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Worker and workplace Artificial Intelligence (AI) coexistence: Emerging themes and research agenda

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ABSTRACT

Workplace Artificial Intelligence (AI) helps organisations increase operational efficiency, enable faster-informed decisions, and innovate products and services. While there is a plethora of information about how AI may provide value to workplaces, research on how workers and AI can coexist in workplaces is evolving. It is critical to explore emerging themes and research agendas to understand the trajectory of scholarly research in this area. This study's overarching research question is how workers will coexist with AI in workplaces. A search protocol was employed to find relevant articles in Scopus, ProQuest, and Web of Science databases based on appropriate and specific keywords and article inclusion and exclusion criteria. We identified four themes: (1) Workers' distrust in workplace AI stems from perceiving it as a job threat, (2) Workplace AI entices worker-AI interactions by offering to augment worker abilities, (3) AI and worker coexistence require workers' technical, human, and conceptual skills, and (4) Workers need ongoing reskilling and upskilling to contribute to a symbiotic relationship with workplace AI. We then developed four propositions with relevant research questions for future research. This review makes four contributions: (1) it argues that an existential argument better explains workers' distrust in AI, (2) it gathers the required skills for worker and AI coexistence and groups them into technical, human, and conceptual skills, (3) it suggests that technical skills benefit coexistence but cannot outweigh human and conceptual skills, and (4) it offers 20 evidence-informed research questions to guide future scholarly inquiries.

1. Introduction

Algorithmic approaches reduce worker involvement and interpretation in workplaces (Holford, 2019). It is generally accepted that workplace AI threatens the continuity and security of worker jobs (Arslan et al., 2021; Rampersad, 2020). AI applications are also projected to take over full-time and permanent jobs while workers will be hired for short-term assignments (Braganza et al., 2020). Therefore, uncertainty about the employment of workers appears to be an integrated element of workplace AI (Costello and Donnellan, 2007). This threat is genuine for jobs requiring repetitive motion, data management and analysis, repeated physical control of equipment, and individual evaluative interaction (Chuang, 2020).

This argument, however, does have limitations. Rather than having a direct influence on worker productivity, workplace AI applications have an indirect influence through the development of new, modified, or unmodified worker routines (Giudice et al., 2021). Further, while AI integration in organisational strategy brings 'deep' changes to jobs and the workforce, we are yet to understand the magnitude of such changes. AI-powered technologies associated with losing human skills, such as driverless vehicles and flying drones (Chuang and Graham, 2018), are yet to work independently of human supervision. Even if such projected perfection of workplace AI is finally achieved, it is unclear whether a complete replacement of human workers with workplace AI is politically, socially, and economically feasible (Willcocks, 2020). Therefore, workers' job loss fear of working with AI might come from perceptions of exaggerated AI capabilities in workplaces (Aleksander, 2017; Willcocks, 2020).

On the other hand, human workers are doubtful about AI decisions, recommendations, and responses and might perceive AI augmenting their abilities as being observed by intelligent systems and spied on (Borges et al., 2021). Also, the empirical literature (Glikson and

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Woolley, 2020) around workers' trust in workplace AI relies on short-term, small sample, and experimental studies. Further, longer-term or when the extent of AI replacing workers in the workplace is known, the development of workers' trust in workplace AI is likely to change (Glikson and Woolley, 2020).

Although there is a persistent fear of job loss in practitioner research (e.g., Agarwal et al., 2019; McKinsey Insights, 2017), the academic literature (e.g., Jaiswal et al., 2021; Wilson and Daugherty, 2019) argues in favour of worker and workplace AI coexistence. The coexistence portrays a proactive approach to AI adoption in the workplace, encouraging businesses to be cautious in how they treat their workers (Li et al., 2019). This line of research also argues that businesses should actively protect workers' interests and cautiously implement technology that supports rather than replaces workers to satisfy the ever-changing consumer demands (Li et al., 2019). Rather than algorithms replacing human workers, such algorithms are projected to augment and benefit from human workers' expertise and experience (Fong et al., 2020).

As documented in Table A1(Appendix), an increase in scholarly interest in artificial intelligence and its likely impact on workers is evident. This recent interest explores challenges in managing the interaction of AI and human workers (Arslan et al., 2021), human workers augmenting intelligent systems' abilities – robots as human apprentices (Wu et al., 2022), intelligent systems being given a role in human workers' recruitment and performance management (Garg et al., 2021), workers' perceptions and attitudes toward technological change (Trenerry et al., 2021).

Ideally, workers and workplace AI augment each other's strengths (Henkel et al., 2020; Raisch and Krakowski, 2021). In this coexistence, workers benefit from AI applications' precision, number calculation, and pattern recognition (Klotz, 2018). They train AI to perform repetitive tasks accurately while focusing their human resources on complex decision-making and critical analysis (Aoki, 2021; Shrestha et al., 2021; Wilson and Daugherty, 2019). Although the existing literature portrays AI as capable of doing more than what is technologically possible (Aleksander, 2017), human workers and workplace AI will coexist in workplaces until workplace AI is perfected (Willcocks, 2020). Therefore, the coexistence of workers and workplace AI is necessary (Wilson and Daugherty, 2019).

While there is a plethora of information about how AI may provide value to workplaces, research on how workers and AI can coexist in AI-enabled workplaces is evolving. Table A1(Appendix) documents that recent studies attempted to shed light on aspects of the likely impact of AI on workers. However, in such research, contradiction is evident. While some scholars (Arslan et al., 2021) argue that workers' fear of AI is due to job loss, others (Aleksander, 2017; Willcocks, 2020) argue that such claims reflect exaggerated AI capabilities. While scholars (Wu et al., 2022) discuss workers augmenting AI abilities, others (Chuang, 2020; Chuang and Graham, 2018) argue that workers make themselves redundant in this process. While some scholars (Glikson and Woolley, 2020) discuss the transparency and reliability of AI systems, these are still technically or logistically unlikely (Davenport, 2019). Even if AI is trained as explainable to enhance transparency, there remains the issue of AI solution providers and whether they will disclose algorithmic details (Davenport, 2019). Therefore, it is critical to explore emerging themes and research agendas to understand the trajectory of scholarly research on the coexistence of workers and AI in workplaces. For that purpose, the overarching research question is how workers will coexist with AI in workplaces.

This paper contributes to the literature in several ways. First, it argues that an existential argument further clarifies workers' trust in workplace AI and adds to the literature research string around workers' cognitive and emotional trust in AI (Davenport, 2019; Gillath et al., 2021; Glikson and Woolley, 2020). The paper also observes limitations in the current literature, such as measuring workers' trust in workplace AI, change in workers' trust during the phases of AI adoption, HR interventions to improve workers' trust in workplace AI, 'trust' in workplace AI between high-skilled and low-skilled workers, critical determinants of workers' trust in workplace AI.

Second, this paper extends the 'skills theory' (Katz, 2009; Peterson and Fleet, 2004) to worker-AI coexistence by using the theory as a lens to group requisite skills for coexistence. The requisite skills are pooled from the literature and grouped into three categories: technical, human, and conceptual. Employing such grouping would urge scholarly research regarding reskilling and upskilling and provide an accessible, simple, and straightforward understanding of the required skills. The paper also observes limitations in the literature, such as characteristics of a symbiotic worker-AI relationship, defining the 'reciprocal' element in a symbiotic relationship, what constitutes long and short-term tasks, allocating tasks between workers and workplace AI, the influence of culture on workers to coexist with workplace AI, defining low, medium, and high skilled workers, skill requirement change during phases of AI adoption.

Third, the paper contributes to recent discussions around the 'Robo-Apocalypse from job loss' (Arslan et al., 2021; Chuang, 2020; Huysman, 2020; Willcocks, 2020). Rather than envisioning a Robo-Apocalypse workplace, this study encourages scholarship to focus on choices about training and education for workers. While there will be skill disruption (Chuang, 2020; Rampersad, 2020), such disruption calls for continuous reskilling and upskilling of workers to avoid 'a collective failure to adjust to skills' (Willcocks, 2020). The paper also observes limitations in the literature, such as appropriate training strategies to support workers adjusting skills, workers' 'unlearning', retaining high-skilled workers in a tight labour market, avoiding a vicious dichotomy of high-skilled vs low-skilled workforce, the longevity of 'high-skilled worker' status as technology further advances.

This paper also has practical implications. While workers' fear of job loss to AI is generally from exaggerated AI capabilities (Aleksander, 2017; Willcocks, 2020), such perceived fear disrupts workplaces and changes worker behaviour, such as knowledge sharing vs hiding (Pereira and Mohiya, 2021). Organisations and management must be transparent about AI adoption and explain the organisational strategy for AI adoption to workers. An organisational strategy must accommodate the trade-offs between reskilling and upskilling workers and external skills recruitment.

The paper has policy implications as well. Suppose workers' interaction with workplace AI is to compensate for AI flaws (Wilson and Daugherty, 2019). In this case, AI benefits from interacting with workers rather than workers directly benefiting from such interactions. Such interaction may not be consistent with the AI Principles of the Organisation for Economic Co-operation and Development (OECD), which state that AI should benefit people (OECD, 2021). Therefore, policymakers should explore how AI may continue to be a human partner rather than a rival. Also, policymakers can push algorithm accountability to emphasise transparency in organisational workplace AI adoption (John-Mathews et al., 2022; B. Kim et al., 2020). They can contribute to policies, guidance, regulations, and legal frameworks to encourage productive employment and decent work in AI adoption in the workplace as part of the Sustainable Development Goal 8 of the United Nations. They should push for policy interventions to maintain a country's labour force prepared for future workplace AI and such policy interventions are through investments in education, reskilling, and ongoing training.

The following is the structure of the article. The background of AI and workers and AI in workplaces is provided in Section 2. The research approach is described in Section 3. The findings are discussed in Section 4. The future research agenda is presented in Section 5. Sections 6 and 7 present the paper's potential contributions and conclusion. Section 8 states the limitations.

2. Background

2.1. Artificial intelligence (AI)

Artificial intelligence (AI) mimics human cognitive functions, including perception, learning, reasoning and decision-making (Batra et al., 2018; Lopes de Sousa Jabbour et al., 2018). However, a definitional issue for 'artificial intelligence' is evident from the literature (see P. Wang, 2019). This issue is around 'intelligence' in 'artificial intelligence,' and the literature has explored what 'intelligence' might mean from the perspectives of structure, behaviour, capability, function, and principle of computer systems (P. Wang, 2019). A common trend emerging from the AI definitions is that machines can perform complex human-like tasks based on algorithms and data in the workplace and society. This manuscript adopts this definition, highlighting the adaptability of intelligence systems with insufficient knowledge and resources in workplaces - something that human workers are capable of (P. Wang, 2019).

