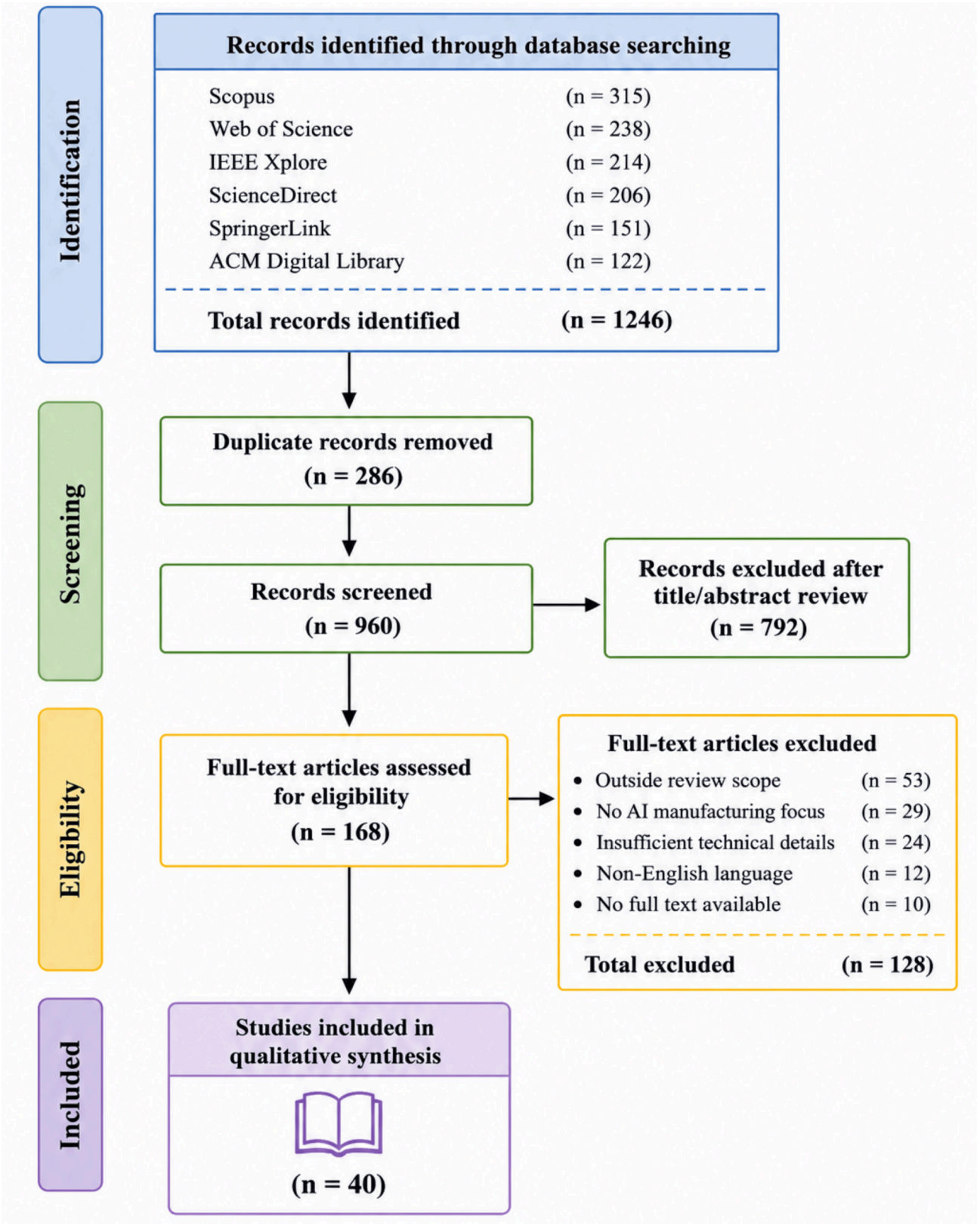


FIGURE 2: PRISMA-inspired literature selection process (developed by the authors)

PRISMA, Preferred Reporting Items for Systematic Reviews and Meta-Analyses

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Protocol Registration

No formal review protocol was registered in PROSPERO or the Open Science Framework because the review addressed an engineering topic rather than a clinical intervention. Nevertheless, the review methodology was established before literature screening and followed the PRISMA 2020 reporting recommendations.

Data Extraction

A standardised data extraction form was developed before full-text review. Information extracted from each eligible publication included:

Authors, publication year, country, manufacturing application, study design, AI technique (ML, DL, RL, Digital Twin, optimisation, hybrid AI), adaptive safety function, task allocation strategy, validation approach (simulation, laboratory experiment, industrial deployment, case study), principal findings, and reported limitations.

Data extraction was independently verified before thematic synthesis as presented in Table 2.

Variable	Description
Authors	Publication
Year	Publication year
Country	Research location
Manufacturing domain	Assembly, inspection, scheduling and others
AI method	ML, DL, RL, Digital Twin and others
Safety application	Hazard prediction, monitoring
Task allocation	Scheduling, planning
Validation	Simulation / Laboratory / Industrial deployment and others
Key findings	Main contribution
Limitations	Reported weaknesses

TABLE 2: Data extraction variables (compiled by authors)

ML, Machine Learning; DL, Deep Learning; RL, Reinforcement Learning

Characteristics of Included Studies

The publications summarised in Table 3 constitute the evidence base selected through the PRISMA-inspired literature selection process. They comprise review articles, conceptual studies, surveys, frameworks, and experimental investigations relevant to AI, human-robot collaboration, adaptive safety, and intelligent task allocation in smart manufacturing.

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Ref.	Year	Study Type	AI Technique / Technology	Manufacturing Domain	HRC Relevance	Adaptive Safety Focus	Task Allocation Focus	Evidence Type	Principal Contribution
[1]	2017	Survey	AI technologies	Industry 4.0	Indirect	No	No	Literature survey	Overview of Industry 4.0 technologies and research challenges.
[2]	2021	Conceptual	Industry 4.0/5.0	Human-centred manufacturing	Indirect	No	No	Conceptual analysis	Defines the evolution from Industry 4.0 to Industry 5.0.
[3]	2016	Conceptual	Smart factory technologies	Smart factories	Indirect	No	No	Framework	Smart factory implementation architecture.
[4]	2018	Review	Data-driven AI	Smart manufacturing	Indirect	Limited	Limited	Literature review	Data-driven manufacturing framework and applications.

[5]	2023	Review	Artificial Intelligence	Manufacturing operations	Indirect	Limited	Limited	Literature review	Comprehensive review of AI applications in manufacturing.
[6]	2025	Survey	Trustworthy AI	Human-centric manufacturing	Direct	Yes	Yes	Literature survey	Trustworthy AI framework for human-centred manufacturing.
[7]	2024	Review	Machine Learning	Production optimisation	Limited	Limited	Yes	Literature review	Learning-based optimisation for production, maintenance and quality.
[8]	2023	Survey	ML, RL	Manufacturing scheduling	No	No	Yes	Literature survey	AI-enabled dynamic scheduling techniques.
[9]	2023	Systematic review	Self-organising AI	Smart manufacturing	Limited	Limited	Yes	Systematic review	Self-organisation strategies for intelligent manufacturing.
[10]	2015	Experimental	Collaborative robotics	Assembly	Direct	Yes	No	Industrial case study	Safe collaborative workplac

									e design principles.
[11]	2021	Systematic review	Collaborative robotics	Human–robot collaboration	Direct	Yes	Yes	Systematic review	Safety trends and challenges in HRC.
[12]	2023	Review	AI-enabled robotics	Smart manufacturing	Direct	Yes	Yes	Literature review	Review of HRC technologies and future directions.
[13]	2020	Review	Hazard analysis	Collaborative robotics	Direct	Yes	No	Literature review	Safety assurance using ISO/TS 15066.
[14]	2023	Review	Task allocation algorithms	Collaborative assembly	Direct	Limited	Yes	Literature review	Human–robot task allocation strategies.
[15]	2024	State-of-the-art review	Digital Twin, AI	Industry 5.0	Direct	Yes	Yes	Literature review	Integration of collaborative robotics and Digital Twins.
[16]	2021	Experimental	Reactive robot intelligence	Smart manufacturing	Direct	Yes	Yes	Experimental study	Intelligent robot behaviour for HRC.
[17]	2021	Review	HRC architectures	Manufacturing	Direct	Limited	Limited	Literature review	Structural components of collaborative robotic systems.

