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AI transformation in working life: A systematic review of usage and attitudes towards AI among workers

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ABSTRACT

The unprecedented development in Artificial Intelligence (AI) is transforming workplaces and work processes, necessitating a broader understanding of how employees perceive and adapt to these changes. Extensive research has examined the implications of AI implementation in the workplace. However, previous studies have mainly focused on historical perspectives or conceptual analyses. This study presents findings from a systematic literature review covering empirical research from five years (2020–2024). We focus on workers' first-hand experiences and appraisals of AI-related *changes* in their workplaces. We also synthesize how attitudes towards AI vary across professional sectors and implementation contexts. Using the PRISMA methodology, we conducted systematic searches across five databases: EBSCOhost (EBSCO), PsycINFO (APA), Scopus (Elsevier), Social Science Premium Collection (ProQuest), and Web of Science (Clarivate) between June 3rd and 10th, 2024. A synthesis of $k = 24$ studies revealed that workers perceive AI as both an opportunity and a source of concern. Automation and decision-support tools in the workplace were related to improved efficiency, productivity, and perceived fairness, but they were also connected to anxiety and uncertainty about role change and job security. Evidence was most prevalent in healthcare and education, indicating a need for broader sectoral and regional research. The findings highlight the importance of transparent and ethical AI integration, ensuring fairness, accountability, and human oversight, supported by workforce training and communication.

1. Introduction

New and innovative technologies have shaped working life and ways of working for centuries, automating labor-intensive and time-consuming tasks. The industrial revolution transformed working life with steam power in the 18th century, followed by machinery and assembly lines in the next. The past few decades have been defined by the digital revolution, where workplace innovation centers around adopting new and emerging digital tools (Dwivedi et al., 2022; Park, 2018). The introduction of artificial intelligence (AI) into working life represents the most recent transformative force with its enormous potential across different domains.

The recent leaps in AI development have led to a situation where its universal adoption is more rapid than ever (Dwivedi et al., 2021; Spencer, 2025). This represents a major societal shift in what is expected of workers and how work is conducted. A growing body of research has examined AI in organizational and technological terms, but relatively little is known about how workers themselves experience and interpret these changes in their daily work. This calls for a synthesis of most recent research. This systematic literature review responds to this need and explores workers' first-hand experiences and attitudes towards AI, including their perceptions, beliefs, and emotional responses to AI technologies in the workplace. This involves examining AI's impact on different work tasks and employees' roles. The aim is to provide a comprehensive overview of AI's multifaceted influence on working life across sectors during the past five years -a period covering rapid AI development and adoption.

Artificial intelligence covers a range of technologies varying in sophistication. Essentially, it refers to technology that is capable of learning and performing tasks at a level requiring human intelligence (Glikson & Woolley, 2020). At the same time, these technologies are designed to exceed human capacity and ease people's lives and workloads. As AI tools increasingly influence how people work and organize their professional lives, organizations and workers are faced with unique opportunities and challenges (Autor, 2015; Frey & Osborne, 2017; Heras García, 2022; Li, Wu, Zhang, & Wu, 2025; Pereira, Hadjielias, Christofi,

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& Vrontis, 2023). Historically, technological change has always been met with a mix of optimism and skepticism, promising to simplify work while demanding new skills, motivation, and trust from users (Glikson & Woolley, 2020). AI implementation, in particular, is characterized by intensified tension. It provokes strong emotions among workers, as its far-reaching implications remain uncertain in the still-evolving technological landscape. As workers are at the frontline of the current AI revolution, their perceptions of and attitudes towards AI are crucial when it comes to successful uptake and acceptance of new technology in the workplace (Kelly, Kaye, & Oviedo-Trespalacios, 2023).

According to a systematic review by Bankins, Ocampo, Marrone, Restubog, and Woo (2024), discussions about future of work are commonly negatively charged, which stems from workers' fear-based or threat-focused attitudes. These are likely related to the fact that AI is often discussed together with job replacement, skill obsolescence, or significant changes in work roles. Such consequences are particularly prominent in production sectors (Acemoglu & Restrepo, 2019; Bhargava, Bester, & Bolton, 2021). AI adoption has also been associated with an overall decrease in employment in fields that already have low labor productivity, as well as the displacement of jobs requiring advanced problem-solving and literacy skills (Pereira et al., 2023). These types of changes can reduce workers' organizational commitment, job engagement, and increase perceptions of job insecurity, contributing to higher turnover intentions, burnout, and resistance to change or new technologies (Bankins et al., 2024). Employees may also feel disregarded or undervalued when employers explore advanced technological alternatives to human workforce, such as AI and robotics (Brougham & Haar, 2018). However, the displacement of work by AI is not always a clear-cut process. Some studies have pointed out that adoption of new technologies tends to progress gradually. This allows time for the development of new tasks and job opportunities, thus mitigating potential job losses caused by automated processes (Howard, 2019).

An additional unique contribution of AI is that it can now be applied or used to create tasks that require not only technical but also “soft” skills, reasoning, and empathy. For instance, it can be used for collaborating across disciplines (von Richthofen, Ogolla and Send, 2022) or improve mindfulness amidst digital experiences and interactions (Jarrahi, Blyth, & Goray, 2023). This matches what Rust & Huang (2021) have considered as *feeling economy*. They suggest that there is a shift from a *thinking* economy to a *feeling* economy as technology and AI are taking over the “cognitive tasks”, leaving humans the “feeling tasks”. However, over time, AI is expected to participate in tasks that require interaction skills and empathy (Huang & Rust, 2018). In fact, we are already witnessing the rise of AI in multiple sectors requiring human-like interactions (Holohan & Müller, 2024; Obrenovic, Gu, Wang, Godinic, & Jakhongirov, 2024; Xu, Dainoff, Ge, & Gao, 2023). These types of developments, while advanced, can induce uneasiness and distrust in such systems.

Today's context of AI disruption is unique in that it extends to sectors that previously had limited or no relevant applications of the technology. Workers' attitudes and appraisals play a central role in understanding the human side of such novel AI integration. How workers perceive, interpret, and emotionally respond to AI technologies can significantly influence their willingness to adopt new systems, their level of engagement, and behavioral responses to technological change. One longitudinal study revealed a connection between the perceived threat of AI (i.e., concerns about one's job security) and stronger negative attitudes towards AI adoption among employees over time. Positive attitudes were associated with relative advantages, compatibility, and observability (Xu, Kee, Li, Yamamoto and Riggs, 2024).

Research has also indicated that AI and advanced technology diffusion is influenced more by institutions and social actors than industrial policy (Lloyd & Payne, 2019). Institutions' transparency about their use of AI is thus a crucial factor. Research shows that distrust in the corporation is related to more negative attitudes towards AI (Park, Ahn, Hosanagar, & Lee, 2021; Schepman & Rodway, 2023). Workers' attitudes towards AI are also closely linked to other important workplace and individual outcomes, such as well-being. Negative attitudes or a perceived threat from AI, for instance, have been associated with heightened stress, anxiety, and feelings of job insecurity (Leong, Bai, Rasheed, Hameed, & Okumus, 2025; Yigit & Acikgoz, 2024). Positive perceptions, on the other hand, can foster engagement, sense of satisfaction, and productivity (Ding, 2021; Hopcan, Türkmen, & Polat, 2024).

In this review, we are interested in the workplace changes AI has brought and what types of attitudes workers display towards AI amidst those changes. While several recent reviews (e.g., Bankins et al., 2024; Budhwar, Malik, De Silva, & Thevisuthan, 2022; Deranty & Corbin, 2024; Pereira et al., 2023; Zirar, Ali, & Islam, 2023) have synthesized research on AI in the workplace, they differ in scope, methodological focus, and time window (see Table 1). Most emphasize organizational or management perspectives, historical developments, conceptual analyses, or investigate a specific sector. The present review focuses specifically on workers' first-hand experiences and attitudes towards AI in the workplace. It covers a recent five-year period (2020–2024) when AI adoption has accelerated. Through a systematic synthesis guided by three research questions, this review offers an updated, evidence-based overview of how workers perceive and experience AI's *transformative* effects on their *work* and *well-being.* In doing so, it also identifies key knowledge gaps in the field (Paul & Criado, 2020), aligning with earlier calls for added structured evidence on AI's workplace implications.

We frame our research in technology-adoption and innovation-diffusion theories that offer conceptual tools for understanding how workers engage with emerging technologies. The unified theory of acceptance and use of technology (UTAUT; Venkatesh, Morris, Davis, & Davis, 2003) has been widely used to explain why and how individuals accept and utilize new technologies. The model posits that behavioral intention is the main determinant of technology adoption, shaped by four core constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions (Khechine, Lakhal, & Ndjambou, 2016). The diffusion of innovation theory (DOI; Rogers, 2003), complements this perspective. It emphasizes that not all innovations are adopted, and diffusion can be explained by three general sets of variables: the attributes of the innovation itself, the characteristics of the adopters, and the broader social and organizational context. Applied to AI in the workplace, the UTAUT and DOI can help explain why workers may simultaneously perceive its applications as a benefit and a threat. Together, they provide a conceptual foundation for interpreting the attitudes, adoption behaviors, and responses identified in this review.