AI uses data and algorithms to perform human-like tasks independently by learning and interpreting data. The performance of intelligent systems depends on the data fed into them (Farrow, 2019; Thesmar et al., 2019). However, intelligent systems cannot obtain missing parts of data. Therefore, data consistency and quantity are significant issues for AI applications in the workplace. Worker interventions to support AI is needed, as human intelligence and behaviour are required to find missing parts of data and categorise appropriate data for AI systems (Shute and Rahimi, 2021). Human intervention is also necessary to override or interpret the outputs of AI systems (Yam et al., 2020).

However, a core issue for workers with workplace AI is the loss of employment (Braganza et al., 2020; Rampersad, 2020). The chances are high that the work performed by workplace AI would no longer need the workers' involvement (Holford, 2019; Wright and Schultz, 2018). Workers, therefore, would not feel comfortable if they could not understand how an AI application helps or affects them. The strategy that appears to help with this dilemma is to let workers see how this workplace AI augments their abilities (Fügener et al., 2022; Klotz, 2018; Wilson and Daugherty, 2019). However, the reality is quite the opposite (Davenport, 2019; Gligor et al., 2021). In such a technological context, while the inner workings of such systems generally remain unknown (Gligor et al., 2021; Klotz, 2018), it is up to workers to upskill and reskill to coexist with AI systems (Jaiswal et al., 2021; Sousa and Wilks, 2018). The following section will further discuss workers and AI in workplaces.

2.2. Workers and AI in workplaces

AI applications are expanding rapidly, transforming organisations by improving operations and decision-making and freeing workers from repetitive, physical, manual, and dull tasks to creative ones. The applications of AI with robotics and machine learning are becoming pertinent in autonomous vehicles (Bridgelall and Stubbing, 2021); chatbots (Desouza et al., 2020; Go and Sundar, 2019); planning, scheduling, forecasting, and capacity planning (Sohrabpour et al., 2021); and gaming, marketing, and strategies on pricing (Jeon et al., 2020). For instance, while helping workers in online training, customer service, and cognitive therapy, chatbots also benefit from the human touch to go beyond machine-like interactions (Go and Sundar, 2019).

The AI literature advocates the relationship between workers and AI to improve business processes (Henkel et al., 2020; Shrestha et al., 2021). For example, TiVo implemented AI with machine learning capabilities to automatically detect, classify and reduce IT events from 2500 to 150 per day (BigPanda, 2019). A virtual assistant, Roxy, was deployed by the Australian Department of Health Services (DHS) to address questions relating to the rules and regulations of its programmes. Roxy currently manages 78 per cent of standard rules and regulatory inquiries while workers handle nuanced inquiries (Coyne, 2016). PlayerXP leverages AI and machine learning to identify and track input from game players and bring their feedback and reviews to a feature-rich dashboard (Player XP, 2020). This automated reporting saves gaming companies' resources and their staff members' time, helps to unify reporting, and empowers workers to have detailed reporting at their disposal to make sense of the data. So far, the discussion suggests that AI can substantially transform workplaces (Chuang, 2020; Dahl et al., 2020).

However, AI is not a panacea to all organisational problems and has issues. A core issue for workers with workplace AI is the loss of employment. It is predicted that workers will lose their jobs to workplace AI and become unemployed (Balsmeier and Woerter, 2019). Consequently, the chances are high that the work carried out by workplace AI would no longer need workers' involvement (Michailidis, 2018). Another issue is explaining the decision-making reasoning process and understanding of AI systems, the 'Blackbox issue', i.e. how and why AI systems make certain decisions (Davenport and Ronanki, 2018). Therefore, workplace AI is like an untouchable area for workers. Workers will feel uncomfortable if they cannot understand how an AI application decides. Thus, AI might not have the opportunity to build trust among workers (Davenport, 2019; Gillath et al., 2021; Siau and Wang, 2018). The fundamental strategy that appears to help with this dilemma is to let workers know how these systems make decisions. However, the reality is quite the opposite (Davenport, 2019).

The limitations of AI systems in workplaces can vary from basic tasks such as reliably picking up objects to showing empathy (Klotz, 2018). Only a symbiotic relationship between workers and intelligent systems in workplaces can compensate for the limitations (Wilson and Daugherty, 2019). That being said, companies need to ensure that specific skills exist within their workforce in the workplace for a symbiotic relationship (Sousa and Wilks, 2018). This analysis thus adds to the current understanding of the skills required from workers to coexist with workplace AI.

'Skills', in this context, is "the ability to use one's knowledge and competencies to accomplish a set of goals or objectives." (Northouse, 2018) These are specific learned activities or behaviour and vary in complexity and nature, such as "floor mopping" to "brain surgery" (Northouse, 2018). With AI applications, workers can be productive and cognitive-oriented to accelerate processes and eliminate unproductive, repetitive, and mundane jobs (Loring, 2018; Loten, 2017). A recent survey suggests that adopting workplace AI has changed 82 per cent of job roles and the required skills (Hupfer, 2020).

In the academic literature, the idea of 'machines replacing humans' in the workplace gets dated (Dwivedi et al., 2019; Wilson and Daugherty, 2019). Human workers have moved up the value chain where AI focuses on enhancing human capacity, skills, and competencies to enable effective workplace collaboration (DIN and DKE, 2020; Dwivedi et al., 2019; Kumar, 2017). Therefore, AI challenges workers to cultivate human-only skills to drive value creation from human-machine collaboration (Chuang, 2020). Consequently, while displacing several skills to intelligent machines, a symbiotic relationship requires human-only skills to be honed (Chuang, 2020; Klotz, 2018; Sousa and Wilks, 2018). These human-only skills include problem-solving, creative thinking, managing difficult conversations, working effectively in teams, etc. (Cook et al., 2020).

However, as other researchers (Chuang, 2020; Rampersad, 2020; Sousa and Wilks, 2018) have already attempted to list requisite skills, this study does not intend to do so. As an alternative, it compiles skills from the literature and uses the skills theory as a lens to categorise them into technical, human, and conceptual skills. Such grouping would stimulate academic analysis on reskilling and upskilling and present a simple, clear, and accessible overview of the necessary skills. To understand the development of academic research on the coexistence of workers and AI, it also explores themes and research agendas.

3. Research method

Tueanrat et al. (2021) refer to several types of reviews. This study adopts a stream-based systematic review to generate relevant themes about worker-AI coexistence. We combined Tranfield et al. (2003) and Braun and Clarke (2006). We reasoned that by doing this, the study would benefit from a systematic and protocol approach for data source identification (Tranfield et al., 2003) and the opportunities that thematic analysis provides to develop analytically driven themes (Braun and Clarke, 2006). We followed Tranfield et al. (2003) to (i) plan the review, (ii) conduct the review, and (iii) report the findings. This approach guided the review protocol, locating the sources, data extraction and inclusion, reporting and giving evidence. We developed a review protocol to document data source identification. We employed "Thematic Analysis" (Braun and Clarke, 2006, 2022). Other studies (e.g., Jones et al., 2011; Vrontis et al., 2021) adopted this approach.

3.1. Review question

This study adopts a worker standpoint to explore worker-AI coexistence by identifying and contextualising the underlying themes. The aim is to integrate the pertinent literature and offer a theoretical foundation for future research development in this area. Table A1 (Appendix) documents that recent studies attempted to shed light on aspects of the likely impact of AI on workers. It is critical to explore themes and research agendas to understand the trajectory of scholarly research on the coexistence of workers and AI. For that purpose, the overarching research question is how workers would coexist with AI in workplaces.

3.2. Review scope and boundaries

After brainstorming and using ProQuest Online Thesaurus (ProQuest, 2020), we developed a four-level-keyword assembly structure (Table 1).

The appropriate search strings were then defined and fine-tuned. We searched three electronic databases (Scopus, ProQuest, and Web of Science) (Falagas et al., 2008) using the four-level keyword assembly structure and the defined search strings to locate a broad range of relevant journal articles. We intended to include multidisciplinary studies published in peer-reviewed journals to ensure inclusive and analytic output (Tranfield et al., 2003).

3.3. Identifying, screening, and selecting relevant studies

The PRISMA method (Preferred Reporting Items for Systematic Reviews and Meta-Analysis) (Fig. 1) guided the screening and selection process of articles (Moher et al., 2009).

A predefined list of criteria for inclusion and exclusion was used to generate the final list of articles (Fulmer, 2012; Tranfield et al., 2003).

Table 1
A four-level-keywords assembly structure.

Keywords or search strings	
Level 1	(competenc* OR skill* OR expert* OR intelligen* OR smart OR savvy OR proficien* OR experience OR accomplish* OR capacit* OR suitabil*) AND
Level 2	("human resource" OR "profession*" OR "HR manage* " OR staff OR "people manage*" OR "talent manage*" OR "staff manage*" OR "people resource*" OR employee* OR operator OR member OR clerk OR agent OR worker* OR lab?r OR people) AND
Level 3	(workplace OR organi?ation OR firm OR homeworking OR "home working" OR "work from home") AND
Level 4	("artificial neural application" OR "artificial intelligence application" OR robot* OR "expert system" OR "machine learning" OR "natural language processing" OR "neural network")

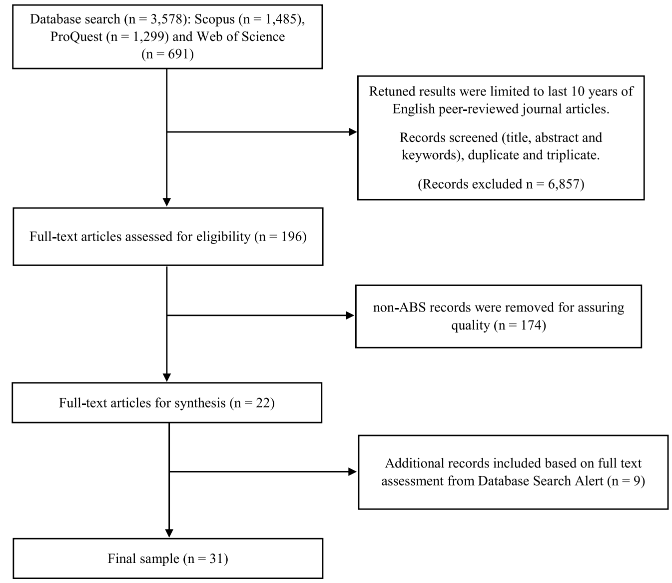


Fig. 1. PRISMA outline.

