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Archetypes of assistance systems and their impacts on manufacturing performance and job quality

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ABSTRACT

As workplaces become increasingly complex, manufacturing companies must adopt technologies that not only fulfill customer requirements but also prioritize high-quality jobs for production workers. Assistance systems are gaining popularity because they can enhance manufacturing performance and support sufficient job quality. However, there is a lack of detailed insights into the application-specific impact of the systems. This study classifies the use of assistance systems in manufacturing, deriving characteristic archetypes and mapping their impacts through a systematic review of existing literature. Analyzing 56 cases from 40 studies using descriptive and cluster analysis, four main archetypes are identified: (1) manually operated physical execution support for routine assembly tasks, (2) automatically operated and adaptable visual task guidance for routine assembly tasks, (3) automatically operated and adaptive visual support for non-routine diagnostics tasks, and (4) automatically operated and adaptive physical execution support for routine assembly. Findings suggest that these archetypes offer potential benefits and risks for job quality and manufacturing performance. However, their successful use requires careful consideration of role division, task execution capabilities, task support capabilities, and long-term impacts. The current literature on assistance systems needs more longitudinal empirical studies to provide clear guidance for both researchers and industry practitioners.

1. Introduction

As customer demands increase, manufacturers adopt smart technologies to enhance overall equipment effectiveness (OEE) (Frank et al., 2019). However, this results in increasingly complex and demanding workplaces for sections of production workers (Eurofound, 2021; Parker and Grote, 2022), which can potentially lead to reduced mental health and performance (Humphrey et al., 2007). This situation may affect the skills gap in Europe (Eurofound, 2021; European Commission, 2023), especially if smart technology overlooks workers' needs. This scenario fuels Industry 5.0 (I5.0) in the manufacturing industry, which promotes integrating advanced digital technologies while prioritizing job quality (Breque et al., 2021). Job quality includes employment factors like work organization, wages, security, flexibility, skills development, and engagement that enhance job satisfaction and well-being (Green, 2013). Smart technologies are expected to mainly impact job quality's work organization aspects (Parker and Grote, 2022; Waschull et al., 2017). Thus, manufacturing organizations should prioritize production workers' needs and capabilities regarding work organization and smart technology to improve job quality and OEE.

Mark et al. (2021c) define assistance systems as "technical systems that support the specific needs of production workers in the execution of manufacturing tasks such as assembly, decision-making, or maintenance" (p. 228). These systems help compensate for production workers' skill gaps, reduce mental and physical work demands, and promote learning (Longo et al., 2017; Romero et al., 2016a, 2016b). Consequently, these aspects of job quality are linked to decreased absenteeism and turnover intentions, alongside enhancements in performance, well-being, and job satisfaction (Humphrey et al., 2007). Studies also highlight the potential of assistance systems to improve manufacturing outcomes (Mark et al., 2021c; Oestreich et al., 2020; Romero et al., 2016b). Overall, assistance systems appear advantageous in the context of I5.0 and are defined in this study as technical systems that interact directly with production workers, facilitating a new way for performing tasks that either reduce work demands or enhance workers' capabilities, thereby contributing to improved overall performance within the

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manufacturing system.

Assistance systems are promising, yet understanding which smart technologies offer specific manufacturing benefits is limited (Di Pasquale et al., 2022; Mark et al., 2022; Pagliosa et al., 2021). Scholars have highlighted the importance of technology applications, technological design and capabilities (Segura et al., 2021), impact on manufacturing performance (Di Pasquale et al., 2022), and job quality (Bal et al., 2021). However, a comprehensive understanding of these four factors is lacking. In addition, while user experience (UX) can provide valuable insights into the alignment between technology and users' needs, few studies focus on UX in human-machine interaction (Bechinie et al., 2024). Overall, the challenges of effective assistance system use stem from the limited understanding of application-specific impacts on OEE and job quality.

To guide practitioners aiming to adopt assistance systems, Mark et al. (2022) developed a matchmaking methodology for identifying suitable assistance systems for task support that fit the needs and capabilities of the production worker. However, the overview is merely a higher-level data catalogue, and the parameters considered by Mark et al. (2022) do not consider the work organization. This is a significant gap since work organization can enhance or constrain the functionalities and usability of an assistance system. This limitation hinders a meaningful analysis of an assistance system's true value in a specific application (Kleineberg et al., 2017; Pacaux-Lemoine et al., 2017; Virmani and Salve, 2021). Additionally, job quality is often not addressed, resulting in an incomplete mapping of the impacts of an assistance system. This highlights the need for an assistance system categorization that includes the capabilities and applications, along with the impact on job quality and OEE, to provide a more comprehensive view of their effects.

This study tackles this challenge by identifying assistance system archetypes in manufacturing applications and mapping their impact on OEE and job quality through a systematic literature review (SLR). It aims to support more effective use of manufacturing assistance systems through an overview of archetypes with their capabilities, use, benefits, and points of attention. Consequently, this study addresses two key questions: How can the literature be categorized into application-level archetypes of assistance systems? Which assistance system archetypes lead to what impact on job quality and OEE?

To answer the research questions, this paper focuses on assistance capabilities and application as design variables. Job quality and OEE are integrated as outcome variables, while UX is considered a potential influencing factor. The resulting scope of this paper is visualized in Fig. 1.

The remainder of this paper is structured as follows. Section 2 describes a theoretical framework for analyzing the archetypes of assistance systems in manufacturing and their impact on OEE and job quality. Section 3 details the methodology for the SLR. Section 4 presents the results of the SLR. Furthermore, section 5 discusses the implications of these results and suggests avenues for future research. Finally, section 6 concludes this research.

2. Theoretical framework

This chapter provides the theoretical basis for categorizing assistance systems and their manufacturing applications, as well as the variables for mapping the impact on job quality and OEE.

2.1. Design and capabilities

In this study, the characteristics of assistance system capabilities are categorized based on (1) type of assistance, (2) functionality types, (3) human-machine interface, (4) form of information input, (5) form of information output, and (6) level of assistance adaptability. Type of assistance refers to the enhancement and augmentation of the specific capabilities of production workers that an assistance system aims to provide.