We pose the following research questions (RQs):

RQ1: How has AI transformed working life during the past five years (2020–2024) as experienced by workers?

RQ2: How are workers' attitudes towards AI related to its usage and changes in work practices?

RQ3: How has the implementation of AI in working life influenced workers' well-being across *hedonic* (e.g., job satisfaction, stress, workload, anxiety) and *eudaimonic* (e.g., sense of purpose, professional identity, fulfilment) dimensions?

2. Methods

The review protocol was preregistered in PROSPERO prior to conducting the literature search (ID: CRD42024553393). We conducted systematic data collection following the Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA; Page et al., 2021). The full PRISMA 2020 checklist is provided in the Supplementary Materials (Table S4). Literature searches were carried out from five different databases: EBSCOhost (EBSCO), PsycINFO (APA), Scopus (Elsevier), Social Science Premium Collection (ProQuest), and Web of Science (Clarivate).

Table 1
Comparison of existing reviews on AI and work with the added contribution of the current review.

Study	Time window	Focus/Scope	Methods	Perspective	Distinctive features / Limitations
Bankins et al. (2024)	Unspecified (mostly pre-2023 studies)	Human–AI collaboration, perceptions, attitudes, algorithmic management	Systematic review, multilevel thematic synthesis	Business/Management and Psychology / Individual, group, organizational	Emphasizes conceptual and organizational factors; limited coverage of well-being outcomes.
Budhwar et al. (2022)	2010–2020	International Human Resource Management (HRM)	Systematic review	Organizational / HRM	Theoretical contribution and detailed synthesis of AI's significance and role in HRM; coverage focused on one sector, fragmented literature.
Deranty and Corbin (2024)	Recent years (unspecified)	Social-science perspectives on AI's impact on work	Narrative review	Socio-political	Theoretical synthesis; lacks systematic empirical inclusion criteria.
Pereira et al. (2023)	1995–2020	AI and workplace outcomes (HRM perspective)	Systematic review and thematic analysis of 60 papers (HR framework)	Organizational / HR	Broad temporal scope; limited focus on worker experiences or attitudes.
Zirar et al. (2023)	2010–2021	Coexistence of workers and AI; skills and distrust	Scoping/systematic hybrid	Worker perspective	Valuable conceptual propositions; few empirical worker-level studies.
This review	**2020–2024**	**Workers' first-hand experiences, attitudes, and well-being impacts of AI**	**Systematic review across multiple databases**	**Worker-focused**	**Synthesizes empirical evidence focused on lived experiences and perceptions; identifies trends in recent (and post-pandemic) AI adoption.**

Our search term aimed to find research articles reporting findings on AI attitudes among adult workers and changes in the workplace.

The search logic was iteratively developed and tested in all databases to achieve an optimal balance between sensitivity (capturing relevant studies) and precision (minimizing irrelevant hits on an overly large scope). Pilot runs using broader queries initially retrieved large volumes of unrelated technical AI papers. Therefore, the Boolean operators and syntax were refined to better capture workers' experiences of AI and attitudes related to its use at work. The final search term structure included three core concepts, reflecting the research questions: (1) "attitudes" identified studies examining workers' cognitive or affective evaluations of AI, also consistent with theories on attitudes; (2) "work life" and "workers/employees" restricted scope to occupational settings, excluding consumer or general-public perspectives; (3) "change" ensured inclusion of research specifically addressing transformations in work practices, transitions, or adaptations linked to AI adoption.

The final search string was: (("artificial intelligence" OR "ai") OR ("machine learning" OR "intelligent systems") OR (robot* OR "computational intelligence")) AND ((transform* OR transition* OR change OR changing) OR (evolve* OR evolving) OR (adapt* OR adaptation) OR (shift* OR shifting) OR (disrupt* OR disruption) OR (revolut* OR revolution)) AND (("attitudes" OR "perceptions" OR "opinions" OR "beliefs" OR "dispositions" OR "views")) AND (("workers" OR "employees" OR "labourers" OR "professionals" OR "staff" OR "personnel" OR "workforce")) AND (("work life" OR "workplace" OR "occupational" OR "work setting")).

We conducted advanced document searches, filtering for peer-reviewed empirical articles published in English within the past five years (2020–2024). The searches targeted matches for the search terms in titles, abstracts, and keywords. The database searches were conducted by the first author and third author between June 3rd and 10th, 2024. Search strings were adapted to each database's syntax and field tags. See Supplementary Table S1 for full search strings for all databases, including Boolean operators and field tags used. The searches yielded a total of 659 results. After removing duplicates, 454 articles were screened for eligibility. The second and third authors independently reviewed the abstracts and rated them based on the pre-set inclusion and exclusion criteria. The inclusion criteria were first tested with a smaller part of the data. Any discrepancies were discussed and mediated by the first and fourth authors. These discussions focused on clarifying terminology and operational definitions, and the criteria were subsequently refined.

The final criteria resulted in identifying articles that: 1) reported qualitative or quantitative original empirical research on AI attitudes among adult employees/workers; 2) reported qualitative or quantitative original empirical research on the use of AI. Here, 'attitude' refers to workers' cognitive or affective evaluations, feelings, or beliefs about AI. 'AI use' was defined as human behavior performed by individuals at the workplace or as part of work tasks. The search strategy aimed to identify research articles reporting findings specifically on AI-brought change and workers' attitudes.

Exclusion criteria were: 1) research on AI development or technical papers about AI and technology, 2) unpublished works, and 3) review reports or meta-analyses. Inter-rater reliability between the raters was tested. Inclusion of an abstract was based on synergy in rating (agreement ranged from 87 % to 100 %). Cohen's kappa inter-rater reliability values ranged from moderate ($\kappa = 0.55$) to substantial ($\kappa = 0.64$). After the abstract screening process, 48 full texts were retrieved for evaluation. The first author read and appraised all reports in detail according to the inclusion and exclusion criteria that had been collaboratively established and tested during the title and abstract screening stage.

Because abstract-level reliability had already been established and inclusion rules were consensus-based, full-text decisions were performed by the first author. The full-text screening stage involved minimal ambiguity, as exclusions were driven by clear and consistently applied criteria (e.g., non-English full-text, not focused on workers, not empirical, or not reporting AI-related workplace change). Based on this process, 24 articles were included in the final synthesis (see Fig. 1, The PRISMA flow diagram of the selection process, including reasons mapped to counts). The methodological quality and risk-of-bias of the included studies were appraised using the Mixed Methods Appraisal Tool (MMAT; Hong et al., 2018). The MMAT evaluates methodological rigor across qualitative, quantitative, and mixed-method designs. Each study was assessed by two authors against five relevant criteria, and the resulting appraisals were used to inform interpretation.

Risk-of-bias was evaluated using a set of workable indicators of bias in empirical studies (Siddaway, Wood, & Hedges, 2019). Supplementary to the MMAT appraisal, (1) transparency and adequacy of data collection procedures, (2) clarity and rigor of analytical approach, (3) completeness of reporting, and (4) alignment between the data and the conclusions drawn, were considered. These indicators reflect core issues that may compromise the internal validity or interpretability of empirical studies. During the appraisal process, the authors discussed the studies in relation to these indicators. Strengths, weaknesses, and potential bias were identified. The assessment was used to add confidence in the evidence base, not as exclusion criteria. This step was taken to ensure best quality evidence (Tranfield, Denyer, & Smart, 2003). See Supplementary Table S2 for the MMAT appraisal.

The analyses involved identifying and grouping results related to any form of workplace change, as well as assessing attitudes (including

