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Human-centred AI in industry 5.0: a systematic review

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ABSTRACT

Industry 4.0 (I4.0) is a manufacturing paradigm revolutionising production by integrating advanced technologies, like AI, for automation and data integration. However, research in I4.0 overlooks human factors, crucial for designing systems that enhance well-being, trust, motivation, and performance. To address this, international bodies have introduced Industry 5.0, aiming to balance technological advancement with human welfare. To transition towards this vision, an understanding of current human-technology interaction is essential. Through a conceptual model aiming to understand the psychological experience of workers within their environment, we identified the studied human factors, their antecedents, consequences, and methodologies. Additionally, we explored how future research can adopt a human-centred approach in designing and implementing technology. Analysis of 67 articles showed the psychosocial dimension of human factors like AI trust, worker autonomy, motivation, and stress are underrepresented. We observed a significant disconnect between empirical and non-empirical studies in terms of theoretical frameworks, variable selection, data collection methods, and research designs. Our findings highlight the necessity for experimental, theory-driven research in human-AI interaction, using a multi-method approach including perceptual, observational, and psychophysiological measures. Lastly, we discuss the integration of these findings into managerial practice to foster workplaces that are technologically advanced yet remain empathetic to human needs.

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SUSTAINABLE DEVELOPMENT GOALS

SDG 3: Good health and well-being

Introduction

Industry 4.0 (I4.0) represents a transformative paradigm, emphasising the integration of advanced technologies to revolutionise products, services, and processes through seamless connectivity and agile decision-making (Moew et al. 2018; Usuga Cadavid et al. 2020). At the forefront of this transformative wave is artificial intelligence (AI), which acts as a catalyst, driving innovative breakthroughs reshaping manufacturing and operational landscapes (Cannas et al. 2024; Jackson et al. 2024; Luo, Thevenin, and Dolgui 2023). This technological evolution is reshaping human interactions with AI-driven systems integral to I4.0, reflecting a profound shift in human-technology interaction (Neumann et al. 2021; Reiman et al. 2023; Rožanec et al. 2023; Sitarević et al. 2023).

Indeed, worker roles, responsibilities, perceptions, attitudes, and behaviours, introducing both opportunities and challenges within the workplace (European Agency for Health and Safety at Work 2022; Flores, Xu,

and Lu 2020; Gagné et al. 2022). For instance, at Siemens' electronics manufacturing facility, AI-driven systems are employed to predict equipment failures before they occur, leading to a decrease in unplanned downtime and a smoother production process (Siemens 2024). Workers have transitioned from performing routine maintenance to focusing on more strategic and cognitively-demanding tasks that require problem-solving skills. While this shift can add a stronger perception of meaningfulness to their job by providing opportunities to exercise creativity in problem-solving, it can also impose high cognitive demands and increase stress levels due to the complexity of the issues they need to address, as well as job insecurity (Ghislieri, Molino, and Cortese 2018; Lu et al. 2022).

This situation exemplifies the dual-edged nature of technological advancements in Industry 4.0. On the positive side, these technologies can offer significant improvements in productivity and create new opportunities for workers to engage in more meaningful and stimulating tasks (Gagné et al. 2022). However, they also introduce

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challenges such as increased cognitive demands, job insecurity, standardised monotonous tasks, and the need for continuous skill development (Alves, Lima, and Gaspar 2023; Ghislieri, Molino, and Cortese 2018; Grosse et al. 2023). Both the positive and negative impacts of technology have significant medium- to long-term effects on workers, including employee well-being, retention, performance, motivation, and engagement (Deci, Olafsen, and Ryan 2017; Szalma 2014). These factors, over time, profoundly influence the overall efficiency and profitability of a company. A workforce that is healthy, motivated, and skilled is essential for maintaining high levels of productivity and innovation, which in turn drive competitive advantage and financial success (Van den Broeck et al. 2021).

However, research in the context of Industry 4.0 has primarily focused on the technical aspects of technology and human performance while using technology. Numerous authors have noted the critical underrepresentation of human factors in this research (Gagné et al. 2022; Grosse et al. 2023; Kadir, Broberg, and da Conceicao 2019; Neumann et al. 2021; Sgarbossa et al. 2020; Reiman et al. 2021; Vijayakumar et al. 2022; Xu et al. 2022). Neumann et al. (2021) emphasise a significant neglect of psychosocial and perceptual aspects in current studies, calling for a systematic integration of these dimensions into Industry 4.0 systems. This gap is echoed by Reiman et al. (2021), who highlight that most research is heavily focused on technical details while insufficiently considering human-centred design principles. Gagné et al. (2022) and Grosse et al. (2023) further underline the necessity for future research to delve deeper into human-machine interactions and the psychosocial impacts of emerging technologies. Vijayakumar et al. (2022) also stress the significant gap in the evaluation of human factors in production and logistics systems, advocating for the development of tools and methods that specifically address these aspects.

Collectively, these perspectives underscore the lack of a balanced research agenda giving equal importance to technological advancements and human factors, thus jeopardising the successful adoption of Industry 4.0 technologies and human well-being at work. This predominant focus on technical and human performance aspects has often overshadowed other human-centric aspects, such as the psychosocial (how workers feel and relate to their work) and cognitive (mental and perceptual processes) dimensions of human factors, essential for a comprehensive understanding of the human-technology relationship. As such, there is a gap in our understanding when it comes to designing and implementing human-centred AI systems, i.e. systems that are safe, trustworthy, performant, and that account for human psychological

and physical needs (Calzavara et al. 2020; May et al. 2015; Rožanec et al. 2023).

In response to these limitations, the European Commission has introduced a progressive approach, termed Industry 5.0 (I5.0), marking a significant evolution to I4.0. I5.0's vision accentuates a more human-centric approach to technological design and integration in the workplace, emphasising a balance between technological progress and human welfare (European Commission 2021; Ivanov 2023). Fundamentally, the introduction of I5.0 aspires to rectify the gaps observed in I4.0, focusing on creating work environments that prioritise the human well-being and empowerment.

To fully embrace the potential of I5.0, we believe it is imperative to amalgamate existing insights about interactions between humans and technology within I4.0 environments. Central to this exploration are the questions: (RQ1) which human factors have been explored in Industry 4.0 research, and what methodologies have been employed to study them?; and (RQ2) how can future research effectively address these human factors, including their antecedents and outcomes, to foster sustainable and human-centred human-AI interactions that enhance long-term employee well-being and performance in Industry 5.0? Consequently, this systematic review is set out to provide an in-depth examination of human factors in I4.0 contexts, identifying their outcomes, antecedents, consequences, and the methodologies used to address them, to uncover gaps in the current literature.

This review serves to characterise and extend some of the future research direction identified by Grosse et al. (2023) in their position paper about human-centric work systems in I4.0/I5.0. They recommended exploring the psychosocial effects of human-technology interaction, specifically through empirical multi-method evaluation. Our review aims to delve deep into the understanding of psychosocial variables by examining their current integration into research, their antecedents, and their consequences. Additionally, we aim to contrast empirical and non-empirical articles, to identify other gaps for future research to address. This includes scrutinising the methodologies and frameworks utilised in current research and proposing approaches that can effectively capture the nuanced dynamics of human-AI interaction.

As a result, the current systematic review offers a depth of analysis that has not previously been achieved by other reviews. For example, in their review of the literature, Enang, Bashiri, and Jarvis (2023) found that trust in technology, job security, and human autonomy, among others, have been raised as possible issues within human-centred I4.0 and I5.0 research. However, they provide only a high-level discussion of these two factors, without

going into detail about how they have been explored. Similarly, many other reviews provide only high-level discussions of human and psychosocial factors within I4.0/I5.0 (e.g. Alves, Lima, and Gaspar 2023; Grabowska, Saniuk, and Gajdzik 2022). Additionally, the current review focuses solely on AI-based systems, whereas others have examined a larger range of I4.0 technologies (e.g. Neumann et al. 2021; Reiman et al. 2021; Sgarbossa et al. 2020) or robots (Panagou, Patrick Neumann, and Fruggiero 2023).

The rest of the review is structured as follows: Section 2 will present the development of our conceptual model, which is central to our exploration of human factors in I4.0/I5.0. Section 3 will present the systematic review's methodology; Section 4 will present its results, including the results of the search and a bibliometric analysis; and Section 5 will discuss and synthesise the results and propose future research directions.

Conceptual model development

The current section will review existing frameworks and conceptual models in production research used to understand the impact of technological and organisational factors on human factors and outcomes. We will then synthesise them and create a new conceptual model through the integration of theories and models from organisational and clinical psychology. This conceptual model will be used to structure the findings from the systematic review and to aid in the identification of research gaps.

Within the optic of I5.0, multiple frameworks and conceptual models within production research are proposed to examine the impact of I4.0 technologies on workers (De Lombaert et al. 2023; Grosse et al. 2023; Setayesh et al. 2022; Sgarbossa et al. 2020; van Oudenhoven et al. 2023; Vijayakumar et al. 2022). At their core, these frameworks indicate that the design and implementation of technological systems, as well as the organisational conditions in which work tasks are performed, both impact human factors. These impacts then cascade to affect operator behaviour and work performance, ultimately influencing overall system and organisational performance. For instance, consider an AI-driven production system that enforces high workloads and strictly dictates workflows, offering minimal decision-making flexibility for operators. The lack of variety and autonomy in their roles can leave workers feeling disengaged, while the overwhelming demands of the system lead to increased stress and mental exhaustion. Consequently, these factors contribute to negative outcomes, including high absenteeism, low productivity, and turnover. Ultimately, such a poorly designed system compromises overall organisational performance, resulting

in unanticipated costs due to errors, dysfunction, and employee burnout.

In their conceptual models and frameworks, Grosse et al. (2023; 2015), Setayesh et al. (2022), Vijayakumar et al. (2022), Sgarbossa et al. (2020), and Longo, Nicoletti, and Padovano (2019) propose that the design, use, and implementation of technology can both positively and negatively impact human factors on a perceptual, cognitive, physical, and psychosocial level. In turn, this impact will directly affect operator performance and overall system performance. De Lombaert et al. (2023) add to this conceptual model by adding skills as an additional level of human factors affected by technology and work design. Van Oudenhoven et al. (2023) propose a similar model based on the Smith-Carayon Work System model (Smith and Sainfort 1989). Specifically, they divide jobs into five domains, each of which can affect worker behaviour (e.g. technology acceptance) and thus their performance. These domains are technology (tools and systems used for tasks), individual (psychological and physical characteristics), tasks (specific activities performed), organisation (structural and cultural context), and environment (physical conditions of the workplace). The model emphasises that changes in one domain can cascade to other domains, impacting worker behaviour and performance.

Building upon the strong foundation of these frameworks and models, we propose a conceptual model that firstly unites them, then expands them through the integration of psychological theories that have long been used to understand workers in a work environment. Figure 1 illustrates our proposed conceptual model, which aims to gain a comprehensive understanding of the psychological experience of workers within their work environment.

On the far left of Figure 1, we have technological and organisational characteristics (work environment), which mutually influence each other, as described in Sociotechnical Systems Theory (STS) (Emery and Trist 1960). For example, the transparency of an AI-powered scheduling tool (technological) can change how teams communicate and collaborate (organisational). Conversely, a supportive organisational culture that encourages learning (organisational) can enhance the continuous improvement of the AI tool (technological). Technological factors refer to the design, implantation, and use of technology. Organisational factors refer to the structural and cultural elements of the workplace, including training opportunities, management support, and the overall organisational culture. Technological and organisational characteristics have a direct impact on human factors, as presented in all of the reviewed models and frameworks. Specifically, they impact the psychosocial and cognitive dimensions of human factors, with this relationship being

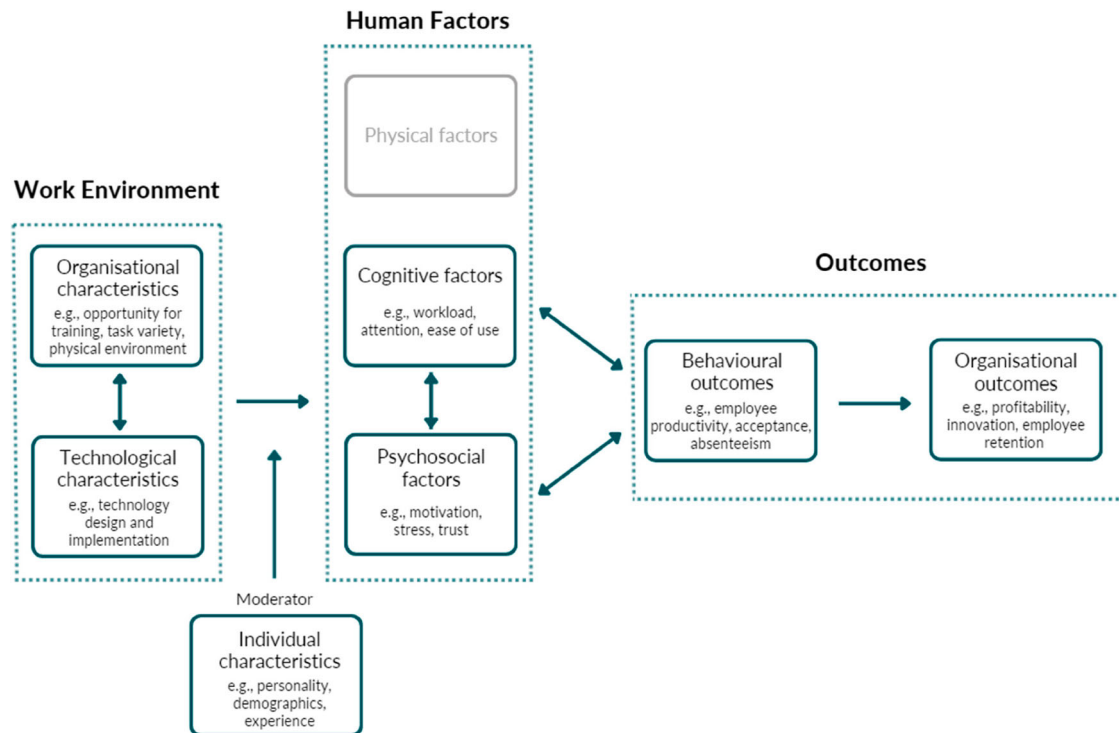


Figure 1. Proposed Conceptual Model.

moderated by individual factors such as personality and demographics. While physical factors may be impacted, they are outside the scope of this model and article, which deal only with psychological aspects. Psychosocial factors pertain to how workers feel and relate to their work environment, encompassing elements such as motivation, engagement, autonomy, work meaningfulness, and stress (Neumann et al. 2021). Cognitive factors relate to mental and perceptual processes, such as attention, cognitive workload, decision-making, learning, and fatigue (Longo, Nicoletti, and Padovano 2019). Psychosocial and cognitive factors both impact behavioural outcomes, such as technology acceptance and worker performance, which then affect organisational outcomes (van Oudenhoven et al. 2023).