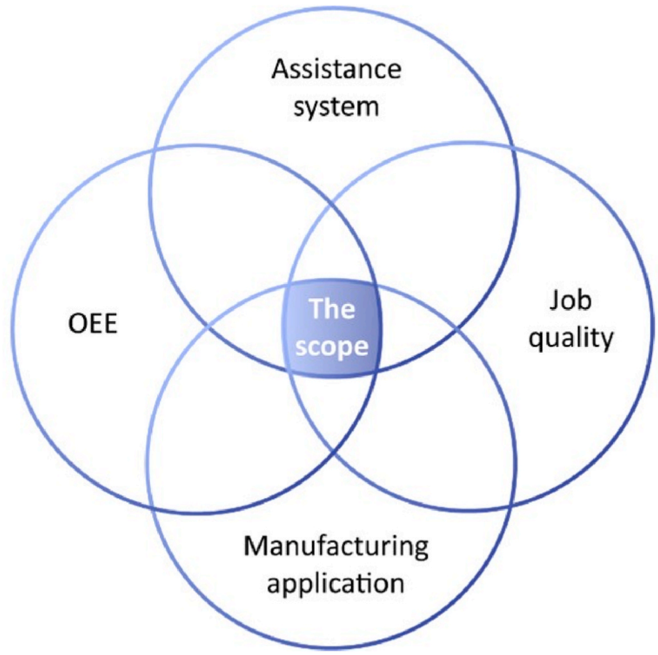


Fig. 1. The scope of this paper.

The **type of assistance** can be categorized into sensorial, cognitive, and physical (Romero et al., 2016b). To provide such assistance, **the systems** can have observation, orientation, decision-making, and action **functions** (Osinga, 2007). Sensorial support utilizes observation functions, including data collection and information feedback, to aid production workers in gathering and processing data from their environment (Osinga, 2007; Romero et al., 2016a). Romero et al. (2016a) classify observation functions as: '(a) the physical ability to collect data (by vision, smell, sound, touch, vibration), and (b) the selective perception where a small percentage of the data enters short-term memory for processing' (p. 7). Examples include position tracking systems and RGB cameras for data collection, as well as warning lights and haptic gloves for feedback (Mark et al., 2021c). Sensorial information is crucial for supporting cognitive tasks such as orientation and decision-making, requiring production workers to filter relevant information for these tasks (Simon and Frantz, 2003). Cognitive assistance enhances workers' capabilities in these orientation and decision-making tasks, such as perceiving, memorizing, deciding, planning, and diagnosing through technology (Romero et al., 2016a). For instance, a cognitive assistance system can supply digital work instructions for novice workers (Mark et al., 2021c). Finally, physical tasks involve 'any bodily movements produced by skeletal muscles that require energy expenditure' (Romero et al., 2016a, p. 6). Assistance systems offer physical support with action functions (e.g., handling, moving, assembling), non-functional properties (e.g., speed, strength, precision, dexterity), tailored to maturity and expertise levels (Romero et al., 2016a).

The morphology of the assistance system can be further categorized through the **human-machine interface** (HMI) that the assistance system uses. A unimodal design means that a specific channel is available for receiving information, primarily visual, and another for entering information, mostly manual. Multimodal interfaces, however, consider various input and output modalities such as text and image data (Hinrichsen et al., 2016; Späker et al., 2021). The **form** in which the **information is entered** into the assistance system can be manually via actuators, verbally via voice control, gesturing via a tracking system, or automatically via sensors (Hinrichsen et al., 2016). Additionally, the **system's output** can be visual, optical, auditory, or via physical movements (based on Hinrichsen et al., 2016; Späker et al., 2021).

Finally, the extent to which the assistance system can **adapt** its **assistance** can vary in fixed, customized, adaptable, and adaptive assistance (Wandke, 2005).

Adaptability levels derive from three possibilities for adapting an assistance system: by the designer, the user, or the system itself. Adaptation can occur beforehand or in real time. Fixed assistance provides the same support for all users, while customized assistance is optimized for a specific context, task, and user group during the design phase. Adaptable assistance systems adjust according to user preferences, tasks, and situations. Lastly, adaptive assistance systems automatically adjust based on the user, task, and situation (Wandke, 2005).

2.2. Manufacturing application

In this section, the application of the assistance system is specified through the following characteristics: (1) type of manufacturing process, (2) function of the manufacturing process, (3) type of supported task, (4) function of the assistance system, (5) level of automation, (6) range of support, (7) capabilities for task execution, and (8) capabilities for task support.

Manufacturing process types can be manual or automated. Manual processes refer to a set of tasks that production workers execute independently, without assistance from automated systems. Automated processes involve machinery and technology that perform tasks or can be utilized to perform tasks with minimal human intervention. Manufacturing processes (manual and automated) are categorized into single, batch, and mass manufacturing (Oberhausen and Plapper, 2015). These **processes** serve specific **functions**, which include machining, assembling, finishing, testing, packing, forming, casting/molding, and other operations (adopted from Wemmerlov and Johnson, 1997). **Types of** supported **tasks** within these operations can be further classified into routine manual, non-routine manual, routine cognitive, and non-routine cognitive tasks (Cimini et al., 2023). **Assistance systems** can utilize these **functions** to support ergonomics, physical execution, sensorial monitoring, work instruction guidance, decision support, and diagnostics support.

As the worker and the assistance system jointly execute tasks, they are mutually dependent on what the other party does over a sustained sequence of actions (Johnson et al., 2014). These joint activities can be divided into monitoring, generating, selecting, and implementing roles. Implementation indicates which party executes the chosen action whilst monitoring, generating, and selection roles support the execution of the task (Endsley and Kaber, 1999). **Level of automation** refers to the extent to which these roles are automated by assistance systems (Endsley and Kaber, 1999). Higher levels of automation can result in unwanted changes in social and psychological (both emotional and cognitive) demands on users, if not appropriately managed (Patel et al., 2018). For instance, both parties require greater interaction capabilities to jointly execute tasks (Johnson et al., 2014). Endsley and Kaber (1999) identified ten levels of automation ranging from manual operations to full automation. Following the definition of this study, an assistance system should at least support the production worker in one of the four functions of a task, and the production worker should always remain in control of the selection role of a task. This means that level two (action support) up to level seven (rigid system) are adopted to exemplify the extent to which the assistance system automates certain tasks through its assistance. Furthermore, it is then specified if the **range of** support provided by the deployed assistance system entails a partial part or the total of the specified task (Hinrichsen et al., 2016; Späker et al., 2021).

To assess if the chosen level of automation and range of support is a suitable application, insights into the capabilities for effective execution and support of the joint activities are required. The **capabilities for task execution** are the abilities to perform the task of interest and are categorized as I can do it all, I can do it all but my reliability is $<$100 %, I can contribute but need assistance, I cannot do it (Johnson et al., 2014). The **capabilities for task** support are the necessary observability, predictability, and directability functionalities to support the activity execution in the chosen task (Johnson et al., 2014). These capabilities are categorized as my assistance could improve efficiency, my assistance could improve reliability, my assistance is required, and I cannot provide assistance (Johnson et al., 2014). Overall, this set of categories provides input on whether the current task division is fitting to the mutual dependencies between the worker and the assistance system. If not, this could potentially lead to a negative impact of assistance systems on job quality and OEE (Johnson et al., 2014).

