Title: Human-AI collaboration and Explainability in manufacturing operations: a systematic literature review

Abstract: Recent advances in artificial intelligence (AI) are accelerating digitalization in manufacturing operations, yet many solutions remain difficult to scrutinize and operate in human-centered ways, which can hinder adoption. This study presents a systematic review to map primary research on AI in manufacturing operations where human-AI collaboration is explicit or explainable artificial intelligence (XAI) and human factors are addressed. Searches in Scopus and IEEE Xplore (2020 – 2026) identified 1.240 publications. After a rigorous screening, 177 studies were included. All studies were coded through an operational lens combining decision domains (scheduling, maintenance, inspection-quality, process control, shop floor) with AI roles and evidence strength. The primary domains are maintenance and inspection-quality, where the decision support is the most explored role. Furthermore, most of the studies lack a specific XAI modality, while lab and simulation environments are the most included studies. The review highlights that a large share of AI research in operations is still maturing in its human-centered operationalization. We provide structured matrices to support evidence-based design and adoption of human-centered AI in manufacturing operations.

Keywords: human-AI collaboration, Explainable AI, manufacturing operations, decision support system, PRISMA, systematic review.

Main Text:

1. Introduction: Artificial intelligence (AI) is increasing the ability to control processes in companies, such as planning, maintenance, and quality. Although Industry 4.0 focused on data-driven automation and increasing the performance of industrial processes, Industry 5.0 has seen a greater need for human-centered systems, seeking to increase system resilience and promote human-machine collaboration [1], [2], [3], [4]. The adoption of AI is often carried out according to “black-box” models. In industrial contexts, a black-box application can increase the risks and probability of negative events occurring, both technical and managerial, from unclear responsibilities to difficulties in acceptance by employees. The transparency and comprehensibility of AI results can influence trust, responsiveness, and full understanding of different scenarios, impacting the adoption of the technology [5], [6], [7].

To improve employees' understanding and responsiveness to AI, Explainable Artificial Intelligence (XAI) introduces methods, approaches, and interfaces, but the design and analysis of the context in which employees operate are necessary to achieve effective results.

In this regard, AI-integrated systems can serve as decision support, shared control, supervised automation, and unsupervised control, but the literature is fragmented with respect to application domains, role, maturity, and design of AI interfaces [8], [9], [10], [11].

Our systematic review addresses this gap by analyzing 177 studies published between 2020 and 2026 that meet criteria A ∧ B ∧ (C ∨ D): AI in manufacturing operations with explicit human–AI collaboration and/or XAI/human factors. We believe that this review can provide four different contributions: (1) an overview of the literature at the intersection of AI, manufacturing operations, and collaboration, or XAI; (2) Distribution of AI methods by domain and Domain × Role matrix; (3) Adoption, using a Domain × Role × Evidence level matrix to distinguish prototype projects from real applications; (4) Interaction design, using a Domain × Role × XAI modality (+ interactivity) matrix.

Our main research questions are:

- RQ1 - What is the distribution of Human–AI/XAI literature in the domains of manufacturing operations?
- RQ2 - How do the decision-making roles of AI (decision support, shared control, supervised automation, unsupervised automation) vary across different operational domains?
- RQ3 - What is the distribution of the literature on application maturity in the different Domain × Role combinations?
- RQ4 - What XAI modalities and levels of interactivity are implemented in the different Domain × Role combinations, and what are the implications for human decision-making support?

The rest of the article is organized as follows: Section 2 describes the PRISMA methodology; Section 3 presents the quantitative results and matrices; Section 4 discusses gaps and implications; Section 5 concludes, summarizes this article, and proposes avenues for future research.

2. Methodology: This review was conducted in line with PRISMA 2020, and the reference, screening, and selection process was carried out using the Rayyan platform[12]. The different stages addressed below consist of: (i) search strategy, (ii) inclusion criteria, (iii) screening process, and (iv) coding scheme[13][14].

