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ARTIFICIAL INTELLIGENCE AND HUMANS IN THE MANUFACTURING SECTOR: WORKING IN SYMBIOSIS OR SEPARATELY?

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Purpose: This paper aims to provide a theoretical analysis of the relationship between humans and artificial intelligence (AI) in the manufacturing sector, exploring whether they operate as symbiotic collaborators within integrated systems or as independent entities with distinct roles and impacts on organizational structures.
Design/methodology/approach: The study employs conceptual analysis grounded in a semi-systematic literature review covering research from 2015 to 2025. The approach identifies, categorizes, and interprets key models of human-AI interaction, system integration strategies, and organizational implications, synthesizing insights across interdisciplinary sources.
Findings: Findings reveal a dominant trend toward cooperative and supportive models of human-AI interaction, where AI augments rather than replaces human roles. Five core design principles are identified: human-centered design, explainability and transparency, adaptive task allocation, strategic role definition, and hybrid intelligence. While benefits such as increased trust, ergonomic improvements, and flexibility are evident, significant challenges persist, particularly regarding system complexity, role ambiguity, and the risk of human skill dequalification.
Research limitations/implications: The study is limited by its reliance on secondary data and the absence of empirical validation in real-world settings. Furthermore, the semi-systematic review may have excluded relevant or unpublished studies. Future research should focus on empirically testing the proposed frameworks and exploring dynamic human-AI co-learning processes in industrial contexts.
Originality/value: This article contributes original value by introducing an integrated conceptual framework for analysing human-AI interaction in manufacturing. It shifts the discourse from purely technical assessments toward socio-technical and relational perspectives. The paper offers actionable guidance for system designers, managers, and policymakers, emphasizing the need for context-aware, human-centered integration of AI technologies.
Keywords: humans, AI, manufacturing sector, collaboration.
Category of the paper: conceptual paper.

1. Introduction

The rapid development of artificial intelligence (AI) technologies within the framework of Industry 4.0 has profoundly reshaped the manufacturing landscape. What was once a domain dominated by rigid automation is now evolving toward flexible, adaptive systems where AI and human agents increasingly co-exist. These changes are not merely technological but also organizational and social, prompting new questions about the nature of human-machine interaction in modern production settings (Jarrahi, 2018). At the heart of this transformation lies the relationship between humans and AI. While AI offers unparalleled capabilities in processing data, optimizing operations, and enabling real-time decision-making, the human contribution remains critical-particularly in areas requiring contextual understanding, ethical judgment, or creativity. As such, the interaction between AI and humans in manufacturing is no longer a question of replacement, but rather of how best to structure their coexistence. This interaction is often framed as a continuum between two models: symbiosis, where human and AI systems collaborate and complement one another; and independence, where AI technologies operate autonomously or displace human roles (Mahmud et al., 2022; Esfahani et al., 2022).

The dominant narrative in contemporary research increasingly supports symbiotic models, emphasizing shared agency, human-in-the-loop systems, and adaptive cooperation in tasks ranging from decision-making to generative design and additive manufacturing (Mahmud et al., 2022; Bendoly et al., 2023; Esfahani et al., 2022). Nevertheless, critical limitations persist. For example, meta-analyses suggest that human-AI combinations do not always outperform either agent working alone, particularly in decision-making domains where coordination challenges can impede performance (Vaccaro et al., 2024). Furthermore, the over-reliance on AI systems may lead to cognitive skill degradation among human operators, raising concerns about explainability, trust, and long-term system sustainability (Becks, Weis, 2022).

Despite growing interest, there remains a notable research gap in terms of theoretical integration and interaction modelling. Current literature lacks cohesive frameworks and unified vocabulary for understanding the complex, dynamic relationships between human and AI actors in real-world manufacturing environments. In particular, there is limited theoretical and practical attention to the design of interaction models, mutual adaptation, and cooperative behaviour over time (Garcia et al., 2021; Rezwana, Maher, 2022). Most contributions are fragmented across disciplinary boundaries, often emphasizing technical capabilities of AI rather than relational and systemic dimensions of collaboration.

This article aims to address this gap by presenting a theoretical analysis of human-AI interaction in the manufacturing sector, situated within the broader context of organizational, technological, and societal transformations. Drawing on a semi-systematic literature review, it develops interpretive frameworks to assess the coexistence of humans and AI as either elements in symbiosis or independent entities. The paper explores how these interaction models manifest in practice, the tensions they produce, and the implications they carry for design, work organization, and long-term human-AI integration.

Filling this gap is important for both theoretical and practical reasons. A deeper understanding of cooperative versus independent system dynamics can inform the design of more resilient, adaptive, and ethically sound production systems. It can also guide policymakers, engineers, and organizational leaders in making informed decisions about how to balance human and AI contributions without sacrificing agency, trust, or long-term learning.