In summary, Table 1 offers the analysis framework for categorizing the design and capabilities of the assistance system and the context in which it is applied.

Table 1
Categorization framework for analyzing assistance systems in manufacturing.

	Feature	Category								
Design and capabilities	Type of assistance	Sensorial	Cognitive	Physical						
	Functionality type	Observe	Orient	Decide	Act					
	HMI	Unimodal	Multimodal							
	Form of information input	Manual (via actuators)	Verbal (voice-control)	Gesturing (tracking system)	Automatic (sensory)					
	Form of information output	Visual/optical	Auditory	Physical movement						
	Level of adaptability	Fixed assistance	Customized assistance	Adaptable assistance	Adaptive assistance					
Manufacturing application	Type of manufacturing process	Manual single manufacturing	Manual batch manufacturing	Manual mass manufacturing	Automated single manufacturing	Automated batch manufacturing	Automated mass manufacturing			
	Function of the manufacturing process	Machining	Assemblin g	Finishing	Inspection /testing	Packing	Forming	Casting/ molding	Maintenance	Other
	Type of supported task	Routine manual	Non-routine manual	Routine cognitive	Non-routine cognitive					
	Function of the assistance system	Workplace monitoring	Work instructions guidance	Decision support	Diagnostics support	Ergonomics support	Physical execution support			
	Level of automation	2. Action support	3. Batch processing	4. Shared control	5. Decision-making	6. Blended decision-making	7. Rigid system			
	Range of support	Partial work	Total work							
	Capabilities for task execution	I can do it all	I can do it all, but my reliability is < 100%	I can contribute, but I need assistance	I cannot do it					
	Capabilities for task support	My assistance could improve efficiency	My assistance could improve reliability	My assistance is required	I cannot provide assistance					

2.3. Overall equipment effectiveness

OEE evaluates the effectiveness of manufacturing equipment by identifying production losses related to performance, quality, and availability (Muchiri and Pintelon, 2008). In this study, it not only indicates the equipment's effectiveness but also reflects the production worker's effectiveness in the manufacturing process. Consequently, performance, quality, and availability losses are supplemented by metrics from the ISO, 2014 standard, which suggests 34 industry-neutral KPIs relevant for either manual, automated, or both production types. Table 2 summarizes these metrics, illustrating how each metric influences OEE according to its definitions.

2.4. Job quality

Work organization factors affecting job quality are structured through task division, detailing how and why tasks are executed. This process, called work design, can be analyzed using work design characteristics encompassing: motivational characteristics (individual job components), social characteristics (interactional components), and work context characteristics (contextual components) (Eurofound, 2017; Hart, 2006; Hart and Staveland, 1988; Humphrey et al., 2007). To assess the impact on job quality, this study lists definitions of the included work design variables and their effect on job quality indicators such as worker attitudes and well-being in Table 3 below (Cazes et al., 2015).

2.5. User experience

This study characterizes UX through the affective, emotional, effective, efficient, and satisfaction-related results of production workers' interactions with assistance systems (Sauer et al., 2020). While frequently utilized, the user-centered approach of UX methods complicates their universal application. Nevertheless, narrower concepts have been identified as partial indicators of UX (Laugwitz et al., 2008; Sauer et al., 2020). This research assesses system usability (Brooke, 1996), ease of use (Venkatesh and Bala, 2008), usefulness (Venkatesh and Bala, 2008), and satisfaction with technology (Demers et al., 2002) as specific concepts that contribute to UX.

Table 2
Overall Equipment Effectiveness metrics and their effect (based on ISO 22400:2014).

	Metric	Description	Effect on OEE
Availability	Availability rate	Proportion of total production time a machine can be used.	Increase
	Major stoppage time	Total time during which manufacturing is interrupted by a major machine malfunction lasting over 10 min.	Reduce
	Equipment failure downtime	Total unplanned downtime due to equipment failure.	Reduce
	Replacement time	Total downtime due to routinely replacing equipment.	Reduce
	Set-up time	The time required to change a process or a machine from one product or operation to another.	Reduce
Performance	Cycle time	Total time between the start and end of the manufacturing processes.	Reduce
	Idle time	Total time when manufacturing is not occurring without a malfunction as a cause.	Reduce
	Minor stoppage time	Total time during which manufacturing is interrupted by a minor temporary malfunction of the machine.	Reduce
	Task completion time	Total time spent on a manufacturing task.	Reduce
	Productivity	Manufactured product quantity over a specified period.	Increase
	Productivity variance	Variance and distribution in time spent on a task.	Reduce
Quality	Quality variance	Variance and distribution of errors made in a task.	Reduce
	Quality rate	Percentage of products failing to meet quality requirements due to faulty task execution.	Reduce
	Error rate	Percentage of errors made by production workers affecting product quality.	Reduce

Table 3
Work design characteristics and their effect on Job Quality (JQ) indicators.

	Variable	Definition	Effect on JQ
Motivational characteristics	Work scheduling autonomy	The freedom to control the schedule and timing of work.	Increase[1]
	Work methods autonomy	The freedom to control which methods and procedures are utilized.	Increase[1]
	Decision-making autonomy	The freedom to make decisions at work.	Increase[1]
	Skill variety	The knowledge and skills necessary to perform a job.	Increase[1]
	Task variety	The degree to which an individual performs various tasks at work.	Increase[1]
	Task significance	The extent to which a job impacts others' lives.	Increase[1]
	Task identity	The extent to which an individual can complete a whole piece of work.	Increase[1]
	Feedback from the job	The extent to which a job imparts information about an individual's performance.	Increase[1]
	Information processing	The extent to which the job necessitates an incumbent to focus on and manage information.	Varying[1]
	Job complexity	The extent to which a job is multifaceted and difficult.	Varying[1]
	Specialization	The extent to which the job requires specific knowledge and skills.	Varying[1]
	Problem solving	The extent to which a job requires producing unique solutions or ideas.	Varying[1]
	Perceived cognitive task load	The extent to which mental and perceptual activities are perceived as demanding, complex, and exacting.	Reduce[23]
Social characteristics	Interdependence	The extent to which a job depends on others' work.	Increase[1]
	Feedback from others	The extent to which other organisational members provide performance information.	Increase[1]
	Social support	The extent to which a job provides opportunities for assistance and advice from supervisors or co-workers.	Increase[1]
	Interaction outside the organization	The extent to which a job requires communication with people external to the organisation.	Increase[1]
Work context characteristics	Physical demands	The amount of physical activity or effort necessary for a job.	Reduce[123]
	Work conditions	The extent to which factors like health hazards, temperature, and noise in the work environment are perceived as satisfactory.	Increase[1]

Note. Indication of sources: [1] Humphrey et al. (2007), [2] Andersen et al. (2016), [3] Hertzum (2022).