The inclusion/exclusion criteria included source type, year, document type, language, subject area, and the Chartered Association of Business Schools (CABS) ranking for the final list of journal articles (Zahoor et al., 2022). Correspondingly, the returned results were narrowed down per the following eligibility, inclusion, and exclusion criteria.

i. Journal publications,
ii. Last ten years (2010–2021),
iii. Peer-reviewed journal articles,
iv. English language
v. Subject areas: business, management, robotics, and automation.
vi. Other academic and non-academic sources, such as book chapters, conference articles, reports, editorials, website links and grey literature, were excluded (Seuring and Müller, 2008).
vii. Only academic articles of CABS ranking 1, 2, 3, 4 and 4* were included in the analysis (Purkayastha & Kumar, 2021; Soundararajan et al., 2018; Zahoor et al., 2022).

The next step was to screen titles, abstracts, and keywords to assess the identified list (Tranfield et al., 2003). Abstracts were manually read to determine the content relevance of the journal articles on the list. Finally, only 22 articles were deemed relevant for further data analysis.

The databases provide an alert service for new articles. While conducting the literature review, we created alerts in the databases to be notified of newly published articles (Burnham, 2006; Zhu and Liu, 2020). The review team added additional academic articles at later stages, bringing the total number to 31 publications using the same inclusion and exclusion criteria.

3.4. Analysis and synthesis

The objective of the data analysis phase was to understand the identified list of articles by breaking the accumulated data into smaller parts and examining these through thematic analysis (Tranfield et al., 2003). We organised the data into themes for the analysis (Braun and Clarke, 2006). Thematic analysis borrows from scholars' areas of expertise and interest (Braun and Clarke, 2006, 2022). NVivo was used to assist with the data analysis process. However, this software did not generate the themes. The researchers generated the themes manually (Braun and Clarke, 2006, 2022).

The themes explore the coexistence of workplace AI and workers from the literature and guide future research directions in this area. In this context, "A theme captures something important about the data in relation to the research question and represents some level of patterned response or meaning within the data set." (Braun and Clarke, 2006, p. 82). In developing our themes, we adopted the 'semantic and latent' thematic levels as defined by Braun and Clarke (2006, p. 84). The thematic analysis was a thorough and interpretive process for identifying emerging themes and highlighting links as key reporting elements in the review process (Braun and Clarke, 2006; Tranfield et al., 2003). Our themes represent an explicit or interpretive level of meaning from the articles we reviewed. Further, our analysis is a 'theoretical' thematic analysis as described by Braun and Clarke (2006, p. 84), which was "driven by the researcher's theoretical or analytic interest in the area, and is thus more explicitly analyst driven."

4. Findings

We used descriptive analysis to reveal the publication trend, geographic distribution, leading journals, and research designs among the list of articles (Tranfield et al., 2003). We employed thematic analysis to look for patterns, meanings, and themes (Braun and Clarke, 2006). The former contributed to section 4.1, while the latter contributed to section 4.2.

4.1. Descriptive analysis

4.1.1. Historical publication list

Figure A2 (Appendix) shows the trend of recent and relevant publications (from January 2010 to 2021) in the subject field. The trend line shows a constant up trend in the subject, indicating the interest of academics and researchers. Research on the worker-AI relationship begins after 2012. However, there are no articles in 2014 and 2015, as of 2016 ($n \leq 1$ per year). The number of publications has steadily increased in 2017–2020 ($n = 9$ in 2019 and $n = 4$ in 2021). Based on the recent trend, more studies on workers' coexistence with AI and the skills for adopting workplace AI are expected in the coming years.

Furthermore, the initial statistics indicate that 23 journals led to the publication of the 31 selected articles after the data screening process, as shown in Table 2. AI and the skills for employing workplace AI continue to be an emerging field. The selected articles appear in cross-disciplinary journals on Information Technology (IT), policy, management, business, manufacturing, training and development, labour, work, information systems economics, behaviour, service and hospitality.

4.1.2. Geographical distribution

The selected articles are geographically grouped by the country from which the data is obtained or by researchers' origin. Figure A3 (Appendix) indicates that the top contributing country is the United States (9 articles), followed by the United Kingdom (4 articles), Australia (4 articles), China (2 articles), Germany (2 articles), Japan (2 articles), and Switzerland (2 articles). India, Korea, Poland, Portugal, Sweden and South Africa contributed 1 article each. Based on the analysis, it could be inferred that the research topic is researched extensively in developed countries such as the United States, the United Kingdom and Australia rather than in emerging economies. Regarding leading publication sources, the study sample suggests that the leading journal in terms of publication count is the Journal of Business Research. Most studies have been published with esteemed publishing houses such as ELSEVIER (15) and EMERALD (7).

4.1.3. Research methodological distribution

The research methodologies adopted in the selected articles are quantitative, qualitative, and mixed methods. The analysis of the popular methods (see Table 3 and Fig. 2) reveals that quantitative methods are the prevalent research method, i.e., adopted in 42% of the articles. Several quantitative techniques such as classic Ordinary Least Square (OLS), Genetic Algorithm (GA), Harman's single-factor test, Probit estimation, multivariate regression and simulation are used to observe competencies and skills for the coexistence of worker-AI in the workplace.

On the other hand, the qualitative research method is employed in 16% of the articles (Bhattacharyya and Nair, 2019; Klotz, 2016; Kokina and Blanchette, 2019; Leavy, 2019; S. Xu et al., 2020). Thematic content analysis is generally employed in a few articles (Bhattacharyya and Nair, 2019; Klotz, 2016; Kokina and Blanchette, 2019; Leavy, 2019; S. Xu et al., 2020).

Two articles from the batch used a mixed research method. Accordingly, the mixed research method is only employed in 6% of the articles (Sousa and Wilks, 2018; Sowa et al., 2021). Other articles

Table 2
Top journals contributing to skills for the adoption of workplace AI.

Journal	Publication Year												
	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	Total
Journal of Information Technology								1					**1**
Research Policy										1			**1**
Journal of Intelligent Manufacturing									1				**1**
Journal of Management Development										1			**1**
Journal of Manufacturing Technology Management										1			**1**
European Journal of Training and Development											1		**1**
MIT Sloan Management Review							1			1			**2**
Business Horizons											1		**1**
Australian Journal of Labour Economics									1				**1**
New Technology, Work and Employment									1				**1**
Management Revue								1					**1**
International Journal of Accounting Information Systems										1			**1**
Computers in Human Behavior									1				**1**
Strategy & Leadership										1			**1**
Economic Inquiry								1					**1**
Technological Forecasting and Social Change										1			**1**
Team Performance Management: An International Journal								1					**1**
Systems Research and Behavioral Science									1				**1**
Computers in Industry				1									**1**
Journal of Service Management									1				**1**
International Journal of Contemporary Hospitality Management											1		**1**
Computers in Human Behavior										2		2	**4**
Journal of Business Research											3	2	**5**
Total				**1**			**1**	**4**	**6**	**9**	**6**	**4**	**31**

Table 3
Methodological approaches among the selected articles.

Reference		Research Methodology			Research design				
#	Author et al. (year)	Quant.	Qual.	Mixed	Review	Survey/Interview	Experimental/Model	Case study	Conceptual
1	Aleksander (2017)				✓				✓
2	Aoki (2021)	✓				✓			
3	Balsmeier and Woerter (2019)	✓				✓			
4	Banziger et al. (2018)	✓					✓		
5	Bhattacharyya and Nair (2019)		✓				✓		
6	Botha (2019)				✓				✓
7	Chuang (2020)	✓				✓			
8	Davenport (2019)				✓				✓
9	Desouza et al. (2020)				✓				✓
10	Edwards et al. (2019)	✓				✓			
11	Garnett (2018)	✓					✓		
12	Gekara and Nguyen (2018)				✓				✓
13	Gillath et al. (2021)	✓					✓		
14	Johansson et al. (2017)				✓				✓
15	Klotz (2016)		✓			✓			
16	Kokina and Blanchette (2019)		✓						✓
17	Koren and Klamma (2018)	✓					✓		
18	Leavy (2019)		✓			✓			✓
19	Makarius et al. (2020)				✓				✓
20	Morikawa (2017)	✓					✓		
21	Nam (2019)	✓					✓		
22	Rampersad (2020)	✓				✓			
23	Richards (2017)				✓				✓
24	Shank et al. (2019)	✓				✓			
25	Shrestha et al. (2021)				✓			✓	
26	Sousa and Wilks (2018)			✓			✓		
27	Sowa et al. (2021)			✓		✓			
28	Stahl et al. (2021)				✓			✓	
29	Wang and Cheung (2013)	✓					✓		
30	Wirtz et al. (2018)				✓				✓
31	Xu et al. (2020)		✓			✓			

Fig. 2. Research methodologies.

(approximately 36%) are review articles that concentrate on concluding the reviewed literature. Interestingly, the case study approach is less prevalent among the selected articles. Future studies should also conduct case study research as it can lead to new perspectives and insights that are not possible in surveys and models (Perera et al., 2019).

4.1.4. Cluster analysis

Clustering is an unsupervised machine-learning algorithm which segments sub-areas or groups (clusters) into similar partitions (Allahyari et al., 2017). We have used agglomerative hierarchical clustering. Agglomerative hierarchical clustering yields an entire hierarchy of clusters based on the similarity of topics from the selected articles. The agglomerative hierarchical clustering algorithm first created separate similarity-based clusters and merged them into larger clusters. *QDA Miner*, a qualitative software package, was used to aid the dendrogram generation (see Fig. 3). Fig. 3 shows the clusters such as AI, robotics, intelligence, data etc., appear. The two most similar clusters are combined, e.g., AI and robotics; human and robot; intelligent and machines, etc. Later, this procedure is iterated to form a more extensive cluster.