The structure of the article is as follows. First, it provides a theoretical background on the evolving dynamics of human-AI interaction in the manufacturing sector, including key collaboration models, enabling technologies, and organizational factors. Next, the research methodology is described, based on a conceptual analysis conducted through a semi-systematic literature review. The main findings are then presented across four analytical dimensions: collaboration patterns, system integration approaches, impact on work organization, and design implications. The article concludes with a synthesis of the benefits and challenges observed, followed by a discussion of theoretical and practical contributions and directions for future research.

2. Theoretical background

Human-AI interaction in the manufacturing sector is undergoing a significant transformation, evolving from traditional automation toward integrated, human-centric systems. This shift reflects the core tenets of Industry 4.0 and the emerging Industry 5.0 paradigm, where artificial intelligence is not viewed as a replacement for human labour but as a synergistic partner that enhances human capabilities, supports decision-making, and enables more flexible, efficient, and adaptive production. The integration of collaborative technologies such as cobots, digital twins, and advanced analytics plays a central role in optimizing workflows, improving product quality, and minimizing errors. AI augments rather than replaces human input, fostering more personalized and innovation-driven environments (Rakholia et al., 2024; Othman, Yang, 2023; Asaad et al., 2024; Anang et al., 2024).

An essential aspect of this evolution is the emphasis on human-centric design. Modern manufacturing systems increasingly prioritize trust, transparency, and participatory processes through the deployment of explainable AI and adaptive interfaces that respond to human input and oversight. These approaches aim to strengthen operator confidence and ensure safe, understandable, and accountable AI behaviour (Li et al., 2025; Rani et al., 2024; Anang et al., 2024). A key theoretical foundation underpinning human-AI collaboration is cognitive synergy, where AI excels in structured, data-intensive operations while humans contribute contextual awareness and problem-solving flexibility. The integration of these complementary strengths, often facilitated by reinforcement learning and real-time interaction mechanisms, enables the development of resilient, semi-autonomous systems that can operate effectively in complex manufacturing settings (Mukherjee et al., 2024; Fan et al., 2025).

In the literature, three primary models of human-AI collaboration in manufacturing have been identified: cooperative, supportive, and independent. In cooperative models, humans and AI systems jointly perform shared tasks, requiring real-time coordination and mutual adaptation. These are exemplified by collaborative robotics and human-in-the-loop systems, where both agents actively contribute to task completion (Trakadas et al., 2020; Murali et al., 2020; Hartikainen et al., 2024). Supportive models assign the AI a more auxiliary role, where it provides information, physical assistance, or recommendations, while decision-making remains primarily in human hands. Applications include AI-supported decision-making systems and ergonomic aids (Roveda et al., 2020; Hartikainen et al., 2024). In independent models, AI and human agents work on parallel tasks with limited interaction, integrating outputs at a systemic level. Although less integrated, this model remains relevant in highly automated environments such as inspection and logistics (Matheson et al., 2019).

Several enabling technologies support these collaborative frameworks. Human-in-the-loop systems ensure that while AI may generate insights or propose actions, humans maintain control over key decisions (Trakadas et al., 2020; Murali et al., 2020). Human-on-the-loop models, on the other hand, allow AI to operate with a higher degree of autonomy, with humans positioned as supervisory agents who can intervene when necessary. Human-out-of-the-loop systems function independently of human input, suitable only for narrowly defined and highly structured scenarios. A particularly promising development is adaptive symbiosis, in which humans and AI systems co-learn over time. This mutual adaptation enhances shared understanding and system responsiveness, as seen in machine tool operation environments where AI systems adjust to operator preferences.

Technological infrastructure such as AI–IoT integration facilitates predictive maintenance and real-time analytics, contributing to more responsive and efficient production processes (Rani et al., 2024; Hartikainen et al., 2024). Formal tools like knowledge graphs and process models support structured, transparent, and accountable interactions between humans and AI by encoding relationships and improving data traceability (Heinzl et al., 2024). Moreover, advanced control methods such as model-based reinforcement learning and variable impedance control, enhance safety and responsiveness during physical collaboration between humans and robotic agents (Roveda et al., 2020).

Effective human–AI collaboration also requires careful attention to design and organizational context. Ergonomic and human-centered workspace design ensures both physical safety and psychological well-being, while task planning mechanisms must be flexible enough to adapt to human behaviour and contextual changes (Simões et al., 2022; Roveda et al., 2020). Finally, organizational factors such as company size, resource availability, and workforce skill levels play a critical role in shaping the success of implementation strategies. Tailored approaches are necessary to align technological integration with specific operational realities (Sun, Song, 2024). In sum, the integration of AI in manufacturing must be approached not only as a technical challenge but also as a socio-technical endeavor grounded in collaborative design, adaptive systems, and organizational readiness.