3. Methodology

An SLR methodology was adopted to identify assistance system archetypes and their impact on job quality and OEE (Page et al., 2021a, 2021b).

3.1. Search strategy

To execute the SLR, the scope and keywords were determined using a thesaurus, experts, and a scoping search to avoid missing important synonyms. To meet the study's goal, the search strategy should consider smart technology, its application, the user, the manufacturing context, and an outcome measure. Five scoping searches were conducted in Scopus with these terms: (1) assistance systems, (2) task support, (3) production worker, (4) manufacturing, and (5) performance indicator. Results from these scoping searches were used to subsequently refine keywords into synonyms, narrower and broader terms. These synonyms, narrower and broader terms were further refined by checking with a thesaurus and experts. This led to the application of the following Boolean operations.

((TITLE-ABS-KEY ("assistance system" OR "human centered technology" OR "human centric technology" OR "exoskeleton" OR "cobot" OR "robot" OR "collaborative robot" OR "chair support system" OR "smart glasses" OR "augmented reality" OR "virtual reality" OR "mixed reality" OR "smart watch" OR "smart glove" OR "big data" OR "data analytics" OR "smart wearable" OR "artificial intelligence" OR "machine learning" OR "internet of things" OR "sensor" OR "IoT" OR "cloud" OR "intelligent personal assistant" OR "smart personal assistant" OR "automated guided vehicle" OR "3D printing" OR "additive manufacturing" OR "digital twin" OR "Industry 4.0″ OR "smart technology" OR "Industry 5.0″ OR "cyber physical system") AND TITLE-ABS-KEY ("manufacturing cell" OR "fabrication cell" OR "production cell" OR "machine cell" OR "work cell" OR "robotic cell" OR "machining cell" OR "welding cell" OR "assembly cell" OR "cellular manufacturing" OR "workstation" OR "manufacturing") AND TITLE-ABS-KEY ("production worker" OR "operator" OR "technician" OR "worker") AND TITLE-ABS-KEY ("operator support" OR "task support" OR "task assistance" OR "operator assistance" OR "digital support" OR "digital assistance" OR "cognitive assistance" OR "cognitive support" OR "sensorial assistance" OR "sensorial support" OR "physical assistance" OR "physical support" OR "sensor-based assistance" OR "sensor-based support" OR "sensor based assistance" OR "sensor based support" OR "decision support" OR "digital working instructions" OR "dwi" OR "projection-based assistance" OR "projection based assistance" OR "projection-based support" OR "projection based support" OR "remote assistance" OR "remote support" OR "laser support" OR "human-robot collaboration" OR "operator 4.0″ OR "operator 5.0″ OR "smart working" OR "human-machine collaboration" OR "human-technology collaboration" OR "augmentation") AND TITLE-ABS-KEY ("manufacturing performance" OR "performance indicator" OR "KPI" OR "defect rate" OR "takt time" OR "first pass yield" OR "productivity" OR "cycle time" OR "first time through rate" OR "process variation" OR "task time" OR "waste reduction" OR "load time" OR "changeover time" OR "distance covered" OR "error reduction" OR "accessibility" OR "technology utilization rate" OR "energy efficiency" OR "resource efficiency" OR "OEE" OR "overall equipment effectiveness" OR "machine utilization" OR "throughput time" OR "makespan" OR "cognitive load" OR "worker safety" OR "worker health" OR "workload" OR "incident rate" OR "job satisfaction" OR "skills" OR "competencies" OR "expertise" OR "employability" OR "quality rate" OR "mental demand" OR "physical demand")))

Fig. 2 shows keyword co-occurrence in the search string using VOSviewer (Van Eck and Waltman, 2023). The lines indicate related

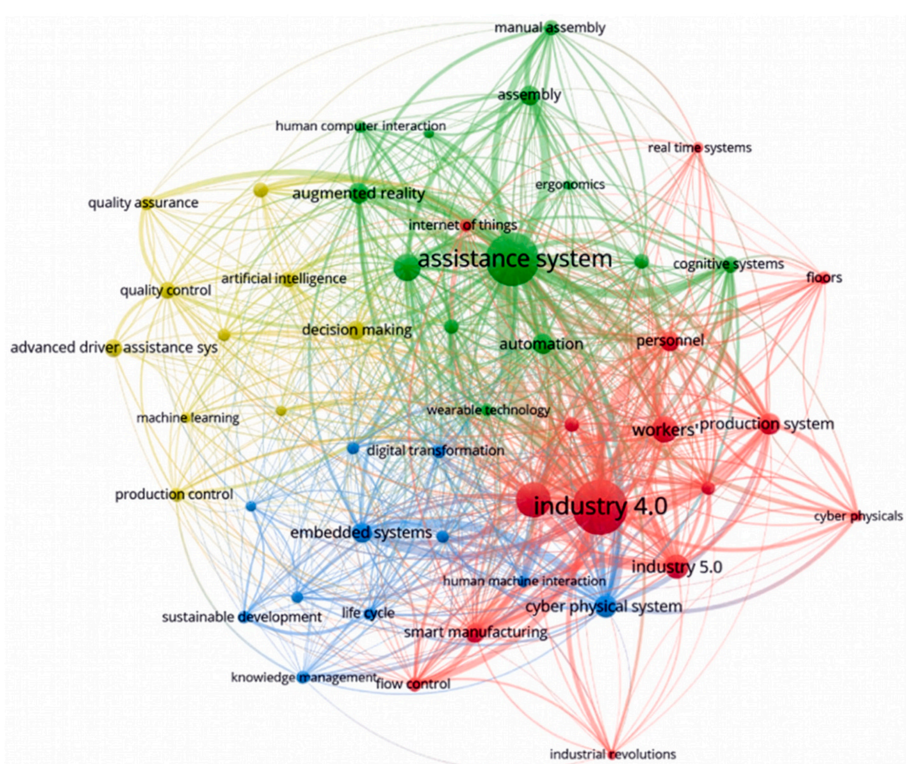


Fig. 2. Co-occurrence map of identified keywords.

concepts in the search strings, and their proximity suggests a strong co-occurrence. Four clusters emerge: assistance systems (green), manufacturing applications of assistance systems (yellow), industrial paradigms (red), and human-machine paradigms (blue).

The search string was used to query relevant databases. Scopus, Web of Science, and IEEE Xplore were chosen for their focus on organizational design science and industrial manufacturing engineering. Other databases were excluded because they were irrelevant or had limited added value.