[18]	2026	Review	Collaborative robotics	Manufacturing	Direct	Yes	Yes	Literature review	Current challenges in HRC systems.
[19]	2024	Survey	Data analytics	Industry 4.0	Indirect	Limited	Limited	Survey	Industrial data analytics techniques.
[20]	2015	Review	Cyber-physical systems	Manufacturing	Indirect	Limited	Limited	Review	Manufacturing cyber-physical systems overview.
[21]	2024	Review	Fault diagnosis AI	Smart manufacturing	Indirect	Yes	No	Literature review	Intelligent fault diagnosis and self-healing.
[22]	2025	Review	Explainable AI	Smart manufacturing	Direct	Yes	Limited	Literature review	Explainable AI techniques for manufacturing.
[23]	2024	Survey	Explainable AI	Industrial CPS	Direct	Yes	Limited	Survey	XAI in industrial cyber-physical systems.
[24]	2020	Review	Digital Twin	Smart manufacturing	Direct	Limited	Limited	Literature review	Digital Twin reference model and applications.
[25]	2018	Review	Smart manufacturing	Manufacturing	Indirect	Limited	Limited	Review	Smart manufacturing principles.

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[26]	2021	Review	Digital Twins	Industry 4.0	Direct	Limited	Limited	Literature review	Digital Twin system design.
[27]	2015	Conceptual	Cyber-physical systems	Manufacturing	Indirect	Limited	Limited	Architecture	CPS architecture for Industry 4.0.
[28]	2016	Conceptual	Multi-agent systems	Smart factory	Indirect	Limited	Yes	Framework	Self-organised smart factory architecture.
[29]	2022	Review	Digital Twin modelling	Manufacturing	Direct	Limited	Limited	Literature review	Digital Twin modelling methodologies.
[30]	2016	Review	Cyber-physical systems	Manufacturing	Indirect	Limited	Limited	Review	CPS technologies for manufacturing.
[31]	2024	Experimental	Multi-agent AI	Plug-and-Produce systems	Direct	Yes	Yes	Experimental study	Safety-aware manufacturing control.
[32]	2025	Experimental	Knowledge Graph + RL	Smart manufacturing	Direct	Limited	Yes	Experimental study	Adaptive scheduling using reinforcement learning.
[33]	2025	Experimental	Multi-agent planning	Human-integrated manufacturing	Direct	Yes	Yes	Experimental study	Safe multi-agent planning strategies.

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[34]	2024	Experimental	Deep Reinforcement Learning	Collaborative assembly	Direct	Yes	Yes	Experimental study	Deep RL for collaborative assembly planning.
[35]	2024	Perspective	Explainable AI	Smart manufacturing	Direct	Yes	Limited	Perspective article	Future directions for explainable manufacturing AI.
[36]	2025	Review	Trustworthy AI	Industry 5.0	Direct	Yes	Limited	Literature review	AI trustworthiness challenges and frameworks.
[37]	2025	Experimental	Computer Vision	Industrial facilities	Indirect	Yes	Limited	Experimental study	Vision-based intelligent industrial automation.
[38]	2025	Experimental	Artificial Intelligence	Smart production	Indirect	Limited	Yes	Experimental study	AI-enabled production management.
[39]	2025	Experimental	AI + Digital Twin	Collaborative work cells	Direct	Yes	Yes	Experimental study	Flexible safety control using AI and Digital Twins.
[40]	2025	Framework	Human-in-the-loop AI	Adaptive manufacturing	Direct	Yes	Yes	Reference framework	Human-in-the-loop framework for

									adaptive smart manufacturing.

TABLE 3: Characteristics of studies included in the PRISMA-inspired literature selection process (n = 40) (compiled by authors)

AI, Artificial Intelligence; CPS, Cyber-Physical Systems; HRC, Human–Robot Collaboration; IIoT, Industrial Internet of Things; ISO, International Organization for Standardization; ML, Machine Learning; RL, Reinforcement Learning; XAI, Explainable Artificial Intelligence; PRISMA, Preferred Reporting Items for Systematic Reviews and Meta-Analyses

Quality Assessment

To improve the transparency and reliability of the evidence synthesis, the methodological quality of the included publications was assessed using criteria adapted for engineering and technology review studies. The assessment considered the clarity of research objectives, methodological description, validation approach, relevance to AI-enabled smart manufacturing, and the reporting of limitations. Each study was qualitatively classified as High, Moderate, or Low quality based on the extent to which these criteria were addressed. The quality assessment was used to support the interpretation of the evidence rather than to exclude studies from the review because the PRISMA-inspired literature selection process intentionally included conceptual papers, review articles, surveys, and experimental investigations to provide a comprehensive overview of the field, and therefore a formal risk-of-bias assessment tool was not considered appropriate. Instead, a qualitative methodological quality assessment was performed.

Ref.	Clear Objectives	Methodology Described	Validation / Evidence	Limitations Reported	Overall Quality
[1]	✓	✓	Moderate	✓	Moderate
[2]	✓	✓	Moderate	✓	Moderate
[3]	✓	✓	Moderate	✓	Moderate
[4]	✓	✓	High	✓	High
[5]	✓	✓	Moderate	✓	Moderate
[6]	✓	✓	High	✓	High
[7]	✓	✓	Moderate	✓	Moderate
[8]	✓	✓	Moderate	✓	Moderate
[9]	✓	✓	Moderate	✓	Moderate
[10]	✓	✓	High	✓	High
[11]	✓	✓	Moderate	✓	Moderate
[12]	✓	✓	Moderate	✓	Moderate
[13]	✓	✓	Moderate	✓	Moderate
[14]	✓	✓	High	✓	High
[15]	✓	✓	Moderate	✓	Moderate
[16]	✓	✓	High	✓	High
[17]	✓	✓	Moderate	✓	Moderate
[18]	✓	✓	Moderate	✓	Moderate
[19]	✓	✓	Moderate	✓	Moderate
[20]	✓	✓	Moderate	✓	Moderate
[21]	✓	✓	Moderate	✓	Moderate
[22]	✓	✓	Moderate	✓	Moderate
[23]	✓	✓	Moderate	✓	Moderate

[24]	✓	✓	High	✓	High
[25]	✓	✓	Moderate	✓	Moderate
[26]	✓	✓	High	✓	High
[27]	✓	✓	Moderate	✓	Moderate
[28]	✓	✓	High	✓	High
[29]	✓	✓	High	✓	High
[30]	✓	✓	Moderate	✓	Moderate
[31]	✓	✓	High	✓	High
[32]	✓	✓	High	✓	High
[33]	✓	✓	High	✓	High
[34]	✓	✓	High	✓	High
[35]	✓	✓	Moderate	✓	Moderate
[36]	✓	✓	Moderate	✓	Moderate
[37]	✓	✓	High	✓	High
[38]	✓	✓	Moderate	✓	Moderate
[39]	✓	✓	High	✓	High
[40]	✓	✓	High	✓	High

TABLE 4: Quality assessment of studies included in the PRISMA-inspired literature selection process (compiled by authors)

PRISMA, Preferred Reporting Items for Systematic Reviews and Meta-Analyses

Assessment performed by the authors in Table *4* is based on predefined methodological criteria; quality classifications were used to support evidence interpretation and were not applied as exclusion criteria. Quality criteria: High = comprehensive methodology with robust validation and clear discussion of limitations, Moderate = adequate methodological description with partial validation or limited discussion of limitations, Low = limited methodological detail or insufficient evidence to support conclusions.

Clarification of Reference Categorisation

The references cited in this review were categorised into two groups: (i) background references used to establish fundamental concepts, including Industry 4.0, smart manufacturing, AI, digital twins, collaborative robotics, and safety

standards; and (ii) the 40 publications identified through the PRISMA-inspired selection process, which constituted the primary evidence base for the analysis. Only the selected studies were included in the qualitative synthesis and quality assessment.

Data Analysis and Synthesis

Selected publications were analysed using thematic synthesis. The literature was categorised into four main themes: (i) AI technologies for smart manufacturing, (ii) AI-enabled adaptive safety, (iii) intelligent task allocation, and (iv) emerging technologies supporting human-centred manufacturing. The reviewed studies were analysed and compared across the themes in terms of methodology, manufacturing application, reported benefits, challenges to implementation, and future directions in research. This approach enabled the identification of common research trends, gaps in knowledge, and opportunities for further research.