3. Research methodology

The paper adopts a method of conceptual analysis (Rocco and Plakhotnik, 2009) based on a semi-systematic literature review (Snyder, 2019). The use of conceptual analysis is justified by the need to systematically identify, categorize, and clarify key concepts and their interrelations within the studied phenomenon. As noted by Miles and Huberman (1994), a conceptual framework serves not only to organize relevant ideas but also to reveal “where the overlaps, contradictions, refinements, or qualifications are” (Miles, Huberman, 1994, p. 18). This method enables the development of a structured analytical lens through which complex qualitative data can be interpreted. By integrating both theoretical insights and empirical findings, conceptual analysis supports the construction of a coherent and transparent framework that enhances the explanatory power of the study.

As a conceptual paper, this study is based on the synthesis of representative literature from a specific domain, integrated to provide a better understanding and conceptualization of the research phenomenon (Rocco, Plakhotnik, 2009). The rapid technological advancements and the ongoing transformation of human–AI collaboration in the manufacturing sector justify the use of conceptual analysis via a semi-systematic literature review in this study. Although research in this field has developed over several decades, supported by a balanced body of theoretical and empirical work, the accelerating pace of innovation calls for a deeper understanding of the evolving conceptual landscape. As noted in recent literature, there remains a pressing need to bridge theoretical frameworks with empirical insights to capture the full complexity and implications of AI integration in human work environments.

Conceptual analysis enables a systematic exploration and clarification of key ideas, roles, and relationships, providing a foundation for future empirical investigations and ensuring analytical coherence in a rapidly changing domain. According to Hulland (2020, p. 27), “conceptual review papers can theoretically enrich the field by reviewing extant knowledge, noting tensions and inconsistencies, identifying important gaps as well as key insights, and proposing agendas for future research”. This approach is crucial in fields where theoretical clarity is needed to guide empirical inquiry. To conduct the semi-systematic literature review and conceptual analysis, the author followed the phases suggested by Snyder (2019). First, the review was designed, including the formulation of a guiding research question.

Second, relevant studies were identified through a systematic search. Third, the selected papers were conceptually analysed, and finally, the review was written. In the first phase, the author formulated the research question, identified key data sources, and developed relevant search phrases. The conceptual analysis was guided by the following research question:

RQ1. *Do AI and humans form collaborative, mutually supportive links within a single system, or are they evolving as independent components, each with its own operational logic and impact on the organization?*

The Scopus and Google Scholar databases were used to search for publications containing the phrases: “human-AI collaboration” OR “socio-technical systems” OR “task allocation” OR “organizational impact of AI”. This combination of search terms and databases enabled the author to identify studies analysing the interaction between AI and humans in the manufacturing sector. The search targeted papers in the field of Business, Management, and Accounting, including all publications from 2015 up to May 1, 2025, and was limited to articles written in English or German. The time frame from 2015 to 2025 was selected because research on artificial intelligence in manufacturing has significantly intensified since 2015, driven by the rise of Industry 4.0. Including publications up to 2025 ensures the analysis captures the most recent developments and reflects the ongoing shift toward human-centric collaboration models associated with Industry 5.0. For the analysis, the author applied inclusion and exclusion criteria (Paul, Criado, 2020). The inclusion criteria comprised studies that focused on the interaction between AI and humans within manufacturing environments. Studies that primarily examined technical aspects of AI or addressed general automation rather than intelligent systems were excluded. In analysing the selected papers, the initial focus was on how the interaction between artificial intelligence systems and human actors is conceptualized and operationalized in manufacturing contexts. Special attention was given to the nature of human-AI collaboration, the distribution of roles and responsibilities, and the assumptions underlying system design. This involved mapping various cooperation models, levels of autonomy, and integration strategies described in the literature.

By systematically applying the inclusion criteria, emphasizing empirical grounding, relevance to the manufacturing context, and a clear focus on intelligent systems, the analysis aimed to develop a coherent conceptual foundation for understanding human-AI dynamics in industrial environments. In addressing RQ1, the analysis highlighted how reviewed studies conceptualize and operationalize the human-AI relationship in manufacturing. As a result, three key elements were identified: (1) insights into cooperative versus independent system dynamics, (2) recognition of main challenges in human-AI collaboration, and (3) directions for future research. These findings underscore the predominance of integrative collaboration models, recurring barriers such as system complexity and skill mismatches, and the importance of human-centered, transparent design approaches. Together, these elements provide a conceptual basis for further investigation into human-AI interaction in manufacturing.