2.1 Search strategy: The research was conducted using two academic databases (Scopus and IEEE Xplore), selected on the basis of their large volume of research related to engineering and computer science, linked to the world of manufacturing and decision support. A series of filters were applied to the search for studies: (i) time frame 2020–2026, (ii) English language, (iii) document type: articles and conference papers (excluding editorials, book chapters, and gray literature), (iv) final publication status. The search was carried out based on four different clusters (A, B, C, and D). To maximize accuracy, the terms in Cluster A were searched exclusively in the Title field, while the remaining

terms were searched in Title-Abstract-Keywords. The complete search string and search log are provided in Appendix A to ensure replicability.

2.2 Inclusion and exclusion criteria: The review was conducted according to the rule: A ∧ B ∧ (C ∨ D). Studies were included only if they simultaneously met the criteria for domain, technology, and at least one of the remaining dimensions, between explainability and interaction.

The domains were defined as follows:

(A) Manufacturing operations: studies must concern process control, scheduling, inspection-quality, maintenance, and shop floor;

(B) AI and analytics method: the use of AI and analytics techniques such as DL, RL, Digital twin, and LLM-agentic must be central to decision-making;

(C) Role and collaboration: Explicit presence of human-machine interaction, such as decision support, unsupervised automation, supervised automation, and shared control;

(D) XAI and Human factors: Focus on human metrics or explainability.

Additionally, all non-manufacturing/industrial operations domains were excluded, as were jobs in which AI and analytics are not central to support, secondary studies, and those in which there are no traces attributable to categories C or D.

2.3 Screening process: The screening process is summarized in the PRISMA diagram (Figure 1). From the outset, 1.240 studies were identified, from which 197 duplicates were removed based on the DOI and, where necessary, on the title, authors, and year of publication. Subsequently, the remaining 1.043 studies were screened based on criteria A, B, and (C ∨ D), resulting in the exclusion of 596 papers. The search for the full text of the 447 papers via DOI and publication portals led to the exclusion of 133 reports, resulting in 314 full-text searches. Through full-text analysis, a further 137 studies were excluded, according to the following codes and reasons:

- FT-CD0: absence of elements relating to cluster C or D, even in the presence of A and B (130 studies);
- FT-B0: AI and analytics not central to decision-making (3 studies);
- FT-A0: non-central industrial operations (2 studies);
- FT-S0: secondary studies (2 studies).

The final screening process yielded a dataset of Z = 177 searches, and all possible ambiguities were resolved using the definitions in Table 1.

2.4 Coding scheme: The 177 studies were analyzed and coded according to a main category logic (only one value per field) to obtain a quantitative summary. Table 1 shows the coding scheme used.

Table 1 - Coding scheme

Scheme	Coding	Description
Domain	Scheduling; Maintenance; Inspection-quality; Process control; Shop floor	The primary operational scope of the application
AI Method	Classic ML; DL; RL; Digital Twin; Hybrid; LLM-Agentic; Optimization	The prevailing AI technology used
Role	Decision support; Shared control; Supervised automation; Unsupervised automation	The role of AI in decision-making compared to humans
Evidence	Simulation, Lab, Pilot, Production	The level of maturity and the validation environment
XAI Modality	None; Textual; Visual-temporal; Attribution; Counterfactual; Example-based	The explanation technique offered to the user
Interactivity	Static; Interactive	Ability for the user to query or influence the model

3. Results: The state of the art on Human-AI collaboration and Explainability in manufacturing operations obtained from the study of 177 research papers led to answers to the Research Questions (RQ1 - RQ4), through a PRISMA flow diagram shown in Figure 1.

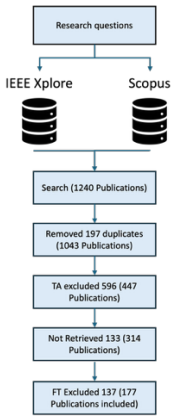


Figure 1 - PRISMA flow diagram

Table 2 - Full-text excluded with reasons

Scheme	Results	Reasons
FT-CD0	130	Autonomous AI without a focus on XAI, human factors and decision making
FT-B0	3	AI not in focus
FT-A0	2	Out of domain
FT-S0	2	Secondary research

3.1 The distribution of Human–AI/XAI literature in the domains of manufacturing operations (RQ1): In the distribution of the 177 studies analyzed, a concentration was observed in Maintenance (n = 75; 42.4%) and Inspection–Quality (n = 52; 29.4%). Scheduling (n = 31; 17.5%), Process Control (n = 10), and Shop Floor (n = 8), with one "unclear" study, were less frequent[15], [16], [17].