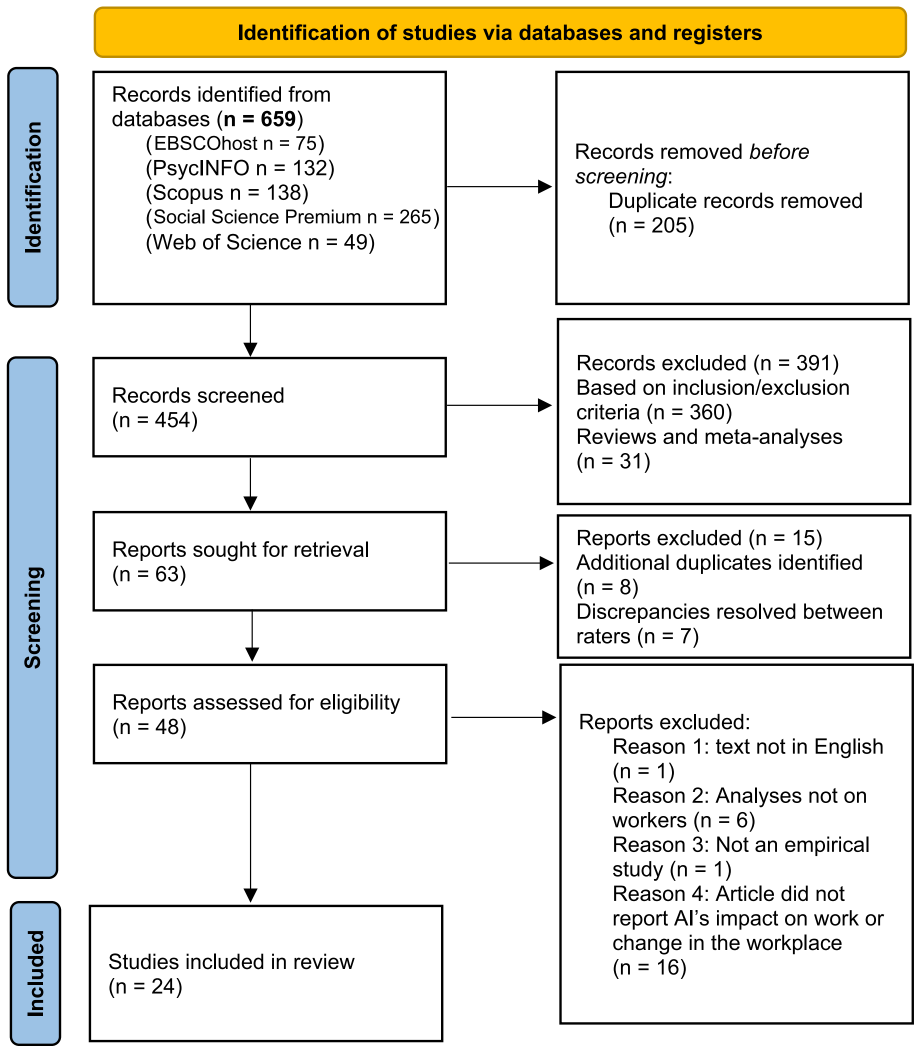

Fig. 1. PRISMA flow diagram depicting the data collection, screening, and study selection process for the systematic review.

feelings, anticipations, or affective evaluations of AI) and potential wellbeing outcomes. The methodologies, measurements, and samples in the selected studies were diverse. Thus, the analyses focused on systematically identifying key markers of change, attitudes, and wellbeing. The synthesis was inductive and interpretive, reflecting the diverse methodologies of the included studies. The first author extracted key information from each article through multiple readings. Findings were summarized along two key dimensions: *Main attitude / appraisal* and *Observed change markers / Change outcomes*. In addition, aspects related to workers' well-being, when explicitly addressed within these findings, were noted as a complementary focus to these dimensions.

In this review, "workers" and "employees" refer to adults in paid employment, "work/ing life" refers to the organizational and experience-related aspects of employment, and "AI" encompasses intelligent systems using algorithmic or machine learning techniques to support, augment, or automate work tasks. Well-being was conceptualized as a multidimensional construct, encompassing both hedonic and eudaimonic aspects. Hedonic well-being referred to affective states such as "job satisfaction", "stress", and "anxiety", whereas eudaimonic well-being was expected to capture deeper senses such as sense of "meaning", "purpose", and "professional fulfilment" in relation to AI in the workplace.

We defined the conceptual boundaries and domains guiding this review in the preregistered protocol. Thus, *attitudes* towards AI, workplace *change*, and *well-being* together functioned as a structured framework and codebook for data extraction. The codebook comprised two complementary parts: The first part captured descriptive characteristics and was analyzed quantitatively, including country or region of study, sample characteristics, study design or method, main AI concept examined (e.g., robotics, generative AI, decision support, IoMT), and participant demographics such as occupation. The second part focused on qualitative analysis of the results, identifying findings related to the three predefined conceptual categories. The final descriptive results are reported in Table 2, and the extracted results are condensed and presented in Table 3.

To strengthen transparency and comparability across heterogeneous findings of the studies reviewed, we employed a direction-of-effect mapping approach. We classified the extracted results from each study for outcomes under the three research questions (e.g., AI changing work, workers' attitudes towards AI, and subsequent well-being). These show a positive (↑), negative (↓), or mixed (↕) effect relationship between AI implementation and the respective outcome. These classifications were based on the reported results and interpretations summarized in Table 3. The counts of studies within each category are reported in Table 4 (Effect-direction summary), which provides an overview of general trends without implying statistical significance. This procedure aligns with established "vote-counting by direction of effect" approaches for mixed-methods systematic reviews (Booth et al., 2021) and complements the narrative synthesis (Siddaway et al., 2019).

Table 2
Descriptive information of the studies included in the review synthesis.

Reference	Year	Sample (*n*)	Method	Country of study*	AI measure
Al-Dhaen et al.	2023	Healthcare professionals (268)	Quantitative survey	Bahrain	AI awareness
Arias-Pérez & Vélez-Jaramillo	2022	Manufacturing and service companies' employees (136)	Quantitative survey	Colombia	AI awareness
Bhargava et al.	2021	Working adults (21)	Qualitative semi-structured interviews	United Arab Emirates	Perceptions of robotics, AI, and automation (RAIA) on job security, job satisfaction, and employability
Cebulla et al.	2023	Data science and technology experts, AI users, and WHS inspectors (30) Organization representatives (12) WHS inspectors (12)	Qualitative interviews Workshops	Australia	AI WHS risks
Chan & Lee	2023	Teachers (184)	Mixed method	China	Perceptions, knowledge, and concerns of GenAI use
Chounta et al.	2022	Teachers (140)	Mixed method	Estonia	Perceptions, attitudes, and familiarity of AI
Chen	2023	AI recruitment stakeholders (15)	Qualitative interviews	China	Experience and perceptions of AI recruitment
Chen et al.	2023	Radiology nurses (3666)	Quantitative survey	China	AI perception and acceptance
Chowdhury et al.	2022	Creative industry employees (164)	Quantitative survey	The UK	AI skills AI trust AI understanding AI job clarity
Fang et al.	2023	Legal professionals and semi-professionals (28)	Qualitative interviews	The United States	Opinions on intelligent technology
Gustilo et al.	2024	University faculty (100)	Mixed method	Philippines	Affordances and encumbrances of algorithmically-driven writing tools
Hah & Goldin	2021	Clinicians (114)	Mixed method	The United States	Experience of AI assistance in diagnostic decision making
He et al.	2024	Service industry employees (297)	Quantitative survey	China	Challenge-hindrance appraisals towards AI
Horodyski	2023	Recruiters (283)	Mixed method	France	Perceptions of and experience with AI tools
Huang	2024	Librarians (472)	Quantitative survey	Taiwan	The implementation and use of AI in academic libraries
Kambur & Akar	2022	Human resource employees and managers (821)	Quantitative questionnaire	Turkey	Perceptions of HR employees towards AI
Kong et al.	2023	Employee–supervisor dyads (447)	Quantitative survey	China	AI trust and employees' career sustainability
López Jiménez & Ouariachi	2021	Experts in communication and PR, education, or technology (7)	Qualitative (Delphi)	The Netherlands	The impact of AI and automation on communication professionals
Man Tang et al.	2022	Analysts (114) Employees (162) Employees (405)	Quantitative surveys and field experiment	The United States	Role of conscientiousness in working with intelligent machines
Mirbabaie et al.	2022	Experts (7) Workers (303)	Mixed method	Germany	AI identity threat
Nitiéma	2023	Healthcare professionals (905)	Qualitative sentiment analysis	The United States	Opinions about AI adoption in health care
Rainey et al.	2022	Radiographers (411)	Quantitative survey	The UK	Perceptions and expectations of AI in radiography
Wang et al.	2023	Healthcare practitioners (404)	Quantitative survey	The UK	Satisfaction with AI Attitudes towards AI Intention of use
Wang, Lin, and Shao	2023	Marketing employees (202)	Quantitative survey	Australia	Trust in chatbots and innovative use of them

*Country of study was determined based on the country in which the first author was affiliated with at the time of the study unless otherwise specified. RAIA = Robotics, AI, and automation. HR = Human relations. WHS = Work health and safety. GenAI = Generative artificial intelligence. ML = Machine learning. IT = Information technology.

3. Results

3.1. Overview of the articles included in the synthesis

Of the 24 articles selected for analysis, 50 % ($n = 12$) utilized quantitative methods, 25 % ($n = 6$) were qualitative, and 25 % ($n = 6$) employed a mixed-methods approach. The most commonly examined group of workers in these studies were healthcare professionals. A total of six studies investigated the role of AI in various healthcare occupations, such as radiographers, clinicians, and general practitioners. Other common groups of professionals examined in the studies were educators ($n = 3$) and HR and recruiting professionals ($n = 3$). Additionally, the studies investigated professionals in marketing, public relations, and communication ($n = 2$), as well as workers from manufacturing and the service industry ($n = 3$). One study focused on AI in technology and data analyses, one in the work of legal professionals, one in librarians, and another on creative workers. Some studies did not specify the field of workers ($n = 3$).