4. Results and findings

In the following section, a synthesis of findings is presented across four key analytical dimensions: summary of study characteristics, outlining the methodological and contextual features of the reviewed research, thematic analysis of human-artificial intelligence collaboration patterns, capturing dominant models of interaction and role distribution between humans and AI, system integration approaches, focusing on technical, organizational, and operational strategies for embedding AI in manufacturing settings; and impact on work organization, examining how AI influences task structures, skill requirements, and human roles. Each dimension contributes to a more comprehensive understanding of the evolving relationship between humans and AI in the manufacturing sector.

Summary of study characteristics

The reviewed studies employed a range of research approaches (see Table 1). Empirical methods were the most commonly used, featured in 13 studies. Additionally, 9 studies adopted theoretical or conceptual frameworks, while 7 relied on case study methodologies. Mixed methods were used in 3 studies, and 2 studies were literature reviews. It is noteworthy that several studies employed more than one methodological approach.

In terms of industry context, 21 studies were conducted within manufacturing or assembly environments, indicating a strong sectoral focus. Four studies explicitly addressed contexts related to Industry 4.0 or Industry 5.0, while one study included multiple sectors, reflecting a broader applicability. Some studies spanned more than one industrial domain.

The nature of the human–artificial intelligence (AI) relationship varied across studies. Twelve studies characterized this relationship as “cooperative,” while 10 described it as “cooperative/supportive.” The term “supportive” was used in 2 studies, with an additional 1 study using the term “supportive/cooperative.” One study introduced the concept of “hybrid intelligence” to describe the interaction between humans and AI.

Several key themes emerged from the reviewed literature. Trust and transparency were highlighted in 5 studies. Other recurring themes included human-centered design, usability, or acceptance (2 studies); ergonomics or operator well-being (2 studies); mutual learning (2 studies); human factors (2 studies); adaptability (2 studies); and fatigue monitoring (2 studies). Additional themes, each addressed in a single study, included: teamwork, augmentation, ethics, productivity, socio-technical focus, strategic planning, training needs, design complexity, peer-to-peer interaction, human-friendly automation, complementary skills, co-creation, risk of dequalification, and joint decision-making.

Table 1.
Characteristics of included studies

Study	Study Focus	Research Approach	Industry Context	Key Findings
Emmanouilidis et al., 2021	Human-AI integration in production; vision-based inspection	Case study, Theoretical/ conceptual	Manufacturing (vision-based inspection, Industry 5.0, digital twins, Explainable artificial intelligence)	Cooperative human-AI model; trust and transparency critical; humans enhance AI capabilities; need for work design considerations
Pacaux-Lemoine et al., 2017	Human-machine cooperation in intelligent manufacturing	Mixed methods (theoretical/ Conceptual + empirical)	Intelligent Manufacturing Systems (adaptive self-organization, Industry 4.0)	Cooperative/supportive model; human-centred design; need for human integration in autonomous systems
Pacaux-Lemoine et al., 2016	Human-machine cooperation principles	Theoretical/ conceptual	Intelligent Manufacturing Systems	Cooperative/supportive; mutual understanding and communication; human-machine cooperation principles improve performance
Bechinie et al., 2024	Human-centered intelligent assistance; Operator 5.0	Theoretical/ conceptual, Literature review	Manufacturing (Digital Twins, extended reality, artificial intelligence)	Cooperative/supportive; usability, acceptance, understandability; challenges in human-centered design
Dimitropoulos et al., 2021	Human-robot collaborative assembly	Case study, Empirical	Elevator manufacturing (digital twins, vision machine learning)	Cooperative/supportive; robot adapts to human needs; improved ergonomics and satisfaction
Habib et al., 2021	Human-machine cooperation in Manufacturing 4.0	Empirical	Manufacturing (digital twins, mobile robots)	Cooperative; teamwork reduces workload; individual factors affect cooperation
Pacaux-Lemoine et al., 2022	Human-system cooperation with cognitive work analysis	Empirical	Industry 4.0 (intelligent systems, digital twin)	Supportive; cognitive work analysis aids situational awareness; complexity challenges; need for better cooperation tools
Oh, 2023	Artificial intelligence impact on workforce competencies	Mixed methods	Advanced Manufacturing (natural Language processing)	Cooperative; artificial intelligence augments but does not replace humans; role clarity needed
Rožanec et al., 2023	Artificial intelligence in defect detection; operator fatigue	Empirical	Manufacturing (quality inspection, machine learning	Cooperative/supportive; artificial intelligence aids defect detection; fatigue monitoring enhances well-being
Peruzzini et al., 2023	Human-automation symbiosis in Industry 5.0	Theoretical/ conceptual	Diverse sectors (Augmented Digital Twin)	Cooperative/supportive; mutual learning; human factors central
Sesana and Tavola, 2021	Artificial intelligence/ augmented reality for resilient manufacturing	Empirical	Manufacturing/assembly (Internet of Things, augmented reality, neural networks)	Cooperative; augmented reality supports operators; trust and transparency; real-time data sharing
Albu-Schäffer et al., 2023	Socio-technical assistive systems; learning	Theoretical/ conceptual, Empirical	Industrial production (knowledgebased, ontologies)	Cooperative; mixed-skill task allocation; learning promotion; risk of dequalification
Süsse et al., 2023	Human-artificial intelligence interaction in remanufacturing	Case study	Automotive/remanufacturing(artificial intelligence agent)	Supportive/Cooperative; joint decision-making; behavioural patterns (cognitive, emotional, social)
Oliff et al., 2020	Human-robot interaction; adaptability	Theoretical/ conceptual, Empirical, Case study	Assembly/manufacturing, (machine learning, cyber-physical systems, virtual reality/ augmented reality)	Cooperative/supportive; adaptability to human variation; need for further research