The effect of characteristics of the work environment on human factors has been extensively studied in the field organisational psychology through prominent theories such as the Job Characteristics Theory (Hackman and Oldham 1976), the Job Demands-Resource Model (Demerouti et al. 2001), and Self-Determination Theory (Deci and Ryan 1980), which we have used to enhance and solidify our proposed model.

Job Characteristics Theory (JCT) posits that certain aspects of the work environment affect a worker's psychological state, with this relationship being moderated by individual characteristics such as personality traits (e.g. growth need, desire for personal development).

Psychological state then affects outcomes related to the worker and the organisation. Specifically, work characteristics such as skill variety, task identity, task significance, autonomy, and feedback affect the psychological states of experienced work meaningfulness, experience work responsibility, and knowledge of results, which in turn affect outcomes such as motivation, satisfaction, performance, absenteeism, and turnover. The relationship between work characteristics (technological, organisational), individual characteristics, psychological states (cognitive, psychosocial), and outcomes (behavioural, organisational) is directly integrated into our model.

The Job Demands-Resource (JD-R) Model presents a similar link between work characteristics, psychological states, and outcomes. This model posits that work characteristics can either be classified as job demands (requiring sustained effort or skill) or job resources (reduce job demands and associated psychological cost). A high amount of job demands (e.g. poorly designed technology leading to high cognitive workload), without sufficient job resources, can lead to stress, disengagement, burnout, and thus a reduction in well-being and performance. Whereas a high amount of job resources (e.g. worker autonomy, opportunities for training) can lead to high motivation, engagement, well-being, and performance. The relationship between job demands/resources and outcomes is moderated by individual characteristics such as resilience and self-efficacy.

Similarly, Self-Determination Theory (SDT) posits that work characteristics can positively or negatively impact workers' innate psychological needs of autonomy, competence, and relatedness, with this relationship being moderated by individual characteristics such as autonomy orientation and personality. The satisfaction of the three psychological needs is a direct antecedent of various psychosocial and cognitive factors, for example, self-determined motivation (drive to engage in activities based on intrinsic interest, personal values, and the inherent satisfaction derived from the activity itself, rather than external pressures or rewards), which itself is an antecedent of positive work outcomes such as high engagement, performance, and well-being.

It is important to note that, within our model, the relationship between psychosocial, cognitive, and behavioural factors/outcomes is bidirectional, indicating, for example, that behavioural outcomes can go on to affect psychosocial or cognitive factors, and vice-versa. This bidirectionality is a foundational component of Cognitive Behavioural Therapy/Theory (CBT) (Beck 2012), which is widely used in psychotherapy to understand how thoughts, feelings, and behaviours are intertwined. CBT posits that cognitive processes, emotional responses (psychosocial factors) and behavioural responses are interconnected and influence each other. For example, consider the implementation of an AI tool in the workplace. This new technology can initially lead to a high cognitive workload and low trust (psychosocial) in the AI's recommendations. However, as employees use the AI tool effectively and begin to accept it (behaviour), their cognitive workload can decrease, and their trust in the technology can increase.

Overall, our conceptual model adds to the models and frameworks of Grosse et al. (2023; 2015), Setayesh et al. (2022), Vijayakumar et al. (2022), Sgarbossa et al. (2020), Longo, Nicoletti, and Padovano (2019), De Lombaert et al. (2023), and van Oudenhoven et al. (2023) by adding specificity through interdisciplinary theoretical foundations, further contributing to the understanding of workers psychological experience within their work environment. First, we emphasise the bidirectionality of the relationship between technological and organisational characteristics of a work environment, as presented in STS. Second, we add individual characteristics as moderators between work environment and human factors, as detailed in the JCT, the JD-R model, and SDT. Third, we add a nuance to the relationship between the psychological dimensions of human factors (psychosocial and cognitive) and behavioural outcomes, emphasising its bidirectionality. Overall, our work bridges the gap between production research and organisational psychology by expanding existing models, thereby enabling

a more comprehensive examination of human factors within production environments.

Systematic review methodology

This section presents the methodology used for the review. We used the PRISMA checklist to ensure transparency and comprehensiveness in the reporting of this systematic review (Shamseer et al. 2015). This review was registered with the International Prospective Register of Systematic Reviews (PROSPERO: CRD42022308729). To ensure transparency, accountability, reproducibility, and ethical conduct, the PRISMA protocol was published, before the start of the review, in the conference proceedings of HCI International (Passalacqua et al. 2022). It can be accessed through the following link: https://doi.org/10.1007/978-3-031-21707-4_34.

Eligibility criteria

We employed the SPIDER Tool for Qualitative Evidence Synthesis, offering directives to construct a systematic search strategy tailored to handle non-quantitative research questions (Cooke, Smith, and Booth 2012). Table 1 shows how the tool was used for our research question.

Information sources

Web of science, Engineering village (Inspec and Compendex), IEEE Xplore, ACM digital library, and PsycInfo databases were used to gather data. They were searched up to July 1st, 2024. Furthermore, we carried out both a backward and forward citation for the articles chosen for data extraction. When articles were unavailable, we reached out to the authors.

Table 1. SPIDER Framework.

SPIDER Facet	Description
(S) Sample	Research that involved employees or users working with AI-based technology in a manufacturing or logistics setting were included.
(PI) Phenomenon of interest	We incorporated studies focusing on human interaction with AI-based systems, emphasising our interest in the dynamics of the human-AI relationship.
(D) Study design	All types of research designs were included.
(E) Evaluation	Research that highlighted the effects of AI-based technology on workers or users, from a psychosocial and human factors perspective. Notably, our focus was on a substantive exploration of human factors and/or psychosocial variables, such as motivation, engagement, stress, cognitive workload, fatigue, well-being, empowerment, trust, acceptance, understandability, explainability, vigilance, job satisfaction, and usability.
(R) Research type	We considered all peer-reviewed studies written in English, French, Italian, and German.

Search strategy

Our search strategy was designed following recommendations of the Cochrane Handbook for Systematic Reviews of Interventions (Lefebvre et al. 2022). The search query used to search the databases is shown in Table 2. The search query was divided into three categories, connected by the Boolean operator 'AND'. The first category contained terms related to the domain or context (for instance, Industry 4.0/5.0); the second encompassed terms linked to human and psychosocial aspects (such as ergonomics and motivation); and the third category incorporated terms associated with AI (like intelligent agent and neural network).

Before proceeding with the application of the search query to the databases, we adopted an iterative approach to identify additional search terms that may have been omitted, ensuring the comprehensiveness our search. Our search terms were expanded in two stages. In the first stage, we used two of the three categories (domain AND human factors) to expand our search and identify additional relevant search terms. In the second step, we used a different combination (domain AND AI). Essentially, using only two of three categories per step broadened our search and allowed us to find search terms that we otherwise would not have found. For each step, we limited the search to a maximum of 50 papers per database across the five databases, totalling a maximum of 250 papers per step. This limit ensured manageability and focus while allowing us to efficiently add to the search terms, enhancing the accuracy and relevance of our search without being overwhelmed by an excessive

Table 2. Search Query (reprinted with permission of Springer Nature from (Passalacqua et al. 2022)).

Category	Search terms
Domain/context	'industr* 4.0' OR 'industry 5.0' OR 'smart manufacturing' OR 'operator 4.0' OR 'connected manufacturing'
	AND
Human factors and psychosocial factors	'human?cent?red' OR 'user?cent?red' OR 'human factor*' OR ergonom* OR sociotechnical OR socio-technical OR anthropocentric OR psychosocial OR psychophysiol* OR motivation OR engagement OR stress OR 'cognitive load' OR 'cognitive workload' OR fatigue OR 'well being' OR well-being OR empowerment OR trust OR distrust OR acceptance OR acceptability OR personality OR comprehensib* OR understandab* OR explainab* OR vigilance OR 'job satisfaction' OR 'work satisfaction' OR Usability OR 'User Experience' OR UX
	AND
AI-related	'artificial intelligence' OR AI OR ML OR 'deep learning' OR 'data mining' OR 'machine learning' OR RL OR 'reinforcement learning' OR 'supervised learning' OR 'unsupervised learning' OR 'autonomo?s agent*' OR 'intelligent agent*' OR 'neural network' OR 'machine intelligence'

number of articles. The iterative refinement of search terms is a common and recommended practice in systematic reviews by both the Cochrane Handbook and PRISMA, allowing for improved accuracy and relevance (Cooper et al. 2018; Lefebvre et al. 2022; Shamseer et al. 2015).

Selection and data collection process

We utilised the Zotero (Corporation for Digital Scholarship 2023) bibliography manager for citation management. Data was extracted and recorded using Covidence (Veritas Health Innovation 2023), a web-based platform designed for systematic review management. The final data was exported to Excel. Zotero automatically identified duplicates, which were subsequently manually removed by one reviewer (MP). Two separate reviewers (MP and LD; MP/FM) undertook the title/abstract screening, full-text screening, and data extraction processes without knowledge of each other's choices. Results from each reviewer were compared, and the inter-rater reliability was examined. Discrepancies between the two reviewers were collaboratively assessed with the aim of reaching a joint consensus. If a resolution was not reached, a third reviewer intervened to finalise the decision. Table 3 shows the data that was extracted from each chosen article.

Risk of bias assessment

Every article selected for extraction was independently assessed by two reviewers (MP and LD/FM) for any bias in the study's methodology, execution, and analysis using the JBI Critical Appraisal Tool (Aromataris and Munn 2020). Given that multiple JBI checklists exist, each tailored for a distinct type of study (<https://jbi.global/critical-appraisal-tools>), our selection was adjusted based on the nature of the study (e.g. near-experimental, qualitative). Discrepancies between the two reviewers were collaboratively assessed with the aim of reaching a joint consensus. If a resolution was not reached, a third reviewer intervened to finalise the decision.

Data synthesis method

We found a predominant number of conceptual and qualitative empirical articles compared to quantitative experimental studies, because of the emerging nature of the field (human-centred AI within a manufacturing context). As a result, our data collection leans more towards qualitative insights but with some quantitative metrics as well. Consequently, we have chosen a narrative synthesis

Table 3. Data extracted from each article.

Article section	Extracted data	Explanation
–	Summary	Two- to three-sentence recap of the article
Introduction	Research question	Research question(s) and objective(s) addressed
	Theoretical framework	Theoretical model(s) referenced (e.g. technology acceptance model, self-determination theory)
Methodology	Article type	Type of article (empirical, review, conceptual, or system/framework design with user test)
	Research design	For empirical articles, the research design used (experimental, observational, case study)
	Participants	If the article is empirical, number of participants and their characteristics (e.g. students, operators)
	Data gathering method	Methodology used to gather data (e.g. questionnaire, interviews, psychophysiological instruments)
	Antecedent/ manipulated variable	The independent variable manipulated by the researchers (e.g. interface design, task complexity, personality traits). Alternatively, the antecedents of the outcome variables (e.g. balanced task complexity (antecedent) lead to lower cognitive load).
	Outcome variables	Outcome or dependent variables highlighted by the paper's authors via experimentation, review of the literature, discussion, or other techniques.
Results	Result synopsis	A synopsis of the results
Discussion	Noteworthy points	Noteworthy observations, encompassing areas of unexplored research, future studies, and elements pertinent to the research question or objectives of the review

approach for data assimilation. This approach has been shown to be effective to integrate diverse forms of data types (e.g. qualitative and quantitative) across different articles. Additionally, this method will aid in describing the primary attributes of the studies while highlighting commonalities and variances among them (Peters et al. 2020; Popay et al. 2006).

To conduct our narrative synthesis, we followed recommendations from the Cochrane-Campbell Handbook for Qualitative Evidence Synthesis (McKenzie and Brennan 2019). Essentially, the synthesis began with developing a preliminary synthesis. This involved systematically extracting data from the selected articles, focusing on key elements such as research questions, theoretical frameworks, methodologies, and findings, as shown in Table 3. The extracted information was then categorised to identify patterns and themes across the studies. We conducted a descriptive analysis to summarise the characteristics of the included studies, such as the types of human factors examined, the methodologies used, and the main findings. Next, we explored relationships within and between studies, identifying recurring themes and concepts related to human factors in I4.0 contexts and how they have been addressed in the literature. A comparative analysis was also conducted to highlight differences and similarities in how various studies approached the same or similar human factors, helping us understand the diversity of methodologies and theoretical frameworks used.

Results

This section will present the bibliometric and descriptive results of the systematic review. For transparency, all raw and processed extracted data is available at <https://doi.org/10.17632/ynptrk357k.1>.