Scope of the Review

The review covers AI techniques that enable intelligent manufacturing, such as ML, deep learning, reinforcement learning, computer vision, explainable AI, trustworthy AI, digital twins, and multi-agent systems. Their contribution to improving adaptive safety and intelligent task allocation in collaborative manufacturing systems is given special consideration. The review focuses on representative applications of AI in various industries but does not aim to provide an exhaustive review of all AI techniques. Instead, it focuses on studies that contribute to improved manufacturing intelligence, operational safety, and human-robot collaboration.

Artificial intelligence in smart manufacturing

Overview

Smart manufacturing combines digital technologies, intelligent automation, and real-time data analytics to enable systems to monitor, adapt, decide and optimise production autonomously. AI has emerged as a key enabling technology, translating vast amounts of industrial data into actionable information that enhances production efficiency, quality and flexibility [26-29]. Sensors, IIoT devices, cyber-physical systems (CPS), industrial robots and manufacturing execution systems can generate large volumes of data in modern manufacturing environments, which collectively form the digital infrastructure required for intelligent manufacturing and autonomous production control [30,31]. These data are analysed using AI techniques to facilitate predictive maintenance, quality inspection, production scheduling, process optimisation and collaborative manufacturing. AI-based automation can continuously learn from operational data, which makes manufacturing systems more responsive to the dynamic production conditions compared with conventional rule-based automation [32,33]. The relationships between manufacturing data sources, AI core technologies, adaptive safety, and intelligent task allocation are illustrated in Figure *3*.

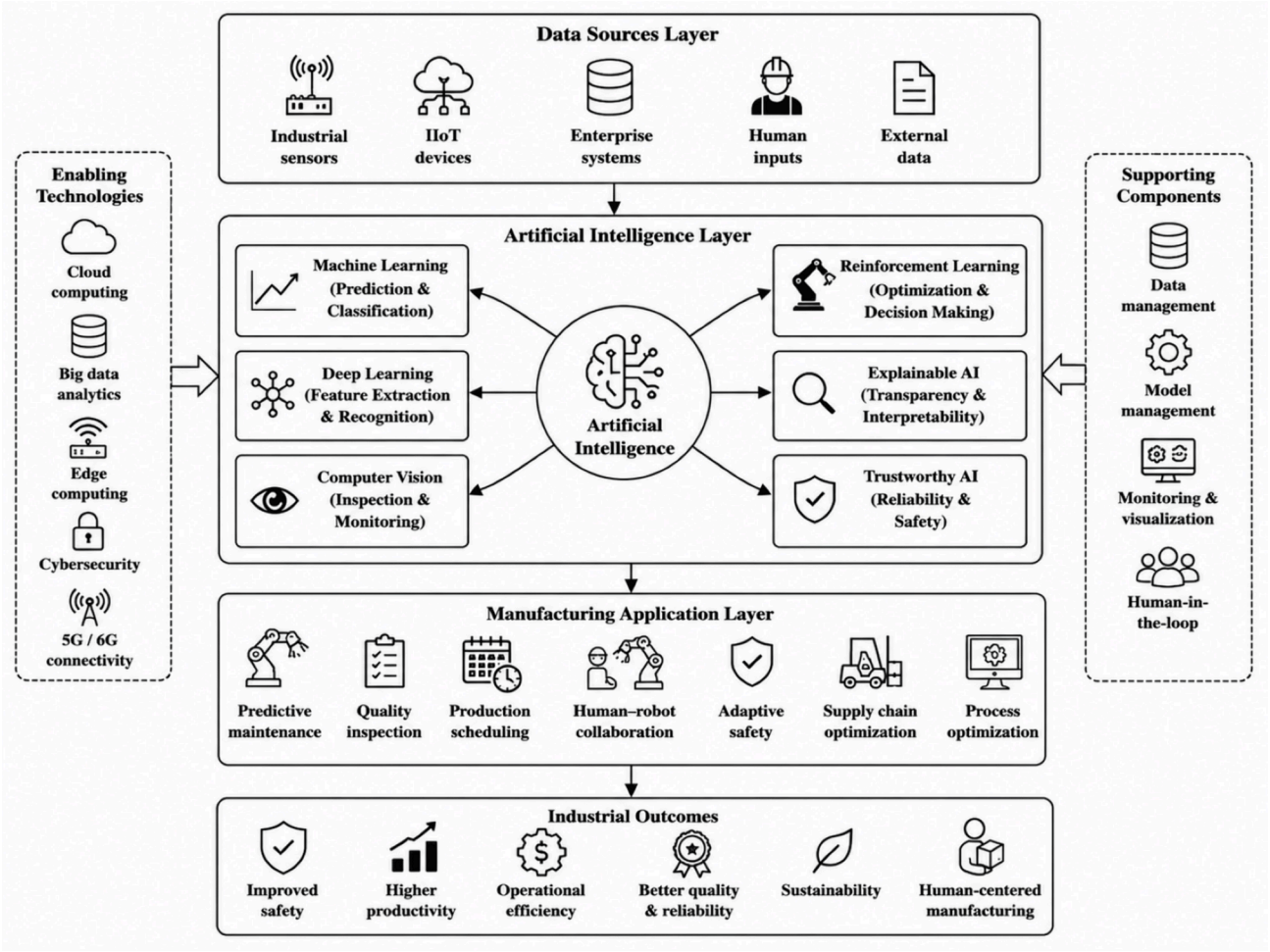


FIGURE 3: Artificial intelligence ecosystem for smart manufacturing (developed by the authors)

AI, Artificial Intelligence; IIoT, Industrial Internet of Things

Machine Learning and Deep Learning

ML can be used to recognise patterns, predict process behaviour and assist in predictive decision-making, using historical and real-time manufacturing data. Supervised learning algorithms are extensively used for defect classification, quality prediction and equipment condition monitoring, and unsupervised learning algorithms are used for anomaly detection and process monitoring [34,35]. Deep learning further enhances these capabilities by extracting hierarchical features from the high-dimensional data space, especially in images and sensor signals. Convolutional neural networks have proven to be very effective for automated visual inspection, while recurrent neural networks and transformers have shown great efficiency in time-series analysis for predictive maintenance and equipment diagnostics. Such approaches minimise the need for manual feature engineering and enhance predictability in intricate manufacturing settings [36,37].

Computer Vision and Reinforcement Learning

Computer vision enables automated inspection, object recognition, human pose estimation, robot perception, by extracting meaningful information from images and industrial scenes. By automatically interpreting images and industrial scenes, computer vision has become an important part of intelligent manufacturing. In the manufacturing industry, vision-based systems can be used to enhance quality control, monitor production processes, and ensure safe collaboration between human workers and robots, which aids in the detection of defects and the tracking of

manufacturing progress. In addition to perception technologies, RL can be used to enhance manufacturing systems by enabling them to make sequential decisions in a way that optimises their performance in their environments through continuous interactions. RL agents learn an optimal policy based on operational feedback while traditional optimisation methods rely on a given policy. RL agents are thus well suited for resource allocation, robotic control and dynamic scheduling in varying manufacturing contexts [38,39].

Emerging Artificial Intelligence Technologies

The research has evolved beyond the traditional learning algorithms to include digital twins, explainable AI, trustworthy AI and multi-agent systems. Digital twins can enable virtual modelling and predictive modelling of manufacturing processes, and enable production strategies to be discussed before they are put into practice. Explainable AI is about transparency, and trustworthy AI is about reliability, robustness and safe use in industrial applications. Multi-agent systems can further be used to achieve distributed coordination of autonomous production resources that improves the flexibility of manufacturing [40]. These technologies are in different maturity phases of industrialisation and are likely to potentially further enrich manufacturing intelligence, making autonomous systems and humans more adaptive, resilient and cooperative. As shown in the literature survey, AI has evolved from supporting individual manufacturing processes to supporting decision-making in the production system. The literature suggests that ML and deep learning are mainly used for prediction and perception; computer vision for operational awareness; RL for adaptive optimisation and emerging technologies for transparency, resilience and system-level coordination. These technologies, when used together, form the technological basis for adaptive safety and intelligent task allocation powered by AI. A comparison of AI techniques in smart manufacturing is presented in Table *5*.