Cont. table 1.

Dvorak et al., 2022	Human role in artificial intelligence-based production	Theoretical/ conceptual	Electric motor Production (artificial Intelligence assistance)	Supportive; artificial intelligence assists complex tasks; focus on socio-technical system
Saßmannshausen, Heupel, 2020	Trust in artificial intelligence in production management	Empirical	Industrie 4.0 (Big Data, Predictive Analytics, Robotics)	Cooperative/supportive; trust is crucial; unpredictability is a challenge
Rožanec et al., ”Predicting Operators Fatigue”	Artificial Intelligence-driven defect detection; fatigue	Empirical	Manufacturing (quality inspection, machine learning)	Cooperative/supportive; artificial intelligence aids workflow; fatigue monitoring
Wahlström et al., 2024	Artificial intelligence and transformation of industrial work	Case study, Theoretical/ conceptual	Glass tempering (machine vision, automation)	Cooperative; hybrid intelligence; ”double black box” challenge
Hartikainen et al., 2024	Human artificial intelligence collaboration in smart manufacturing	Literature review	Manufacturing (artificial Intelligence enabled agents)	Cooperative; trust, transparency, ethics; operator well-being
Waschull, Emmanouilidis, 2022	Human-centric co-creation for artificial intelligence systems	Empirical	Manufacturing (artificial Intelligence enabled systems)	Cooperative; trust; human factors in design; co-creation workshops
Schierhorst et al., 2024	Hybrid intelligence in production	Case study	Industry 4.0 (artificial Intelligence applications, coating/ machining)	Cooperative; human-friendly automation; productivity focus
Yamamoto et al., 2024	Human-centered artificial intelligence system design	Case study	Manufacturing (machine learning anomaly detection, casting)	Cooperative; design complexity; need for structured approach
Umbrico et al., 2022	Enhanced cognition for human-robot collaboration	Empirical	Human-robot collaboration Manufacturing (artificial intelligence, cyber-physical systems)	Cooperative/supportive; peer-to-peer interaction; adaptability
Żywiołek, 2024	Trust-building in artificial intelligence human partnerships	Empirical	Manufacturing (pattern recognition, classification)	Cooperative; trust, transparency, ethics; training needs
Gabriel et al., 2023	Strategic planning for human-artificial intelligence collaboration	Mixed methods	Manufacturing (no further details found)	Cooperative; complementary skills; need for strategic planning

Source: own elaboration.

Thematic analysis of human–artificial intelligence collaboration patterns

The thematic analysis of the reviewed studies reveals a coherent and evolving pattern of human–artificial intelligence (AI) collaboration within industrial contexts. A prevailing model observed across the literature is that of cooperative or supportive integration, in which AI systems are not designed to function independently but rather to augment, assist, or collaborate with human operators (Emmanouilidis et al., 2021). This paradigm reflects a shift toward human-centered automation, where human agency and oversight are preserved. Such cooperative arrangements are particularly evident in applications like vision-based inspection (Emmanouilidis et al., 2021), collaborative robotic assembly (Dimitropoulos et al., 2021), and remanufacturing processes (Süsse et al., 2023), where AI enhances human capabilities by providing computational precision, real-time assistance, and decision support. In a smaller subset of studies, the concept of hybrid intelligence is introduced, emphasizing the synergistic fusion of human cognitive flexibility and ethical judgment with the data-processing efficiency and consistency of AI systems (Wahlström et al., 2024; Nikolas et al., 2024).

This model proposes a more integrated approach to task execution, wherein both agents contribute unique and complementary strengths.