Results of the search

A total of 1611 records were identified through the database search. After title and abstract screening, full text screening, and backward–forward citation search, 67 articles were retained for extraction. Figure 2 presents a flow diagram that details the process through which we obtained the retained articles.

There was substantial agreement between the reviewers (MP and LD/FM) for title and abstract screening (87% agreement rate, Cohen's kappa of 0.63). Similarly, there was substantial agreement for the full-text screening (90% agreement, Cohen's kappa of 0.76).

Bibliometric analysis

This section presents the bibliometric analysis of the literature.

Looking at the 67 human-focused articles selected for this review, the number of publications per year has been steadily increasing since 2017. Note that 2024 represents half of a year (January 1st to July 1st). Figure 3 show the number of articles published per year.

When looking at the number of publications by country of the first author's affiliation, Italy has the most, with a total of 13 articles, representing 19% of all selected articles. Germany is close behind (10), followed by the USA (5), UK (four), Spain (three), Canada (three), and India (three).

Pertaining to the publication outlet, the *International Journal of Production Research* has published four of the 67 included articles. *Ergonomics*, the *International Journal of Environmental Research and Public Health*, the *Journal of Manufacturing Systems*, and the International Conference on Advances in Production Management Systems have each published three articles. A total

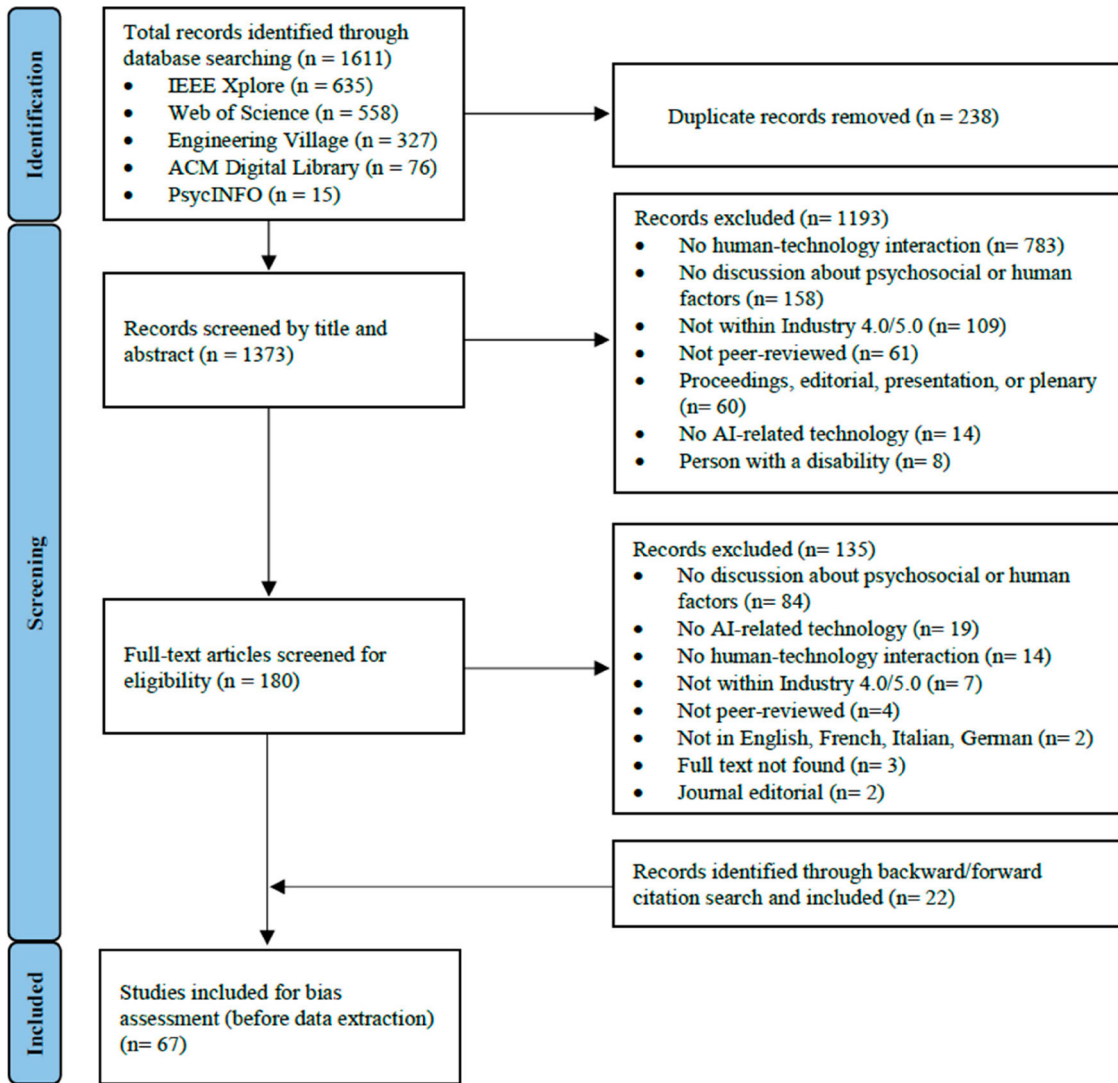


Figure 2. PRISMA Flow Diagram.

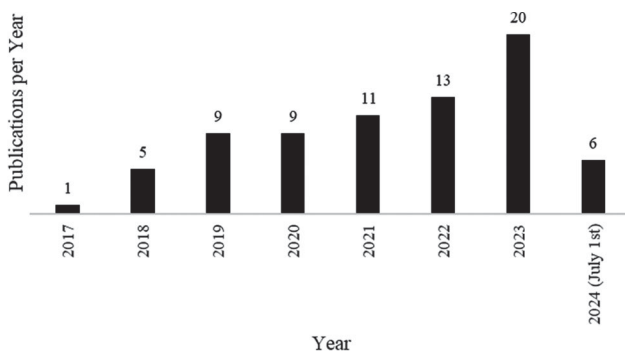


Figure 3. Number of Publications per year.

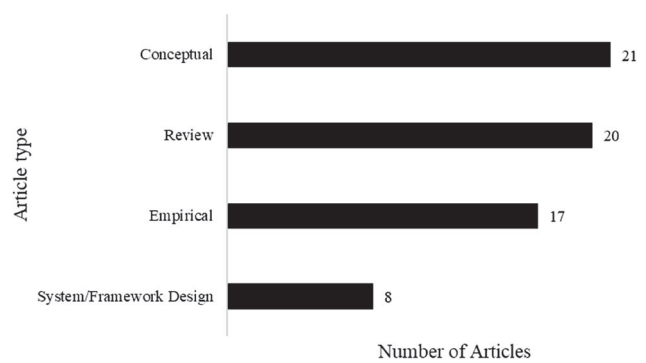


Figure 4. Distribution of Article Type.

of 53 articles (79%) have been published in journals, while 14 articles (21%) have been published in conference proceedings.

As for the distribution of article types within our sample, conceptual and review were the most common type,

with 21 and 20 articles respectively. Figure 4 presents the full results.

Through analysis of the 67 selected articles, we have derived 9 meta-topics, as shown in Table 4. Some articles appear in more than one category.

Table 4. Topics in All Articles.

Topic (number of articles)	Article
Defining and transitioning to human-centred smart manufacturing (12)	(Alves, Lima, and Gaspar 2023; Bocklisch and Huchler 2023; Cagliano et al. 2019; Enang, Bashiri, and Jarvis 2023; Ghislieri, Molino, and Cortese 2018; Gladysz et al. 2023; Grabowska, Saniuk, and Gajdzik 2022; Kadir, Broberg, and da Conceicao 2019; Kumar and Lee 2022; Langer and Landers 2021; Lindner and Reiner 2023; van Oudenhoven et al. 2023; Xu et al. 2022)
Trust in AI and trustworthiness (7)	(Adadi and Berrada 2018; Alexander, Chau, and Saldaña 2024; De Visser, Pak, and Shaw 2018; Grigsby 2018; Ismatullaev and Kim. 2022; Sassmannshausen et al. 2021; Shneiderman 2020)
Organisational adoption of AI (5)	(Chatterjee et al. 2021; Ismatullaev and Kim. 2022; Malik et al. 2021; Marcon et al. 2021; van Oudenhoven et al. 2023)
Use of AI (11)	(Arana-Landín et al. 2023; Bechinie et al. 2024; Colombo et al. 2023; Fügener et al. 2022; Hertel et al. 2019; Jain, Garg, and Khera 2022; Klumpp et al. 2019; Lee et al. 2022; Passalacqua et al. 2024; Tortorella et al. 2024; Wellsandt, Hribernik, and Thoben 2021)
Acceptance of AI (6)	(Del Giudice et al. 2023; Dimitrakopoulos et al. 2024; Ismatullaev and Kim. 2022; Klumpp et al. 2019; Molino, Cortese, and Ghislieri 2020; Molino, Cortese, and Ghislieri 2021; van Oudenhoven et al. 2023)
Work satisfaction and absenteeism (3)	(Ghislieri, Molino, and Cortese 2018; Sitarević et al. 2023; Winkelhaus, Grosse, and Glock 2022)
Algorithm aversion (3)	(Burton, Stein, and Jensen 2019; Jain, Garg, and Khera 2022; Klumpp et al. 2019)
AI design and implementation guidelines/frameworks (13)	(Adattil, Thorvald, and Romero 2024; Angulo, Chacón, and Ponsa 2023; Bednar and Welch 2020; Cachada et al. 2019; De Visser, Pak, and Shaw 2018; Kaasinen et al. 2022; Longo, Padovano, and Umbrello 2020; Lu et al. 2022; Neumann et al. 2021; Ngoc, Lasa, and Iriarte 2021; Reiman et al. 2021; Sgarbossa et al. 2020; Shneiderman 2020; Waschull and Emmanouilidis 2023)
Evaluation of worker state (11)	(Bousdekis et al. 2022; Brunzini et al. 2021; Ciccarelli et al. 2022; Cohen et al. 2018; Diamantopoulos and Weitian 2021; Grigsby 2018; Longo, Nicoletti, and Padovano 2019; Papetti et al. 2020; Peruzzini, Grandi, and Pellicciari 2020, 2017; Vijayakumar and Sgarbossa 2020)

Empirical articles

This section will focus on the 17 empirical articles. Through analysis of the articles, we derived multiple topics, as shown in Table 5.

Most empirical articles (11) used an observational, cross-sectional research design, meaning that data was collected at only one point in time and that no variables were manipulated. To collect data, nine articles used questionnaires, four used interviews, and one used a focus group.

Three articles used an experimental research design, implying the manipulation of independent variables and random assignment of participants to groups. Two articles used questionnaires and task performance measures

as means of data collection. The other article used physiological data (heart rate, respiration), questionnaires, and performance measures.

Finally, three articles employed case study designs in diverse organisational settings, engaging employees, managers, and experts across industries including manufacturing, aerospace, and IT.

Within the empirical articles, the job demands-resource model (Demerouti et al. 2001; Karasek Jr 1979), sociotechnical systems theory (Emery and Trist 1960), and the technology acceptance model (TAM) (Davis 1989) were most commonly used, appearing in four articles each. The unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al. 2003) and job characteristics theory (Hackman and Oldham 1976) appeared twice.

Within the empirical article, multiple relationships between variables were examined. Table 6 outlines these relationships. Figure 5 then maps the statistically significant relationships onto each category of the proposed conceptual model (Figure 1). Notably, no two articles statistically tested the same relationship.

To enhance our analysis of the variables examined in the empirical articles, we have mapped all these variables, as well as their occurrence, onto our proposed conceptual model, as shown in Figure 6. This mapping includes both statistically analysed variables and those that were not, ensuring that all variables within the empirical articles are considered. Regarding the technological characteristics explored, technological complexity was the most frequently examined (three articles). For organisational characteristics, task variety and complexity were the most commonly studied (five articles),

Table 5. Topics in Empirical Articles.

Topic (number of articles)	Article
Identifying antecedents of AI adoption or use (3)	(Chatterjee et al. 2021; Jain, Garg, and Khera 2022; Marcon et al. 2021)
Examining how smart manufacturing affects work design (2)	(Cagliano et al. 2019; Winkelhaus, Grosse, and Glock 2022)
Evaluating the impact of use of AI on task performance and human factors (6)	(Arana-Landín et al. 2023; Colombo et al. 2023; Hertel et al. 2019; Lee et al. 2022; Malik et al. 2021; Passalacqua et al. 2024; Tortorella et al. 2024)
Identifying the antecedents of AI acceptance and how it impacts work engagement (2)	(Molino, Cortese, and Ghislieri 2020; Molino, Cortese, and Ghislieri 2021)
Examining optimal delegation between human and AI for task performance (1)	(Fügener et al. 2022)
Identifying the antecedents of trust in AI (1)	(Sassmannshausen et al. 2021)
Identifying the antecedents of absenteeism (1)	(Sitarević et al. 2023)

Table 6. Relationships from empirical articles.