AI technique	Primary capability	Manufacturing application	Key advantage
Machine learning	Pattern recognition and prediction	Predictive maintenance	Early fault detection
Deep learning	Feature extraction	Automated quality inspection	High detection accuracy
Computer vision	Image and video analysis	Visual inspection	Real-time defect detection
Reinforcement learning	Adaptive decision-making	Dynamic production scheduling	Continuous optimisation
Explainable AI	Transparent decision support	Human supervision	Improved trust
Digital twins	Virtual process modelling	Process optimisation	Predictive evaluation

TABLE 5: Comparison of artificial intelligence techniques in smart manufacturing (compiled by the authors)

AI, Artificial Intelligence

Artificial intelligence for adaptive safety in smart manufacturing

Adaptive Safety in Human-Robot Collaboration

The proliferation of collaborative robots (cobots) has revolutionised manufacturing by giving humans and robots shared workspaces. In contrast to traditional industrial robots that operate in segmented safety areas, collaborative manufacturing demands ongoing monitoring of human actions, surroundings and dangers to achieve safe and effective

cooperation. Therefore, adaptive safety has become an indispensable feature of smart manufacturing, which enables safety strategies to adapt dynamically to the varying production conditions instead of depending on preset protective measures [11-14]. AI enhances adaptive safety by interpreting information from various sensing technologies, such as cameras, force sensors, wearable sensors and IIoT networks. These technologies can detect potential hazards, anticipate collisions, and take preventive actions before hazardous situations develop. AI-based safety methods provide greater operational flexibility and protection of workers than traditional rule-based safety methods in collaborative manufacturing environments [15-18].

Artificial Intelligence Techniques for Adaptive Safety

Manufacturing systems are now far better at detecting unsafe operating conditions using industrial sensor data through ML and deep learning techniques. These methods are applicable to anomaly detection, risk forecasting, and equipment and operator behaviour monitoring, providing proactive rather than reactive safety management [19,20]. Computer vision can also be used to identify workers, tools, and production equipment in real time, thus improving adaptive safety. In a collaborative workspace, vision-based systems provide real-time information for autonomous safe interventions and estimate human posture, track the motion of the operator. Recent works also demonstrate the importance of multimodal sensor fusion, using visual data along with force, proximity and environmental sensing to enhance hazard detection in complex manufacturing situations [21]. The ability to adaptively acquire safe operation strategies via continuous interaction with manufacturing environments has been extended by the capability of RL. Unlike conventional rule-based control, RL enables robotic systems to adapt their behaviour to varying production parameters while satisfying safety constraints. This adaptability is especially useful in dynamic collaborative manufacturing, in which the workspace layout and manufacturing needs can vary greatly [32,34]. A layered architecture for AI-enabled adaptive safety is presented in Figure *4*, demonstrating how sensing, AI processing, decision-making, and execution interact to improve workplace safety.

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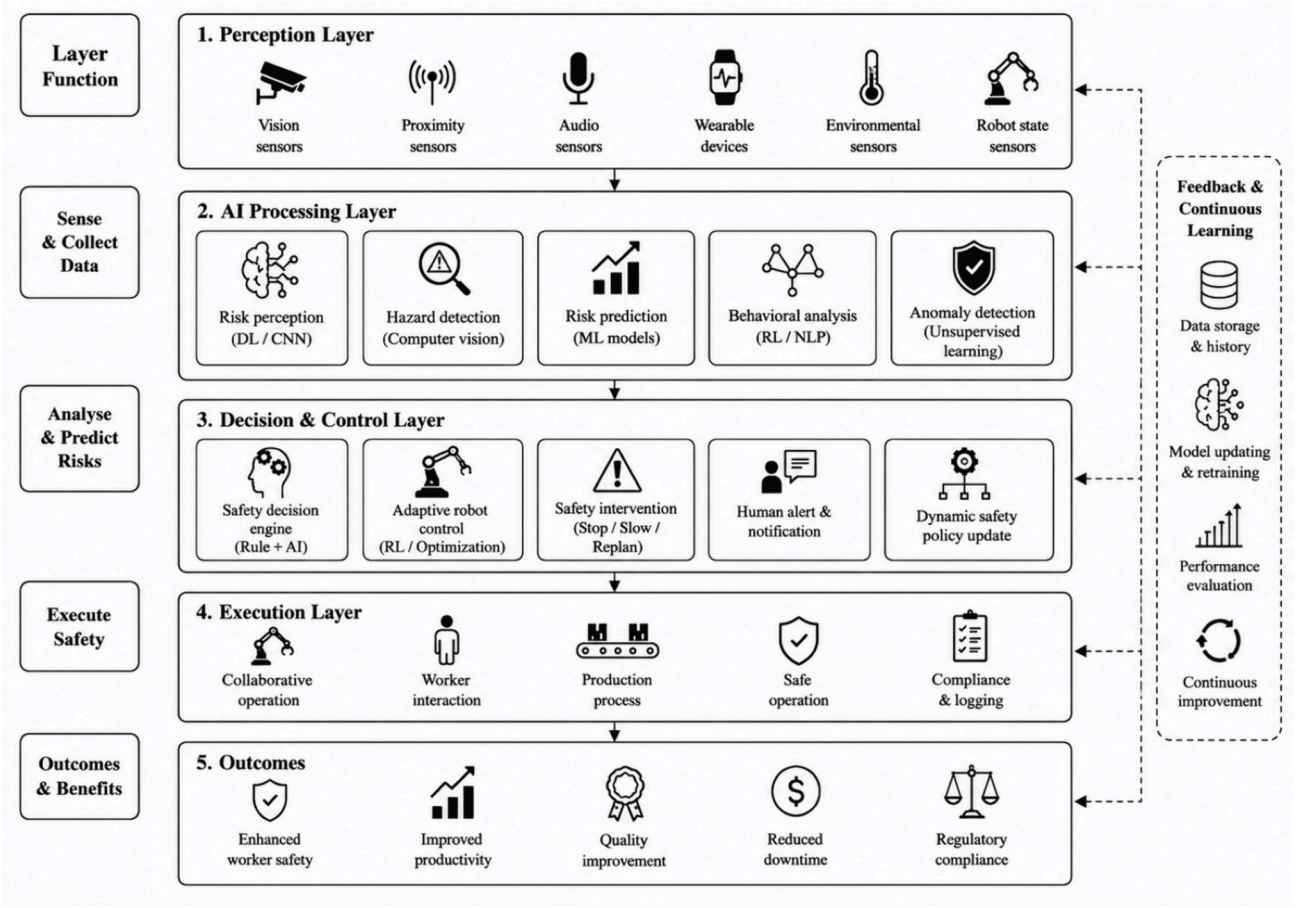


FIGURE 4: Artificial intelligence-enabled adaptive safety framework (developed by the authors)

Emerging Trends in Adaptive Safety

The recent developments in digital twins and explainable AI have further enhanced adaptive safety in manufacturing. Digital twins enable virtual simulation of manufacturing processes, allowing potential hazards and alternative safety strategies to be evaluated prior to physical implementation. Recent research also shows that AI-driven digital twins enable adaptive safety management of human-robot collaborative work cells by continuously monitoring and assessing the risks to humans [24,26,39]. This capability supports predictive risk assessment and minimises process reconfiguration and system design disruption. Explainable AI enables manufacturing engineers and operators to understand the reasoning behind predictive safety models. Transparent AI recommendations enhance the trustworthiness of autonomous safety systems and support the validation of safety-critical decisions, especially in shared settings where human oversight is still vital [22,23]. The new technologies are increasingly aligned with the principles of Industry 5.0, which focuses on smart and human-centred manufacturing and the integration of intelligent automation with the well-being of workers. As a result, adaptive safety is moving beyond hazard prevention and towards ongoing risk management, backed by predictive intelligence and collaborative decision-making.

Challenges and Future Direction

While there have been great strides in the development of adaptive safety through AI, there are still some challenges that need to be overcome for it to become more widely adopted. Current solutions are mostly based on controlled laboratory experiments or simulation environments and have been validated only to a limited extent. In addition, dealing with the uncertainty of the sensors, the dynamic human behaviour and changing production requirements is still an active

research challenge [18,31]. Integrated safety frameworks should be a priority for future studies, which should incorporate unified decision-support architectures, perception, predictive analytics, and explainable AI. These methods can enhance transparency, operational resilience, regulatory compliance, and enable safer interactions between humans and intelligent manufacturing systems [35,36]. Overall, the AI technologies discussed in this section provide complementary capabilities, all contributing to the goal of adaptive safety in smart manufacturing. ML and deep learning facilitate predictive risk assessment and anomaly detection. Computer vision enables real-time recognition of workers, equipment, and workplace conditions. RL supports continuous adaptive safety strategies based on dynamic manufacturing environments. The capabilities are further enhanced with the help of new technologies like digital twins and explainable AI that facilitate virtual safety evaluations, predictive risk management and explainable decision-making. These technologies combine perception, prediction, adaptive control and human-centred decision support into a single adaptive safety system. Their combined capabilities are expected to improve hazard prevention, operational robustness, regulatory compliance and safe human-robot interaction, moving traditional rule-based safety mechanisms to intelligent Industry 5.0 manufacturing systems. A comparison of AI techniques for adaptive safety is summarised in Table *6*.