On the other hand, in the "AI Methodologies" category, the most common items were Hybrid (n = 48; 27.1%), Deep Learning (n = 45) and classic ML (n = 39), while Digital Twin (n = 15) and LLM-agentic AI (n = 12) are less common, demonstrating that there is increasing research into AI architectures. indicating a growing interest in architectures oriented towards the generation of scenarios and more semantic forms of interaction with the user[18], [19], [20].

3.2 The decision-making roles of AI (RQ2): From the analysis of the 177 studies and through a Domain × Role cross-analysis (Table 3 - Domain × Role cross-analysis), it is possible to observe differences in the implementation of AI depending on the task to be performed. In this regard, the predominant role of decision support (n = 131; 74.0%) highlights how AI is used to produce advice, recommendations, and identify priorities to be validated by people, while the frequency of studies highlighting unsupervised automation (n = 18) is low[21][22]. Going into greater detail, decision support in maintenance is extremely prevalent (n = 65/75; 86.6%)[23], [24], [25], [26], unlike Shared Control[27], which is not observed (n = 0/75), probably due to the technical-operational nature of maintenance activities. Unlike maintenance, in Inspection–Quality, in addition to decision support (n=30), there is also supervised automation (n=9) and unsupervised automation (n = 7), thanks to a greater cross-functionality of the application domain[28], [29][30], [31], [32].

Table 3 - Domain × Role cross-analysis

Operational Domain	Decision support	Shared control	Supervised automation	Unsupervised automation	Total
Maintenance	65	0	3	7	**75**
Inspection-Quality	30	6	9	7	**52**
Scheduling	22	5	0	4	**31**
Process control	7	0	3	0	**10**
Shop Floor	6	2	0	0	**8**
Unclear	1	0	0	0	**1**
Total	131	13	15	18	**177**

3.3 Evidence level and readiness (RQ3): When analyzing the evidence level (Table 4 - Distribution of Evidence Levels; Figure 2 - Maintenance Domain x Evidence levelFigure 3 - Inspection-Quality x Evidence levelFigure 4 - Scheduling x Evidence level), it appears that the majority of research remains confined to the laboratory (n=79) [33] and simulations (n=45) [34], with only a limited number observable directly in production (n=21). Finally, there is mention of pilot (n=31), albeit in limited industrial contexts. Meanwhile, highlighting the level of maturity by domain, maintenance and inspection-quality are the areas of greatest application in production (n=19) and for pilot (n=26), highlighting a limitation in scheduling and process control for all evidence level [35].

Table 4 - Distribution of Evidence Levels

Evidence Level	Results
Lab	79
Simulation	45
Pilot	31
Production	21
Unclear	1
Total	**177**