Article	Relationship			Direction of effect	Statistical testing?
	Antecedent	Moderator/ mediator/ covariate	Outcome		
Arana-Landín et al. 2023	Type of application of AI	Surveillance by AI	Anxiety, Stress	Mediation	No
	Proper communication and pretraining to use AI		Anxiety, Stress	Negative	No
Cagliano et al. 2019	Technological complexity	–	Number of tasks performed, Job autonomy, Cognitive demand, Decentralised decision making	Positive effect	No
Chatterjee et al. 2021	Organisational complexity	–	Perceived usefulness, perceived ease of use	Negative effect	Yes
	Competitive advantage	–	Perceived ease of use, Perceived usefulness	Positive effect	Yes
	Organisational competency, Organisational readiness, Partner support, Perceived ease of use	–	Perceived usefulness	Positive effect	Yes
	Perceived ease of use, Perceived usefulness	Leadership support	Intention to adopt AI	Positive effect Moderation	Yes
Colombo et al. 2023	Automation technologies	–	Perceived autonomy	Positive	No
Augmentation technologies	Task breadth/ enlargement		Positive	No	
Fügener et al. 2022	AI-human teams (versus human or AI alone), AI delegates tasks to humans when uncertain (compared to AI alone)	–	Task performance	Positive effect	Yes
Hertel et al. 2019	Availability of decision-support system	–	Quality of decisions	Positive effect	Yes
	Availability of decision-support system	–	Strain	Negative effect	Yes
Jain, Garg, and Khera 2022	Availability of decision-support system	High trust	Recall of single data point	Moderation	Yes
	Effort expectancy, social influence to use AI, facilitating conditions to use AI	–	Use of AI	Positive effect	Yes
(Lee et al. 2022)	Facilitating conditions, Social influence	–	AI aversion	Negative effect	Yes
	More performance expectancy	Less AI aversion	More use of AI	Moderation.	Yes
	Adoption of AI	Employer-provided training (vs. self-paid)	Work engagement, job satisfaction	Positive	Yes
	Adoption of AI		Job insecurity	Positive (moderation buffers effect)	Yes
Job insecurity	Self-paid training (vs. employer-provided)	Job satisfaction	Negative (moderation exacerbates effect)	Yes	
Job insecurity	Self-paid training (vs. employer-provided)	Work engagement	Negative (moderation exacerbates effect)	Yes	
Malik et al. 2021	Adoption of AI	–	Job insecurity, Work flexibility, Worker autonomy, Performance, Creativity, Technostress, Work overload, Work complexity	Positive effect	No

Marcon et al. 2021	Development of company sociotechnical subdimensions (social, organisational, environmental)	–	Company adoption of I4.0 technology	Positive effect	Yes
Molino, Cortese, and Ghislieri 2020	Opportunities for information and training	Technology acceptance	Work engagement	Positive effect. Partial mediation	Yes
Molino, Cortese, and Ghislieri 2021	Resilience Supervisor support, Role clarity	Technology acceptance Technology acceptance	Work engagement Work engagement	Positive effect. Full mediation Positive effect. Partial mediation	Yes Yes
Passalacqua et al. 2024	Partial automation of decision selection during training (vs. full or no automation)	Trait engagement (covariate)	Skill acquisition, self-determined motivation (identified), autonomy, behavioural engagement	Positive effect	Yes
Sassmannshausen et al. 2021	Perceived ability of AI, Perceived comprehensibility of AI, Digital affinity	–	Trust	Positive effect	Yes
Sitarević et al. 2023	Friendship, Skill variety, Human autonomy, Feedback, Work identity, Cooperation, Mental health	–	Absenteeism	Positive effect (less absenteeism)	Yes
(Tortorella et al. 2024)	Implementation/use of AI according to Lean principles		Employee engagement (physical, cognitive, and emotional dimensions), psychological conditions (safety, meaningfulness, and availability), and performance	Positive effect	No
(Winkelhaus, Grosse, and Glock 2022)	Digitisation, automation	Reduced process complexity, performance measurement/display, and ergonomics for utilisation, task enlargement, task enrichment, increased efficiency, and social cooperation	Work satisfaction	Positive effect on work satisfaction. Mediation	No
	Digitisation, automation	Standardisation, process rigour, division of labour, equipment complexity, substitution of tasks, need for utilisation of automation equipment, substitution of knowledge, and limitation of tasks	Work satisfaction	Negative effect on work satisfaction. Mediation	No

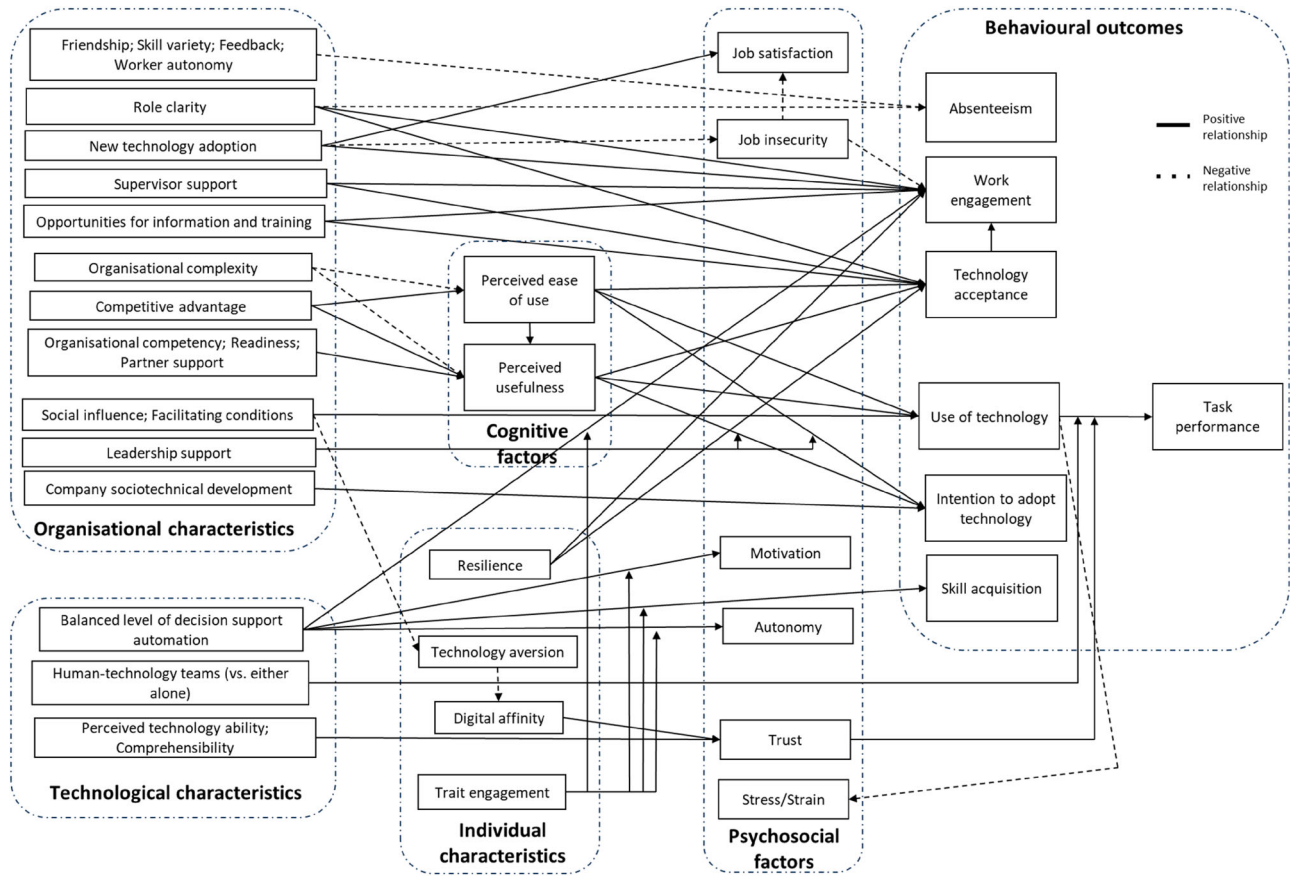


Figure 5. Map of Statistically-Significant Relationships.

followed by opportunities for training/information and leadership/partner support (three articles each). In the realm of cognitive factors, cognitive workload was the most investigated (four articles). Among psychosocial factors, perceived autonomy and stress/strain were the most explored (three articles each). Lastly, in terms of behavioural outcomes, worker performance was the most frequently analysed (five articles), followed by work engagement (four articles).

Conceptual articles

This section will focus on the 21 conceptual articles. Table 7 presents the topics addressed in the conceptual articles. Most articles (12) are about integrating human factors in the design, implementation, and evaluation of AI.

Within conceptual articles, the most common theoretical framework used is sociotechnical systems theory (five), followed by joint cognitive systems and TAM (two each), and, cognitive systems theory, unified theory of cognition, actor-network theory, and Maslow’s hierarchy of needs (each occurring once).

To investigate the variables discussed in the conceptual article, we have mapped them and their occurrences onto our proposed conceptual model, as shown in Figure 7. This mapping includes all variables that were significantly discussed, rather than simply mentioned. Concerning the technological characteristics explored, human-centred design (considering human factors) was the most frequently discussed (six articles), followed by human control/ decision-making authority and AI transparency (five articles each). For organisational characteristics, task variety and complexity were the most commonly studied (four articles), followed by social support, employee training, and social pressure to accept technology (three articles each). In terms of individual characteristics, personality was the most discussed (two articles). For cognitive factors, cognitive workload was the most investigated (five articles), followed by usability (three articles). Regarding psychosocial factors, trust was by far the most discussed variables (14 articles), followed by motivation (seven articles), emotion, worker autonomy/agency, and well being (five each). In terms of behavioural outcomes, worker performance was the most frequently discussed (eight articles), followed by technology acceptance (five articles). Lastly, for organisational

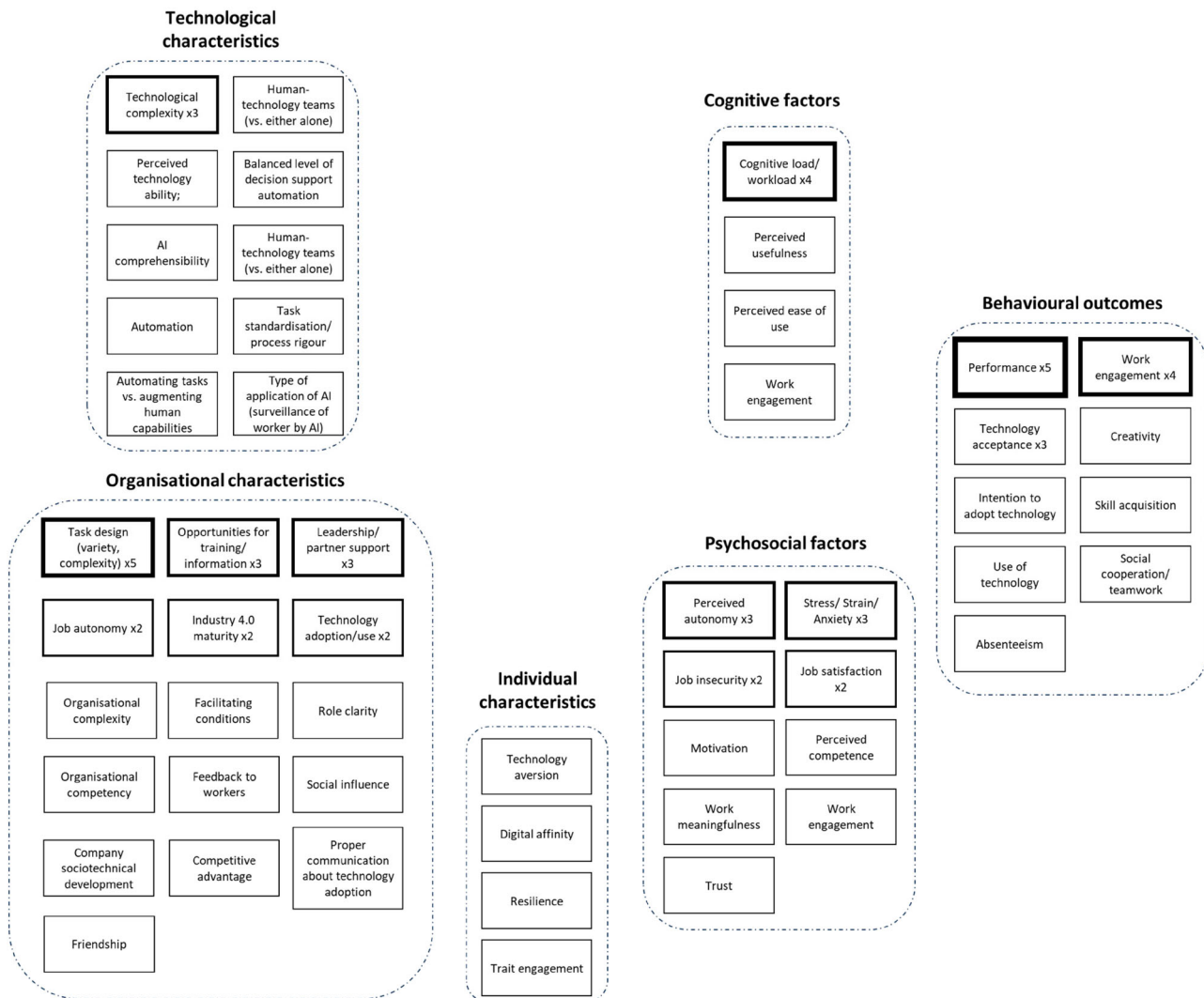


Figure 6. Variables Examined in All Empirical Articles.

Note: Border thickness is an indicator of a greater occurrence of the variable.

outcomes, employee safety was the most discussed (two articles).

Review articles

This section will focus on the 20 review articles. Table 8 presents the topics of the review articles. Similar to the conceptual articles, many review articles (six) discuss the importance of examining the human factors associated with I4.0.

System/framework design with user test articles

This section will focus on the eight articles including system/framework design with user tests. Table 9 presents the topics of the system/framework design with user

test articles. Most articles (five) developed and tested a methodology to evaluate the operator's state.

The user tests conducted in these eight articles are as follows. Questionnaires were the most used method (6), followed by heart rate sensors (5), eye-tracking (3), electrodermal activity (2), skin temperature (1), and emotion recognition (1).