The distribution of roles and the allocation of tasks between humans and AI agents emerge as critical dimensions of collaborative system design (Dimitropoulos et al., 2021). Numerous studies report the implementation of dynamic task allocation mechanisms, allowing AI systems to adapt to individual human operators based on real-time performance metrics, preferences, or situational demands (Dimitropoulos et al., 2021). These systems often rely on mixed-skill allocation strategies, assigning tasks based on the respective advantages of human and artificial capabilities (Albu-Schäffer et al., 2023). Human involvement is most commonly positioned in supervisory and decision-making roles (Emmanouilidis et al., 2021), where contextual understanding and ethical reasoning are essential, as well as in direct operational tasks requiring manual dexterity and adaptability (Dimitropoulos et al., 2021). Additionally, humans frequently assume responsibility for workflow coordination, overseeing the sequencing and interaction of hybrid teams (Rožanec et al., 2023). This adaptive and complementary role distribution underscores the importance of flexibility and situational responsiveness in the design of collaborative systems.

A central enabling factor in effective human-AI collaboration is the quality of communication interfaces. The studies consistently emphasize the need for transparent, interpretable, and user-centered interaction mechanisms to foster trust, enhance usability, and ensure operational safety (Emmanouilidis et al., 2021). Explainable AI is identified as a key approach, allowing AI systems to convey their reasoning processes in an accessible manner, thereby supporting human understanding and accountability (Emmanouilidis et al., 2021). Augmented reality interfaces are also reported as valuable tools, providing contextualized visual information that supports task performance and situational awareness (Bechinie et al., 2024). Natural language processing capabilities further facilitate intuitive and low-friction communication, enabling users to interact with AI systems using everyday language (Oh, 2023). In several cases, participatory design practices, such as co-creation workshops, are employed to integrate end-user perspectives and human factors into system development from the outset (Bechinie et al., 2024; Waschull, Emmanouilidis, 2022). These methods contribute to the alignment of technological capabilities with user needs, promoting acceptance, usability, and long-term sustainability of AI integration.

In summary, the reviewed studies converge on a model of human-AI collaboration that is grounded in cooperation, mutual adaptability, and transparent interaction. Rather than displacing human labour, AI systems are increasingly conceptualized as collaborative partners that enhance human potential while maintaining essential human oversight and judgment. This integrative perspective reflects a broader socio-technical orientation in the design of intelligent systems and offers a foundation for future research and practice in human-centered AI deployment.

System integration approaches

The reviewed studies identify three major dimensions of system integration in the context of human–artificial intelligence (AI) collaboration (Emmanouilidis et al., 2021; Albu-Schäffer et al., 2023; Oliff et al., 2020): technical integration frameworks, organizational adaptation strategies, and performance optimization methods. In terms of technical integration, AI systems are incorporated into industrial environments through advanced frameworks such as digital twins, knowledge-based systems, and cyber-physical systems. These architectures facilitate real-time data exchange, continuous process monitoring, and adaptive system control, enabling responsive and context-aware collaboration between human operators and AI agents (Emmanouilidis et al., 2021). Despite their potential, several studies emphasize challenges associated with the complexity of these systems, particularly the need for reliable and timely data sharing across heterogeneous technological infrastructures (Emmanouilidis et al., 2021; Pacaux-Lemoine et al., 2021; Sesana, Tavola, 2021).

At the organizational level, integration efforts are supported by a variety of adaptation strategies aimed at aligning technological capabilities with human and institutional needs (Bechinie et al., 2024). Key approaches include human-centered design methodologies, co-creation workshops, and strategic planning focused on role definition and capability mapping (Bechinie et al., 2024; Waschull, Emmanouilidis, 2022; Hartikainen et al., 2024). These strategies are designed to ensure that the deployment of AI technologies supports both organizational goals and individual user needs. Numerous studies stress the importance of structured training programs and clearly defined role allocations to facilitate smooth integration and promote acceptance among human workers (Hartikainen et al., 2024; Żywiołek, 2024; Gabriel et al., 2023).

From a performance optimization perspective, AI systems contribute to enhanced operational efficiency through real-time process monitoring, ergonomic assessment, and adaptive task allocation based on system or human conditions (Dimitropoulos et al., 2021; Bechinie et al., 2024; Emmanouilidis et al., 2021; Albu-Schäffer et al., 2023). While these applications offer measurable benefits in productivity and safety, several studies also identify critical barriers. These include the inherent complexity of integrated systems (Emmanouilidis et al., 2021; Pacaux-Lemoine et al., 2021), the skill demands placed on human operators (Hartikainen et al., 2024; Żywiołek, 2024), and the so-called "double black box" problem, where both the AI system's decision-making logic and the human operator's cognitive processes are non-transparent (Wahlström et al., 2024; Yamamoto et al., 2024). This opacity presents challenges for accountability, interpretability, and effective human-machine collaboration.