AI technique	Safety function	Manufacturing application	Primary benefit
Computer vision	Worker monitoring	Human–robot collaboration	Hazard detection
Machine learning	Risk prediction	Predictive safety	Accident prevention
Deep learning	Behaviour recognition	Operator monitoring	Improved situational awareness
Reinforcement learning	Dynamic safety control	Robot motion planning	Adaptive responses
Digital twins	Safety simulation	Virtual risk assessment	Safer production planning

TABLE 6: Comparison of artificial intelligence techniques for adaptive safety (compiled by the authors)

Artificial intelligence for intelligent task allocation in smart manufacturing

Intelligent Task Allocation in Collaborative Manufacturing

Efficient task allocation is essential for achieving productive, flexible, and safe human-robot collaboration in smart manufacturing. It is the process of assigning production tasks to either human operators, collaborative robots, autonomous mobile robots or automated workstations based on the capabilities of these resources, production goals, and operational constraints. Unlike conventional scheduling, intelligent task allocation dynamically reallocates production tasks in response to changes in production demand, equipment availability, and workforce requirements [14,18]. AI-driven solutions assist in this shift by analysing production data, assessing resource availability, and optimising task assignments to ensure efficient and safe operations. In collaborative manufacturing environments, where both humans and robots are expected to work in the same workspace, these adaptive capabilities are particularly important because task allocation must simultaneously consider the capabilities of both human operators and robotic systems [31,15].

Artificial Intelligence for Dynamic Task Allocation

ML models utilise historical and real-time manufacturing data to estimate production times, predict resource utilisation, and optimise production scheduling. These prediction models assist decision-makers in the identification of efficient task assignment and the prediction of potential production disruptions [5,19]. RL takes these functions a step further by allowing manufacturing systems to learn adaptive allocation strategies through continual interaction with the manufacturing environment. RL agents optimise sequential decisions by taking into account production goals, operational constraints, and environmental feedback without having to rely on static scheduling rules. RL has demonstrated significant improvements in workflow efficiency, reduced idle time and increased manufacturing flexibility under dynamic operating conditions [32,34]. Multi-agent systems for decentralised task allocation have also been studied recently, where each manufacturing resource acts as an autonomous agent that coordinates its activities by cooperating with other agents to allocate tasks to the resources. This distributed decision-making enhances the scalability and responsiveness, especially in complex manufacturing systems that feature multiple collaborative robots, mobile platforms, and human operators [28]. The proposed intelligent task allocation framework is illustrated in Figure *5*, showing the interaction between data acquisition, AI processing, optimisation, and execution.

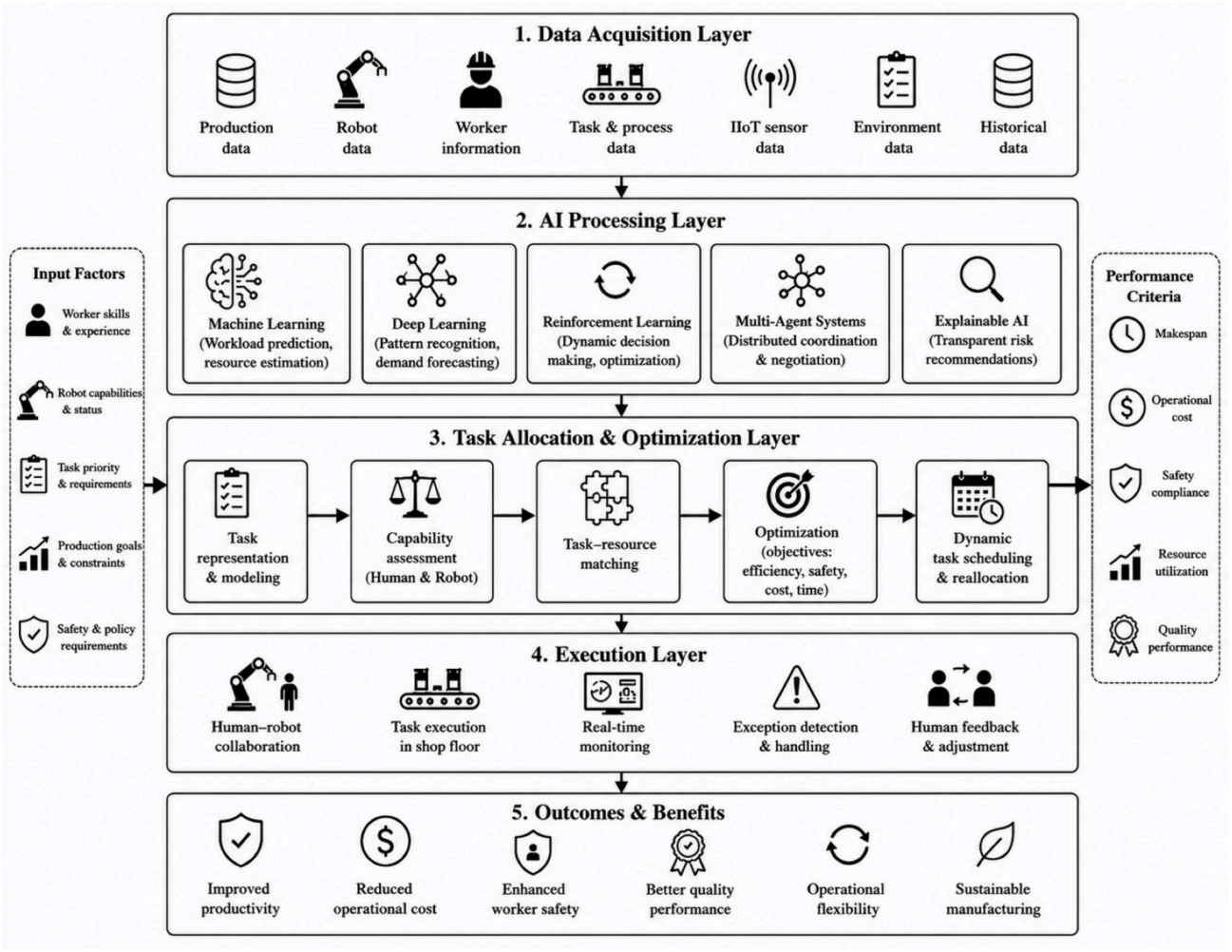


FIGURE 5: Artificial intelligence framework for intelligent task allocation in smart manufacturing (developed by the authors)

Emerging Approaches

The use of digital twins in conjunction with AI has expanded the concept of intelligent task allocation by allowing production scenarios to be tested in virtual manufacturing environments before they are deployed in the real factory. This function allows manufacturers to explore different production scenarios, efficiently allocate resources, and to quickly adapt to the changing production needs without disrupting current production processes [24,26]. Knowledge graphs are also becoming popular because they provide context for manufacturing resources, skills of operators, characteristics of equipment and production restrictions. They can be applied in complex manufacturing systems to ensure consistency and transparency of task-allocation strategies when making decisions based on semantic knowledge in AI [33]. Another significant aspect of intelligent task allocation is explainable AI. Explainable AI can improve operator trust, validate decisions, and support regulatory compliance in collaborative manufacturing environments by offering transparency on the decisions taken when scheduling and assigning tasks. It is especially important where an AI's recommendations impact the distribution of workload, production efficiency, and worker safety. In general, the complementary features of the AI technologies introduced in this section facilitate intelligent task allocation to smart manufacturing. ML can help make production forecasts and make better use of production resources, RL can be used to allocate production tasks in an adaptive manner based on continuous interaction with the manufacturing environment, and multi-agent systems can be used for decentralised coordination of various manufacturing resources. This is reinforced by new technologies such as digital twins, knowledge graphs, which enable virtual evaluations, context-aware reasoning and transparency in decisions, and explainable AI, which increases understanding and explanation of AI-driven insights. These technologies enable the integration of prediction, optimisation, coordination and human-centred decision support within a single task allocation framework that enables manufacturing systems. Collectively, these technologies are expected to improve production efficiency, flexible operation, adaptive safety, and human-robot collaboration, which represent the transformation of traditional scheduling practices into intelligent Industry 5.0 manufacturing systems.