Discussion

The current review aimed to identify which human factors have been explored, their antecedents and consequences, and the methodologies used to address them. Our analysis revealed a theoretical and methodological disconnect between empirical and non-empirical studies, specifically related to theoretical frameworks, variables,

Table 7. Topics in Conceptual Articles.

Topic (number of articles)	Article
Considering human factors or human centricity in the design, implementation, or evaluation of AI systems (12)	(Angulo, Chacón, and Ponsa 2023; Bechinie et al. 2024; Bednar and Welch 2020; Bousdekis et al. 2022; Del Giudice et al. 2023; Kaasinen et al. 2022; Lindner and Reiner 2023; Lu et al. 2022; Shneiderman 2020; van Oudenhoven et al. 2023; Vijayakumar and Sgarbossa 2020; Waschull and Emmanouilidis 2023)
Integrating operator and/or workstation state into AI systems (3)	(Cohen et al. 2018; Golan, Cohen, and Singer 2019; Grigsby 2018)
Designing serious games to (re)train workers (1)	(Brauner and Ziefle 2022)
Developing a framework to integrate trust repair in the design of AI systems (1)	(De Visser, Pak, and Shaw 2018)
Introducing guidelines for achieving trustworthy AI (1)	(Floridi 2019)
Creating a human factors taxonomy and examining each factor's correlation with work performance (1)	(Longo, Nicoletti, and Padovano 2019)
Exploring the benefits of digital assistants (1)	(Wellsandt, Hribernik, and Thoben 2021)

research design, and data collection method. The next subsections will elucidate this disconnect, shedding light on our first research question. Additionally, this review sought to understand how future research can adopt a human-centred approach in designing and implementing technology in the context of I5.0, promoting long-term employee well-being and performance. The Future Research Directions subsection will explain how our proposed conceptual model and results can contribute to this effort, thereby addressing our second research question.

Theoretical frameworks

Within the literature, there is a consensus that technological and organisational factors significantly influence various aspects of human factors, which in turn affect both employee and organisational outcomes. Multiple authors have noted the lack of examination of this relationship within the context of I4.0/I5.0, with particular emphasis on the underrepresentation of psychosocial factors, despite being flagged as the most significant risk factors for workers in I4.0/I5.0 (Bispo and Amaral 2024). Consequently, several frameworks and models in production research have been developed to highlight the need for a comprehensive evaluation of all components for a holistic understanding of human-technology interaction (De Lombaert et al. 2023; Grosse et al. 2023; Setayesh et al. 2022; Sgarbossa et al. 2020; van Oudenhoven et al. 2023; Vijayakumar et al. 2022). Additionally, many authors of

non-empirical articles advocate for integrating theoretical frameworks from organisational psychology to better understand human factors, particularly psychosocial factors (De Visser, Pak, and Shaw 2018; Gagné et al. 2022; Ghislieri, Molino, and Cortese 2018; Jain, Garg, and Khera 2022; Lu et al. 2022; Sitarević et al. 2023; Xu et al. 2022). Notable framework recommendations include the Job-Demands Resources model (Karasek Jr 1979), Self-Determination Theory (Deci and Ryan 1980), and the Job Characteristics Theory (Hackman and Oldham 1976). While some empirical articles have begun utilising these theoretical frameworks (Lee et al. 2022; Molino, Cortese, and Ghislieri 2020; Molino, Cortese, and Ghislieri 2021; Passalacqua et al. 2024; Tortorella et al. 2024; Winkelhaus, Grosse, and Glock 2022), many have not. This gap indicates a substantial shortfall in connecting theoretical models with empirical evidence, which is crucial for informed decision-making and practical applications.

Recognising this gap, we identified the need to merge relevant theoretical frameworks and models into a cohesive, multi-disciplinary conceptual model (Figure 1) to guide the human-centred design and implementation of technology within production environments. This conceptual model integrates research from production and psychological (organisational and clinical) research. From production research, we incorporated frameworks designed to understand how technological and organisational characteristics influence human factors and individual and organisational outcomes (De Lombaert et al. 2023; Grosse et al. 2023; Setayesh et al. 2022; Sgarbossa et al. 2020; van Oudenhoven et al. 2023; Vijayakumar et al. 2022). From organisational psychology, we included sociotechnical systems theory, which emphasises the interaction between technological and organisational characteristics of a work environment. Additionally, we integrated the JD-R model, SDT, and JCT, providing a robust foundation for understanding the antecedents and consequences of psychosocial, cognitive, and behavioural factors. Lastly, from clinical psychology, we incorporated cognitive-behavioural theory/therapy, which underscores the bidirectional relationship between psychosocial, cognitive, and behavioural factors.

Guided by our conceptual model, we examined the key technological and organisational characteristics, as well as psychosocial and cognitive factors, and outcomes, that contribute to effective human-centred human-technology interaction. We then conducted a comparative analysis of the variables identified as important in non-empirical articles (Figure 7) against those addressed in empirical articles (Figure 6). This analysis uncovered a significant disconnect between the variables emphasised in theoretical discussions and those investigated in empirical studies.

Table 8. Topics Discussed in Review Articles.

Topic (number of articles)	Article
Examining the measure, application, or importance of human factors in Industry 4.0 (6)	(Kadir, Broberg, and da Conceicao 2019; Kumar and Lee 2022; Neumann et al. 2021; Ngoc, Lasa, and Iriarte 2021; Reiman et al. 2021; Sgarbossa et al. 2020)
Exploring the transition between Industry 4.0 and human-centred 5.0 (4)	(Alves, Lima, and Gaspar 2023; Enang, Bashiri, and Jarvis 2023; Gladysz et al. 2023; Grabowska, Saniuk, and Gajdzik 2022)
Multidisciplinary analysis of human-computer interaction in highly-automated environments (3)	(Bocklisch and Huchler 2023; Klumpp et al. 2019; Xu et al. 2022)
Understanding the impact of Industry 4.0 technology on workers (2)	(Adattil, Thorvald, and Romero 2024; Ghislieri, Molino, and Cortese 2018; Langer and Landers 2021)
Identifying the factors that contribute to AI acceptance and adoption (2)	(Dimitrakopoulos et al. 2024; Ismatullaev and Kim. 2022)
Exploring the state of the art on explainable AI (2)	(Adadi and Berrada 2018; Alexander, Chau, and Saldaña 2024)
Examining algorithm aversion and misuse (1)	(Burton, Stein, and Jensen 2019)

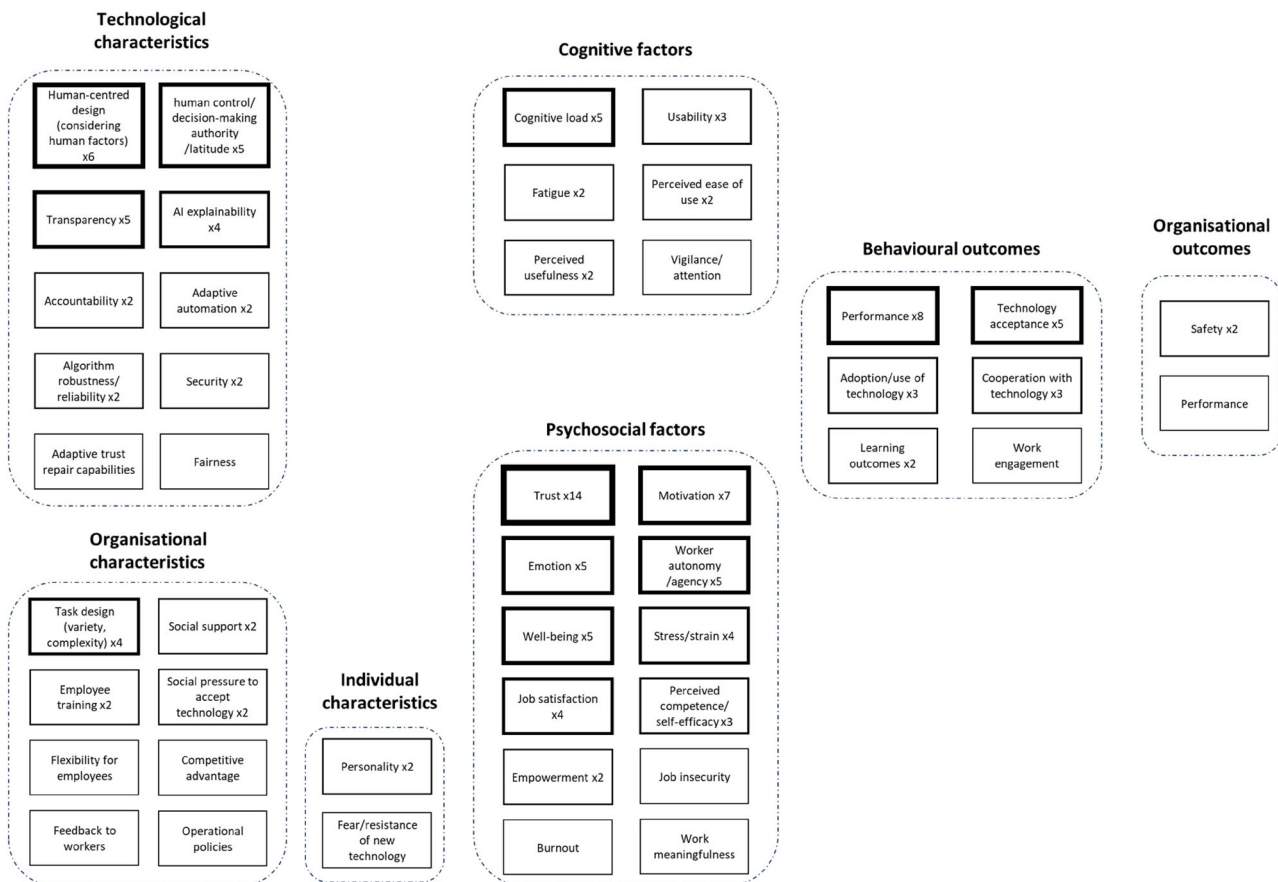
Choice of variables

Within our sample of non-empirical articles, there is a strong emphasis on specific technological, psychosocial,

Table 9. Topics Discussed in System/Framework Design with User Test Articles.

Topic (number of articles)	Article
Developing a methodology to assess operator state and/or factory environment to improve worker welfare (5)	(Brunzini et al. 2021; Ciccirelli et al. 2022; Papetti et al. 2020; Peruzzini, Grandi, and Pellicciari 2017; Peruzzini, Grandi, and Pellicciari 2020) (Cachada et al. 2019)
Applying ISO guidelines to design ergonomic user interfaces in the context of cyber-physical systems (1)	(Diamantopoulos and Weitian 2021)
Developing a co-bot that recognise human emotions and adapt itself to aid human learning (1)	(Longo, Padovano, and Umbrello 2020)
Providing guidelines for designing systems that consider human values and welfare in factories of the future (1)	

cognitive, and behavioural variables due to their significant impact on various outcomes related to worker well-being, organisational performance, and overall system performance in the context of human-technology interaction. The key psychosocial variables include trust, motivation, perceived autonomy, and stress. The primary

**Figure 7.** Variables Examined in All Conceptual Articles.

Note: Border thickness is an indicator of a greater occurrence of the variable.

cognitive variable is cognitive workload, while the main behavioural variable is technology acceptance.

Technological characteristics

Within non-empirical articles, many authors suggest the need to understand how technology and task design choices affect workers on a psychosocial and cognitive level (Angulo, Chacón, and Ponsa 2023; Bechinie et al. 2024; Kaasinen et al. 2022; Langer and Landers 2021; Lu et al. 2022; Ngoc, Lasa, and Iriarte 2021; Shneiderman 2020; Vijayakumar and Sgarbossa 2020). For example, examining the effects of various levels of automation, levels of human control, delegation strategies, task allocation, levels of system reliability, system complexity, or ways of presenting information on human perceptions of autonomy, empowerment, or stress. However, within our sample of empirical articles, only one study experimentally manipulated characteristics of technology to evaluate the effect on human factors (Passalacqua et al. 2024). They manipulate the level of automation of AI decisional control to evaluate the impact on perception of autonomy, motivation, engagement, and skill acquisition. Rather, authors often focused on performance as an outcome variable (Fügenger et al. 2022), focused on organisational factors (Chatterjee et al. 2021; Jain, Garg, and Khera 2022; Marcon et al. 2021), adopted a binary view of AI use (Hertel et al. 2019), or were unable to perform statistical analyses due to data type (Arana-Landín et al. 2023; Cagliano et al. 2019; Colombo et al. 2023; Malik et al. 2021; Tortorella et al. 2024; Winkelhaus, Grosse, and Glock 2022). This highlights a significant gap in the empirical investigation of how technological characteristics impact human factors, suggesting a need for more experimental studies in this area.

Notably, Sassmannshausen et al. (2021) manipulated task characteristics (predictability and error cost) to understand human perceptions about AI (trust, comprehensibility, ability). Additionally, Colombo et al. (2023), using multiple case studies, compared augmentation (human-machine collaboration) versus automation (machines taking over tasks), highlighting their distinct effects on the social dimensions of a purchasing department. Automation enhances efficiency by handling routine tasks, increasing decision-making autonomy in operational and tactical roles. Conversely, augmentation transforms job roles by expanding task scope and enhancing collaboration. It enables high-value activities requiring human judgment and machine insights, such as strategic decision-making and complex negotiations, leading to job enlargement. Thus, while automation increases autonomy in routine tasks, augmentation enriches job roles and fosters a more collaborative, skill-intensive work environment.