The majority of the studies were conducted in China ($n = 5$), followed by the United States ($n = 4$) and the U.K. ($n = 3$). One came from Australia and one from Germany. Other studies represented a diverse range of countries, including Bahrain, Colombia, Estonia, France, the Netherlands, the Philippines, Taiwan, Turkey, and the United Arab Emirates. The studies investigated various aspects of AI usage, including general workplace applications and specific modalities such as healthcare imaging (radiography), decision-support systems, chatbots, writing tools, and robotics. The impact on workers was examined through a range of attitudinal and experiential constructs, including perceived usefulness, trust, awareness, acceptance, and perceived threat.

Attitudes were defined as workers' cognitive and affective evaluations, feelings, or beliefs about AI and its implications for their work. Change in the workplace was reflected in indicators of transformation, such as altered work processes, learning new skills, or changes in role clarity and task distribution. In addition, several studies reported indicators related to workers' well-being, including job satisfaction, work-life balance, stress, and anxiety. Wellbeing was therefore conceptualized as workers' perceived emotional and psychosocial state in relation to AI use or implementation in the workplace. In the following, we stratify the results according to construct (change, attitudes, wellbeing) and AI modality, to clarify reporting.

Table 3
Summary of key findings on employee attitudes towards AI and associated workplace change outcomes.

Reference	Main attitude / Appraisal of AI	Observed change markers / Change outcomes
Al-Dhaen et al. (2023)	Continuous intention to use the Internet of Medical Things (IoMT) is determined by diffusion of innovation factors: relative advantage, complexity, and compatibility; indirectly through motivation and training.	The use of IoMT with AI is embraced by healthcare professionals who perceive it is compatible with their values and existing practices, bringing relative advantage to work (e.g., improve healthcare).
Arias-Pérez and Vélez-Jaramillo (2022)	AI and robotic awareness are associated with concern, negative feelings, and expectations.	Introduction of intelligent robots and automation to workplace is associated with employees' knowledge hiding and hindering progress.
Bhargava et al. (2021)	Employees' perceptions of robotics, AI, and automation (RAIA) reflect a need to accept, adapt, and expand knowledge to remain relevant and employable in the future.	RAIA allow better utilization of time and skills but emphasizes the need for "human touch" and soft skill. Keeping up to date with technology advancements is necessary.
Cebulla et al. (2023)	Experts identified perceived risks and hazards of AI.	Shifting decision making from humans to machines: Shifts occur in interaction, especially between dyads (e.g., worker-supervisor).
Chan and Lee (2023)	Experience and perceptions of AI among teachers indicate stronger hesitance of usefulness of AI in education.	Lack of appropriate policies for teachers to guide students in using AI tools effectively and responsibly. AI signifies increases in workload for teachers.
Chounta et al. (2022)	Teachers show generally positive attitudes towards the use of AI in education.	Teachers expressed a need for support and increased awareness of AI tools they are currently using in practice. Smart technologies should lessen workload and improve work methods.
Chen (2023)	Recruiters generally view AI as a valuable and useful tool in job performance.	AI enhances recruitment processes by effectively identifying talented applicants who are a good fit for the organization and the job available. AI affords a competitive edge to companies by speeding up hiring process.
Chen et al. (2023)	Experience with AI predicts its perceived usefulness.	AI in radiology is found beneficial when usage is combined with support from a standardized training program.
Chowdhury et al. (2022)	AI understanding has a positive influence on AI job clarity and trust in AI systems.	Strong understanding of AI with employees' skills and knowledge sharing enhance an organization's flexibility and adaptiveness to evolving in an uncertain, and competitive business environment.
Fang et al. (2023)	Lawyers are sceptic about AI's ability to represent clients and had concerns about AI's useability in the field of law. Law librarians hold more optimistic views of AI's useability in their work.	AI-induced change in the legal field is still limited. Semi-professionals (librarians) see that intelligent technologies can further enhance their professional value. Professionals (lawyers) expect AI to undermine their work and increase workload as AI is unable to understand the nuances of law.
Gustilo et al. (2024)	Faculty members express concern over AI's impact on students' learning.	AI tools improve efficiency and aids with creativity. Utilization AI allows better use of time, reducing repetitive tasks.
Hah and Goldin (2021)	Positive and negative aspects of AI relate to accessibility, convenience, instructiveness, lengthy processes, steep learning curve, and technical difficulties.	AI assistance hinders clinicians' ability to formulate subjective diagnoses based on their clinical reasoning.
He et al. (2024)	Appraisal of AI as a hindrance or challenge has differing outcomes on work performance.	For employees with a hindrance appraisal work insecurity increases and negatively impacts job performance. Challenge appraisal associates positively with job performance.
Horodyski (2023)	Perceived advantages and disadvantages of AI tools relate to use intention.	The use of AI tools in recruiting improves accuracy, increases objectivity, and saves time in hiring processes.
Huang (2024)	Knowledge activities relate to positive attitudes towards AI applications in the workplace. Concerns are expressed over security and privacy.	AI improves efficiency and accuracy in information services and saves time, energy, and labor of librarians.
Kambur and Akar (2022)	HR professionals do not perceive AI as a threat and express willingness to accept AI as a colleague.	HR professionals experienced a reduction in training and development costs, as well as a faster feedback process.
Kong et al. (2023)	Employee-AI collaboration and trust in AI relate to protean career orientation.	Collaboration between AI and employees is related to increases in productivity, especially among lower education employees (below bachelor's degree).
López Jiménez and Ouariachi (2021)	Experts have a positive view about the role of AI and automation in the field of communication, showing confidence and trust in the technology.	AI complements communication professionals' work, simplifies tasks, saves time, and enables working more efficiently.
Man Tang et al. (2022)	Workers felt ambiguity after working with AI.	Working with robots increases role ambiguity and negatively impacts job performance.
Mirbabaie et al. (2022)	Workers' higher sense of importance and sense of responsibility predict identity threat due to AI.	Introduction of new technology and AI brings uncertainty.
Nitiéma (2023)	Impacts of AI in the field; worry over lower quality of care.	AI interferes with care operations.
Rainey et al. (2022)	Most radiographers' perception of AI is that their daily clinical practice will be impacted with the introduction of AI.	Standardization of reporting and treatment planning.
Wang, Chen, et al. (2023)	Attitude towards AI. Intention to engage with AI is influenced by beneficence, explainability, justice, and non-maleficence.	When healthcare practitioners perceive AI technology is adding extra work load, it negatively impacts their user satisfaction and intentions, hindering benefits of IA in the field.
Wang, Lin, and Shao (2023)	Trust in chatbots.	Chatbots improve work-life balance through knowledge support and increased efficiency.

Note. IoMT = the Internet of Medical Things. RAIA = Robotics, AI, and automation. HR = Human relations.

Table 4
Effect-direction summary of the findings of the reviewed (k = 24) studies.

Outcome / theme	Outcome linked to RQ	Direction of findings across studies	Example indicators / evidence	Interpretation
Workload / efficiency/work performance	*RQ1 – Transformations in working life*	↑ Positive (11); ↕ Mixed (3); ↓ Negative (6)	AI reduces repetitive tasks and increases workers' time, and accuracy in work (Bhargava et al., 2021; Chen, 2023), yet increases oversight demands (Chan & Lee, 2023)	Generally positive workload relief but unevenly distributed benefits.
Job insecurity / role or identity threat	*RQ1 – Transformations in work roles*	↓ Negative (4); ↕ Mixed (2)	Concerns about redundancy, loss of autonomy (Mirbabaie et al., 2022; Man Tang et al., 2022)	Overall direction negative: AI adoption associated with heightened job insecurity and identity threat.
Trust in AI / perceived usefulness	*RQ2 – Attitudes towards AI*	↑ Positive (7); ↕ Mixed (6); ↓ Negative (4)	Higher trust and perceived usefulness were reported when AI was experienced as complementary and enhancing work processes (Kong et al., 2023; López Jiménez & Ouariachi, 2021), or when workers had prior experience with AI (Al-Dhaen et al., 2023; Chen et al., 2023). Lower trust when AI introduced increased responsibility, uncertainty, or reduced transparency (Cebulla et al., 2023)	Predominantly positive or mixed trust and acceptance when implementation is transparent and supportive.
Perceived safety / bias reduction / quality	*RQ2 – Attitudes towards AI*	↑ Positive (4); ↓ Negative (4); ↕ Mixed (3)	Context dependent perceptions and attitudes; HR/recruitment show perceived fairness gains (Kambur & Akar, 2022), others show algorithmic bias concerns (Horodyski, 2023)	Balanced evidence: AI both alleviates and introduces bias perceptions depending on context, application, and transparency of the technology and institution.
Wellbeing (stress, balance, affect)	*RQ3 – Wellbeing impacts of AI at work*	↑ Positive (4); ↓ Negative (3); ↕ Mixed (2)	Reported improvements in work–life balance via chatbots (Wang et al., 2023); stress from surveillance-type AI (Nitiéma, 2023)	Modest positive trend; wellbeing benefits contingent on perceived autonomy and fairness.
Job satisfaction / engagement	*RQ3 – Wellbeing impacts of AI at work*	↑ Positive (5); ↓ Negative (2); ↕ Mixed (1)	AI perceived to increase efficiency and creativity (Gustilo et al., 2024); increased workload or job insecurity in some settings (Man Tang et al., 2022)	Mixed but predominantly positive associations with job satisfaction when AI supports rather than replaces tasks.