Challenges and Future Directions

While AI has made significant strides in task allocation, there are still several challenges. A number of existing techniques have been tested in simulated environments, and to a lesser extent in large-scale industrial applications. Moreover, because it is important to consider productivity, worker safety, energy efficiency and production cost together in a single optimisation, it remains an important research challenge [31]. Further studies are needed to explore integrated AI architectures, which include predictive analytics, digital twins, explainable AI and distributed decision-making, for enabling transparent and adaptive manufacturing systems. Real-time scheduling, resource coordination and predictive decision-making are closely linked to intelligent manufacturing systems, which is another key research direction that is valuable to increase efforts in AI production management [38]. Comparison of artificial intelligent task allocation approaches in smart manufacturing is provided in Table *7*.

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AI approach	Primary function	Manufacturing application	Key benefit
Machine learning	Resource prediction	Production planning	Improved scheduling accuracy
Reinforcement learning	Dynamic task allocation	Robot coordination	Real-time optimisation
Multi-agent systems	Distributed decision-making	Collaborative manufacturing	Scalable coordination
Digital twins	Virtual evaluation task	Production planning	Reduced operational risk
Knowledge graphs	Context-aware reasoning	Resource allocation	Improved decision consistency

TABLE 7: Comparison of artificial intelligent task allocation approaches in smart manufacturing (compiled by the authors)

AI, Artificial Intelligence

Emerging artificial intelligence for smart manufacturing

Emerging Trends

Smart manufacturing has evolved rapidly over the past decade, with AI progressing beyond prediction and automation towards intelligent, transparent, and human-centred decision-making. In recent years, several emerging technologies, including digital twins, explainable AI, trustworthy AI, knowledge graphs, and foundation models, have expanded the application of AI in manufacturing, enhancing agility, resilience, and collaboration across production systems [22-26]. They do not just optimise production processes, but allow manufacturing systems to understand how they operate, simulate future situations, and make decisions in the context of increasingly complex production processes. The convergence of emerging AI technologies within smart manufacturing is summarised in Figure *6*, highlighting the relationships among ML, digital twins, RL, explainable AI, and knowledge graphs.

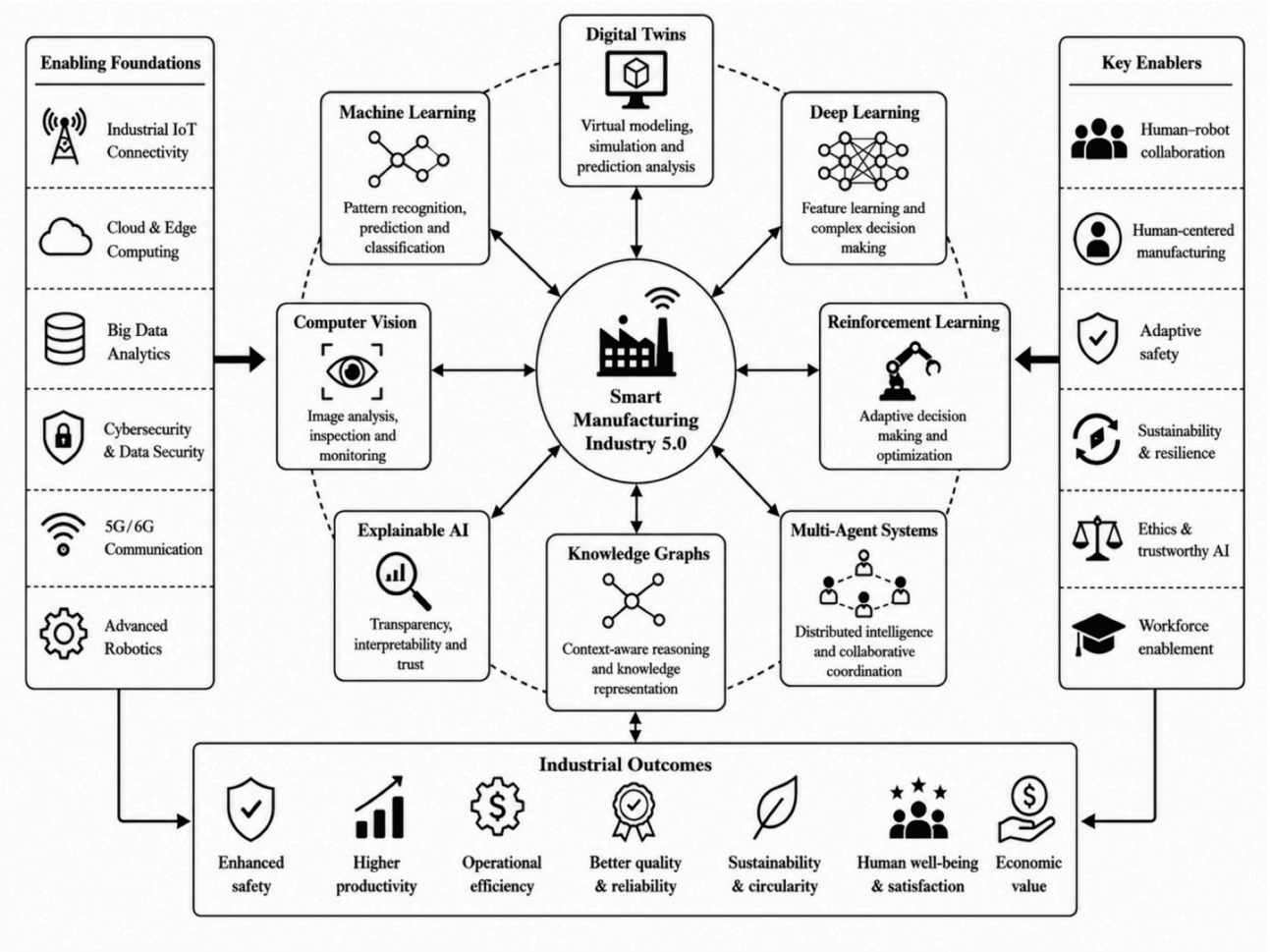


FIGURE 6: Convergence of artificial intelligence technologies in smart manufacturing (Developed by the authors)

Digital Twins and Explainable Artificial Intelligence

Digital twins are a key technology for virtual modelling and predictive optimisation in manufacturing. Digital twins maintain physical production systems in synchronisation with their digital counterparts, allowing manufacturers to evaluate different production strategies, safety procedures, and manufacturing performance. This allows for lower operational risks as well as better production planning and resource utilisation [24,26,29]. Explainable AI is another crucial need that enhances the transparency of intelligent decision-making. Interpretable models enable engineers to understand the recommendations of AI systems and increase confidence in autonomous manufacturing systems, particularly regarding safety monitoring and task allocation for production planning. Explainability also supports regulatory compliance and human oversight of safety-critical decisions [22,23].

Knowledge-Driven and Human-Centred Manufacturing

Knowledge graphs are increasingly being adopted to represent semantic relationships among manufacturing resources, production processes, operational constraints, and human expertise. They enhance contextual reasoning and enable more consistent decision-making in production planning and execution, especially in collaborative production environments, through their integration with AI [33,36]. Human-centred manufacturing has been increasingly emphasised in recent research, where intelligent systems are designed to augment rather than replace human capabilities. Human-in-the-loop AI and human digital twins are technologies that enable adaptive collaboration by

incorporating operator skills, workload, ergonomic conditions and human oversight into the manufacturing decision-making processes. These methods improve transparency, accountability, and trust, and facilitate better collaboration between humans and smart manufacturing systems [29,40]. In general, the new AI technologies discussed in this section are complementary technologies that collectively support next-generation smart manufacturing but are not the solution themselves. Digital twins support simulation and predictive optimisation, explainable and trustworthy AI enable transparency and confidence in AI decisions, knowledge graphs support semantic reasoning and contextual understanding, and human-in-the-loop AI and foundation models enable intelligent human-AI collaboration. Together, these technologies enable manufacturing systems to integrate perception, reasoning, prediction, and adaptive decision-making in a single system. The current technological convergence is expected to contribute to safer human-robot interaction, intelligent task allocation, robust production management, and sustainable manufacturing, representing the transition from isolated applications of AI to integrated Industry 5.0 manufacturing ecosystems.