In summary, successful system integration in human-AI collaboration relies not only on sophisticated technical frameworks but also on adaptive organizational strategies and targeted performance optimization efforts. These components must be cohesively aligned to address the sociotechnical challenges of complexity, transparency, and human-system coordination.

Impact on work organization

The integration of artificial intelligence into work environments results in substantial changes to work organization, particularly in the nature of tasks, skill requirements, and operational performance (Emmanouilidis et al., 2021; Dimitropoulos et al., 2021; Pacaux-Lemoine et al., 2021; Oh, 2023).

In terms of task transformation, the implementation of AI systems leads to a marked shift in human roles from manual task execution to higher-level responsibilities such as supervision, decision-making, and workflow coordination (Emmanouilidis et al., 2021; Pacaux-Lemoine et al., 2021; Oh, 2023). As AI systems increasingly handle routine and computational tasks, human operators are more frequently engaged in complex, context-dependent activities that require situational awareness and judgment (Wahlström et al., 2024; Hartikainen et al., 2024; Żywiołek, 2024). Several studies also report trends toward upskilling, indicating a growing need for workers to acquire new competencies in response to evolving job demands (Wahlström et al., 2024; Hartikainen et al., 2024; Żywiołek, 2024).

Skill requirements are a recurring theme throughout the literature (Habib et al., 2021). The emergence of AI-driven work processes is associated with increasing demands for higher-order cognitive abilities, technical skills, and collaborative competencies, particularly in multidisciplinary and human-AI teams (Habib et al., 2021; Oh, 2023; Hartikainen et al., 2024). Additionally, some studies highlight the influence of individual factors, such as previous experience, adaptability, and personal characteristics, on how effectively workers engage with and adapt to AI systems (Wahlström et al., 2024; Hartikainen et al., 2024; Żywiołek, 2024).

With respect to operational efficiency, most studies report improvements in productivity, workplace ergonomics, and user satisfaction when human-AI collaboration is carefully designed and implemented (Dimitropoulos et al., 2021; Habib et al., 2021; Rožanec et al., 2023). These benefits are often linked to the complementary capabilities of humans and AI, as well as to systems that are user-centric and transparent. However, the available evidence is frequently derived from case studies or simulated environments, limiting the generalizability of findings (Dimitropoulos et al., 2021; Süsse et al., 2023; Oliff et al., 2020; Schierhorst et al., 2024). Furthermore, challenges such as lack of trust, limited system transparency, and technical complexity are commonly identified as barriers that may diminish or obstruct the realization of expected benefits (Emmanouilidis et al., 2021; Pacaux-Lemoine et al., 2021; Sesana, Tavola, 2021; Saßmannshausen, Heupel 2020; Wahlström et al., 2024).

In summary, the impact of AI on work organization is multifaceted. While it offers significant opportunities for performance improvement and job enrichment, it also introduces new demands on skills, human-system interaction, and organizational adaptation.

Design Implications

The Table 2 presents the results of a literature-based analysis of key design principles for effective human-AI collaboration. It outlines five foundational principles identified as critical for integrating artificial intelligence into work environments. For each principle, the table summarizes typical implementation approaches, observed benefits, and associated challenges. The findings highlight that while the adoption of advanced design strategies can enhance trust, operational flexibility, and collaborative efficiency, they are also accompanied by significant organizational, technological, and skill-related challenges that require careful and systematic consideration.

Table 2.
Design implications

Desing Principle	Implementation Approach	Benefits	Challenges
Human-centered design	Co-creation workshops, participatory design, human factors integration	Improved trust, usability, early identification of issues	Lack of structured methods, complexity in integrating human factors
Explainability and transparency	Explainable artificial intelligence, augmented reality interfaces, real-time data sharing	Enhanced trust, operator acceptance, better decision-making	Complexity, ”double black box” effect, need for expert networks
Adaptive task allocation	Mixed-skill concepts, knowledge-based systems, ergonomic assessment	Flexibility, learning promotion, operational efficiency	Risk of dequalification, objectification trap, misuse for performance monitoring
Strategic role definition	Capability assessment, strategic planning, training	Clearer roles, improved collaboration, readiness for artificial intelligence integration	Organizational resistance, varying stakeholder priorities, training needs
Hybrid intelligence	Integration of human and artificial intelligence strengths, mutual learning	Productivity, human-friendly automation, resilience	Skill mismatches, need for upskilling, system complexity

Source: own elaboration.