The overall methodological quality of the included studies was moderate to high. Most met at least four of the five MMAT criteria for their respective design types, with the most frequent limitations or bias relating to sampling representativeness and reporting transparency. See Table 2 for summarized descriptive details of all included articles.

3.2. How has AI transformed working life during the past five years as experienced by workers?

A substantial body of research has explored workers' attitudes, perceptions, and willingness to adopt AI technology. However, this review found that fewer studies in the past five years have directly investigated how AI implementation has transformed work practices and everyday experiences at the workplace. Much of the literature focuses on workers' expectations or perceptions of AI rather than first-hand experiences with it. However, studies that do investigate such experiences reveal a range of transformations, from shifts in workflow and task automation to alterations in job roles, skill requirements, and broader organizational dynamics.

3.2.1. AI, intelligent robotics, and automation

The technologies implemented in the investigated studies ranged from algorithmic systems that enhance data analytics and automate decision-making processes, to physical or virtual agents such as robots, chatbots, and virtual assistants that perform or augment work tasks. Collectively, these applications have redefined worker-technology interaction and influenced workplace communication, perceptions of autonomy, efficiency, and skill relevance.

3.2.1.1. Defensive responses and interruptions. A small number of studies highlighted that the introduction of AI through automation or intelligent robotics was perceived by employees as threatening to their roles and expertise. Workers in manufacturing and service companies ($k = 3$, $N_{TOTAL} = 433$) were increasingly aware of AI and described its implementation largely as undesirable. They responded, for example, with defensive strategies, such as actively engaging in knowledge hiding (Arias-Pérez & Vélez-Jaramillo, 2022), characterized by intentionally withholding or concealing knowledge, information, or expertise from others. While such behavior may provide short-term protection for individuals, it undermines organizational learning and slows technological adaptation. In contrast, research in hospitality and services sectors revealed more adaptive responses when employees appraised AI as a challenge rather than a threat.

Workers who viewed robot-assisted systems as opportunities for learning or performance enhancement were more likely to engage in job crafting and reported improved service performance. Conversely, those perceiving AI as a hindrance experienced heightened job insecurity, which was negatively related to work performance (He, Teng, & Song, 2024). These findings indicate that workers' behavioral responses to AI not only depend on the perceived risk to their roles but also on the organizational context and the support available to develop AI competence.

3.2.1.2. Knowledge and readiness for AI collaboration. In contrast, other research showed that increased familiarity and competence in AI use supported positive changes. Workers in creative industries with a strong understanding of AI, coupled with skills and shared expertise, reported higher flexibility and organizational adaptability (Chowdhury, Budhwar, Dey, Joel-Edgar, and Abadie (2022). A solid understanding of AI systems was also related to improved employee digital readiness and the capability to thrive in a working environment that required AI-employee collaboration. Similar trends were observed in service sectors, where AI, robotics, and automation were perceived to reduce routine and repetitive tasks while allowing better utilization of human skills, time, and judgment (Bhargava et al., 2021). The findings suggest that workers' digital literacy and readiness, with perceived complementarity between the technology and humans, are key factors in successful and constructive adaptation.

3.2.1.3. Role boundaries. The rise of autonomous decision-making systems in the workplace has blurred boundaries between humans and machines, which was associated with diminished accountability and oversight. Professionals noted that AI systems increasingly influence or override decisions made by humans, altering traditional hierarchies and responsibility (Cebulla, Szpak, & Knight, 2023). Such systems were further seen as having the potential to replace or alter interactions between humans by introducing a third medium into traditional two-person relationships (e.g., those between a worker and supervisor). Similar observations were made among service industry employees, showing that those working with robots felt greater role ambiguity which negatively impacted job performance, especially among individuals high in conscientiousness (Man Tang et al., 2022). Maintaining responsibility in an environment characterized by hybrid decision-making remains a crucial organizational challenge.

3.2.1.4. Efficiency gains and work-life balance. In human resources (HR) context, automation and AI tools were associated with reduced administrative burden and lower time spent on training. HR professionals also perceived improvements in fairness and transparency, for example, through AI-assisted performance evaluation (Kambur & Akar, 2022). In another context, the use of conversational agents such as chatbots was also perceived to be beneficial. Marketers and communications professionals reported that such AI tools increased their efficiency and knowledge support through allowing greater flexibility in working schedule and work arrangement, which was associated with improved work-life balance (Wang, Lin and Shao, 2023).

Studies further suggested that collaboration between employees and AI systems can enhance productivity and task engagement, particularly among workers with lower educational attainment who benefit most from task simplification (Kong, Yin, Baruch, & Yuan, 2023). Likewise, communications professionals participating in a Delphi study described AI as a complementary tool. Its use was associated with simplified routine tasks, supported data-driven decision-making, and expanded analytical capabilities across functions such as audience analysis, content creation, and trend prediction (López Jiménez & Ouariachi, 2021). The studies indicate that when AI applications are aligned with workers' roles and skill levels, they can promote efficiency, equity, and flexibility. However, the benefits depend on whether AI serves to augment rather than replace human expertise.

3.2.2. Generative AI and algorithmically driven writing tools (ADWT)

Generative AI refers to intelligent systems that can autonomously produce new text, images, or other content using large-scale language or multimodal models. Algorithmically driven writing tools (ADWT), such as AI-assisted writing, summarizing, and content generation platforms, represent widely used applications that enable users to automate drafting and editing tasks. These tools also raise questions about authorship, ethical use, and skill transformation especially in educational and professional contexts.

3.2.2.1. Perceived changes in roles. Across the studies reviewed, educators expressed broadly positive but cautious expectations towards the integration of generative AI in teaching and assessment. Teachers and faculty acknowledged the potential of these tools to streamline teaching processes (e.g., retrieving material, organizing lessons), enhance productivity, and support creativity (Chounta, Bardone, Raudsep, & Pedaste, 2022; Gustilo, Ong, & Lapinid, 2024). However, they also emphasized the current lack and need for institutional guidance and clear ethical frameworks to manage responsible use (Chan & Lee, 2023; Gustilo et al., 2024). Many educators perceived themselves as key intermediaries between AI integration in educational settings and students, responsible for fostering critical awareness of AI's capabilities and limitations rather than prohibiting its use.

3.2.2.2. Perceived change in workload. The introduction of ADWTs was described as both empowering and burdensome. AI-assisted writing tools were seen as effective for reducing repetitive tasks and improving workflow efficiency, especially for those who know how to leverage the features of such tools and have the necessary skills and access to them (Gustilo et al., 2024). However, teachers highlighted that the responsibility to teach AI literacy and evaluate AI-generated student work increased their own workload (Chan & Lee, 2023; Chounta et al., 2022). This tension underscores how perceived efficiency gains at the system level can translate into added cognitive and administrative demands for educators overall.

Collectively, the findings suggest that generative AI and ADWT adoption in education is characterized by optimism about potential benefits but also reveal gaps in preparedness in terms of responsibility, policy, and sustainability of workload. Educators' willingness to integrate AI successfully and efficiently depends largely on institutional support and their own sense of competence and control.

3.2.3. Digitalized libraries and legal information

AI-enhanced information and knowledge management systems, automatic indexing and classification, intelligent analysis for collection and circulation management, and text-analytics tools, represent an emerging category of workplace AI used in libraries, archives, and legal research environments. These systems apply algorithmic learning to organize and retrieve information more efficiently, representing a set of technologies supporting decision-making and content-management.

3.2.3.1. Efficiency and service improvement. Studies in academic library settings indicate that AI-based automation of indexing, classification, and circulation management has improved information-service efficiency while reducing manual workload and routine tasks (Huang, 2024). Librarians perceived these applications as enabling faster, more consistent information retrieval and better allocation of time and energy to user-focused activities.

3.2.3.2. Role transformation and upskilling. The digitization of legal information has similarly reshaped professional roles. Law librarians reported that maintaining effective AI-assisted legal databases now requires competencies resembling those of data scientists, combining domain expertise with data analytics and system oversight (Fang, Wilkenfeld, Navick, & Gibbs, 2023). This shift expands professional identity and highlights the need for continuous digital upskilling of information professionals to adapt to data-intensive work environments.

3.2.4. Recruitment tools

Recruitment-related AI systems use machine learning algorithms and are utilized to develop and advertise jobs, screen applications, identify suitable candidates (e.g., predict candidate-job fit), and assist decision-making in hiring. These systems are designed to enhance objectivity, streamline candidate evaluation, and reduce time spent on manual screening.