Challenges and Future Outlook

Although emerging AI technologies are quite promising, their industrial adoption remains uneven. Interoperability, computational scalability, cybersecurity, data quality, and industrial validation are other challenges that remain major barriers to their widespread industrial adoption. In addition, the challenge of combining several AI technologies into integrated manufacturing architectures is significant, due to the complexity of coordinating several heterogeneous data sources, decision models and autonomous manufacturing resources [20,35]. Digital twins, explainable AI, trustworthy AI, and knowledge-driven decision support will be integrated into manufacturing systems in the future. This convergence will improve adaptive safety, intelligent task allocation and collaborative production, and contribute to the overall goals of sustainable and human-centred manufacturing. The roles and industrial applications of emerging AI technologies are summarised in Table *8*.

Technology	Primary role	Manufacturing application	Key challenge
Digital twins	Virtual modelling	Process optimisation	System integration
Explainable AI	Transparent AI	Decision support	Model interpretability
Trustworthy AI	Reliable AI deployment	Safety-critical systems	Validation
Knowledge graphs	Context-aware reasoning	Resource management	Industrial adoption
Human-in-the-loop AI	Human supervision	Collaborative manufacturing	Real-time integration
Foundation models	Intelligent assistance	Manufacturing knowledge management	Domain adaptation

TABLE 8: Emerging artificial intelligence technologies and their roles in smart manufacturing (compiled by the authors)

AI, Artificial Intelligence

Evidence-based interpretation of AI for adaptive safety and task allocation

The reviewed studies consistently indicate that AI has considerable potential to improve adaptive safety and task allocation in smart manufacturing. However, the evidence also demonstrates that these benefits are highly dependent on the specific AI technique employed, the manufacturing context, and the degree of experimental or industrial validation.

Consequently, AI should not be regarded as a universal solution for improving safety but rather as an enabling technology whose effectiveness depends on appropriate implementation and integration with established industrial safety practices. Several studies reported that ML and data-driven approaches improve predictive decision-making by analysing sensor data, identifying operational patterns, and anticipating equipment failures or hazardous situations before they occur [5,6,19]. Similarly, RL techniques have demonstrated promising performance for adaptive scheduling and dynamic task allocation by continuously optimising production decisions under changing manufacturing conditions [32,34]. Nevertheless, these approaches have primarily been evaluated using simulation environments or controlled laboratory experiments, and further validation in large-scale industrial production systems remains necessary. Digital twin technologies further enhance adaptive safety by enabling continuous monitoring of manufacturing assets, virtual testing of production scenarios, and predictive assessment of potential operational risks [15,24,26,29,39]. The integration of AI with digital twins allows manufacturing systems to update operational decisions in near real time based on sensor feedback and environmental changes. However, the reviewed studies also recognise that successful deployment depends on accurate data acquisition, reliable communication infrastructure, and effective synchronisation between physical and virtual systems. Human-robot collaboration represents another area in which AI contributes to adaptive safety. The reviewed literature indicates that AI supports safer collaborative operation through dynamic risk assessment, intelligent motion planning, real-time perception, and adaptive task allocation between human operators and robotic systems [10,12,14,16,18]. These capabilities improve operational flexibility while reducing unnecessary production interruptions. Nevertheless, AI-based decision-making should complement rather than replace established safety engineering practices and must remain consistent with recognised collaborative robot safety standards such as ISO 10218 and ISO/TS 15066. Recent studies also emphasise that explainable and trustworthy AI are becoming increasingly important for industrial adoption [6,22,23,35,36]. Transparent decision-making, model robustness, and human oversight are essential for ensuring that AI-generated recommendations are understandable, reliable, and acceptable to operators. Without these characteristics, the practical deployment of AI-enabled manufacturing systems may be limited despite strong algorithmic performance. Overall, the evidence synthesised in this review suggests that AI can significantly support adaptive safety and intelligent task allocation in smart manufacturing when combined with robust sensing technologies, reliable industrial communication, comprehensive validation, and internationally recognised safety standards. Future research should therefore prioritise industrial-scale validation, interoperability, cybersecurity, and trustworthy AI to facilitate broader deployment in human-centred manufacturing environments.

Industrial Validation of AI-Enabled Smart Manufacturing

Although the reviewed studies demonstrate significant progress in AI-enabled smart manufacturing, the extent of industrial validation varies considerably across the literature. Many AI techniques, including ML, deep RL, and digital twin-based optimisation, have been evaluated primarily through simulations, digital testbeds, or laboratory-scale experiments rather than long-term deployment in operational manufacturing environments [15,24,29,32,34]. While these studies provide valuable proof-of-concept evidence, they may not fully capture the complexity of industrial production systems, where equipment heterogeneity, changing operating conditions, human variability, and legacy infrastructure can influence system performance. Several recent investigations have reported successful industrial implementations of AI-supported safety monitoring, predictive maintenance, and intelligent production management [31,33,37-40]. These studies demonstrate that AI can improve operational efficiency and support adaptive decision-making under realistic manufacturing conditions. However, the available evidence remains limited compared with the large number of simulation-based studies, indicating a need for broader validation across diverse industrial sectors. Future research should prioritise large-scale industrial case studies, standardised performance benchmarks, and long-term evaluations to assess the reliability, robustness, scalability, and safety of AI-enabled manufacturing systems. Such validation will strengthen confidence in AI adoption and facilitate wider implementation in human-centred smart manufacturing.

Critical analysis and future research direction

Critical Analysis

The literature reviewed shows that AI has significantly transformed smart manufacturing, with benefits in predictive analytics, process optimisation, adaptive safety, and intelligent task allocation. Today, manufacturing systems are increasingly flexible and data-driven and are becoming more responsive to the evolving production requirements due to ML, deep learning, computer vision, RL, and digital twins [5,19,24,32,37]. These developments have not been aggregated in a systematic way, so there is a need for further research. Most studies review individual AI techniques or a specific manufacturing application but do not consider the integration of a series of technologies into a single manufacturing system. Likewise, adaptive safety and intelligent task allocation are often studied as distinct research areas, and both are clearly linked to effective human-robot collaboration and operational performance [18,31,39]. Another critical constraint is industrial deployment. Although numerous studies have been published using simulation environments or laboratory experiments, relatively few have been validated through long-term deployment in real manufacturing environments. Thus, scalability, interoperability, reliability and system integration are still significant challenges for industrial deployment [26,35]. The comparative analysis of AI techniques in smart manufacturing safety applications is presented in Table *9*.

AI Technique	Main Application	Advantages	Limitations	Representative Studies
Machine Learning	Predictive maintenance, quality monitoring, risk prediction	Effective for pattern recognition from industrial data	Requires large labelled datasets	[5], [7], [19]
Deep Learning	Vision-based perception and autonomous decision-making	High accuracy for complex sensory data	Limited interpretability and high computational demand	[8], [37]
Reinforcement Learning	Adaptive scheduling and task allocation	Enables autonomous optimisation under changing conditions	Requires extensive training and safety constraints	[32], [34]
Explainable AI	Transparent decision support	Improves trust and human acceptance	Trade-off between accuracy and interpretability	[22], [23], [35]
Digital Twin + AI	Real-time monitoring and predictive control	Enables simulation and adaptive optimisation	Data integration and cybersecurity challenges	[15], [24], [29], [39]

TABLE 9: Comparative analysis of AI techniques in smart manufacturing safety applications (compiled by authors)

AI, Artificial Intelligence

Research Gaps

The literature reviewed identifies a number of research gaps. First, there is a critical need for increased integration of AI technologies that can simultaneously enable adaptive safety, intelligent task allocation and collaborative decision-making. Most of the available methods optimise individual functions of manufacturing, instead of thinking in terms of the manufacturing system as a whole [31]. Secondly, there is a lack of high-quality industrial datasets, which is still

hindering the development and validation of AI models. Limited availability of manufacturing data decreases the generalisability of the models and comparison of various AI approaches becomes more complicated [6]. Third, explainability and human oversight are still critical issues in intelligent manufacturing. With the growing autonomy of AI systems, it is even more important to ensure transparent and interpretable decision-making processes that allow engineers and operators to understand, verify and monitor the AI-generated recommendations [22,35]. Lastly, further industrial validation should be completed to validate the practical applicability of new technologies, such as digital twins, knowledge graphs and human-in-the-loop AI, under realistic manufacturing conditions [33,40]. A comparative analysis of major AI technologies, including their strengths, limitations, and future research opportunities, is presented in Table *10*.