Psychosocial factors

Trust and Trustworthiness: Non-empirical articles have emphasised the importance of AI trustworthiness and trust in AI for technology acceptance, efficient cooperation, and system performance, among others. In fact, as seen in Figure 7, trust was the most discussed variable, appearing in 14 articles. According to Floridi (2019), a trustworthy AI is defined as one that supports human autonomy, ensures security and robustness, maintains transparency, and upholds ethical standards. Thus, AI should be designed according to those principles. The level of workers' trust in AI is important, as exemplified in the concept of calibrated trust (Grigsby 2018): it must not be too low to induce disuse, nor too high to prevent overuse. Adadi and Berrada (2018) further characterise trust as a measure that evolves through time. Antecedents to trust are AI transparency, explainability and interpretability which can be achieved through explainable AI (XAI) and Interpretable AI methods (Alexander, Chau, and Saldaña 2024; Bechinie et al. 2024; Gladysz et al. 2023; Lindner and Reiner 2023). Additionally, individual characteristics, such as education and experience are antecedents (Adadi and Berrada 2018; Ismatullaev and Kim. 2022).

Integrating these antecedents into AI design is crucial for creating systems that users feel comfortable relying upon. The three-layered model of trust (Hoff and Bashir 2015), identifying dispositional, situational, and learned layers, serves as a guide for pinpointing these antecedents. This model informs AI design by emphasising the importance of: (1) Tailoring user experiences to align with individual differences in trust propensity, which may involve personalised interfaces or adaptive levels of autonomy in AI systems (dispositional trust); (2) Ensuring that AI systems are transparent in operation and decision-making, providing clear context-specific information and appropriate responses to users' expectations and the environment they operate in (situational trust); and (3) Designing AI systems with the capability to learn and adapt from user interactions, thereby demonstrating reliability and competency over time, which are key for users to develop a sustained trust in the system's capabilities (learned trust). This comprehensive approach is essential, particularly when considering the complex psychosocial impacts of technology adoption in fields like UX design, where understanding and addressing human factors is paramount.

Despite its importance, trust was examined in only two empirical articles. Sassmannshausen et al. (2021) found that the situation predictability decreased, and error cost increased trust, with both relationships being mediated by the AI's perceived ability and comprehensibility. Additionally, the authors found that workers'

digital affinity (attraction or interested in technology) is associated with higher trust in AI. Hertel et al. (2019) found that the use of AI led to better information recall, but only when participants had high trust in the AI.

Motivation: In non-empirical articles, multiple authors (seven) identified worker motivation as crucial for system long-term performance, worker well-being, worker engagement, and worker retention, among others (Bocklisch and Huchler 2023; Ghislieri, Molino, and Cortese 2018; Neumann et al. 2021; Sgarbossa et al. 2020; Vijayakumar et al. 2022; Xu et al. 2022). Authors stressed the importance of evaluating the impact of changing technological and organisational characteristics of the work environment, such as human control/decisional latitude, task variety, task complexity on worker motivation. However, only one empirical article has addressed worker motivation (Passalacqua et al. 2024). In this study, we manipulated the level of automation of an AI's decisional authority. We found that a balanced level of automation, one in which the AI assisted the human, but final decisional authority remained with the worker, led to the best outcomes in terms of motivation, perceived autonomy, and skill acquisition. In line with these findings, within the non-empirical articles, decision-making authority/control/latitude has been raised as an important technology design characteristics affecting human factors, specifically employee perception of autonomy, motivation, job satisfaction, performance, well-being, among others. (Lu et al. 2022; Shneiderman 2020; van Oudenhoven et al. 2023; Vijayakumar et al. 2022; Washull and Emmanouilidis 2023). As presented during the development of our conceptual model, both Job Characteristics Theory and Self-Determination theory also emphasise the importance of decision-making autonomy for similar outcomes, highlighting the need for further research on this technological characteristic.

Perceived Autonomy: In non-empirical articles, workers' perception of autonomy (sense of control) has been discussed in multiple papers, emphasising its importance for increasing worker well-being, performance, and reducing AI aversion/resistance (Burton, Stein, and Jensen 2019; Floridi 2019; Klumpp et al. 2019; Longo, Padovano, and Umbrello 2020; Reiman et al. 2021). Others have raised the point that AI and automation could both enhance or reduce workers' perceptions of autonomy (Enang, Bashiri, and Jarvis 2023; Ghislieri, Molino, and Cortese 2018; Langer and Landers 2021; Wellsandt, Hribernik, and Thoben 2021; Xu et al. 2022). The reduction of perceived autonomy is due to a decrease in task variety or an increase in task rigidity. Conversely, the enhancement of perceived autonomy can be attributed to

the automation of monotonous, repetitive tasks, consequently allowing employees to engage in more meaningful and engaging activities.

In empirical articles, we also find that automation/AI can both increase and decrease perceived autonomy, depending on technological factors. Passalacqua et al. (2024) found that balanced levels of AI decisional authority led to higher levels of perceived autonomy, while high levels of decisional authority led to decreased autonomy. Cagliano et al. (2019) found that low levels of technological complexity are associated with low task variety, low worker autonomy, and low cognitive demand. Higher levels of technological complexity are associated with higher task variety and positively correlated with worker autonomy. Winkelhaus, Grosse, and Glock (2022) found that automation is negatively correlated with autonomy. Conversely, Malik et al. (2021) found that the adoption of AI increases worker perceived autonomy. Lastly, Sitarević et al. (2023) found that higher perceived autonomy is associated with less absenteeism.

Stress: In non-empirical articles, stress has been flagged as an important variable to evaluate due to its significant impact on both mental and physical well-being (Brunzini et al. 2021; Ciccarelli et al. 2022; Papetti et al. 2020). Authors emphasise that the increased prevalence of human collaboration with automated systems could increase stress by reducing worker autonomy, by reducing co-worker informal support (by reducing the number of human relationships), by increasing technology complexity, or by increasing job security concerns, among others (Ghislieri, Molino, and Cortese 2018; Grigsby 2018; Langer and Landers 2021; Xu et al. 2022). To mitigate stress, Bispo and Amaral (2024) found, in their review, that adequately training employees, giving sufficient support systems, and allowing for a healthy work-life balance are effective solutions.

In empirical articles, three studies explored the effects of AI use/adoption on stress. Hertel et al. (2019) found that a decision-support system significantly reduced participant strain (stress). Contrarily, Malik et al. (2021) found that AI adoption can increase stress due to work overload, job insecurity, technology complexity, and role ambiguity. Providing a balanced perspective, Arana-Landín et al. (2023) found that the type of application of AI can affect stress differently. For instance, the study found, using interviews, that AI applications for voice recognition reduced stress by automating routine tasks for operators, whereas AI used in surveillance systems increased stress due to employees feeling monitored and privacy concerns.

Cognitive factors

Cognitive workload: Non-empirical articles discussing AI and cognitive workload generally explore how AI technologies impact cognitive demands on workers and propose frameworks or methods to manage these demands effectively. Angulo, Chacón, and Ponsa (2023) introduce a conceptual framework for AI-assisted cognitive support in manufacturing, emphasising the reduction of cognitive workload through the integration of human factors like trust and usability. Bednar and Welch (2020) advocate for a socio-technical approach to smart working, highlighting the importance of considering social and cultural components to manage cognitive workload. Bousdekis et al. (2022) propose an evaluation framework for AI-based digital assistants that assesses cognitive workload using tools like the NASA TLX (Hart and Staveland 1988), emphasising the need for systems that adapt to human cognitive limits. Brauner and Ziefle (2022) suggest using serious games for training, which can help workers manage increased cognitive tasks due to AI integration. Cohen et al. (2018) focus on adaptive automation that modulates cognitive workload dynamically based on real-time physiological data, ensuring operator well-being and efficiency. These articles collectively stress the importance of designing AI systems that consider and mitigate cognitive workload to enhance overall performance and worker satisfaction. To alleviate high cognitive workload, Bispo and Amaral (2024) identified in their review that effective strategies include offering comprehensive training for employees, implementing strong support systems, and ensuring a healthy work-life balance.

Within empirical article, cognitive load was well represented. Cagliano et al. (2019) used case studies to show that higher technological complexity in smart manufacturing increases cognitive demand for operators, necessitating enriched roles. Fügener et al. (2022) conducted an experimental study on human-AI collaboration, revealing that efficient delegation and metaknowledge – knowledge about what one knows and does not know – improves outcomes, emphasising the role of metaknowledge in managing cognitive workload; the study highlighted poor human delegation decisions due to insufficient metaknowledge. Hertel et al. (2019) used an experimental design to study Decision Support Systems (DSS), finding they improve decision quality and reduce cognitive strain when trusted; the availability of DSS increased decision quality and well-being while reducing mental strain. Malik et al. (2021) employed interviews to highlight the cognitive challenges and technostress from AI adoption in Industry 4.0, underscoring the need for strategic training to manage cognitive workload, drawing a parallel with Bispo and Amaral's (2024) review

results. Malik et al. (2021) also identified job insecurity, work overload, and work complexity as key sources of technostress. Tortorella et al. (2024) found, in expert interviews and case studies, that the use of AI can reduce the cognitive demand by handling routine tasks. This reduction in cognitive demand was linked to increased meaningfulness in work, as employees could engage in more challenging and value-added tasks. By freeing up mental capacity, AI enables employees to perform activities that they find more meaningful and satisfying, thus enhancing their overall engagement and sense of purpose in organisations.

Behavioural outcomes

Technology Acceptance: Within non-empirical articles, technology acceptance was often referenced. Ismatullaev and Kim's (2022) review provides a structured framework to understand the antecedents of AI and Industry 4.0 technology acceptance, categorising influencing factors into four distinct domains.

Technology-Related Factors: Key aspects include transparency, reliability, complexity, and compatibility, essential for clear and user-friendly AI solutions (Ismatullaev and Kim. 2022).

Organisation-Related Factors: van Oudenhoven et al. (2023) stress the importance of worker decision-making control, and that understanding managerial motivations lead to better acceptance. While Dimitrakopoulos et al. (2024) found that facilitating conditions, such as the availability of resources and support, can increase initial and sustained technology acceptance

Perception/Behaviour-Related Factors: Perceived usefulness, ease of use, perception of autonomy, trust, sufficient cognitive resources, and perceived risks are highlighted as antecedents to acceptance (Dimitrakopoulos et al. 2024; Ismatullaev and Kim. 2022; Klumpp et al. 2019; van Oudenhoven et al. 2023). Attitudes are also important predictors; these attitudes are composed of the rational sphere (information retrieved, education and analytical skills of the individual), the emotional sphere, the cognitive sphere, and social pressure to use AI (Del Giudice et al. 2023; Dimitrakopoulos et al. 2024). Within the same vein, Dimitrakopoulos et al. (2024) found that trust can significantly positively influence initial and sustained technology acceptance.

Human-Factors-related: Age, gender, education, and experience are significant in AI acceptance (Ismatullaev and Kim. 2022).

Within empirical articles, the TAM was used by four articles to examine technology acceptance, indicating that this variable was relatively well represented. Perceived ease of use and perceived usefulness were found to be antecedents of acceptance. In turn, organisational

complexity (complexity of systems and processes) negatively affected both perceived usefulness and ease of use, while the level of competitive advantage associated with AI positively affected them. Additionally, organisational competency (employees' skills, knowledge, capabilities), organisational readiness (to adopt AI), support from the company's external partners, and perceived ease of use positively impacted the AI's perceived usefulness (Chatterjee et al. 2021). Technology acceptance itself was found to be a mediator in the relationship between opportunities for information, opportunities for training, resilience, supervisor support, role clarity, and work engagement (Molino, Cortese, and Ghislieri 2020; Molino, Cortese, and Ghislieri 2021).

In conclusion, we observe a significant gap between non-empirical and empirical research. Non-empirical articles have significantly explored various variables such as trust, technology acceptance, perceived autonomy, stress, and worker motivation, emphasising their critical roles in shaping worker well-being, organisational performance, and system efficiency. Empirical articles, on the other hand, have not sufficiently addressed these factors. This disparity suggests a need for more empirical investigations that specifically focus on these identified variables. Additionally, as depicted in Figure 5, no two empirical articles examined the same relationship, highlighting a significant fragmentation in the empirical landscape. This lack of consistency and cohesion among studies makes it challenging to draw comprehensive and reliable conclusions about the impacts of AI on human factors. Bridging these gaps is essential for a more comprehensive and practical understanding of the dynamics of human-AI interaction, ensuring that theoretical insights are adequately tested and validated in real-world scenarios, in order to guide the development of more effective and human-centric AI systems in the workplace.

Research designs

Within the non-empirical articles, there is an evident push for researchers to employ experimental methodologies when probing into the human factors (especially psychosocial) that affect workers interacting with AI systems (Adadi and Berrada 2018; Bispo and Amaral 2024; Del Giudice et al. 2023; Ismatullaev and Kim. 2022; Kadir, Broberg, and da Conceicao 2019; Lu et al. 2022; Peruzzini, Grandi, and Pellicciari 2020). By utilising experimental designs, researchers have the opportunity to systematically vary independent variables – such as the degree of automation or the extent of human oversight – and gauge their impact on various dependent variables, which could include metrics like worker trust, job satisfaction, and perceived autonomy. The controlled

manipulation of these variables not only facilitates a clearer observation of their effects but also strengthens the potential to draw causal links. Through such deliberate modifications within an experimental framework, insights can be derived that are pivotal for the iterative design of AI systems that are attuned to the nuanced needs of the workforce.

Moreover, the precision inherent in experimental design means that researchers can isolate specific aspects of the human-AI interface for scrutiny. For instance, they could manipulate the frequency and type of feedback provided by AI to users to measure direct impacts on user stress, cognitive load, or decision-making efficacy. The ability to control extraneous variables and directly observe the outcomes of these manipulations allows for a more granular understanding of how different facets of AI systems influence worker perception, attitudes, and behaviour. Additionally, experimental research can facilitate longitudinal studies that track changes in human factors over time, offering a dynamic view of the adaptation process as workers interact with evolving AI technologies (Ghislieri, Molino, and Cortese 2018). This is critical because the effects of AI on human factors, especially the psychosocial dimension, might not be immediately apparent but could develop or change as individuals become more experienced with the technology.