Figure 2 - Maintenance Domain x Evidence level

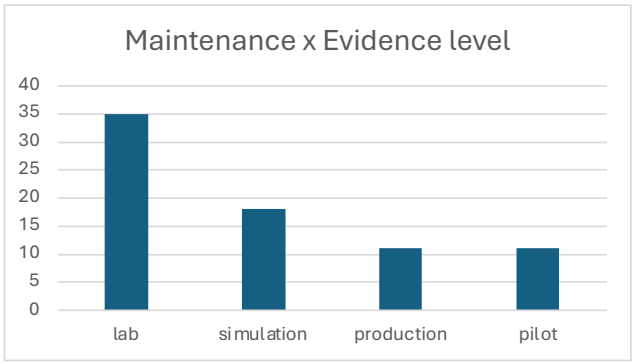


Figure 3 - Inspection-Quality x Evidence level

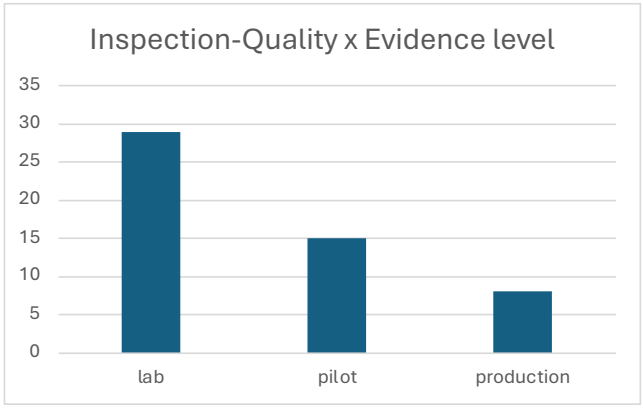
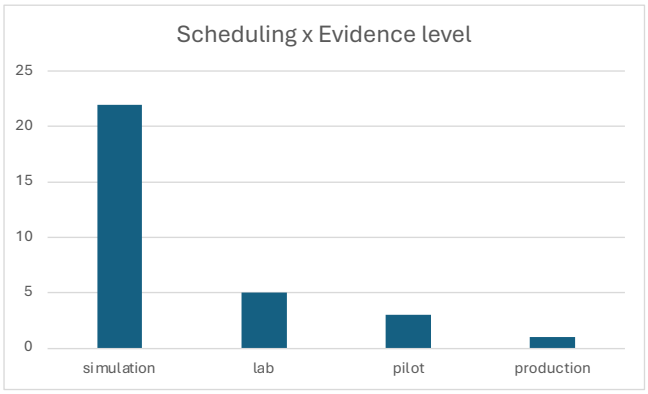
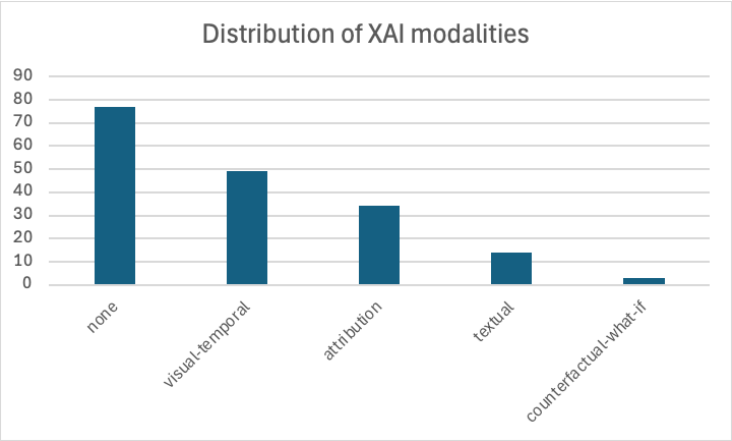


Figure 4 - Scheduling x Evidence level



3.4 XAI modality and Interactivity (RQ4): The analyses highlight a distribution of XAI modalities with n = 77 not specified (none). Despite this, the most prevalent XAI modalities are Visual-temporal (n = 49) [36], [37], [38]and Attribution-based (n = 34) [39], [40], [41], while Textual modalities are much less frequent (n = 14). With regard to interactivity (Table 3), there is roughly parity between Static (n = 93; 52.5%) and Interactive (n = 84; 47.5%) systems. In detail, when crossing XAI modality and interactivity, static and interactive solutions for the XAI modality attribution (n = 29 static vs. n = 5 interactive) resulting in predominantly 'post-hoc' explanations that cannot be queried[42].