Further, we used dendrograms to find natural groupings based on the correlation of characteristics, similarities, and dimensionality between clusters (Huang et al., 2017). As a hierarchical system, the dendrogram was generated by creating successive clusters. The height of the branches represents the similarity of the topics amongst the clusters, and

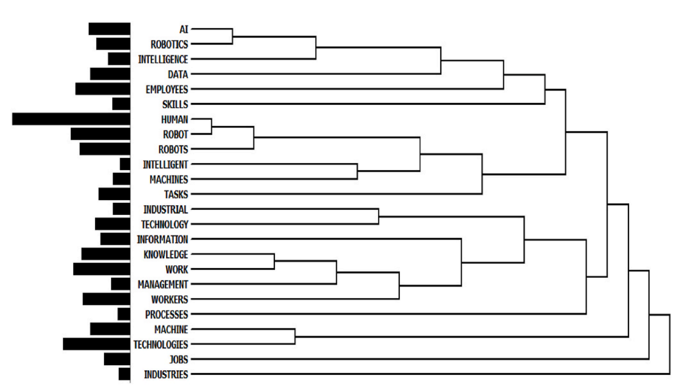


Fig. 3. Agglomerative hierarchical clustering.

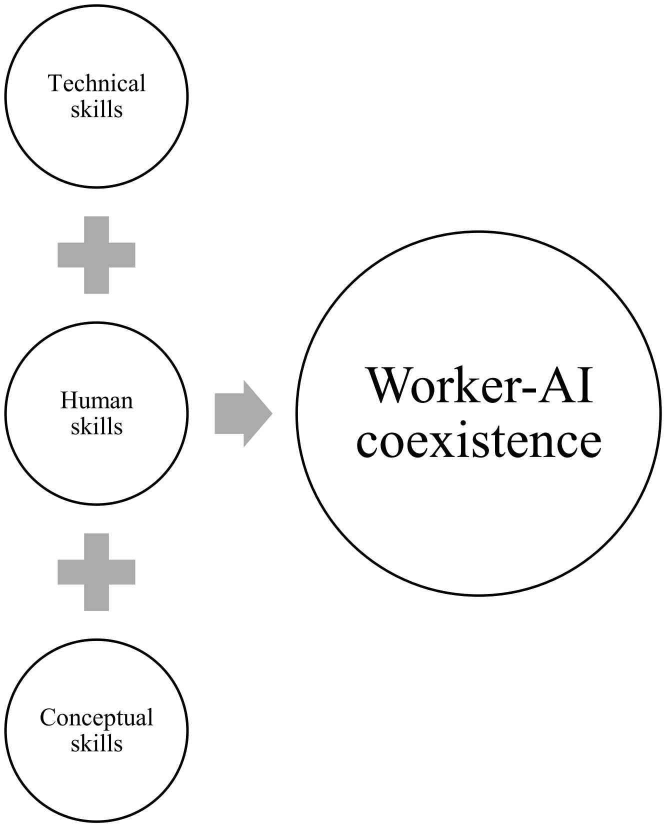


Fig. 4. Skills framework for worker-AI coexistence.

the closer the branches/clusters, the more similar the topics are. The distance between the clusters allows us to compare the temporal features. In Fig. 5, it can be seen as industries are considering intelligence, robots, data, technology, skills, employees, tasks, humans, work etc., to do the jobs.

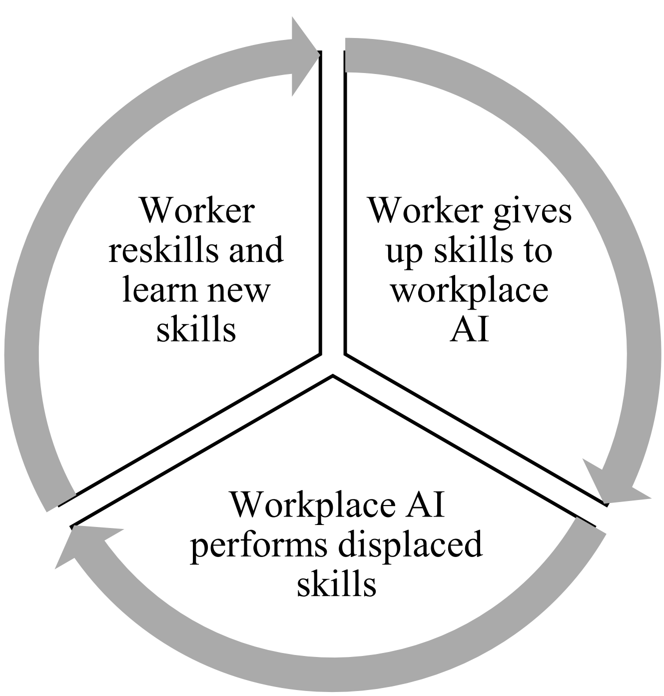


Fig. 5. A cyclical perpetual race between worker and workplace AI.

4.2. Thematic analysis

The thematic analysis suggests that over-promising AI capabilities in the workplace erode trust between workers and AI systems. The 'trust' issue hints at an existential concern among workers that they will be replaced in the workplace by AI. On the other hand, organisations appear to gradually realise the benefits of a symbiotic relationship between workers and AI in the workplace. However, such a potential symbiotic relationship necessitates workers to develop the requisite technical, human, and conceptual competencies for AI adoption in the workplace. As a result, organisations and their workers need to invest in ongoing training and spend time upskilling and reskilling in today's workplace. The four themes identified during the analysis are reported in this section: 1) Workers' distrust in workplace AI stems from perceiving it as a job threat, 2) Workplace AI entices worker-AI interactions by offering to augment worker abilities, 3) AI and worker coexistence require workers' technical, human, and conceptual skills, and 4) Workers need ongoing reskilling and upskilling to contribute to a symbiotic relationship with workplace AI.

4.2.1. Workers' distrust in workplace AI stems from perceiving it as a job threat

Intelligent systems in the workplace increase workers' dependence on workplace AI (Richards, 2017). However, over-promising the capabilities of workplace AI erodes trust between workers and intelligent systems (Davenport, 2019; Gillath et al., 2021). Therefore, the 'trust' issue between workers and workplace AI remains a significant emerging theme. This section elaborates on this theme.

Workplace AI is reshaping working arrangements and the need for workers' competencies (Gekara and Nguyen, 2018; Palumbo, 2021). Therefore, an existential argument may clarify workers' 'trust' issues in workplace AI. Workplace AI offers opportunities only to workers with high skills (Garnett, 2018). It substitutes low-skilled workers in the workplace (Garnett, 2018). This may suggest that the 'trust' issue between low-skilled/unskilled workers and workplace AI is greater. However, one can argue that the 'trust' issue may progressively improve as workers work on their skills (or as organisations improve the skill level of workers) (Gillath et al., 2021).

While the current literature (e.g., Sousa and Wilks, 2018) can support this logic, there is another side to this argument. As workplace AI progresses, such systems will continue to displace higher human skills and tasks. Therefore, it is rational to expect that further development will eventually displace the higher skills of workers, resulting in fewer opportunities.

Workers can also wonder if they can count on AI systems not to spy on them but also report to management (Garnett, 2018). However, if workplace AI is programmed to do so, it can spy on its human partner now and in the future (Johansson et al., 2017). Although such algorithms may be defined as strategies to maximize organisational efficiency, workers might see this differently. Here, the scepticism of workers in workplace AI is often for two reasons: (i) the reluctance of organisations to reveal the 'true' purpose of such systems and how they will be used, and (ii) the absence of external certification bodies to analyse the underlying algorithms of such systems (Davenport, 2019).

Some scholars (e.g., Davenport, 2019) suggest that organisations reveal as much information as possible to workers about AI systems to improve 'trust'. However, the current context of workplace AI suggests that this is rarely the case. It is also logistically and technically challenging to set up external bodies for that purpose (Davenport, 2019).

Further, through practitioner literature (e.g., Batra et al., 2018) and academic literature (e.g., Botha, 2019), visionaries often portrait intelligent systems high in terms of their capabilities (Willcocks, 2020). Intelligent systems also draw press and media attention which often blurs the difference between the actual state of the art and misleading claims (Aleksander, 2017). Over-promising AI capabilities negatively impact workplace AI (Baum et al., 2011; Davenport, 2019). Workers are disappointed when they realise that AI applications do not meet their expectations (Davenport, 2019). Workers might choose not to trust AI systems' choices, responses, or recommendations. Therefore, tasks performed by intelligent systems in the workplace appear to be generally mistrusted (Davenport, 2019). This theme is summarised in Proposition 1.

Proposition 1. *Workers' trust issue with workplace AI stems from perceiving AI as a threat and being dissatisfied with overpromised AI capabilities.*

On one end, the existing literature promises capabilities beyond what current AI systems can do and underlines the threat of AI to jobs (Gekara and Nguyen, 2018; Palumbo, 2021). Conversely, it describes AI as a "young boy" who requires constant human supervision (Davenport, 2019; Gillath et al., 2021). This proposition links 'AI as a threat' and 'overpromised AI capabilities' to workers' trust in workplace AI. How is this phenomenon in the context, for example, using case study research? Findings from multiple case studies will help establish AI in the workplace by first understanding and reporting on workers' experiences with AI capabilities and the threats that such capabilities pose to their employability. Table 5 proposes relevant research questions for further investigation of this proposition.

4.2.2. Workplace AI entices worker-AI interactions by offering to augment worker abilities

No matter how worker-AI tasks are allocated, further improvements in workplace AI eventually lead to assigning long-term tasks to AI systems and short-term tasks to workers (Bhattacharyya and Nair, 2019). This could indicate that a symbiotic relationship in the workplace could mean workers are only involved in the initial design, development and deployment (short-term tasks) of workplace AI (Desouza et al., 2020). Once these systems are operational, they take over the workers' assignments for good. This section elaborates on the worker-AI symbiotic relationship theme.

Organisations slowly realise the significance of worker-AI coexistence in engaging workers in training AI solutions and benefiting from workplace AI. Recent examples (Waterson, 2020a, 2020b) suggest that

Table 4
Requisite competencies for workplace AI adoption.