Within the empirical articles, 11 used an observational cross-sectional design, while only three used an experimental design. The dominance of observational cross-sectional studies, while not optimal for establishing causal relationships, does provide immediate and accessible insights into the current state of human-AI interactions in the workplace. These studies can quickly map out the landscape, identifying prevalent trends and associations that are critical for hypothesis generation. They serve as a foundational step, offering a broad understanding that is essential for informing future research directions.

In combining the strengths of both observational and experimental methods, the research community can gain a more holistic view of human-AI interactions. Observational studies set the stage by revealing the real-world complexities of these interactions, while experimental studies can then test the causal hypotheses that emerge from these observations. Together, these methods can provide a comprehensive understanding that is both reflective of actual workplace dynamics and rigorous in its causal conclusions.

Data collection method

To evaluate human factors, there is a consensus among authors of non-empirical articles to use a multi-method

approach. This approach involves using perceptual, psychophysiological, and observational measures to gain a well-rounded, more complete understanding of workers' state (Bousdekis et al. 2022; Brunzini et al. 2021; Ciccarelli et al. 2022; Cohen et al. 2018; De Lombaert et al. 2023; Diamantopoulos and Weitian 2021; Golan, Cohen, and Singer 2019; Grigsby 2018; Papetti et al. 2020; Peruzzini, Grandi, and Pellicciari 2017; Peruzzini, Grandi, and Pellicciari 2020; Vijayakumar and Sgarbossa 2020). Perceptual measures involve the measurement of workers' subjective experience and perceptions through questionnaires or interviews. For example, Adattil, Thorvald, and Romero (2024) recommend using the Work Design Questionnaire (Morgeson and Humphrey 2006), the Online interactive Risk Assessment (Senior Labour Inspectors Committee 2018), or the International Labor Organisation Stress Checkpoints (Owen and Dollard 2018) to assess psychosocial factors. Psychophysiological measures involve the use of various sensors to capture workers' physiological data, such as heart rate, galvanic skin response, eye tracking, etc. For example, heart rate monitoring can be used to measure worker stress and cognitive workload (Khairai, Sutarto, and Wahab 2020; Peruzzini, Grandi, and Pellicciari 2020). Observational measures involve the analysis of worker behaviour, usually through performance metrics or video/audio recordings.

Within empirical articles we reviewed, all used perceptual measures (questionnaires, interviews, or focus groups). Two experimental studies in our sample used both perceptual and observational measures. While only one study, our own, used perceptual, observational, and physiological measures (Passalacqua et al. 2024). The incorporation of psychophysiological measures has the potential to significantly enrich our understanding of human-AI interaction. These measures bring a level of objectivity that perceptual data, being self-reported, inherently lacks. For example, while a questionnaire might capture a worker's subjective feeling of stress, concurrent measurement of galvanic skin response provides objective evidence of physiological arousal, which can be a physical manifestation of stress. The use of eye-tracking can objectively determine where a worker's attention is focused during an interaction with AI, and heart rate variability can offer insights into cognitive workload and emotional states.

Psychophysiological measures can also help mitigate mono-method bias, a limitation that occurs when researchers rely on a single method of data collection (De Guinea, Titah, and Léger 2013). Mono-method bias can lead to skewed data or false confirmations of hypothesised relationships. By combining psychophysiological data with perceptual and observational metrics,

researchers can improve the validation of the findings across multiple streams of evidence, leading to more robust and reliable results.

Furthermore, although not discussed within the selected articles, neurophysiological measures, a subset of psychophysiological measures focusing mostly on brain activity, can offer direct insights into the brain's responses to AI interactions, providing a window into the unobservable mental processes of workers. Neurophysiological measurement tools such as electroencephalography or functional near-infrared spectroscopy can, for instance, help identify the precise moments when a worker may be experiencing cognitive overload or the points of an interaction that trigger engagement or disengagement.

The inclusion of these various methods enriches the research design, ensuring a comprehensive analysis that encompasses subjective experiences, observable behaviours, and objective physiological responses. While our empirical articles predominantly used perceptual measures due to their methodological design, the experimental studies incorporated both perceptual and observational measures, suggesting a move towards more integrative approaches. There is, however, still room for these studies to expand their methodologies to include psychophysiological and neurophysiological measures. Doing so would not only enhance the depth and breadth of the research findings but would also contribute to a better understanding of human factors at play in human-AI interactions. This multi-method approach would be particularly valuable in experimental research, where the manipulation of variables provides an opportunity for observing and measuring the complex interplay of perceptions, behaviours, and physiological responses in real-time.

Future research directions

Our proposed conceptual model integrates frameworks from production and psychological research, offering a foundation for understanding the interplay between technological, organisational, individual, psychosocial, cognitive, and behavioural factors. The model provides a structured method for investigating the impacts of AI technologies on workers, addressing theoretical and methodological gaps identified in current studies on human-centred AI in Industry 5.0. Future empirical research should leverage this model to explore various dimensions of human factors and their relationships with technological and organisational characteristics, thereby advancing the field and ensuring that AI advancements promote both human well-being and organisational effectiveness.

Technological characteristics

Future research should focus on the manipulation of technological characteristics to assess their impact on psychosocial and cognitive factors.

Varying the levels of automation can provide insights into how different degrees of automation influence workers' autonomy, motivation, and stress. For instance, studies can experiment with fully automated systems versus semi-automated systems where workers have more control over decision-making. The findings of Passalacqua et al. (2024) demonstrate that balanced levels of AI decisional authority, where AI assists but does not fully control, result in higher motivation, perceived autonomy, and skill acquisition. These outcomes suggest that partial automation might be more beneficial for worker engagement and satisfaction than full automation. Research should thus further explore control schemes that allow workers to adjust and override AI decisions, enhancing their sense of control and reducing stress, among others. Understanding these dynamics can help design systems that balance efficiency and worker well-being.

Evaluating how system reliability affects trust and perceived stress is also an important avenue for research. System performance consistency can significantly influence workers' trust in AI systems and their overall stress levels. High reliability may enhance trust and reduce stress, whereas frequent system failures might lead to increased stress and decreased trust. Research should focus on how different levels of system reliability impact these psychosocial factors and the subsequent effects on worker performance and job satisfaction.

AI transparency, or the extent to which AI decision-making processes are visible and understandable to users, is another critical factor. Transparent AI systems that provide clear explanations for their decisions can foster greater trust and acceptance among workers. Studies should investigate how varying levels of AI transparency impact trust and cognitive workload. For instance, Adadi and Berrada (2018) highlighted the importance of explainable AI in building trust.

By focusing on these various technological characteristics, future research can provide a better understanding of how the design of AI systems impact workers' psychosocial and cognitive factors. This knowledge will be instrumental in designing human-centred AI technologies that enhance worker well-being and organisational effectiveness.

Organisational characteristics

Empirical studies should examine organisational factors such as task variety and complexity to observe their

effects on trust, motivation, and perceived autonomy. Task design, particularly in terms of variety and complexity, plays a crucial role in shaping workers' experiences and attitudes towards their jobs. Research should also explore how the integration of advanced technologies affects task variety and complexity, as these changes can significantly influence worker outcomes. High task variety can lead to greater job satisfaction and motivation by providing workers with diverse and engaging responsibilities. Conversely, tasks with low variety and high repetition may contribute to worker disengagement and increased stress. Understanding the optimal balance of task variety and complexity can help organisations design roles that maximise worker engagement and minimise negative outcomes.

Training programmes that improve digital literacy and resilience are critical for helping workers adapt to AI-driven environments. These programmes should be designed to enhance workers' technical skills and their ability to cope with the dynamic and often challenging nature of AI-integrated workplaces. Effective training can reduce stress and enhance motivation by making workers feel more competent and confident in their abilities to interact with advanced technologies. Research should explore different training approaches, such as hands-on workshops, e-learning modules, and mentorship programmes, to identify the most effective methods for improving digital literacy and resilience.

The physical context of the workplace, including plant size, plant age, and unionisation, significantly impacts technology implementation and adoption (Tortorella et al. 2020; Yüksel 2022). Larger plants may have more resources and infrastructure to support AI integration but may also face greater complexity in managing change. Older plants might struggle with integrating modern technologies due to legacy systems and entrenched processes. Unionisation can influence worker acceptance of new technologies, particularly in terms of how changes are communicated and managed. Research should examine how these organisational factors affect the success of AI integration, focusing on strategies to overcome challenges and leverage opportunities within different organisational contexts.

Moreover, organisational support and leadership play pivotal roles in shaping worker perceptions and experiences with AI technologies. Leaders who actively support AI initiatives and foster a culture of innovation can positively influence worker attitudes towards AI adoption. Clear communication about the benefits and challenges of AI, coupled with opportunities for worker feedback and participation in the integration process, can enhance trust and acceptance. Research should explore the impact

of different leadership styles and communication strategies on the success of AI implementation, aiming to identify best practices that promote positive organisational outcomes.

In conclusion, by studying various organisational characteristics, future research can provide valuable insights into how different factors influence the integration and effectiveness of AI technologies in the workplace. These insights will be crucial for developing strategies that not only enhance worker well-being and performance but also ensure the successful adoption and utilisation of AI systems within diverse organisational contexts.

Individual characteristics

Considering individual differences is crucial for understanding how personality traits and prior experience with technology influence workers' responses to AI. These individual characteristics can significantly affect how workers perceive and interact with AI systems, ultimately impacting their performance and well-being. Future research should explore how these individual characteristics moderate the impact of AI on worker outcomes, providing insights into how to tailor AI integration strategies to different types of workers.

For example, studies could examine how resilience and self-efficacy influence workers' ability to adapt to AI-driven changes and maintain high levels of motivation and performance. Resilience may impact how workers cope with the challenges and uncertainties associated with AI adoption, with higher resilience potentially leading to better adaptation and positive perceptions of AI. Similarly, self-efficacy may influence workers' confidence in their ability to learn new skills and remain motivated, affecting their overall performance in AI-integrated environments.

Personality traits, such as openness to experience, conscientiousness, and neuroticism, may impact how workers respond to AI. Openness to experience might lead to more positive attitudes towards AI adoption, while conscientiousness could influence how diligently workers engage with AI systems. Conversely, high levels of neuroticism may result in greater resistance to AI and increased stress levels.

Additionally, prior experience with technology can shape workers' comfort levels and proficiency with AI systems, which may impact their attitudes and performance. Workers with positive experiences with technology might be more receptive to AI, whereas those with limited or negative experiences may require additional support and training.

Demographic factors such as age, education level, and cultural background may also impact how workers

perceive and interact with AI. For instance, younger workers might find it easier to adapt to AI, while older workers might face more challenges. Educational background and cultural influences may affect attitudes towards technology and change, influencing worker responses to AI integration.

Understanding these individual differences is essential for designing AI systems and implementation strategies that are inclusive and effective. By considering the unique characteristics of each worker, organisations can create environments where all employees feel supported and capable of thriving in AI-enhanced roles.

Human factors and behavioural outcomes

Future research should delve into underexplored psychosocial variables, considering the bidirectional relationship among psychosocial, cognitive, and behavioural factors. This approach is crucial to fully understand how these dimensions influence each other and ultimately affect worker outcomes.

Investigating the antecedents and outcomes of trust in AI systems can provide valuable insights into how trust influences worker behaviour and performance. Trust in AI can determine the extent to which workers rely on and effectively use these systems, impacting their efficiency, satisfaction, and overall job performance. Understanding the factors that build or erode this trust, such as transparency, reliability, and explainability of AI systems, can help in designing AI technologies that workers are more likely to accept and use effectively.

Research should also explore how AI systems can enhance or diminish worker motivation and the subsequent effects on job performance and satisfaction. AI can potentially increase motivation by automating mundane tasks, allowing workers to focus on more engaging and meaningful activities. However, if not implemented thoughtfully, AI could lead to job monotony or insecurity, reducing motivation. Investigating these dynamics can guide the development of AI applications that support worker engagement and satisfaction.

Perceived autonomy is another critical factor that needs exploration. Workers' perception of autonomy, or their sense of control over their work, significantly affects their motivation, job satisfaction, and overall well-being. AI systems that allow workers to have some degree of control over decision-making processes can enhance their perceived autonomy, leading to better engagement and performance. Conversely, systems that overly constrain workers' control can diminish their sense of autonomy, leading to dissatisfaction and disengagement.

Examining the factors that contribute to worker stress in AI-integrated environments and developing strategies to mitigate these stressors is essential for promoting

worker well-being. Stressors might include the complexity of new technologies, the pace of required skill acquisition, and fears of job displacement. Strategies such as adaptive automation, which adjusts the level of AI intervention based on the worker's current state, and real-time feedback, which provides continuous performance support and reassurance, can help manage cognitive demands and enhance worker performance and well-being.

Investigating how the physical dimension of human factors interacts with psychosocial and cognitive dimensions, as well as behavioural outcomes, can provide a comprehensive understanding of how different aspects of the work environment influence organisational outcomes. It would be particularly interesting to explore the bidirectionality of the relationships between physical, psychosocial, cognitive, and behavioural factors. For instance, chronic stress and overly high cognitive workload may exacerbate physical symptoms like musculoskeletal discomfort, creating a cycle of declining health and performance. Conversely, physical discomfort may increase cognitive load and stress, impacting overall job performance and satisfaction. Understanding these bidirectional relationships can inform the development of interventions that address both physical and psychological aspects of the work environment.