3.2.4.1. Efficiency and competitive advantage. Across the reviewed studies, recruiters consistently viewed AI-based hiring tools as improving accuracy and productivity. Automated candidate screening and matching were perceived to increase objectivity and speed, helping organizations identify qualified applicants more efficiently and maintain a competitive advantage in talent acquisition (Chen, 2023; Horodyski, 2023). Some recruiters estimated that AI-assisted screening was substantially more effective than traditional human screening, approximately 25 % more effective in identifying suitable applicants (Chen, 2023). Regular use of AI systems appeared to reinforce acceptance and integration of these tools into daily recruitment practices (Horodyski, 2023).

3.2.4.2. Human judgment and ethical awareness. Despite the identified benefits, recruitment professionals notified that AI lacks the emotional intelligence and contextual sensitivity characteristic of human judgment. Participants emphasized that automated hiring systems can inadvertently reproduce bias through their algorithms, underscoring the need for human oversight and ethical accountability in AI-driven decision-making (Horodyski, 2023).

3.2.5. Medical AI tools

AI has extensive potential and applications in the field of medicine. Medical AI tools encompass diagnostic and decision-support systems that apply machine learning, for instance, to analyze medical images (e.g., AI for interpreting electrocardiograms (ECG)), predict clinical outcomes (e.g., AI for cardiac monitoring), or assist in treatment planning (e.g., personalized medicine). These systems are increasingly integrated into radiology, diagnostics, and other healthcare work systems.

3.2.5.1. Performance, skills, and professional judgment. In the reviewed studies, clinicians recognized the potential of AI to enhance diagnostic accuracy and efficiency, yet many reported that current systems can interfere with the interpretive reasoning that underpins clinical experience and expertise. AI assistance was sometimes perceived to interfere with subjective diagnostic thinking rather than improve care performance, reinforcing the importance of human education, experience, and contextual judgment (Hah & Goldin, 2021). Further, although healthcare professionals emphasized that AI could streamline some tasks, core human competencies like empathy, ethical reasoning, and clinical intuition, remain irreplaceable. Some professionals expressed concern that reliance on automated systems could alter the quality of clinician-patient relationship or shift the boundaries of professional responsibility (Nitiéma, 2023). Others, particularly radiologists with structured training in AI applications, viewed these tools more as beneficial, reporting enhanced confidence in their use (Chen et al., 2023). Whereas radiography professionals noted that AI contributes to standardized reporting and treatment planning, there was also confusion about what qualifies as “AI” in practice. Variability in definitions and exposure led to inconsistent awareness of AI integration within daily routines (Rainey et al., 2022).

3.3. How are workers' attitudes towards AI related to its usage and changes in work practices?

Across sectors, workers' attitudes towards AI were generally positive but highly contextual, shaped by professional norms, perceived usefulness, ethical awareness, and exposure to the technology.

3.3.1. Usefulness, compatibility, and professional benefit

Many employees expressed enthusiasm for AI, especially when it aligned with existing practices and values, and was related to improved performance. In healthcare, perceived relative advantage, compatibility, and training were the strongest predictors of intention to adopt Internet-of-Medical-Things (IoMT) and diagnostic AI systems (Al-Dhaen, Hou, Rana, & Weerakkody, 2023; Chen et al., 2023; Rainey et al., 2022). Experience and institutional support reduced uncertainty and strengthened trust in AI. Similar patterns appeared across knowledge sectors: recruiters valued AI for its applicability in accelerating candidate screening, enhancing job performance, and improving objectivity (Chen, 2023; Horodyski, 2023).

HR professionals expressed they could view AI as a “colleague”; they described it increased fairness in performance evaluation and decisions relating to promotions and salaries (Kambur & Akar, 2022). Academic librarians viewed AI-driven indexing as enhancing service efficiency. Their positive attitudes towards AI were related to increased knowledge and the activities they engaged in the workplace rather than threatening employment (Huang, 2024). Across these employment groups, exposure, training, and task complementarity associated with positive engagement.

3.3.2. Perceived threats and defensive responses

In manufacturing and service settings, heightened awareness of AI and robotics sometimes produced anxiety and resistance. Employees described fears of job displacement and responded through defensive behaviors such as knowledge hiding or resistance to automation (Arias-Pérez & Vélez-Jaramillo, 2022). Likewise, workers with a strong occupational identity or status were more likely to perceive AI-induced identity threat, particularly when technological change implied loss of control or prestige (Mirbabaie, Brünker, Möllmann Frick, & Stieglitz, 2022). Conversely, employees who adopted a growth mindset or had a protean career orientation viewed AI as an opportunity for autonomy, job security, and further job satisfaction, rather than seeing it as a threat (Bhargava et al., 2021; Kong et al., 2023). However, this required the willingness to upgrade one's skillsets.

3.3.3. Ethical and quality concerns

Even among users who valued AI and were optimistic about its implementation, concerns persisted about reliability, bias, and accountability. Clinicians worried that diagnostic algorithms could compromise reasoning and patient-care quality (Hah & Goldin, 2021; Nitiéma, 2023). Educators shared a concern that increased reliance on generative AI could erode students' creativity, proficiency, and critical thinking, thus highlighting the need for guidance to ensure responsible use of such tools (Chan & Lee, 2023; Gustilo et al., 2024). Legal professionals voiced similar hesitations. They doubted AI's ability to handle the interpretive and persuasive dimensions of legal practice, which require flexibility and human creativity (Fang et al., 2023). These concerns were tied to professional pride; the legal profession was described as complex, constantly evolving, subjective, and novel. These characteristics were tied to the belief that intelligent technologies were more of a hindrance than a help in lawyers' work. Safety concerns were also raised regarding threats to personal data and privacy, with emphasis on minimizing harm in the event of data breaches. The findings reflect a shared expectation that AI must remain explainable, just, and non-maleficent to sustain user trust (Wang, Chen, et al., 2023).

3.3.4. Sector-specific differences

Taken together, the reviewed studies indicate that workers' attitudes towards AI reflect pragmatic optimism; while many workers have confidence in AI's potential to improve efficiency and fairness, they also exhibit caution about bias, accountability, and job identity. Positive engagement is reinforced by training and experience, transparency, and participatory implementation, whereas ambiguity, ethical uncertainty, and loss of autonomy associate with resistance or defensive behavior. In healthcare ($k = 6$, $N_{TOTAL} = 5768$), a quantitative survey of healthcare professionals ($N = 268$) using diagnostic and IoMT tools valued AI for its accuracy and efficiency in clinical decision-making. Simultaneously, they consistently emphasized that human judgment cannot be replaced. Trust in AI was dependent on transparency and the preservation of professional autonomy.

In education ($k = 3$, $N_{TOTAL} = 424$), users of generative AI and algorithmically driven writing tools expressed cautious optimism. While they recognized the potential of these technologies to foster innovation and streamline teaching tasks, they also voiced strong concerns about academic integrity, student dependence, and workload. Among legal and information professionals ($k = 3$, $N_{TOTAL} = 554$), AI was perceived as beneficial primarily for information retrieval, indexing, and document analysis. However, the legal professionals of an interview study ($N = 28$) viewed AI systems as limited in interpretive reasoning and unable to replicate the nuanced, discursive judgment essential to legal work. This was also reflected in lawyers' relatively little experience with AI.

Finally, human resource and recruitment practitioners demonstrated relatively high trust in AI's capacity to improve efficiency and fairness. However, they underscored the importance of ethical oversight and the continued need for human involvement in decision making such as candidate selection and performance evaluation. These sectoral differences highlight that workers' acceptance of AI is less dependent on the technology itself but more on its perceived suitability with professional expertise, values, and responsibility.

3.4. How has the implementation of AI in working life impacted workers' well-being?

The changing landscape of work brings both opportunities and challenges for worker well-being, with effects that can be either positive or negative. Across the reviewed studies, AI implementation was associated with both hedonic and eudaimonic well-being dimensions in varied ways. While automation and collaboration with AI often enhanced satisfaction and engagement, they also introduced new forms of overload and anxiety. Reported effects were therefore mixed and highly context-dependent (see Supplementary Table S3 detailing the wellbeing effects of AI per sector).

3.4.1. Relief, job satisfaction, and engagement

Many workers described a sense of relief and job satisfaction when AI and automation replaced repetitive or physically demanding tasks. In professional services, AI-assisted robotics and automation were associated with increased productivity, accuracy, and the opportunity to focus on more meaningful, cognitively engaging work (Bhargava et al., 2021). Similarly, creative industry workers highlighted that collaboration with AI could enhance collaborative intelligence and business performance, particularly when accompanied by training, flexibility, and role clarity (Chowdhury et al., 2022). Quantitative evidence also showed that trust in AI was positively linked with job satisfaction through perceptions of employee–AI collaboration (Kong et al., 2023). Together, the findings indicate that well-being benefits are most likely when AI is perceived as a supportive partner rather than a replacement for one's work.

3.4.2. Anxiety, overload, and strain

In some sectors, AI implementation generated more psychological strain and uncertainty. Educators expressed distress and anxiety about potential job losses, the devaluation of academic work and integrity, and the erosion of professional identity as AI technologies entered teaching and assessment (Chan & Lee, 2023). Teachers also reported information overload, noting that adapting to new tools while managing existing responsibilities increased their workload and made it more difficult to maintain instructional quality (Chounta et al., 2022). Teachers and faculty described a need for institutional support and ongoing training to maintain confidence and prevent role strain as AI technologies evolve (Chan & Lee, 2023; Chounta et al., 2022). However, there was also a sense among teachers that, despite these concerns, increased exposure to and familiarity with AI in education would help alleviate anxieties over time.