Figure 5 - Distribution of XAI modalities



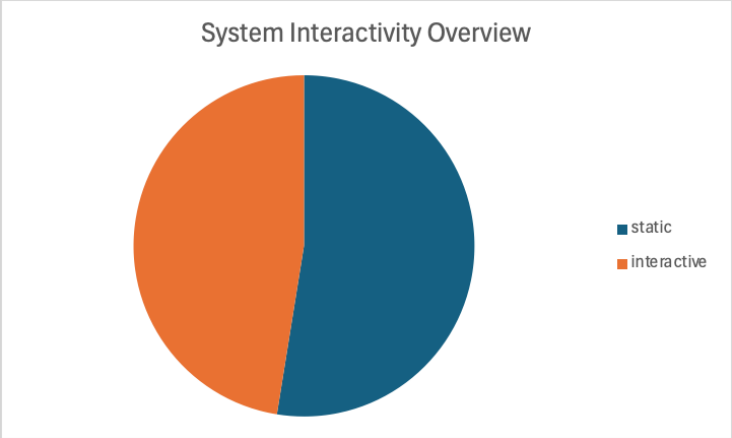


Figure 6 - XAI Modality x Interactivity

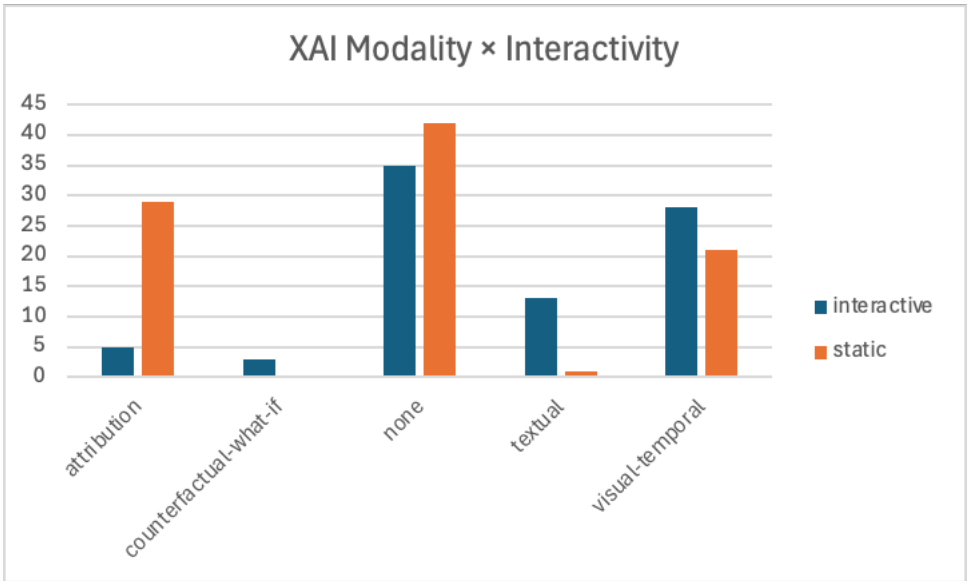
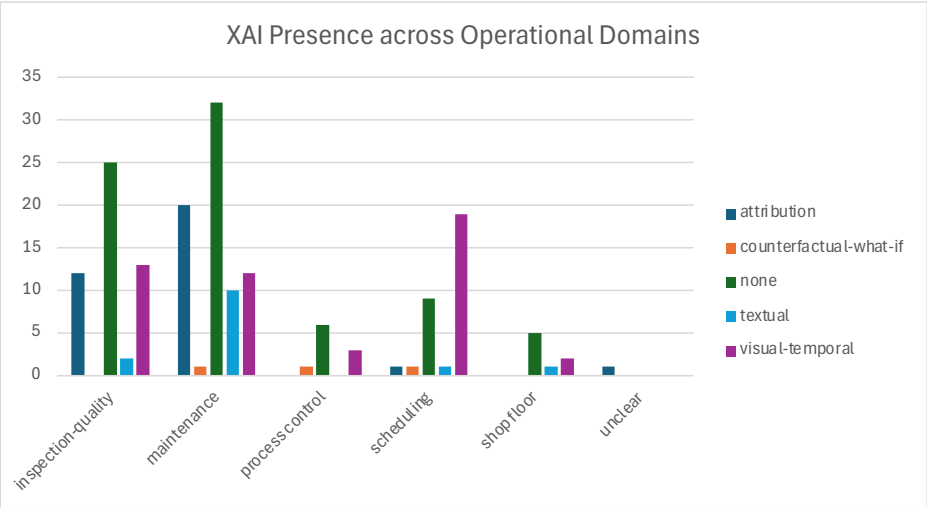


Figure 7 - XAI Presence across operational Domains



4. Discussion: The review of 177 studies provided insight into the current state of human-AI collaboration in industrial operations for the period 2020-2026, highlighting a gap between the maturity of technologies and their integration into industrial processes.

4.1 AI archetypes and domain-awareness: The Domain × Role matrix (RQ2) highlights that there is no single approach to Human-AI collaboration, which can be translated into AI archetypes applicable to different industrial contexts.

(i) "The Oracle" - maintenance: the analysis seems to show that AI acts as a decision support (n=65, 86% of maintenance searches). Following a report from the information systems, AI intervenes to provide support with final human validation. This is reflected in the high costs and operational constraints arising from specific maintenance activities.