3.2. Selection process

This step followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) to select relevant articles (Page et al., 2021a, 2021b). Steps included (1) removing duplicates, (2) abstract screening to eliminate irrelevant articles, and (3) full-text screening to exclude studies that did not meet the inclusion criteria. The review criteria were that the article:

1. Had full text available in English;
2. Was published between 2015 and 2024 (ten years);
3. Was peer reviewed.
4. Concerned production workers. Production workers are defined as '*those who are directly involved in the execution of operational processes of manufacturing*';
5. Focused on assistance systems in a manufacturing setting. Manufacturing is defined as '*the conversion of raw materials into physical products by production workers*';
6. Described technology that fulfilled the criteria of an assistance system, as defined in this study;
7. Categorized assistance systems, or made it possible to categorize assistance systems;
8. Contained results that describe the effect that an assistance system has on job quality and/or OEE;
9. Specified the effect of an assistance system compared to a situation without an assistance system.

A log, available upon request, was maintained for all full-text screened articles, indicating which inclusion criteria were met and which were not. This evaluation resulted in 40 articles being selected for analysis. Fig. 3 provides a visual representation of the selection process.

3.3. Data extraction and analysis

The SLR used deductive coding to analyze selected articles. The study used Tables 1–3 as a codebook to categorize the capabilities, applications, and impact of assistance systems in an Excel file (available upon request). Several studies featured multiple assistance systems with distinct capabilities and applications, resulting in 56 cases identified from 40 studies. See Table 4 for a selection of relevant sample characteristics.

A hierarchical and k-means analysis determined assistance system

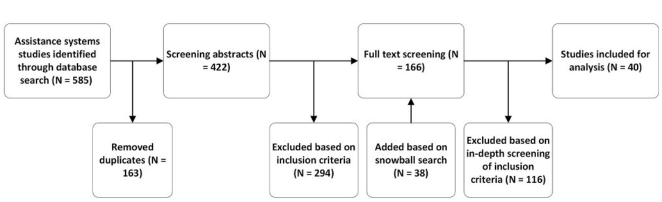


Fig. 3. Review process of the systematic literature review.

Table 4
Sample distribution.

Descriptive variable	Categories	Proportion of sample (n = 56)
Type of study	Experimental study	46 (82,1 %)
	Case study	10 (17,9 %)
Participants	Test subjects	37 (66.1 %)
	Production workers	19 (33,9 %)
Type of manufacturing process	Described	19 (33,9 %)
	Not described	37 (66,1 %)
Capabilities for task execution	Described	24 (42,9 %)
	Not described	32 (57,1 %)
Capabilities for task support	Described	21 (37,5 %)
	Not described	35 (62,5 %)
OEE - Availability	Measured	4 (7,1 %)
	Not measured	52 (92,9 %)
JQ – Social work characteristics	No variable measured	56 (100 %)
User experience	Measured	10 (17,9 %)
	Not measured	46 (82,1 %)

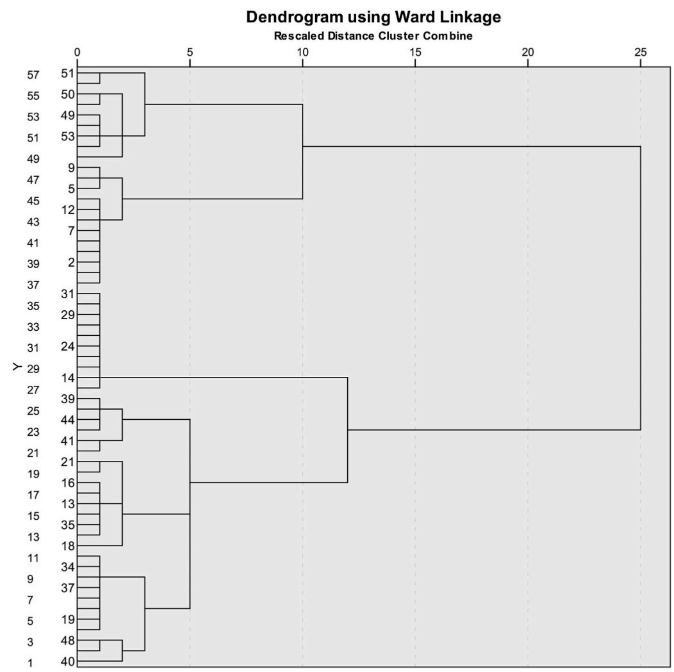


Fig. 4. Dendrogram for identifying the number of archetypes.

archetypes and their characteristics based on capabilities and application variables. The range of support, capabilities for task execution, capabilities for task support, and the type of manufacturing process were excluded due to missing values. Categorical variables were one-hot encoded according to the predefined analysis framework (using IBM SPSS). To enable comparability with other variables, two ordinal variables were converted into Z-scores. Furthermore, four clusters were identified using hierarchical cluster analysis with Ward's method and Euclidean distance measure. The number of clusters was chosen based on the dendrogram in Fig. 4, aiming to maximize the clusters' robustness and minimize heterogeneity within the clusters. Finally, the values were grouped into four clusters using k-means cluster analysis.

To assess the impact of assistance systems on job quality and OEE, ordinal variables were encoded into a three-point scale: '-1' and '1' indicate 'decreases' or 'increases' respectively, while '0′ shows no significant effects. Similarly, ordinal UX variables were encoded on a five-point scale where '0' to '5' respectively refer to low, low/moderate, moderate, moderate/high, and high scores. Next, averages, standard deviations, and case counts were utilized to map the impact of each archetype. For an outcome category to be recognized as significant in the mapping, it must have at least five cases linked to a specific archetype. Significant results were subsequently examined at the variable level, showing each category's proportions of outcome variables and standard deviation. A case count of five indicates noteworthy outcomes at the variable level.

4. Results

Results indicate insights aligned with this paper's two goals: (1) assistance system archetypes in manufacturing applications, and (2) mapping their impact on job quality and OEE.

4.1. Deriving assistance system archetypes in manufacturing applications

Four assistance system archetypes emerge from the SLR, namely (1) Manually operated physical execution support for routine assembly tasks, (2) automatically operated and adaptable visual task guidance for routine assembly tasks, (3) automatically operated and adaptive visual support for non-routine diagnostics tasks in inspection/testing processes, and (4) automatically operated and adaptive physical execution support for routine assembly tasks. Archetypes 2 and 3 predominantly provide cognitive assistance, and archetypes 1 and 4 provide physical support. Archetypes 2 and 3 have similar capabilities, apart from the differing adaptability levels they can offer. Most notably, the main difference lies in the application, as archetype 2 is applied for task guidance and routine assembly tasks, whilst archetype 3 assists with non-routine diagnostics in inspection and testing processes. Moreover, archetypes 1 and 4 have similar application domains but differ in capabilities. Archetype 1 provides fixed action support and requires manual operation, and archetype 4 accommodates adaptable action support due to its observation, orientation, and decision functionalities.