Grouping	Skills	Reference
Technical	IT literacy to machine-based digital technologies such as artificial intelligence, nanotechnology, virtual reality, digitisation, robotics, 3D printing, Internet of Things, natural language processing	(Aleksander, 2017; Balsmeier and Woerter, 2019; Gekara and Nguyen, 2018; Kokina and Blanchette, 2019; Siau and Wang, 2018; Sousa and Wilks, 2018; Sowa et al., 2021)
Human	managing people, coordinating with others, emotional intelligence, knowledge sharing, teamwork, collaboration, delegation, and negotiation	(Aleksander, 2017; Banziger et al., 2018; Gekara and Nguyen, 2018; Klotz, 2016, 2018; Kokina and Blanchette, 2019; Makarius et al., 2020; Richards, 2017; Sousa and Wilks, 2018; Sowa et al., 2021; Stahl et al., 2021; W. M. Wang and Cheung, 2013; S. Xu et al., 2020)
Conceptual	critical thinking and analysis; creativity and initiative; judgement and decision making; data analysis, synthesis and sense-making; cognitive flexibility	(Banziger et al., 2018; Bhattacharyya and Nair, 2019; Botha, 2019; Chuang, 2020; Davenport and Ronanki, 2018; Desouza et al., 2020; Duan et al., 2019; Gekara and Nguyen, 2018; Hill, 2020; Klotz, 2016; Koren and Klamma, 2018; Leavy, 2019; Rampersad, 2020; Sousa and Wilks, 2018)

Table 5
Research questions for future studies.

Thematic area	Research questions
Workers' distrust in workplace AI stems from perceiving it as a job threat	1. What constructs to consider in measuring worker 'trust' in workplace AI? 2. How does worker 'trust' in workplace AI change during the design, development, and deployment phases of AI adoption? 3. What human resource interventions can improve worker 'trust' in workplace AI? 4. How does 'trust' in workplace AI differ between high-skilled and low-skilled workers? 5. Which touchpoints and phases are the most critical determinants of workers' 'trust' in workplace AI?
Workplace AI entices worker-AI interactions by offering to augment worker abilities	1. What are the characteristics of a symbiotic worker-AI relationship? 2. How can we define this relationship's 'reciprocal' element considering the various stakeholders of workplace AI? 3. Long-term tasks for workplace AI and short-term tasks for workers, what constitutes long and short-term in this context? 4. What factors should organisations consider when allocating tasks between workers and workplace AI? 5. What do we need to know about the worker-AI relationship from academic vs practitioner research?
AI and worker coexistence require workers' technical, human, and conceptual skills	1. Is it about 'one-size-fits-all' when it comes to 'technical, human, and conceptual' competencies on an individual and organisational level to coexist with workplace AI? 2. What will be the influence of organisational culture and culture in general on workers when improving 'technical, human, and conceptual' competencies to coexist with workplace AI? 3. How do we define low, medium, and high-skilled workers as we continually progress with workplace AI? 4. How do 'technical, human, and conceptual' competency requirements reflect workplace AI's design, development, and deployment? 5. How does the role of workplace AI differ between displacing and enabling the conceptual skills of workers?
Workers need ongoing reskilling and upskilling to contribute to a symbiotic relationship with workplace AI	1. What are the appropriate training strategies to support workers in adjusting their skills and changing job responsibilities in workplace AI? 2. How do workers' 'unlearning' impact their 'learning' to upskilling and reskilling for workplace AI? 3. How does an organisation retain high-skilled workers in a labour market where they are scarce? 4. How does an organisation avoid a vicious dichotomy of high-skilled vs low-skilled workers in its workforce? 5. How does future advancement impact workers with high skills? Does such advancement gradually make them low-skilled if they do not enrol in ongoing training?

workplace AI benefits hugely from worker-AI collaboration rather than replacing workers. Therefore, the priority in adopting workplace AI is to understand how workers perceive technology usage and its implications on short- and long-term task assignments (Nam, 2019).

A symbiotic relationship is generally suggested in the academic literature (e.g., Sousa and Wilks, 2018; Wilson and Daugherty, 2019) as opposed to practitioner research (e.g., Hupfer, 2020; Lambert and Cone, 2019). A symbiotic relationship denotes that human-like activities – dull, routine, manual, risky and tedious – are carried out by AI applications, amplifying workers' abilities (Aleksander, 2017; Kokina and Blanchette, 2019; Sowa et al., 2021). One can argue that this arrangement allows organisations to meet the growing demand for flexibility in the workplace. However, a symbiotic relationship can be the case for assignments and skills. For instance, Botha (2019, p. 1250; emphasis added) suggests that '*innovation will gradually evolve from a human-only activity, to human–machine co-innovation, to incidences of autonomous machine innovation*'. However, this is a visionary perspective, and workplace AI is still in the narrow artificial intelligence stage (Aleksander, 2017; Willcocks, 2020).

The worker-AI symbiotic relationship is partly determined by using workplace technologies to amplify workers' abilities (Baum et al., 2011; Nam, 2019). However, a common assumption among workers, which contributes to any form of symbiotic relationship in the workplace, may be that as technology increases, more jobs traditionally performed by workers will be taken over by AI applications (Nam, 2019). In practitioner literature (e.g., Cheatham et al., 2019; Lambert and Cone, 2019), such understanding is illustrated by presenting workplace AI's disadvantages. Although skills will be lost to workplace AI in a symbiotic relationship (Chuang, 2020), certain essential skills will remain with workers (Rampersad, 2020; Sousa and Wilks, 2018). This theme is summarised in Proposition 2.

Proposition 2. *Worker-AI symbiotic relationship is partly influenced by leveraging workplace technologies to amplify workers' abilities. While skills and competencies will be lost to workplace AI in this relationship, critical skills and competencies will remain with workers.*

The reviewed literature in this section can be divided into two categories: displaceable skills (Chuang, 2020) and sustainable skills (Sousa and Wilks, 2018). Skills for jobs requiring repetitive motion, data management and analysis, repeated physical control of equipment, and individual evaluative interaction has been lost to AI in the workplace (Chuang, 2020). On the other hand, the literature suggests that workers can benefit from long-term skills such as critical thinking, problem-solving, communication, and teamwork to coexist with intelligence systems (Rampersad, 2020; Sousa and Wilks, 2018). This literature suggests that humans are in a perpetual race with workplace AI to learn new skills that are complex for AI to perform as part of this coexistence which is labelled as a 'symbiotic relationship'. This proposition will contribute to this line of thought, and the findings will reveal whether there is a never-ending cyclical process. Research designs to explore this proposition can go beyond statistical analysis or archival studies, and the context can be other than small and medium-sized enterprises (Chuang, 2020; Rampersad, 2020; Sousa and Wilks, 2018). Table 5 lists research questions that could be used to investigate this proposition further.

4.2.3. AI and worker coexistence require workers' technical, human, and conceptual skills

As the level of technology usage increases in the workplace, AI applications take over more jobs traditionally conducted by workers (Nam, 2019; Palumbo, 2021). The workplace AI displaces skills and competencies, leaving workers with job insecurity (Chuang, 2020). This influences the type of employment available within businesses and the skills needed for workers (Garnett, 2018). This section delves deeper into the requisite skillsfor worker-AI coexistence.

A general perception among workers is that workplace AI mainly brings job insecurity (Nam, 2019). Therefore, workplace AI could leave workers with limited job prospects, resulting in long-term unemployment (Garnett, 2018). This perception also implies that AI benefits an organisation while workers' jobs and required skills are lost to workplace AI (Holford, 2019). However, while highlighting a potential disadvantage of workplace AI, such perception is overwhelmingly promoted in the practitioner literature (e.g., Cheatham et al., 2019; Lambert and Cone, 2019).

While a list of 30 skills that are already shifted to workplace AI is drawn (Chuang, 2020), it is still unclear if we will gradually lose human-only skills such as creativity to intelligent systems (Botha, 2019; Rampersad, 2020; Willcocks, 2020). Certain activities performed by low-to medium-skilled workers are at risk of being taken over by workplace AI (Balsmeier and Woerter, 2019). These activities involve physical motion and performance, process and analysis of information, repetitive physical control of equipment, and effective individual performance (Chuang, 2020). Therefore, it can be argued that workplace AI only disadvantages low-skilled and unqualified workers with lower wages and employment prospects (Garnett, 2018).

It is fair to say, however, that while jobs and related skills are going to be lost to workplace AI, AI applications often require the oversight of workers and involve the presence of flexible and knowledgeable workers in the workplace (Brunetti et al., 2020; Koren and Klamma, 2018; N. Xu and Wang, 2019). This interpretation indicates that new tasks arise from workplace AI which requires high-skilled labour (Balsmeier and Woerter, 2019). Workers with high in-demand skills get better pay and job opportunities (Garnett, 2018). This reasoning also indicates that an implied list of skills and the adoption of AI in the workplace is just a matter of losing certain skills to intelligent systems (Morikawa, 2017). Accordingly, increased workplace AI will bring opportunities for flexible and skilled workers in the workplace (Koren and Klamma, 2018).

Consequently, to use technology deliberately and remain relevant in a digital world, workers need to hone certain abilities and give up others (Chuang, 2020; Rampersad, 2020; Sousa and Wilks, 2018). The literature (e.g., Gekara and Nguyen, 2018; Rampersad, 2020; Sousa and Wilks, 2018) indicates that workers are required to hone complex problem-solving, critical thinking, creativity, people management, coordination with others, emotional intelligence, judgment and decision-making, service orientation, negotiation, cognitive flexibility, ability to identify opportunities. This literature (e.g., Chuang, 2020; Rampersad, 2020) also indicates that workers need to give up on other stills and competencies to AI systems, including monitoring, near vision, control precision, multi-limb coordination, arm-hand steadiness, deductive reasoning, information ordering, manual dexterity, operating vehicles and equipment, getting information, identifying objects and actions, planning and prioritising work, determine compliance of information with standards, analyse data, documenting information, interacting with computers, handling and moving objects, processing information, self-control, independence, persistence, operation and control, selective attention, equipment inspection, performing physical activities, repeating tasks, being accurate, and using safety equipment (e.g., Chuang, 2020).

Adopting this approach, however, is confusing and challenging. Rather than specifying which skills workers must acquire and which skills they must give up to AI in the workplace, the needed skills must be presented in a more accessible, clear, and straightforward manner. One way to achieve this is to structure the required workplace AI skills around technical, human, and conceptual categories (Katz, 1974; Peterson and Fleet, 2004).

So possibly, 'requisite skills' is about knowing what skills are required to coexist with workplace AI rather than what skills workplace AI eventually displaces (Gekara and Nguyen, 2018; Wirtz et al., 2018). The adopted grouping from skills theory provides the framework for organising the skills: proficiency in a specific activity (*technical skills*), being able to work with people (*human skills*), and being able to work with concepts and ideas (*conceptual skills*) (Katz, 1974; Peterson and

Fleet, 2004) – see Table 4 and Fig. 4.