(ii) "The filter" - inspection–quality: The repetitive and high-volume nature typical of quality control activities allows for an increase in automation (supervised + unsupervised, n=16, 31%), reducing the burden on people, except for outliers.

(iii) "the co-pilot" - scheduling: despite the limited number of studies identified, it would appear that there is constant human-AI collaboration in scheduling activities (decision support + shared control = 27.81%), due to possible technological constraints and unspoken organizational difficulties on the shop floor.

Because of this, it appears that the role, interface design, and collaboration methods must be adapted according to the domain and operational decision, ensuring greater final control in maintenance and greater interactivity in scheduling.

4.2 The implementation of scheduling: From the intersection of the Domain x Role x Evidence matrices, it can be observed that scheduling, despite its collaborative role, remains confined to non-real contexts (simulation + lab = 27.87%)[43], [44], [45], [46], [47], where only one study highlights applications in real industrial contexts[48]. This may be the result of difficulties arising not only from scheduling's inability to take into account resistance to change among shop floor personnel, but also from its limited integration with real human decision-making factors. Furthermore, another limitation could be dictated by interfaces and human-AI interaction in evaluating, analyzing, and adapting scheduling plans. The results suggest that, in addition to algorithmic progress, a critical factor for readiness may be the design of interfaces and interaction mechanisms that allow the planner to control, verify, and adapt the generated plans[49], [50].

4.3 XAI in industrial operations: In answering RQ4, it emerged that research on explainable AI fails to meet the real needs of companies. The limited number of existing studies highlights the limited current research (n=29 studies). Furthermore, there is a limited number of papers addressing "what-if" questions, where employees are interested in "what happens if I change this element?" situations[51], [52]. The limited number of identified studies may represent a limitation in designing resilient systems suitable for Industry 5.0 contexts[53], [54], [55], [56].

4.4 Management implications: The results show that many applications are more realistic when AI supports the person rather than completely replacing them (decision support research = 131, 74%), especially in contexts where there are operational constraints and high-cost risks[57], [58], [59], [60], [61]. Inspection quality, on the other hand, appears to be the domain most immediately amenable to automation, compared to scheduling, shop floor, and maintenance activities, where investment in interactive tools and greater attention to design would reduce the rejection of solutions perceived as “black boxes” by people, generating resistance to change.

4.5 Research limitations: The research is limited to the Scopus and IEEE Xplore databases and to the English language, covering the period 2020-2026, and the fact that subdominant categories (domain, role, etc.) have been clustered simplifies systems that in practice may be hybrid or multi-domain. Furthermore, rapid developments may require future updates.

5. Conclusion: 177 studies published between 2020 and 2026 were analyzed, revealing an intersection between AI, industrial operations, and human-AI collaborations. In this transition from Industry 4.0 to human-centric Industry 5.0, the maturity of technologies does not translate into instant integration of solutions, due to configurations that are not aligned with operational activities. The results highlight three conclusions:

(i) Asymmetric distribution by domain: The most frequent applications are in maintenance and inspection quality, with decision support as the predominant role. On the other hand, scheduling, despite being the third most frequent domain, has an immature empirical profile.

(ii) Readiness gap. Most studies remain in non-productive contexts, where labs, simulations, and pilots represent 87% of the sample, with a prevalence in scheduling, due to the operational and human complexities of the shop floor.

(iii) XAI and interactivity: Despite the evident importance of developing collaborative systems that maintain a high level of trust, AI systems are highly static (n=93 out of 177 papers). This leads to interpretations and results that passively impact the company employee, who can only be affected by these results.

5.1 Future research agenda: Three priority areas emerge:

(i) From pilot to shop floor: we need to increase the number of studies in industrial contexts (pilot and shop floor), evaluating human-centered dynamics.

(ii) Actionable XAI: Interfaces and integration of AI systems for decision support must evolve from static and homogeneous interfaces to interactive and heterogeneous interfaces based on roles, areas, and responsibilities, based on spatial and temporal constraints.

(iii) LLM and agentic: the growing presence of LLM-agentic applications (n=12, 7%) allows us to study the importance of dynamic person-AI interaction and design.

In conclusion, designing decision-making-oriented systems, with the support of those directly involved in industrial applications, is the key driver for reducing the gap between research and adoption for the various application domains and roles identified.

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