Although sensorial assistance is identified as a separate assistance type in the literature, they are infrequently researched and commonly integrated with cognitive or physical assistance systems. More specifically, observation functionalities are regularly integrated with assistance systems' orientation, decision-making, and action functionalities. Additionally, these capabilities are combined with the ability to automatically administer information through sensors and an increased level of adaptability of the assistance systems. Finally, support for non-routine manual tasks or workplace ergonomics does not come forth in one of the four archetypes. Table 5 summarizes the four assistance system archetypes with their respective capabilities and applications.

4.2. Mapping the impact of assistance systems archetypes on OEE and job quality

This study found no articles that examined how assistance systems influence the social attributes of jobs. Furthermore, the cases evaluating UX indicators for any specific archetype were limited to no more than five. Consequently, Fig. 5 illustrates how the four types of assistance

Table 5
Assistance system archetypes in manufacturing applications.

	Archetype 1	Archetype 2	Archetype 3	Archetype 4
# of cases	12	26	7	11
Studies	(Bosch et al., 2016; Bouillet et al., 2023; Gervasi et al., 2022; Gualtieri et al., 2020; Lagomarsino et al., 2023; Mouhib et al., 2024; Moyon et al., 2018; Puttero et al., 2024; Zigart et al., 2023)	(Blattgerste et al., 2017; Bosch et al., 2020; Brizzi et al., 2017; Eder et al., 2020; Funk et al., 2015a; Funk et al., 2017; Mark et al., 2021b; Papetti et al., 2023; Riedel et al., 2021; Schuster et al., 2021; Simões et al., 2021; Smith et al., 2020; Syberfeldt et al., 2015; Techasarntikul et al., 2020; Tong et al., 2024; Yang et al., 2020; Wilschut et al., 2019)	Eimontaite et al. (2022); Hoerner et al., 2023; Mietkiewicz and Madsen, 2024; Park et al. (2020); Papavasileiou et al. (2024); Traub et al. (2018); Vukicevic et al. (2019)	(Bettoni et al., 2020; Chan et al., 2022; Chu and Liu, 2023; Huysamen et al., 2018; Kim et al., 2019; Lagomarsino et al., 2023; Murali et al., 2020; Pérez et al., 2020; Puttero et al., 2024)
Feature	**Design and capabilities**			
Assistance type	Physical	Cognitive	Cognitive	Physical
Functionalities	Act	Observe Orient Decide	Observe Orient Decide	Observe Orient Decide Act
HMI	Unimodal	Multimodal	Multimodal	Multimodal
Input type	Manual	Automatic	Automatic	Automatic
Output type	Physical movement	Visual/optical	Visual/optical	Physical movement
Adaptability level	Moderately low [-,86]	Moderate [-,25]	High [1,16]	Moderately high [,79]
Feature	**Manufacturing application**			
Man. Process function	Assembly	Assembly	Inspection/testing	Assembly
Supported task type	Routine manual	Routine cognitive	Non-routine cognitive	Routine manual
Function of assistance system	Physical execution support	Work instructions guidance	Diagnostics support	Physical execution support
Automation level	Low [-1,55]	Moderately high [0,44]	High [1,07]	Moderate [-,03]

Note. Adaptability and automation levels indicate how the value deviates from the variable mean.

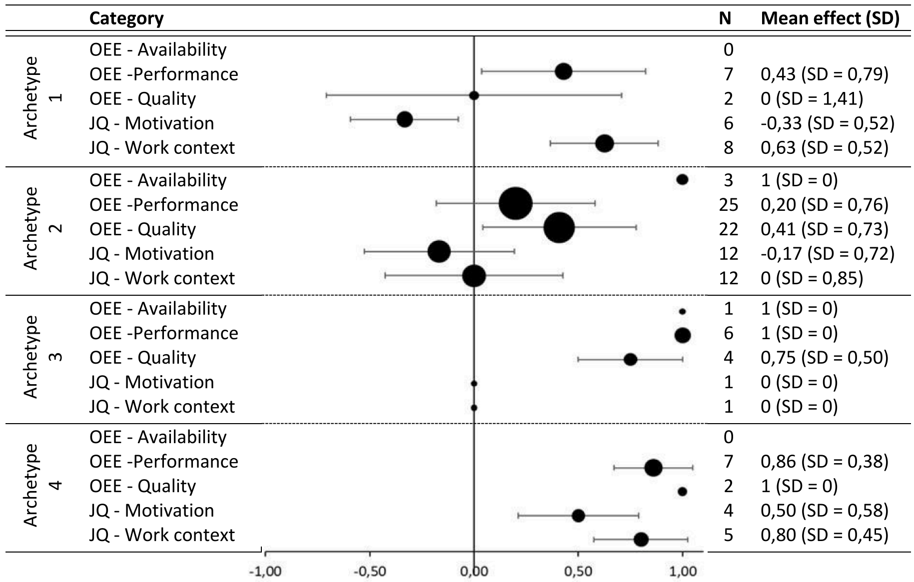


Fig. 5. The impact of assistance system archetypes on job quality and OEE categories.
Note. The size of the bells indicates the number of cases studied for the outcome category of interest.

systems affect the availability, performance, and quality of manufacturing equipment, along with the motivational and work context characteristics of a job.

Archetypes 1 and 4 positively affect work context features. While archetype 4 consistently enhances performance, the effect of archetype 1 is positive but inconsistent. Variability in archetype 1's performance outcomes may arise from different studies and their specific outcome variables. For instance, Bouillet et al. (2023) found negative impacts on idle time and productivity, while other studies showed positive outcomes in cycle time (Gualtieri et al., 2020) and task completion time (Puttero et al., 2024). Furthermore, archetype 1 shows potential risk for motivational work characteristics as the cognitive demands, frustration levels, and temporal demands tend to increase.

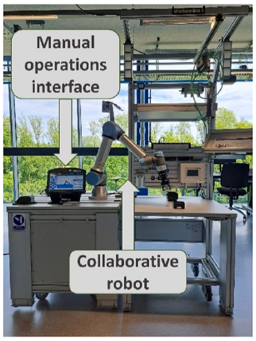
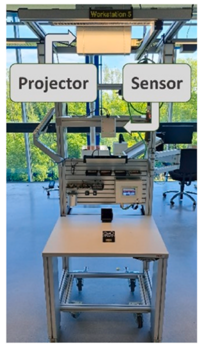
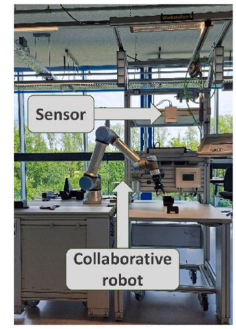
Archetypes 2 and 3 seem to have a slight positive effect on quality. Notably, although both archetypes have similar capabilities, their effect on performance differs (mean difference = 0,8). Archetype 2 shows a slight increase in performance, whilst archetype 3 shows convincing evidence for a performance increase. This performance increase is typically achieved through task completion time reductions. A closer look at the underlying variables for archetype 2's varying effects on performance shows that the effects on task completion time raise questions about the underlying reasons. Moreover, archetype 2 shows varying, yet negative average effects on motivational work characteristics and varying effects on work context characteristics. This indicates a risk of increasing mental demands and frustration among workers who use archetype 2. Finally, the varying yet mostly positive effects of archetype 2 are present at the predominant outcome variable 'error rate'.