The 'skills theory' (Katz, 1974; Peterson and Fleet, 2004) from leadership literature drives the grouping of the pooled requisite skills to coexist with workplace AI. The review collects the requisite skills for adopting AI in the workplace from the chosen empirical articles (Table 4 and Fig. 4). It then divides the required skills into three categories: technical, human, and conceptual (Katz, 1974; Peterson and Fleet, 2004; Sowa et al., 2021). Employing such grouping, the researchers reasoned, would guide thinking regarding reskilling and upskilling and provide an accessible, simple, and straightforward understanding of the required skills.

In line with this rationale, and as depicted in the conceptual framework (Fig. 4), while 'technical skills' are crucial to coexist with workplace AI (Desouza et al., 2020), 'human skills' and 'conceptual skills' (soft, generic, and transferable skills) would increasingly be oriented to promote productive work in a highly digitised working environment (Gekara and Nguyen, 2018; Leavy, 2019; Sowa et al., 2021).

4.2.3.1. Technical skills. Working with AI systems and intelligent robots is commonly referred to as 'computer skills' (Gekara and Nguyen, 2018), 'information technology skills' (Aleksander, 2017) and 'disruptive technological skills' (Sousa and Wilks, 2018). These skills fall into the 'technical skills' category, enabling workers to take advantage of 'things' from technological-related activities (Katz, 1974; Peterson and Fleet, 2004). For workplace AI, the technical competency of workers enables an organisation to secure the needed technical capacity (Kokina and Blanchette, 2019). Technical skills are learned and learnable behaviour that allows workers to work with intelligent systems (Kokina and Blanchette, 2019).

Further, the progress in adopting workplace AI depends on the workers' technical capability (Aleksander, 2017; Kokina and Blanchette, 2019). These technological capabilities range from IT literacy to machine-based digital technologies, such as artificial intelligence, nanotechnology, virtual reality, digitisation, robotics, 3D printing or the Internet of Things, and the processing of natural languages.

However, a more profound observation of the existing literature indicates that as further technological progress is made, 'technical competency' evolves. For example, 'technical competency' has recently come to mean 'disruptive technological skills' such as proficiency in artificial intelligence, nanotechnology, robotization, the internet of things, augmented reality, and digitalisation (Sousa and Wilks, 2018, p. 399). Hence, the concept might attract proficiency in other technological areas in the future.

4.2.3.2. Human skills. Human skills – working with people – aims at a worker's capacity to connect with a human colleague (Katz, 1974; Peterson and Fleet, 2004). In the context of workplace AI, these abilities include managing people, coordinating with others, emotional intelligence, knowledge sharing, teamwork, collaboration, delegation and negotiating (Richards, 2017; Sousa and Wilks, 2018; W. M. Wang and Cheung, 2013). These are essential skills for adopting AI because the amount of data to set up workplace AI requires 'honest' knowledge sharing and teamwork amongst workers (W. M. Wang and Cheung, 2013).

However, the growing number of AI systems in the workplace might also change the composition of teams (Wu et al., 2022). Teams in the future will have not only humans but also smart robots/systems – behaving and feeling like humans – as team members (Aleksander, 2017; S. Xu et al., 2020). Team-working may move to a composition of human agents in which a group of human agents would share objectives through delegating authority among members (Edwards et al., 2019; Richards, 2017).

However, this human-robot collaboration is suggested to help workers amplify their workplace abilities (Banziger et al., 2018; Klotz, 2018). It could also gradually determine the allocation (or delegation) of tasks between a worker and their AI assistant, in which the AI assistant is given structured, repeated, rules-based tasks, etc. (Banziger et al., 2018; Kokina and Blanchette, 2019).

Therefore, the relationship between workers and smart robots/systems might primarily take the form of interaction and collaboration based on agents (Shank et al., 2019; Wu et al., 2022). Such 'collective human agent' teamwork involves workers honing teamwork abilities beyond the human-human teamwork abilities that have existed in a 'traditional human team' (Richards, 2017).

4.2.3.3. Conceptual skills. Conceptual skills – working with concepts, ideas, topics, etc., to develop solutions – refers to the ability of a worker to visualize AI applications in the workplace, understand how different components of AI systems rely on each other, identify relationships and perceive key factors relevant to workplace AI, and act in a way which progresses workplace AI (Katz, 1974; Klotz, 2016; Peterson and Fleet, 2004). Complex problem-solving; analytical thinking and innovation; active learning; critical thinking and analysis; creativity and initiative; judgment and decision-making; data analysis; synthesis and sense-making, and cognitive flexibility are among those skills and competencies (Bhattacharyya and Nair, 2019; Hill, 2020; Koren and Klamma, 2018; Rampersad, 2020; Sousa and Wilks, 2018).

AI systems, for example, can manage a massive amount of data in the workplace (Koren and Klamma, 2018). On the other hand, workers need to do data analysis, synthesis and sense-making to work with the data (Bhattacharyya and Nair, 2019; Koren and Klamma, 2018). Creativity in discovering data trends and relationships remains with workers (Klotz, 2018; Koren and Klamma, 2018; Leavy, 2019). Therefore, when adopting workplace AI, an organisation is expected to enable workers' creativity rather than manage it with intelligent systems (Leavy, 2019).

However, workplace AI technologies are also expected to perform some logical decision-making in the next two decades (Klotz, 2018). When AI systems take over analytical decision-making capabilities (Klotz, 2018), well-educated, highly skilled and qualified workers are often required to steer their energies into tasks that involve conceptual skills that intelligent systems do not perform (Gekara and Nguyen, 2018). Also, workers' creativity and innovation will be further pushed (Haefner et al., 2021; Klotz, 2018).

However, visionaries (e.g., Botha, 2019; Holford, 2019) envisage the possibility that creativity and innovation (and other conceptual skills and competencies) might gradually shift to AI systems. Others (e.g., Klotz, 2018; Richards, 2017; Willcocks, 2020) disagree and imply that intelligent workplace systems introduce innovative ways by which workers can amplify their abilities. Given the workplace AI capabilities now (Davenport, 2019; Davenport and Ronanki, 2018) and the constant need to maintain these systems in the workplace (Waterson, 2020a, 2020b), it is unlikely that creativity and innovation will be transferred from the workers to workplace AI in the near future (Aleksander, 2017; Richards, 2017). These systems, however, will introduce new ways to improve creativity and innovation for workers (Aleksander, 2017; Haefner et al., 2021; Richards, 2017). This theme is summarised in Proposition 3.

Proposition 3. *A worker's ability to coexist with AI systems requires combining technical, human, and conceptual skills. While technical proficiency is essential in this coexistence, it cannot outweigh human and conceptual abilities in a digitised workplace.*

There is a general understanding of the extent of each skill category a manager needs from a level of management in the leadership literature where the Skills Theory (technical, human, and conceptual skill categorization) appears (Katz, 1974; Peterson and Fleet, 2004). While the Skills Theory drives the 'Competency framework for worker-AI coexistence,' this proposition invites research into the framework and how reflective it is in explaining the worker skill requirements to coexist with workplace AI. Furthermore, this proposition leads future studies into whether artificial intelligence in the workplace will eventually replace human and conceptual skills in a digitised workplace. By extending this line of research (Holford, 2019), for example, by applying ethnographic inquiry, this proposition will further establish AI in the workplace. Table 5 offers a list of research questions that will assist with investigating this proposition further.

4.2.4. Workers need ongoing reskilling and upskilling to contribute to a symbiotic relationship with workplace AI

AI technologies are commonly depicted as 'a very young boy' reflecting the existing drawbacks of AI in the workplace that go beyond technical innovation, such as the amount of investment that an organisation needs to train these systems and the categorical discrepancies between the 'algorithmic' vs 'life-need' AI (Aleksander, 2017; Banziger et al., 2018; Ransbotham, 2020). An organisation is also less likely to make a significant return on investment in workplace AI without investing in the expertise and talent of its workers (Ransbotham, 2020). Investments in upskilling and reskilling workers have two purposes: (i) to encourage workers to help make these systems operational and (ii) to enable workers to deliver measurable results from these systems (Cheatham et al., 2020; Hupfer, 2020). This section elaborates on the 'ongoing training, upskilling and reskilling' theme.

Appropriate training strategies are required to support workers in adjusting their skills, changing job responsibilities, becoming versatile and coexisting with AI systems in a technologically evolving workforce (Chuang, 2020). While early attention to education, ongoing training, and reskilling of workers in the workplace can lead to an effective symbiotic relationship between workers and AI-systems (Aleksander, 2017), McKinsey & Company believes that there are often different aspirations for different stakeholders involved in 'education and reskilling' and in 'early focus' of workplace AI (Illanes et al., 2018).

Despite that, to prepare 'competent workers' to jumpstart workplace AI, an early focus on preparation for requisite skills is suggested (Aleksander, 2017; Koren and Klamma, 2018). Although this sounds simple, the definition of a 'competent worker' in this context remains unclear. The issue is that workers in organisations need to enrol in training programmes for their skills to implement workplace AI. It is also difficult to forecast who will benefit the most from specialised training programmes (Willcocks, 2020). Therefore, even though organisations enrol their workers in training programmes to make their expertise applicable to workplace AI (Sousa and Wilks, 2018), the outcome of these training programmes also depends on the enrolment of 'competent workers'.

Besides, traditional classroom-based instructor-led training programmes are unlikely to serve as an innovative way to prepare workers for workplace AI. They are known to be slow and costly (Gratton, 2020). However, existing awareness continues to grow around what creative forms of training organisations can use to cultivate a symbiotic relationship between workplace AI and workers. Recent examples of such creative forms of training include work-integrated learning (WIL) (Rampersad, 2020).

Though 'unlearning' is not considered a hindrance to workplace AI, 'learning' is suggested to assist workers' constant need for skill enhancement (Bhattacharyya and Nair, 2019). Consequently, when a human worker is employed (Bhattacharyya and Nair, 2019), 'learning' is supposed to become a lifelong process in their career. As 'learning' becomes a lifelong process, it can be argued that 'unlearning' of displaceable skills also becomes a lifelong workplace necessity for a worker (Bhattacharyya and Nair, 2019; Chuang, 2020).