Based on the analysis presented in the Table 2 , the review identifies and synthesizes five core design principles that shape effective human-AI collaboration: human-centered design, explainability and transparency, adaptive task allocation, strategic role definition, and hybrid intelligence. Each principle is linked to specific implementation approaches and has demonstrated distinct benefits and challenges in practice. Observed benefits include enhanced or improved trust (reported across two principles), as well as a range of individual benefits reported once each: increased usability, early issue detection, operator acceptance, better decision-making, flexibility, learning promotion, operational efficiency, clearer role definitions, improved collaboration, readiness for AI integration, productivity, human-friendly automation, and system resilience. These findings reflect a broad spectrum of positive outcomes that stem from aligning design approaches with both technical and human factors. On the challenge side, system complexity and the complexity of integrating human factors were the most commonly cited issues, appearing in relation to three design principles. Additionally, a series of unique but critical challenges such as lack of structured methods, the “double black box” effect, need for expert networks, risks of dequalification, misuse for monitoring, and organizational resistance, highlight the multifaceted nature of obstacles faced in implementing these principles.

5. Conclusions, research limitations and further research directions

This study offers a conceptual and integrative framework that contributes to both theoretical and practical understandings of human-AI collaboration in the manufacturing sector. It identifies five core design principles: human-centered design, explainability and transparency, adaptive task allocation, strategic role definition, and hybrid intelligence, that form the basis for effective integration of AI technologies alongside human actors. These principles are not only theoretically grounded but also empirically substantiated through literature-based evidence of their practical benefits and implementation challenges.

The article's aim was to address a persistent research gap in the theoretical integration and modelling of human-AI interactions, particularly the lack of cohesive conceptual tools to assess whether AI and humans function as elements in symbiosis or as independent entities in manufacturing environments. Drawing on a semi-systematic literature review, the paper has successfully fulfilled this objective by developing a structured analytical framework that situates human-AI collaboration within the broader context of organizational, technological, and societal transformation. It explores the dynamic tensions and manifestations of interaction models: cooperative, supportive, and independent and links them to implications for system design, work organization, and long-term integration. Thus, the main research question has been answered, the findings confirm that human-AI relationships in manufacturing predominantly align with models of adaptive symbiosis rather than strict independence, while also highlighting challenges that hinder this integration.

Theoretically, the paper advances the field by reframing design principles as operational constructs rather than abstract prescriptions. It provides a vocabulary and structure for analysing the degree of coupling between human and AI agents, offering a differentiated view of how these relationships materialize in practice. In doing so, it enriches the theoretical discourse on socio-technical systems and contributes to a more granular understanding of hybrid intelligence in the industrial domain.

Practically, the framework provides valuable guidance for system designers, managers, and policymakers, enabling them to anticipate barriers such as system complexity and human-factor integration, while capitalizing on proven advantages like trust enhancement, flexibility, improved collaboration, and organizational readiness for artificial intelligence integration. For system designers, the results support the development of user-centered technologies aligned with human cognitive and operational capacities. For managers, the findings help inform strategic decisions on workforce transformation and process redesign. Policymakers can use the insights to shape regulations and incentives that foster responsible and effective AI adoption in manufacturing. The analysis confirms that successful human–artificial intelligence collaboration hinges on aligning technological design with human capabilities and organizational context. However, numerous challenges persist, including system-level complexity, lack of structured implementation methods, risks of dequalification, and organizational resistance. These findings underscore the need for nuanced, context-aware approaches that go beyond mere technological optimization.

Despite these contributions, several limitations must be recognized. First, the study is based on a semi-systematic literature review, which, although methodologically rigorous, may have excluded relevant but unpublished or non-English sources. Second, the analysis relies primarily on secondary data from academic literature and does not include empirical field studies or firsthand accounts from manufacturing practitioners. Third, although the proposed framework is conceptually robust, it remains theoretical and has not yet been empirically tested or validated in real-world industrial settings. These limitations suggest caution in generalizing the findings and point to the necessity of further empirical exploration.

Future research should aim to operationalize and validate the proposed design principles in varied industrial environments through longitudinal case studies, controlled experimental research, and participatory design projects involving direct collaboration with end-users. Particular emphasis should be placed on sectors such as automotive manufacturing and precision engineering, where human expertise remains central and AI integration is advancing rapidly. There is also a clear need to deepen our understanding of system integration strategies, especially regarding data quality, interface transparency, and the dynamics of human-AI co-learning in high-stakes environments. Additionally, ethical and social dimensions of AI adoption such as worker participation, trust development, and long-term cognitive engagement-require more systematic, interdisciplinary investigation, combining insights from engineering, organizational science, and human factors. Such integrative efforts will be essential for developing actionable, sustainable, and ethically grounded models of human-AI collaboration.

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