Further analysis reveals outcome variables by category. First, task completion time is commonly used as a performance variable. Second, variables that stem from the NASA TLX are the most used indicators for motivational and work context outcomes. Finally, error rates serve as the main measure for OEE quality in archetype 2. Findings on variable-level outcomes of assistance system archetypes can be found in Table 6 below, and a summary of the findings is given in Table 7.

Table 6
Variable-level outcomes of assistance system archetypes.

Archetype	Variable	n	Proportion	Mean effect	SD
Archetype 1	Task completion time	4	50,00 %	0,50	0,58
	Cycle time	2	25,00 %	1,00	0,00
	Productivity	1	12,50 %	−1,00	
	Idle time	1	12,50 %	−1,00	
	Subtotal OEE – performance	8	100 %		
	Frustration level	4	36,36 %	−0,25	0,50
	Stress level	1	9,09 %	−1,00	
	Mental workload	6	54,55 %	−0,33	0,52
	Subtotal JQ – motivation	11	100 %		
	Temporal demands	4	23,53 %	0,00	0,00
	Physical demands	8	47,06 %	0,63	0,52
	Subtotal JQ – work context	12	100 %		
Archetype 2	Task completion time	21	87,50 %	0,10	0,77
	Cycle time	1	4,17 %	1,00	
	Productivity	2	8,33 %	0,50	0,71
	Subtotal OEE – performance	24	100,00 %		
	Error rate	20	86,96 %	0,45	0,76
	Task success	2	8,70 %	0,50	0,71
	Product quality	1	4,35 %	0,00	
	Subtotal OEE – quality	23	100,00 %		
	Frustration level	9	33,33 %	−0,33	0,71
	Mental workload	12	44,44 %	−0,42	0,79
	Task complexity	3	11,11 %	0,00	0,00
	Feedback from the job	3	11,11 %	1,00	0,00
	Subtotal JQ – motivation	27	100,00 %		
	Temporal demands	9	42,86 %	−0,33	0,71
	Physical demands	12	57,14 %	0,00	0,85
	Subtotal JQ – work context	21	100,00 %		
Archetype 3	Task completion time	3	50,00 %	1,00	0,00
	Cycle time	1	16,67 %	1,00	
	Productivity	2	33,33 %	1,00	0,00
	Subtotal OEE – performance	6	100,00 %		
Archetype 4	Task completion time	3	42,86 %	0,67	0,58
	Cycle time	1	14,29 %	1,00	
	Productivity	3	42,86 %	1,00	0,00
	Subtotal OEE – performance	7	100,00 %		
	Physical demands	5	100,00	0,80	0,45
	Subtotal JQ – work context	5	100,00 %		

Table 7
Overview of assistance system archetypes and their impact.

	Archetype 1: Fixed physical support for routine tasks in assembly	Archetype 2: Adaptable visual task guidance for routine tasks in assembly	Archetype 3: Adaptive visual diagnostics support for non-routine tasks in inspection/testing	Archetype 4: Adaptive physical support for routine tasks in assembly
Examples				
Cap-abilities	• Unimodal, and manually operated • Fixed support	• Automatic input and various operation types • Adaptability varies	• Automatic input and manual operation • Adaptive support	• Automatic input and various operation types • Adaptive support
Positive effects	• Work context (M = 0,63, SD = 0,52); • Performance (0,43, SD = 0,79).	• Error rate reduction (M = 0,45, SD = 0,76);	• Performance (M = 1, SD = 0,00).	• Work context (M = 0,80 SD = 0,45); • Performance (M = 0,86, SD = 0,38).
Risks	• Can increase mental demands (M = -0,33, SD = 0,52) – • Limited variable-level evidence.	• TCT effect (M = 0,10, SD = 0,77) and physical demands effect (M = 0,00, SD = 85) vary • temporal demands (M = −0,33, SD = 0,71); • Mental demands (M −0,33, SD = 0,71) and frustration levels (M = −0,42, SD = 0,79).	• Limited use cases found for this archetype.	• Limited variable-level evidence.

5. Implications and future research

This study addresses the limited understanding of the application-specific impacts of assistance systems by mapping four archetypes in manufacturing and their impact on OEE and job quality. The following discussion highlights key points for scholars and practitioners to consider.

5.1. Implications for theory and manufacturing scholars

Selecting the right assistance technology for the preferred way of working and work requirements of the production workers remains an open challenge for manufacturing scholars (Mark et al., 2021a, 2022). While some studies report job quality improvements (e.g., Huysamen et al., 2018) or better manufacturing performance (e.g., Funk et al., 2015a), others show declines in job quality (e.g., Lagomarsino et al., 2023) or manufacturing performance (e.g., Bouillet et al., 2023). These findings align with other reviews indicating outcomes vary by context (Bal et al., 2021; Di Pasquale et al., 2022). For instance, Funk et al. (2015b) found that the benefits of augmented reality were greater the more steps each task had. However, a trend can be observed when looking at the more consistent positive results that emerge from assistance systems with high adaptability capabilities. These results make sense as customized, adaptable, and adaptive assistance counter the 'one size fits all' approach of fixed assistance and are more tailored towards addressing the unique capabilities and needs of the production worker in a given context (Wandke, 2005). Thus, this study notably confirms the importance of the manufacturing context and reveals the potentially more consistent positive job quality and OEE outcomes associated with assistance systems that exhibit high levels of adaptability.

Another key implication for manufacturing scholars is the application-specific categorization of four assistance system archetypes. In alignment with earlier research (Yang and Plewe, 2016), task support in manual processes such as assembly and inspection/testing seems most common. Researchers should, however, also note that although other application domains such as workplace ergonomics, sensorial monitoring, and decision support are regularly described as promising (Bechinie et al., 2024; König and Winkler, 2025; Mark et al., 2021c), no robust clusters were found regarding these assistance system functions. Similarly, non-routine assembly tasks are identified as promising applications of assistance systems (Gan et al., 2023), yet did not emerge from the analysis. These outcomes show the modest number of comparative studies executed for these specific fields of application. In summary, manufacturing scholars could expand their research on the assistance system archetypes for manual processes and the observed lack of comparative studies in other applications.