While some scholars (e.g., Chuang, 2020) attempt to provide techniques to assist a worker in becoming 'robot-proof', no set of methods will act as a 'one-size-fits-all' considering the lifelong 'learning' and 'unlearning' required from a worker to coexist with workplace AI. Workplace AI needs an atmosphere in which change is welcomed and open-mindedness to workplace technical innovation is nurtured (Haefner et al., 2021; S. Xu et al., 2020). Workers who fit in such a workplace are highly qualified professionals (Morikawa, 2017) who partake in the process of lifelong learning (Bhattacharyya and Nair, 2019) and are actively trained to develop their skills (Koren and Klamma, 2018). This theme is summarised in Proposition 4.

Proposition 4. *Competent workers contribute to an effective worker-AI symbiotic relationship, and workers should be enrolled in ongoing training to become competent workers.*

While businesses can hire workers with the necessary set of skills, new research (Grimpe et al., 2022) reveals that even if they wanted to, they would be unable to do so due to the high demand for competent workers. Per this line of research, such individuals are more drawn to an organisation's training opportunities than financial rewards. An organisation can provide ongoing training to attract such individuals; such training is also expected to maintain the relevance of their workforce. Furthermore, ongoing training will prepare an organisation's workforce to engage in the much-needed training of AI systems. This proposition encourages the advancement of knowledge by using ongoing training, such as upskilling and reskilling, to establish AI in the workplace. Considering the peer-reviewed nature of academic publications, ongoing attempts at using content analysis of practitioner research from organisations like Accenture, Chartered Institute of Personnel and Development (CIPD), Deloitte, McKinsey & Company, and others may help to determine what ongoing training is required to coexist with AI in the workplace. Table 5 offers a list of research questions to investigate this proposition further.

4.2.5. A perpetual race with workplace AI

A worker's ability to coexist with AI in the workplace requires combining technical, human, and conceptual skills. However, this coexistence indicates a never-ending cyclical race (Fig. 5), i.e. between workers and AI at work. Workers will have to continue to learn new skills that are difficult for AI to perform. On the other hand, AI technology will continue to gain such skills. Workers will have to reskill and learn something new in response, which AI will be unable to do for the time being but will eventually catch up.

5. A future research agenda

Although it is frequently envisioned that workplace AI will perform human-only skills in the future (Holford, 2019; Willcocks, 2020), this projection blurs the reality of the actual technology and unrealistic statements (Lambert and Cone, 2019; Wirtz et al., 2018). In intelligent systems and humans, cognition and awareness remain different (Aleksander, 2017). For instance, we do not yet know how or whether workplace AI can respond to life-need situations in the workplace beyond "algorithmic scripts." (Aleksander, 2017). Through a 'category error' viewpoint (Aleksander, 2017), future research can determine workplace AI's realistic cognition and awareness capabilities.

Further, practitioner publications (e.g., Agarwal et al., 2019; McKinsey Insights, 2017) generally negatively envision the future of work. However, those publications (practitioner publications) are limited from a scholarly perspective. The critical area of interest to study is allocating human-AI tasks (Banziger et al., 2018; Sowa et al., 2021). Current understanding suggests that intelligent systems are given tasks that can be automated while human-type activities such as creativity remain with workers (Klotz, 2018; Wirtz et al., 2018). However, as we progress with workplace AI, we are still unsure what happens to worker-AI task allocations. Although there are already attempts in the literature to investigate the type of service tasks that intelligent systems will control and the service tasks that will stay with workers (Wirtz et al., 2018). Future work can investigate this field to enhance an established understanding of service tasks for workers vs intelligent systems. Research into AI-empowered service delivery ethics and the cultural aspects of robot-service delivery acceptance would also be of significant interest (Stahl et al., 2020).

Complemented with emerging technologies (Morikawa, 2017), the underlying view is that human skills and conceptual skills (soft, generic and transferable skills) keep a workforce highly qualified (Gekara and Nguyen, 2018). However, suppose workplace AI continues to gain insights from workers and convert them into a structured format (W. M. Wang and Cheung, 2013). In that case, these intelligent systems will gradually displace skills that are, for now, human-only skills. Therefore, future research may take the form of reflections and considerations (Johansson et al., 2017) and update scholarly understandings of the distribution of AI-human tasks and skills.

Current literature (e.g., Balsmeier and Woerter, 2019; Johansson et al., 2017) suggests a correlation between an increase in high-skilled workers with an increase in workplace AI adoption. Although such references are rational, highly qualified workers must be more technologically competent in leading an organisation to adopt workplace AI further. There is a dire need to investigate this correlation between high skilled workers and the adoption of workplace AI. In addition, as more advances are made in workplace AI, one can imagine that workers deemed high-skilled at one level of AI applications will become low-skilled in future AI applications.

Workplace AI also activates various perceptions among workers (Nam, 2019). Are these systems – digital employees (Kokina and Blanchette, 2019), robot colleagues (Klotz, 2016), assistant agents (Coyne, 2016), human apprentices (Wu et al., 2022) – threats, colleagues, agents, slaves or enslavers? Organisations may attempt to reassure workers that such systems are designed to empower creative workers (Klotz, 2018; Leavy, 2019). However, the perception of workers of job insecurity (Nam, 2019) remains an issue with workplace AI (Garnett, 2018). Therefore, workers might perceive that these systems are merely in the workplace to convert tacit knowledge into a structured format to replace workers (Haefner et al., 2021; W. M. Wang and Cheung, 2013).

'Job creation/destruction' or 'technological redundancy' is another worker's concern with workplace AI (Balsmeier and Woerter, 2019). The literature (e.g., Botha, 2019) refers to 'smartness' and 'human creative abilities' for workers to fill the jobs generated by workplace AI. There are, however, questions about whether 'smartness' and 'creative human skills' go beyond the ability of a human worker to interpret, sense-make and synthesize data (Bhattacharyya and Nair, 2019). While workers' creativity allows for trends and patterns to be recognised from data generated by workplace AI (Klotz, 2018; Koren and Klamma, 2018; Leavy, 2019), how an organisation enables workers' imagination and creativity in the workplace remains unclear (Leavy, 2019). Consequently, if 'smartness' and 'human creative abilities' denote the possession of specific skills by workers in the workplace, we have yet to learn further about such skills.

The threats to jobs from workplace AI are understandable (Chuang, 2020). Focusing on reskilling and ongoing training can lead to an effective symbiotic relationship (Aleksander, 2017) and avoid collective failure (Willcocks, 2020). There are, however, suggestions that such initiatives should be built around innovative training approaches (Gratton, 2020; Koren and Klamma, 2018; Morikawa, 2017; Sousa and Wilks, 2018). Future research needs to explore innovative training approaches from the context of an unknown future. Future research also needs to explore how best reskilling and ongoing training can ensure that organisations retain a workforce that can create a symbiotic relationship with workplace AI. In addition, more clarification is necessary on adapting such training programmes to different phases of workplace AI (Desouza et al., 2020).

Hence, from the academic perspective, this study offers essential insights to scholars and practitioners interested in advancing these hot topics on artificial intelligence in the workplace and the coexistence of workers with AI applications. As shown in Figure A2 (Appendix), an increasing publication trend is predicted to broaden existing knowledge of AI application adoption in the workplace. This study's propositions and tabulated research questions provide an exciting research agenda for future research.

6. Contribution to theory, practice, and policy

This paper first argued that an existential argument further clarifies workers' trust in workplace AI and adds to the literature research string around workers' cognitive and emotional trust in AI (Davenport, 2019; Gillath et al., 2021; Glikson and Woolley, 2020). While the threat of workplace AI replacing human skills may lead to 'fear' among workers, this threat is genuine for tasks that require repetitive motion, data management and analysis, repeated physical control of equipment, and individual evaluative interaction (Chuang, 2020). Therefore, certain tasks displaced to workplace AI will be discontinued for workers (Braganza et al., 2020; Chuang, 2020). However, threats to human-only skills can be perceptions from exaggerated AI capabilities (Willcocks, 2020).

Therefore, workers' scepticism of workplace AI, in the context of Rogers' innovation theory (2003), could also be explained by an existential argument (Farrow, 2019; Keeler and Bernstein, 2021), along with the five main factors that influence adoption: relative advantage, compatibility, complexity, trialability, and observability (Rogers, 2003). While Rogers' innovation theory (2003) divides AI adopters into five groups based on their adoption rate, it needs to account for the 'trust' dimension between workers and AI systems (Davenport, 2019; Gillath et al., 2021; Glikson and Woolley, 2020).

One implication is that workplace AI reduces various forms of human engagement and interpretation in the workplace (Holford, 2019; Y. J. Kim et al., 2017). Workers' ability to perform behavioural tasks and cognitive processes characterise their employment (Peterson and Fleet, 2004). On the other hand, workplace AI disrupts the skills that comprise this employment (Chuang, 2020; Raj and Seamans, 2019). It also changes the relative value of the skills required for a particular task (Chuang, 2020; Sousa and Wilks, 2018).

Another implication is that workers enter a perpetual race with workplace AI to learn new complex skills to perform to coexist with AI. Recent reviews (Table A1 (Appendix)) delved into workplace AI, such as AI to reshape innovation (Haefner et al., 2021), AI to transform human existence (Matthews et al., 2021), AI to combat the COVID-19 pandemic (Khan et al., 2021), and AI to solve tasks autonomously (Cebollada et al., 2021), etc. These reviews focus on the transformational strengths of AI. However, the 'transformational strengths of AI' will unlikely be realised when the workforce of an organisation lacks the requisite skills for AI adoption. Skilled personnel, for example, must fix errors made by intelligent robots so that customers are not dissatisfied and their organisation is not adversely affected (Yam et al., 2020).

Skilled personnel, therefore, require technical skills and several other skills that help them coexist with workplace AI. However, skills continue to be lost as AI advances further (Chuang, 2020; Rampersad, 2020). This study also extends prior reviews by identifying the requisite skills from the existing literature to promote a symbiotic relationship in the workplace between workers and AI (Wilson and Daugherty, 2019). Identifying every requisite skill from the existing literature and tabulating skills workers must develop and abilities to give up to AI is confusing and challenging. An alternative approach needs to be accessible, clear, and straightforward. One way to achieve this is to structure the requisite skills around technical, human, and conceptual skills (Katz, 1974; Peterson and Fleet, 2004).