Organisational outcomes

The conceptual model links individual outcomes to broader organisational impacts, emphasising how changes at the individual level drive organisational success. Future research should explore how improvements in worker outcomes, such as increased job satisfaction and reduced stress, enhance organisational benefits like higher productivity and innovation. Also, understanding the factors contributing to employee retention in AI-integrated workplaces is crucial. Research should investigate how job satisfaction, stress levels, motivation and organisational support influence turnover rates. Creating a supportive work environment that addresses psychosocial needs can enhance overall organisational performance.

Integration of interdisciplinary theoretical frameworks

Future research should integrate and expand established theories, such as the Job Demands-Resources Model, Self-Determination Theory, and Job Characteristics Theory, to provide a deeper understanding of the dynamics between technological, psychosocial, cognitive, and behavioural factors. Expanding these theories to include AI-specific variables and contexts can reveal how these elements interact and influence worker outcomes in

AI-integrated environments. Using and adapting these frameworks ensures a comprehensive examination of variables and factors, facilitating the development of AI systems that enhance both individual well-being and organisational performance.

Data collection strategy

A diverse and robust data collection strategy is essential for future research on the impact of AI on workers. Employing multiple methods allows for a more comprehensive understanding of how AI technologies affect various aspects of worker experiences and outcomes.

To establish cause-and-effect relationships, experimental designs are essential. By systematically manipulating key technological and organisational characteristics, researchers can evaluate their impact on human factors such as psychosocial and cognitive outcomes. Controlled experiments allow for the isolation of specific variables, providing clear evidence of how different aspects of AI technology influence worker well-being and performance. This rigorous approach ensures that findings are robust and can guide the development of AI systems that balance technological efficiency with the enhancement of worker experience and satisfaction.

Longitudinal designs are also useful for capturing the dynamic nature of human-AI interactions. These studies can track how workers' perceptions and behaviours evolve over time, providing valuable insights into the long-term sustainability and effectiveness of AI interventions. By observing changes over extended periods, researchers can identify trends and patterns that may not be apparent in short-term studies.

Combining perceptual, psychophysiological, and observational measures offers a holistic view of worker experiences. For example, self-reported stress and cognitive workload levels can be supplemented with physiological data, such as heart rate variability and eye-tracking, to provide a more accurate and nuanced assessment of stress and cognitive load. Additionally, neurophysiological measures like electroencephalography can offer deeper insights into cognitive functioning, capturing the full breadth of the human experience with AI and revealing discrepancies between perceived and actual cognitive demands (Riedl et al. 2020). This comprehensive approach ensures a thorough understanding of how AI impacts worker well-being and performance.

Utilising deep learning techniques to analyse physiological data can further enhance worker safety and well-being. Developing algorithms capable of detecting early signs of stress or cognitive overload from physiological signals can enable real-time interventions, preventing negative outcomes before they escalate. These advanced analytical methods can identify subtle patterns in data

that may indicate emerging issues, allowing for proactive management of worker health and performance.

In summary, a comprehensive data collection strategy that integrates longitudinal, perceptual, psychophysiological, observational, and advanced analytical methods is essential for advancing our understanding of the human-AI interaction. This multifaceted approach will ensure that future research captures the complexity of these interactions and informs the development of AI systems that support worker well-being and organisational effectiveness.

To conclude the future research directions, we present some general questions raised in this systematic review.

- Which technological characteristics, specifically related to the design and implementation of AI, significantly impact human factors (psychosocial, cognitive, physical)?
- How can the design and implementation of AI be approached to positively impact psychosocial factors such as motivation, trust, and autonomy?
- How do technological and organisational characteristics interact to affect human factors?
- How do demographic factors like age and education influence workers' adaptation to AI, and how can these differences be addressed?
- Which human factors significantly impact the adoption, acceptance, and efficient use of AI?
- How can the processes for designing, deploying, and validating AI-based solutions be adapted to include human factors?
- How can human factors be accurately and unobtrusively measured in a real-world context?

Practical and managerial implications

The transformative potential of Industry 4.0 (I4.0) technologies, particularly artificial intelligence (AI), necessitates a comprehensive approach that balances technological advancements with human-centric considerations. The implications derived from the introduction of AI into the workplace offer valuable insights for practitioners and decision-makers striving to optimise both productivity and employee well-being.

Firstly, the integration of AI technologies has significantly altered worker roles and responsibilities. Workers have transitioned from performing routine maintenance tasks to engaging in more strategic and cognitively demanding activities. This shift presents an opportunity for enhanced job satisfaction and a deeper sense of meaningfulness in their work. To capitalise on this, managers should prioritise providing ample opportunities for skill

development and training, thereby equipping workers to handle complex roles effectively.

However, the dual-edged nature of AI also imposes high cognitive demands and stress. To mitigate these challenges, decision-makers must ensure a balanced workload and robust support systems. By designing AI systems that enhance worker autonomy and reduce monotony, organisations can alleviate stress and improve overall well-being. Additionally, addressing job security concerns through continuous learning initiatives and clear pathways for career advancement can foster a more positive outlook towards AI among employees. A human-centric approach in AI development is crucial, focusing on designing systems that complement and empower rather than replace human work, especially in decision-making processes. This approach can significantly enhance workers' perceptions of autonomy, motivation, and overall job satisfaction, thereby improving their performance and well-being (Legaspi et al. 2024; Nazareno and Schiff 2021).

Employee well-being and retention are critical factors influenced by the introduction of AI. Organisations that focus on both the positive and negative impacts of AI can enhance motivation, engagement, and long-term retention. Implementing policies that prioritise mental health and work-life balance will create a supportive work environment conducive to high performance. Additionally, incorporating psychosocial factors into managerial decision-making processes is essential. Managers and leaders must understand AI's potential impacts on employee trust, autonomy, and motivation, using this knowledge to develop effective change management strategies. This includes tailored communication and training in AI deployment, which equips leaders to address employee concerns, foster adaptability, and manage the technical transition effectively (Bispo and Amaral 2024; Lee et al. 2022; Malik et al. 2021; Molino, Cortese, and Ghislieri 2020; Passalacqua et al. 2024; Reiman et al. 2021; Wellsandt, Hribernik, and Thoben 2021; Winkelhaus, Grosse, and Glock 2022).

A holistic approach to AI integration is essential for its successful deployment. Practitioners must consider the psychosocial and cognitive impacts of AI on workers, moving beyond a purely technical and efficiency focus. A human-centred approach in designing AI systems ensures they are safe, trustworthy, and aligned with human needs. This approach not only improves worker acceptance and satisfaction but also enhances the overall efficacy of AI systems. A data-driven approach in human resource management is indispensable, using insights on technology acceptance and employee experiences with AI to refine training and retention strategies that align

with the changing workplace dynamics introduced by AI (Reiman et al. 2021).

Strategic planning for AI deployment involves a thorough assessment of the work environment and the specific needs of the workforce. Decision-makers should develop strategies that align AI capabilities with organisational goals while addressing human factors. Such alignment enhances overall performance and competitive advantage. Continuous monitoring and adaptation of AI systems based on employee feedback is crucial for maintaining high levels of productivity and innovation. Regular organisational assessments of worker perceptions and attitudes towards AI are recommended to fine-tune AI strategies effectively. Monitoring key indicators such as employee satisfaction, productivity, and stress levels will provide insights into the long-term impact of AI integration, allowing for informed adjustments (Klumpp et al. 2019; Langer and Landers 2021).

Moreover, recognising the medium- to long-term effects of AI on workers is vital. Organisations should foster an environment of open communication where employees feel comfortable expressing their concerns and suggestions related to AI use. This inclusive approach ensures that AI technologies evolve in ways that benefit both the organisation and its workforce. Cross-functional collaboration can also be beneficial in AI implementation, involving teams from various departments, including IT, HR, and operations, to ensure a balanced and holistic approach. This collaboration should harmonise technical feasibility with worker well-being and operational efficiency, reflecting a commitment to effective and empathetic deployment of AI in the workplace (Cadden et al. 2022).

Our conceptual model (Figure 1), developed by integrating frameworks from production research, and organisational and clinical psychology, can significantly aid practitioners and decision-makers in several ways. Firstly, by understanding the bidirectional relationship between technological and organisational characteristics, practitioners can design and implement AI systems that positively impact worker motivation, engagement, and performance. For instance, ensuring transparency in AI-powered tools can improve communication and collaboration, fostering a supportive organisational culture.

Secondly, the model highlights the importance of psychosocial and cognitive factors, such as trust, autonomy, stress, motivation, and cognitive workload. Decision-makers can use this understanding to implement targeted interventions that enhance worker autonomy and enhance job satisfaction. For example, balancing AI decisional authority can maintain high levels of perceived autonomy among workers.

Thirdly, the model's emphasis on the interconnections between cognitive, psychosocial, and behavioural factors allows for comprehensive assessments of AI's impact on the workforce. Regular monitoring of these factors can help organisations make informed adjustments to their AI strategies, ensuring they align with employee needs and organisational goals.

Fourthly, by incorporating individual characteristics as moderators, the model underscores the need for personalised training and development programmes. Managers can design training initiatives that cater to different personality traits and growth needs, enhancing overall workforce adaptability and resilience.

Finally, understanding the cascading effects of technological and organisational changes on human factors and organisational outcomes enables decision-makers to foster environments that promote well-being and high performance. This holistic approach can lead to reduced absenteeism, lower turnover rates, and increased productivity.

In conclusion, the successful integration of AI in the workplace hinges on a balanced approach that values both technological advancements and human-centric considerations. By prioritising skill development, managing cognitive demands, addressing job security, and fostering a supportive work environment, practitioners and decision-makers can create a symbiotic relationship between AI technologies and human workers. This approach, guided by our conceptual model, not only enhances productivity and innovation but also ensures the well-being and motivation of the workforce, driving long-term organisational success.

Limitations

Despite our comprehensive approach, several limitations exist within this review. Firstly, our reliance on peer-reviewed articles, including both journal and conference papers, may introduce publication bias by potentially excluding relevant studies from grey literature. Additionally, the tendency for non-significant results to remain unpublished may further skew the literature, resulting in an overrepresentation of significant findings and potentially overlooking important data that could provide a more balanced understanding.

Our focus on AI-based systems within Industry 4.0 and 5.0 may not fully capture the breadth of human factors related to other advanced technologies (e.g. robots, augmented reality), possibly limiting the applicability of our findings to other sectors. While our review provides valuable insights into AI within a production environment, other contexts might exhibit different dynamics and challenges, necessitating broader investigations.

Furthermore, the predominance of observational cross-sectional designs in empirical studies, with limited use of experimental methodologies, restricts the ability to establish causal relationships and understand the dynamic impacts of AI on workers over time. This reliance on cross-sectional data provides snapshots of current conditions but lacks the depth to uncover long-term effects and causal pathways.

Lastly, the narrative synthesis approach, chosen due to the qualitative nature of much of the data, while effective in integrating diverse data types, may lack the quantitative rigour that other synthesis methods, such as meta-analyses, could provide. Although it allows for a rich, detailed understanding of themes and patterns, it falls short in providing statistically robust conclusions.

Conclusion

Industry 5.0 marks a significant evolution in the industrial landscape, emphasising the synergy between advanced AI and human creativity to redefine manufacturing and operational processes. This era extends beyond the technological advancements of Industry 4.0, seeking to balance efficiency with the enrichment of the workforce's psychosocial and cognitive well-being. Our systematic review aimed to explore the integration of psychosocial, cognitive, and behavioural factors within AI-based work systems, which have been largely overlooked in favour of technical capabilities and human performance. The research objectives were to provide an in-depth examination of these factors in I4.0 contexts, identifying their outcomes, antecedents, consequences, and the methodologies used to address them, to uncover gaps in the current literature.

The review unveiled a significant underrepresentation of pivotal factors such as trust in AI, worker autonomy, motivation, and stress within current research. This shortfall is compounded by a theoretical and methodological disconnect between empirical and non-empirical studies, particularly evident in the selection of theoretical frameworks, variables, research designs, and data collection methods.

In light of these findings, our review suggests several future research trajectories for developing human-centred AI systems. Future studies should manipulate technological characteristics like automation levels, system reliability, and AI transparency to assess their impact on worker psychosocial, cognitive, and behavioural factors. Research should also examine organisational factors such as task variety, complexity, and workplace context to understand their effects on trust, motivation,

and perceived autonomy. Additionally, research should consider individual differences, exploring how personality traits, prior experience with technology, and demographic factors influence workers' responses to AI, providing insights into tailoring AI integration strategies. Investigating underexplored psychosocial variables, their relationships with cognitive and behavioural factors, as well as their antecedents and outcomes can be beneficial to designing and implementing human-centred systems. Lastly, a diverse data collection strategy integrating experimental or longitudinal research designs, along with perceptual, psychophysiological, and observational measure is essential for advancing our understanding of human-AI interactions and informing AI systems that support worker well-being and organisational effectiveness.

The shift towards Industry 5.0 necessitates a conscientious integration of AI into work systems, with particular attention to the psychosocial and cognitive effects on the workforce. Future research, guided by the findings of this review, must continue to incorporate knowledge from organisational psychology and human factors in the design and implementation of AI systems. This integration is crucial to ensure that AI coexists with, and amplifies, the human element within the workforce. Achieving this balance will enable a transition from the technology-centric orientation of Industry 4.0 to the human-centric vision of Industry 5.0, creating an industrial ecosystem where technology and human potential are synergistic, ultimately realising the full promise of both.

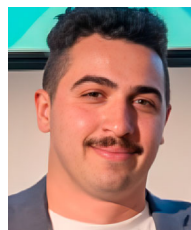
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Data availability statement

All raw extracted data and processed data are openly available in the Mendeley Data repository at <https://doi.org/10.17632/ynptkr357k.1>

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