AI Technology	Strengths	Manufacturing Applications	Current Limitations	Future Research Opportunities
Machine Learning	Predictive modelling	Maintenance, forecasting, quality prediction	Data dependency	Federated and online learning
Deep Learning	Feature extraction	Vision inspection, defect detection	Poor interpretability	Explainable deep learning
Computer Vision	Real-time perception	Safety monitoring, inspection	Lighting and occlusion issues	Multimodal sensing
Reinforcement Learning	Adaptive decision-making	Scheduling, task allocation	Simulation-to-reality gap	Safe and multi-agent RL
Digital Twins	Virtual Optimisation	Process simulation, planning	Integration complexity	Real-time digital twins
Explainable AI	Transparent decisions	Safety, planning	Accuracy–interpretability trade-off	Human-centred explainable AI
Knowledge Graphs	Contextual reasoning	Resource management	Limited industrial adoption	Semantic manufacturing
Human-in-the-loop AI	Human oversight	Collaborative manufacturing	Coordination complexity	Industry 5.0 integration

TABLE 10: Comparative analysis of artificial intelligence technologies for smart manufacturing (compiled by the authors)

AI, Artificial Intelligence; RL, Reinforcement Learning

Future Research Directions

Future research is needed to create unified manufacturing architectures with the integration of AI elements such as perception, predictive analytics, adaptive safety, intelligent task allocation and human-centred decision support. Digital twins, explainable AI, and trustworthy AI are expected to work more closely together to enhance transparency and interpretability in AI-driven decisions and enable resilient manufacturing operations [24]. Moreover, greater interaction

and integration between academia and industry are needed to evaluate AI technologies in real-world manufacturing environments to assess their impact and outcomes. This partnership will enhance technology transfer, standardise the criteria for technology evaluation and accelerate the adoption of trustworthy AI applications in manufacturing. The identified research priorities and future research directions are summarised in Table *11*.

Research Area	Current Challenge	Proposed Direction	Expected Impact
AI Integration	Fragmented AI solutions	Unified AI architectures	End-to-end intelligent manufacturing
Adaptive Safety	Limited real-time adaptation	Human-aware safety systems	Safer human–robot collaboration
Intelligent Task Allocation	Static scheduling	Multi-agent and RL- based allocation	Higher flexibility
Explainable AI	Black-box models	Transparent AI	Improved operator trust
Digital Twins	High implementation cost	Real-time AI-integrated twins	Better production optimisation
Industrial Validation	Mostly simulation studies	Large-scale industrial deployment	Technology readiness
Human-centred AI	Limited human involvement	Human-in-the-loop AI	Industry 5.0 adoption

TABLE 11: Research priorities and future directions for artificial intelligence in smart manufacturing (compiled by the authors)

AI, Artificial Intelligence; RL, Reinforcement Learning

The proposed integrated framework for adaptive safety and intelligent task allocation is presented in Figure *7*, combining the key technologies and industrial outcomes identified in this review.

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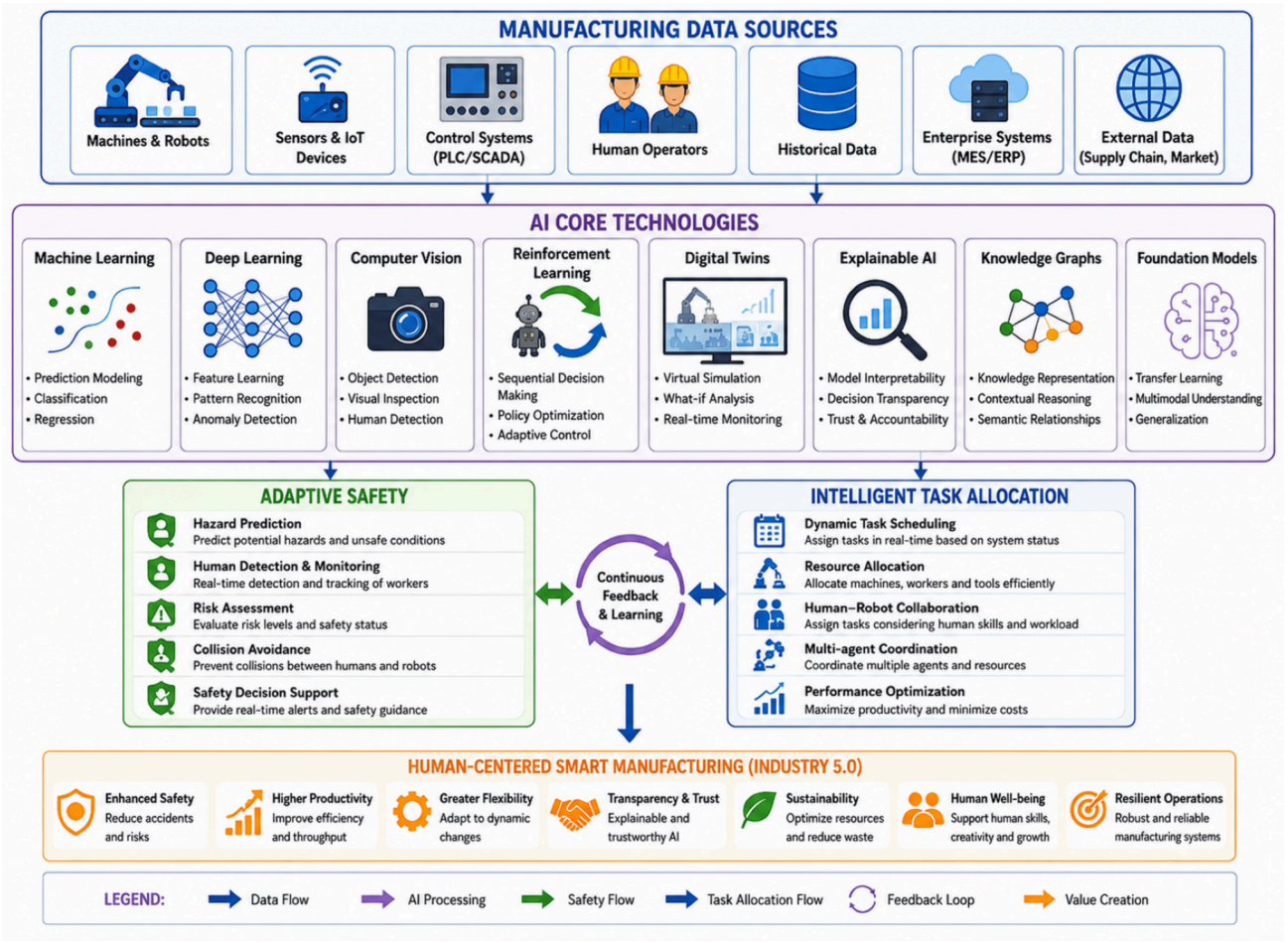


FIGURE 7: Integrated artificial intelligence framework for adaptive safety and intelligent task allocation in smart manufacturing (developed by the authors)

Conclusions

AI is transforming smart manufacturing by enabling intelligent decision-making, adaptive automation, and enhanced collaboration between humans and manufacturing systems. In this review, the use of AI in adaptive safety and intelligent task allocation has been explored, with ML, deep learning, computer vision, RL, digital twins, explainable AI and other promising technologies featured as playing an important role in the modern manufacturing environment. Together, these technologies have enhanced production efficiency, flexibility, predictive capacity, and workplace safety and facilitated the shift to smarter, more human-centred manufacturing systems. The findings show that adaptive safety and intelligent task allocation are closely related and cannot be regarded as research disciplines independent of each other, but rather as complementary aspects of smart manufacturing. AI can enable manufacturing systems to observe their production environments, predict potential operational hazards, allocate resources optimally, and enhance human-robot collaboration. Concurrently, new technologies like digital twins, explainable AI, and knowledge-driven decision support are improving the transparency, reliability, and adaptability of intelligent manufacturing systems. But there remain some issues to be addressed. The real-world application of AI in manufacturing industries remains influenced by factors like industrial validation, interoperability, explainability, data quality and scalable implementation. These challenges must be overcome by improving and scaling up the use of complementary AI technologies, fostering closer ties between academia and industry, and building comprehensive evaluation frameworks to facilitate the effective deployment of AI

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technologies in real manufacturing contexts. In general, this review offers a comprehensive overview of the existing use of AI in adaptive safety and intelligent task allocation for smart manufacturing and points out key challenges and research directions. The study highlights the importance of creating more robust and user-focused AI systems that combine intelligent decision-making processes with transparency, flexibility and reliability. These will be key strategies in the development of sustainable, resilient and collaborative manufacturing systems to satisfy the changing needs of Industry 5.0.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

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Disclosures

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Data Availability Statements

The datasets (and/or code) supporting this study are available from the corresponding author upon reasonable request.

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