Concerns arose among data scientists and work health and safety experts. They warned that poorly designed AI systems can amplify complexity, reduce users' control over workloads and prolong work durations, thus risking both psychological and physical well-being (Cebulla et al., 2023). Among healthcare professionals, techno-overload was linked to diminished engagement and lower perceptions of AI's usefulness, suggesting that stress undermines trust and adoption (Wang, Chen, et al., 2023).

4. Discussion

4.1. Main findings

This systematic review examined how the integration of AI has transformed the workplace and workers' roles in the last five years, covering evidence on employees' attitudes towards AI and its implications for wellbeing. The synthesis of 24 peer-reviewed research articles provides valuable insight into workers' experiences across sectors such as healthcare, education, law, and service industry. However, it also reveals substantial variation in how AI is perceived and enacted in practice. When synthesizing the findings, we considered the methodological rigor and potential sources of bias identified through the MMAT appraisal. Studies with clearer reporting and stronger methodological coherence were weighed more heavily in interpreting consistent patterns, whereas studies with limited transparency or weaker designs were used more cautiously to contextualize emerging themes. Three research streams emerged from the analysis: antecedents of positive change, antecedents of negative change, and implications for worker well-being, highlighting both areas of convergence and significant knowledge gaps.

4.1.1. Antecedents of positive AI-induced change at work

Across sectors, workers tended to respond positively to AI when certain conditions co-occurred. These antecedents highlighted the situational nature of positive AI-related change. First, AI aligning with existing workflows and professional values is critical. Second, when employees have prior experience with AI or relevant training on how to use and apply it, change is experienced in a positive way. Third, visible improvements in efficiency or reductions in routine work emerged as factors. These observations suggest that positive experiences of AI at work are less about the technology's capabilities but more about its perceived compatibility with existing practices and values. However, this review also reveals an important gap as many studies lacked rigorous examination of why prior experience improves acceptance.

4.1.2. Antecedents of negative AI-induced change at work

Antecedents of negative change were related to a sense of loss of control, lack of transparency, uncertainty about responsibility, and role ambiguity. These outcomes were especially pronounced in fields where professionals rely on specialized experience, judgment, and ethical accountability such as medicine and law. Under conditions in which workers described these experiences, AI is more likely to generate strain or resistance.

Across the studies, negative attitudes were not merely reactions to workload or fear of being replaced. Rather, they reflected perceived threats to status or professional identity, or AI's misalignment with existing practices or core values. This suggests that AI disrupts tasks but also psychological contracts that structure and bring meaning to the work or profession. Whereas several studies raised these issues using different samples and research designs, only one study directly operationalized and investigated identity threat (Mirbabaie et al., 2022), leaving a gap for deeper expansion on what AI means in terms of worker identity in the long run.

4.1.3. AI implementation and worker well-being

The findings highlight mixed implications for worker well-being. Workers reported increased efficiency, reduced routine tasks, opportunities for skill development, and improved work-life balance. But also described techno-overload, stress, and uncertainty about future roles. These patterns align with prior technostress literature that has found that digital systems increase workload, role ambiguity, and perceived threat (Ayyagari, Grover, & Purvis, 2011; Tarafdar, Cooper, & Stich, 2019). What is notable is that these outcomes are not merely individual reactions. Instead, they depend on the degree of clarity on AI in the workplace, the availability of support, and clear guidance from the organization. Additionally, whether the technology is framed as augmenting rather than replacing human expertise.

These patterns suggest that AI introduces well-being dynamics consistent with prior digitalization research but also extends them as the scale and speed of recent AI developments create more pronounced and far-reaching disruptions to work. However, the literature covered does not fully capture well-being outcomes as most did not explicitly measure them. Rather, they were reported or implied by the workers or related to attitudes, highlighting an important area for future research.

4.1.4. Cultural factors and AI at work

Although cultural factors were not the primary focus in most included studies, cross-national patterns reveal meaningful insights. Workers in European context, operating under regulatory frameworks such as the General Data Protection Regulation (GDPR), placed emphasis on fairness and explainability. These are tied closely to institutional expectations of accountability. Studies from the United States were consisted with the individualistic and litigation-sensitive environment. Concerns mostly centered on work quality, professional liability, and judgment. In Chinese studies, AI expectations and changes highlighted productivity, workload, and institutional demands. These covered studies reflect that AI expectations and attitudes cannot be fully explained by individual-level factors. Cultural norms and regulatory environments, as well as sector-specific traditions, play a role in shaping how workers perceive and adapt to AI.

This review underscores the need for cross-cultural comparative studies that can identify culturally relevant and meaningful mechanisms of trust, identity negotiation, and readiness for AI in the workplace. More systematic cross-cultural understanding can further contribute to existing adoption and well-being models that lack the integration of cultural and institutional moderators in the novel AI context.

4.2. Theoretical implications

Today's AI disruption differs from earlier digital transformations in speed, depth, and scope (Brynjolfsson, Chandar, & Chen, 2025). This review reveals that theoretical developments have not yet fully caught up with this scope of the change. While empirical studies are proliferating, existing frameworks are often used to describe rather than explain the mechanisms through which AI reshapes work. This highlights a gap in existing models and the need to adapt and extend established frameworks, especially as AI enters professions and domains where digital technologies were previously absent.

Traditional technology-adoption theories such as UTAUT (Tamilmani, Rana, Wamba, & Dwivedi, 2021; Venkatesh et al., 2003) and DOI (Rogers, 2003) continue to offer valuable insights, particularly regarding communication, perceived usefulness, and facilitation. However, the synthesis of recent studies suggests that these models are no longer sufficient to capture the complexities of today's AI adoption. AI is not a single tool, but a family of quickly evolving systems that covers a wide range of applications. They differ in transparency, autonomy, and embeddedness in daily tasks, adding complexity and potential ambiguity. As such, technology adoption processes now involve not only attitudes and organizational readiness, but also workers' ability to make sense of where AI is present, what it does, and how it affects different aspects of their role.

By centering workers' first-hand *experiences* in understanding AI adoption, this review extends existing models and digital transformation theories that primarily emphasize organizational or technical determinants. Our synthesis reveals that workers' uncertainty about whether their work even involves AI represents a previously underexplored antecedent of adoption readiness. We frame this as a form of "unrecognized exposure," suggesting that successful diffusion now depends as much on awareness, visibility, and shared understanding of AI as perceived usefulness or social influence. This concept foregrounds sensemaking and visibility as a precondition for successful AI diffusion, offering a theoretical mechanism that complements and extends UTAUT and DOI.

The findings also highlight the need to broaden theoretical lenses beyond adoption models. In the context of AI-brought change, the resource-based view can be enhanced by evidence that employee capabilities, psychological safety, and well-being conditions function as critical complementary assets. AI-related skills, transparency, and clarity about task boundaries emerge as resources that shape an organization's ability to leverage AI for positive performance outcomes. Conversely, ambiguity, stress, and threats to professional identity represent restraints that can diminish the value of AI investments. These insights suggest that AI transformation is not merely a technological or strategic process but a human-centered one. Sustainable implementation depends on whether organizations can harness the cognitive, emotional, and relational resources.

In terms of well-being, our observations raise critical questions whether existing work-stress models (Ganster & Rosen, 2013; Tarafdar et al., 2019) can adequately contextualize the role of AI that shifts tasks and job meaning rapidly. The findings point to gaps in existing models on work stress and job demands and resources. AI challenges the existing assumptions about role stability and expectations, and who is in control of the workflow. These are central dimensions of well-being theories (Bakker & Demerouti, 2007; Demerouti, Bakker, Nachreiner, & Schaufeli, 2001; Siegrist & Rödel, 2006). The current transformation may require reconceptualization that accounts for AI-driven reconfigurations of work demands, autonomy, and identity. Whether AI is perceived as enabling or constraining human capability has implications not only for attitudes towards technology but also for employee health, engagement, and long-term employability.

Overall, this synthesis highlights that theoretical integration across disciplines and occupational contexts is lacking. Although studies have examined AI use across a wide range of sectors, the underlying mechanisms that explain workers' attitudes, experiences, and well-being outcomes are often treated separately. Future research should identify and account for the key general and context-specific factors that shape AI adoption and use in different occupation and cultural settings. This would facilitate the generalizability of findings across diverse disciplines and compare the findings systematically. These steps would further develop theoretical insights and accumulate knowledge in a way that supports conceptual advancements rather than listing the findings from a diverse set of studies.