Manufacturing scholars should note the sample bias in experimental comparative studies (82,1 %) and test subjects (66.1 %) versus case studies (17,9 %) and production workers (33,9 %). Mark et al. (2021c) emphasized the need for more case studies with specific user groups. This study's findings align with that need, revealing it was often impossible to determine the manufacturing process type (66,1 %), UX (82,1 %), task execution capabilities (57,1 %), and task support capabilities for the application (62,5 %). Thus, it remains unclear if the assistance system effectively supported user-specific needs (Johnson et al., 2014). This study reaffirms this critical gap in existing literature.

5.2. Limitations and avenues for future research

The insights indicate limitations and promising research avenues. Addressing methodological challenges in the state-of-the-art literature on assistance systems' outcomes is essential. This study mainly incorporated comparative experimental studies supplemented by comparative case studies. By utilizing longitudinal studies, researchers could gain a more detailed and nuanced insight into the outcomes. For example, such studies may illustrate significant initial increases while revealing a later learning curve that may heighten stress and frustration or decreased performance over time (Jaber, 2016; Wilschut et al., 2019). Additionally, longitudinal research could shed light on the usage of skills and opportunities for skill development, which are thought to mediate the beneficial effects of high-quality work organization on workers' well-being (Holman and Wall, 2002). These factors might be overlooked in comparative studies. Longitudinal studies should ideally be conducted with production workers to address their unique needs. Additionally, the sample varied in outcome variables and participant types, complicating cross-study comparisons, which presents another research opportunity for scholars comparing assistance system impacts.

The study's findings on the four assistance system archetypes open new research questions. Future studies could explore additional archetypes, including sensorial monitoring, decision-support, and workplace ergonomics functions of assistance systems, as well as support for non-routine manual tasks. Moreover, although this study followed a rigorous systematic procedure (following Page et al., 2021a, 2021b), the search strategy and case selection are limited by the authors' subjective assessments. Thus, enriching the analysis framework and dataset would enhance comprehensiveness. Additionally, enriching the dataset would enable variable-level outcome analysis of the archetypes, which contributes to addressing methodological challenges and clarifying contradictory results.

The varying impact of assistance system archetypes requires more empirical research to enhance understanding of decisive contextual variables. While worker and assistance system capabilities were considered in mapping outcomes, the description in the sample lacked sufficient details to determine them for the task of interest. As worker skills are an important contextual factor (Nair et al., 2024), scholars could explore whether the fit between assistance systems and worker capabilities affects outcomes. Including UX indicators like usability could further refine this analysis. This study did not incorporate UX indicators due to insufficient sample sizes, despite their importance for aligning user needs with assistance system applications (ISO, 2019; Sauer et al., 2020). Additionally, the lack of availability and social work outcome assessments in evaluating assistance systems warrants deeper investigation, as both categories are vital indicators of respectively OEE and job quality (Eurofound, 2017; Muchiri and Pintelon, 2008).

Finally, researchers should explore application-specific approaches to adopting human-centric assistance systems. The literature already offers design rules and approaches for human-centric technology adoptions (De Sitter et al., 1997; Gualtieri et al., 2020; ISO, 2019; Oeij et al., 2017; Rega et al., 2025). However, this study, again (Mark et al., 2021c), highlights the absence of case studies that provide hands-on guidance for applying these principles and design rules within the specific, work-related context of manufacturing organizations. Scholars can fill this gap by conducting human-centric design studies that utilize existing frameworks and implement these in the specific manufacturing context.

5.3. Implications for manufacturing practitioners

Manufacturing professionals can integrate two types of assistance systems to provide physical execution assistance for workers in routine assembly operations. Although results are limited, investing in developing observation, orientation, and decision functionalities can be worthwhile when offering physical execution support, allowing the assistance to be more adaptive. This is due to manually operated physical execution support systems that pose risks by increasing workers' mental demands, which can consequently decrease their job quality (Humphrey et al., 2007). Similar risks are highlighted for visual task guidance systems in routine assembly operations. These systems can be adapted and operated in multiple ways, typically possessing observation, orientation, and decision functionalities. Although practitioners might consider this to improve error rates, the potentially increased physical, temporal, and mental demands present a risk for workers and the achievement of sustainable system-level goals (Andersen et al., 2016; Hertzum, 2022). Prior research shows the context-specific effects of increased work demands and reduced resources on various individual workers (Parker, 2003). Therefore, this study further underscores the necessity for manufacturing professionals to consider the specific needs of users, not only concerning the application of the technology but also in their work design.

Another important observation is the promising performance improvements that adaptive visual support seems to offer for non-routine diagnostics tasks in inspection/testing processes. The use cases from Hoerner et al. (2023) and Traub et al. (2018) could provide guidance on the design and implementation of effective assistance systems for support of non-routine diagnostic tasks.

6. Conclusion

This unique study offers an archetypal overview of the impact of assistance systems on job quality and OEE in manufacturing applications, which scholars can build upon. Cognitive assistance archetypes are distinct in supporting routine work guidance tasks in assembly and non-routine diagnostic tasks in inspection and testing processes. Physical support archetypes are applied in routine assembly but have distinct capabilities. The study shows that the contradicting impact of the archetypes on job quality and OEE may be influenced by the differences in the capabilities of the assistance system archetype. Scholars could better understand the underlying reasons for the contradictory results by assessing the fit between the role division of the worker and the assistance system and their respective capabilities. Methodological variations, such as longitudinal research and case studies utilizing a coactive design method, could serve as viable approaches to address the gap identified in the comparative study sample of this SLR. Finally, more research is needed on social characteristics and the availability of production equipment to enhance the comprehensive understanding of assistance systems on job quality and OEE.

In conclusion, while assistance systems offer various potential benefits for job quality and OEE, their successful use requires careful consideration of worker capabilities, assistance system capabilities, applications, and long-term deployment effects. This study enriches the existing literature on assistance systems and can serve as a foundational basis for the needed further longitudinal empirical testing to provide application-specific insights and guidance to scholars.

CRediT authorship contribution statement

Koen Nijland: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Aijse de Vries:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Paul Preenen:** Writing – review & editing, Supervision, Resources, Methodology, Funding acquisition, Conceptualization. **Sri Kolla:** Writing – review & editing, Validation, Supervision, Software, Methodology, Investigation, Conceptualization. **Sebastian Thiede:** Writing – review & editing, Validation, Supervision, Resources, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors report there are no competing interests to declare.

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Data availability

Data will be made available on request.

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