4.3. Implications for workplaces and policy

The results of this review indicate that organizational support and clear implementation strategies play a decisive role in shaping workers' attitudes towards AI. Employees who reported receiving adequate training, communication, and institutional guidance during AI adoption expressed more positive outlooks and reported smoother transitions. Conversely, where organizations lacked clear policies or user guidance, employees reported ambivalence, workload increases, and reduced trust. These findings are consistent with prior research on the social and institutional dimensions of technological change (Lloyd & Payne, 2019) and underscore that effective AI governance in workplaces requires policies that prioritize transparency, inclusion, and sustained dialogue.

Sector-specific findings further illustrate these dynamics. In education, institutions should establish explicit AI-use policies that define how educators can integrate AI meaningfully into teaching while receiving adequate training and resources to guide students. The absence of clear institutional policies for educators represents a critical gap, underscoring the urgent need for structured guidance and professional development in AI use. In manufacturing and service industries, AI policies should focus on training that helps employees understand how AI complements rather than replaces their work. This can foster adaptive, protean attitudes that are linked to higher job satisfaction. More broadly, policymakers should promote worker-centered AI frameworks that ensure automation enhances human capabilities and aligns technological innovation with fairness, inclusion, and sustainable employment.

For future workplaces, the key question is not only *who* uses AI, but *why* and *how*. Building familiarity and competence with AI is becoming increasingly important. The findings show that workers with prior experience in using AI tend to hold more positive attitudes towards it and are more willing to integrate it into their work. At the same time, many professionals, such as educators and healthcare workers (e.g., radiographers), reported uncertainty about whether their tasks already involved AI. Organizations must ensure that employees are equipped with foundational knowledge and skills through targeted training, workshops, and institutional guidelines.

In legal contexts, professionals such as lawyers often perceive limited need or relevance for AI applications, reflecting ongoing uncertainty about its role in professional judgment. Although only a few studies in this review examined legal practitioners, AI is increasingly being used to assist in tasks such as text retrieval and document analysis. While these tools can rapidly process large volumes of legal material, interpretation and application of the law still require human expertise. In today's context where AI systems have even been used experimentally to represent clients, there is a pressing need to establish clearer boundaries for appropriate use, including standards for accountability and ethical oversight. Developing sector-specific guidelines for AI use in legal services is essential as automation becomes more deeply integrated into legal processes.

Building on these insights, we derive several actionable recommendations to guide managers and policymakers seeking to support responsible AI transformation in the workplace. First, organizations and workplaces should develop and implement structured AI literacy programs tailored to the specific work context and employee groups. Importantly, such programs should not rely solely on top-down instruction; rather, they should be bidirectional, drawing on employees' existing knowledge and involving them in the change-process to maintain motivation and support smooth transitions. These practices can reduce uncertainty and strengthen AI readiness.

Second, implementation should be accompanied by transparent communication and accessible knowledge transfer, including clear guidelines that outline responsibilities as well as the opportunities and limitations associated with AI use. Employee participation should be enabled when evaluating AI systems and their use in relevant tasks. Because workers directly interact with AI tools and applications, they are uniquely positioned to recognize usability issues, emerging risks, and highlight practices that support effective integration. Regular feedback can therefore inform system refinements, strengthen trust, and enhance long-term adoption. Third, managers should evaluate potential well-being impacts by regularly reviewing changes in workload, cognitive demands, role clarity, and professional identity.

This review shows that well-being outcomes are context-dependent and sector-specific, shaped by whether AI is perceived as enabling human capability or introducing uncertainty and control. Organizations therefore play a central role in shaping the psychological impact of AI through design choices, communication practices, and support mechanisms. To guide workers during this unique period of increased AI integration at work, employers are in a key position; they should clearly define AI's expected role in tasks and organizational workflows. This includes providing a common definition of what constitutes AI in each context, as inconsistencies and uncertainties regarding its definition and application at work emerged as prevalent themes in recent literature.

Finally, policy recommendations should account for cultural and regulatory contexts in which they unfold. In European settings, strong regulatory frameworks like the EU AI Act promote a human-centric approach that emphasizes transparency, risk minimization, and the protection of fundamental rights. Our findings suggest that employees working within this framework expect AI-use guidelines that clearly define rights, responsibilities, and ethical safeguards. To be effective, policies in this context should translate these expectations into accessible communication, sector-specific guidelines, and actions that ensure oversight and accountability in everyday work practices.

In China, workers are within a distinct institutional environment. Our analysis of workers' experiences in this context found both increased demands and opportunities associated with AI use. This suggests that policies here may need to balance efficiency gains with employee safeguards for autonomy, workload management, and upskilling opportunities. In the US, the current administration has highlighted a worker-first AI agenda. Given that professional judgment and individual responsibility are central in many US professional roles, AI policies should prioritize maintaining work quality and ensure that AI augments rather than replaces human expertise.

4.4. Limitations

Although utilizing rigorous systematic review methodologies, our study has limitations. The initial search and screening phases may have unintentionally excluded relevant studies if they were not reached by the search term or due to subjective judgments during the selection process. For instance, although our search strategy was designed to comprehensively capture studies on workers' attitudes and experiences with AI-related change, some relevant studies using alternative terminology (e.g., *AI adoption*, *employee experience*) may not have been retrieved. Our study was also restricted to the past five years, which captures recent research, but excludes foundational studies and limits the ability to observe long-term trends.

We focused on published peer-reviewed articles. This may have overlooked valuable contributions from grey literature, preprints, or unpublished works submitted, for instance, to conference proceedings. Full-text screening was conducted by a single author, which may introduce selection bias despite the use of clearly defined inclusion and exclusion criteria. In addition, the review was limited to studies published in English. This decision was made to ensure methodological comparability and accessibility of findings but may have excluded relevant research published in other languages, particularly from regions where AI integration in workplaces is developing and expanding. Our literature searches focused on five specific databases, thus some relevant studies from other databases may have been missed. The 24 studies reviewed represented a range of methodological approaches, though longitudinal investigations were scarce.

The evidence base gathered from the studies showed an overrepresentation of healthcare and education samples. In medical contexts, AI implementation has a long history which may explain why the perceived changes were less pronounced. In education, the rapid introduction of AI in the form of generative and decision-support tools has been associated with more visible transformations in teaching, assessment, and student support. Consequently, insights gained from these sectors may not be fully generalizable to other occupational domains where AI is emerging under different conditions, such as manufacturing or service industries.

The reviewed studies also reflected uneven regional coverage. While research was conducted in a variety of countries with most studies coming from China, United States, and the U.K., there exists a geographic bias that highlights the need for cross-cultural and comparative research that captures the diversity of AI adoption and labor market structures worldwide. This is particularly crucial as AI labor impacts vary by national and sectoral context (Mandon, 2025; OECD, 2018). Research on regions where infrastructural, economic, and social contexts shape the integration and experience of AI differently are a particularly valuable future direction.

5. Conclusions

The recent progress in different AI tools has been rapid yet the consequences of this transformation on workplace changes and worker experiences remain only partly understood. The studies reviewed here show that, although the changes reported by workers have not been as dramatic as the technology's capabilities might suggest, AI is nonetheless reshaping workflows and skill requirements across sectors. AI and its application in the workplace is eliciting a wide spectrum of employee responses, from enthusiasm and engagement to uncertainty and anxiety. Although AI-brought change is underway, its future directions and long-term developments are not yet fully certain. A consistent pattern across literature showed that workers' attitudes towards AI are shaped by the technology, the clarity of its role at work, the support structures in place, employees' prior experience with it, and the context in which it is used.

To ensure that continuing AI adoption contributes positively to working life, organizations should prioritize transparent and ethical AI policies, accompanied by comprehensive education and training that strengthen employees' sense of competence and control. These are also significant factors in workers' positive AI attitudes, and its successful uptake and continuation of use. When AI implementation aligns with workers' values and career goals, they are more likely to report positive work-well-being outcomes. Successful integration requires intentional organizational design, clear communication, and opportunities for employees to participate meaningfully in shaping AI-related changes.

This review points to several areas for future research. A large proportion of the studies included here investigated healthcare or HR professionals, indicating a need for more research on AI's effects in other occupational groups, particularly in knowledge-intensive and highly regulated fields. Longitudinal studies would help clarify how initial reactions or experiences during periods of technological disruption evolve over time, and under what conditions workers transition from uncertainty to acceptance or resistance. Global studies representing a wider range of cultures and geographic regions would also provide a more comprehensive understanding of what AI-driven change means for workers' roles and wellbeing. Further research should also examine how organizational policies, sector-specific regulations, and emerging forms of AI governance interact to shape worker well-being and professional development. Ultimately, the key to supporting future work performance and employability lies in staying up to date with technological advancements and adapting oneself to the ongoing changes (Bhargava et al., 2021).

CRediT authorship contribution statement

Iina Savolainen: Writing – review & editing, Writing – original draft, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Lotta Ylinen:** Writing – review & editing, Writing – original draft, Investigation, Data curation, Conceptualization. **Roope Grönroos:** Writing – review & editing, Writing – original draft, Investigation, Data curation, Conceptualization. **Atte Oksanen:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation.

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Declaration of competing interest

The authors declare no conflicts of interest.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.digbus.2025.100162.

Data availability

Data will be made available on request.

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