This study employed the 'skills theory' from the leadership literature (Katz, 1974; Peterson and Fleet, 2004) to categorise the requisite skills for workers to coexist with AI systems (Rampersad, 2020; Sousa and Wilks, 2018; Sowa et al., 2021). Skills and abilities to coexist with workplace AI from the literature are classified under the technical, human, and conceptual pillars. While technical skills are needed to promote productive work in a highly digitised working environment in the foreseeable future (Desouza et al., 2020), human and conceptual skills will increasingly outweigh technical skills (Gekara and Nguyen, 2018; Leavy, 2019; Sowa et al., 2021).

This positioning suggests that workers must embrace workplace AI. It directs worker efforts towards innovative and collaborative work, enabling worker ingenuity. Another implication, therefore, is what happens to workers when worker ingenuity is no longer needed to overcome the existing AI limitations. Suppose AI adoption in the workplace gradually reduces the human element (Holford, 2019). In that case, this further implication does not appear favourable to workers, let alone a motivation to develop human and conceptual skills to coexist with workplace AI. Is it not a reason to avoid adopting AI in the workplace? While future projection suggests that AI advancement reduces the human element in the workplace, Holford (2019, p. 143) argues that if such progress minimises the human element, it will fail to recognise "the unique and inimitable characteristics of human creativity and its associated tacit knowledge." While intelligent robots may be less likely to make mistakes in the future, workers still need a combination of technical, human and conceptual skills, for example, to understand AI system outputs.

This discussion so far suggests that the future of jobs is uncertain (Aleksander, 2017; Bhattacharyya and Nair, 2019; Gekara and Nguyen, 2018). Therefore, another implication is that a unique symbiotic relationship requires investments in reskilling and upskilling workers to coexist with workplace AI (Wilson and Daugherty, 2019). While workers will continually hand over tasks and their related skills to AI systems (Bhattacharyya and Nair, 2019; Gekara and Nguyen, 2018; Klotz, 2016), this study cannot elaborate on the balance of duties between workers and AI. Organisations must carefully examine the balance of responsibilities between workers and AI applications before and throughout the adoption of workplace AI (Wirtz et al., 2018; S. Xu et al., 2020). This balance shapes the experience of workers of workplace AI. If this balance is 'correct', the work climate nurtures open-mindedness to change and establishes a symbiotic partnership between workers and AI to augment each other's strengths (Baum et al., 2011; S. Xu et al., 2020). Rather than workers fear workplace AI, they will develop complex skills to work with it. Therefore, the paper contributes to recent discussions around the 'Robo-Apocalypse from job loss' (Arslan et al., 2021; Chuang, 2020; Huysman, 2020; Willcocks, 2020). Rather than envisioning a Robo-Apocalypse workplace, this study encourages scholarship to focus on choices about training and education for workers. While there will be skill disruption (Chuang, 2020; Rampersad, 2020), such disruption calls for continuous reskilling and upskilling of workers to avoid 'a collective failure to adjust to skills' (Willcocks, 2020).

A practical implication is that while workers' fear of job loss to AI is generally from exaggerated AI capabilities (Aleksander, 2017; Willcocks, 2020), such perceived fear disrupts workplaces and changes worker behaviour, such as knowledge sharing vs hiding (Pereira and Mohiya, 2021). Organisations and management must be transparent about AI adoption and explain the organisational strategy for AI adoption to workers. An organisational strategy must accommodate the trade-offs between reskilling and upskilling workers and external skills recruitment.

The paper also has a policy contribution. Suppose we consider workers' interaction with the workplace AI a perpetual race for skill development and displacement. In that case, such interaction may be inconsistent with the OECD AI Principles (OECD, 2021) and the United Nations' Sustainable Development Goal 8 (SDG 8), promoting productive employment and decent work (Braganza et al., 2020), which state that AI should benefit workers. In this context, AI primarily benefits from interactions with workers rather than workers directly benefiting from such interactions. Therefore, another implication is who will take the responsibility of reskilling and upskilling workers to coexist with workplace AI. If the relationship between workers and workplace AI enters a perpetual race, so does the race of developing skills that workplace AI cannot take over for the time being. A symbiotic relationship is not achieved by assuming a worker's responsibility to acquire complex skills to coexist with AI (Ransbotham, 2020). While an organisation might engage in reskilling and upskilling its workforce (Illanes et al., 2018), the perpetual race of workers with workplace AI goes beyond an organisation. Workplace AI disrupts the labour market (Garnett, 2018; Y. J. Kim et al., 2017). Interactions with workplace AI that eventually replace workers create emotional and social dilemmas (Botha, 2019; Shank et al., 2019). The emotional and social dilemmas may lead to mental issues for workers because the workplace AI offers fewer opportunities and lower pay (Garnett, 2018). If mass unemployment results from the continuous integration of workplace AI, there could also be social unrest (Bhattacharyya and Nair, 2019). Early attention to the implications of the constant integration of workplace AI helps society (Willcocks, 2020).

Therefore, policymakers should explore how AI may continue to be a human partner rather than a rival. Also, policymakers can push algorithm accountability to emphasise transparency in organisational workplace AI adoption (John-Mathews et al., 2022; B. Kim et al., 2020). They can contribute to policies, guidance, regulations, and legal frameworks to encourage productive employment and decent work in AI adoption in the workplace as part of the Sustainable Development Goal 8 of the United Nations. They should push for policy interventions to maintain a country's labour force prepared for future workplace AI and such policy interventions are through investments in education, reskilling, and ongoing training (Bhattacharyya and Nair, 2019; Chuang, 2020).

7. Conclusion

This multidisciplinary review drew on psychology, computer science, robotics, human-computer interaction and collaboration. The future landscape of the worker-AI relationship and requisite skills for worker-AI coexistence in the workplace implies that low and moderate knowledge-centred assignments are taken over with workplace AI (Bhattacharyya and Nair, 2019). Even skills such as 'analytical decision-making', currently mastered by workers, are expected to shift to intelligent systems in the next two decades (Klotz, 2016). This, however, depends on an organisation's ability to continuously incorporate AI applications in the workplace (Ransbotham, 2020).

One implication is that workers need to reskill and upskill to remain relevant in the workplace (Rampersad, 2020). This realization comes from the understanding that long-term assignments and the necessary competencies for such assignments are also gradually taken over by workplace AI (Bhattacharyya and Nair, 2019). Organisations seem to progressively follow this approach to workplace AI, enabling, for example, the reduction of dedicated workspaces (Bhattacharyya and Nair, 2019). However, future worker interaction with workplace AI continues to influence perceived and actual job insecurity (Nam, 2019; Richards, 2017; Shank et al., 2019; Wirtz et al., 2018). Therefore, future workplace AI continues to transfer tasks and their requisite skills to AI and disrupt job design and the required competencies of the workforce (Bhattacharyya and Nair, 2019; Gekara and Nguyen, 2018).

Regardless, appropriate training strategies are necessary to help workers develop technical, human, and conceptual skills; shift job roles; become flexible and coexist with AI systems in a technologically changing workforce. For various stakeholders such as organisations, governments, HR practitioners and workers, there continues to be a keen interest and attention to the projected future changes in tasks and their required skills in the workplace (Nam, 2019; Richards, 2017; Wirtz et al., 2018; S. Xu et al., 2020).

8. Limitations

This study has some limitations. First, it is limited to ABS-ranking peer-reviewed journal publications, with non-peer-reviewed or non-ABS ranking papers, books and book chapters, and practitioner research excluded. The review team of future studies can choose to disuse the ABS list criterion or use other quality ranking lists (Tranfield et al., 2003). Second, the search strings were developed to locate relevant articles. The search strings may not have retrieved all relevant research papers from or outside the listed databases. Third, we obtained the keywords from research articles and used a "four-level-keywords assembly structure" to limit the scope of the study. We were interested in articles discussing workers' coexistence with workplace AI, and we wanted to capture the human worker in returned articles with the first two levels. With the third and fourth levels, we tried to limit this to studies on artificial intelligence in workplaces. However, we understand that no list of keywords, levels, or search strings is perfect. Our keyword selection and "four-level-keywords assembly structure" may not have retrieved all relevant publications. Future research might use other approaches to limit the scope of studies on workers' coexistence with workplace AI. Fourth, different databases provide their subject area categories. When choosing the categories, we chose the ones that we thought would be more pertinent to the coexistence of workplace AI and workers (see 3.3). Future research can choose different subject areas to explore if the returned articles yield different themes than the one in this study concerning worker-AI coexistence. While acknowledging these limitations, this research aims to inspire more inquiry into researching and improving our knowledge of worker and AI coexistence in workplaces.

Data availability

Data will be made available on request.

Appendix

Table A1
Recent reviews on artificial intelligence and workers

Source	The focus of the study	Findings
Wu et al. (2022)	To review approaches to help robots learn skills from human demonstrations in the construction industry	A perspective on robot skill learning as human apprentices in the construction industry
Garg et al. (2021)	To identify machine learning adoption in the core HRM functions	Machine learning (decision trees and text-mining algorithms) is mainly employed in recruitment and performance management HRM functions.
Borges et al. (2021)	To provide a critical review of artificial intelligence integration in organizational strategy	A conceptual framework of sources of value creation from AI integration in organisational strategy, and one such area is employee engagement
Trenerry et al. (2021)	To identify and consolidate critical factors for an organization's digital transformation	This review proposes that workers' perceptions and attitudes toward technological change and skills and training are relevant factors to an organisation's digital transformation.
Arslan et al. (2021)	To review the associated HRM challenges with the interaction of AI and human workers at a team level	The associated HRM challenges with the interaction of AI and human workers at a team level include workers' job loss, fear and distrust of working with AI.
Willcocks (2020)	To question assumptions associated with automation and the future of human work	This review argues that the 'job loss' claim is exaggerated, but skill disruption is highly likely, while the magnitude of such disruption is yet to be known.
Fong et al. (2020)	To review developmental efforts in functional capacity evaluations that incorporate machine learning algorithms	Machine learning-based functional capacity evaluations blend robotic systems' benefits with human therapists' expertise and experience.
Glikson and Woolley (2020)	To review the determinants of human worker "trust" in AI	Workers' cognitive trust in workplace AI is influenced by its tangibility, transparency, reliability, and immediacy, and their emotional trust in it is influenced by its anthropomorphism.
Chuang and Graham (2018)	To review technological unemployment	HRD professionals need to influence developmental efforts on employees' human skills
Aleksander (2017)	To review the 'actual' level of robotics competence from research laboratories and the likelihood consequence of such advancement for human jobs	While robots can carry out certain algorithmic' category tasks, such capabilities do not translate to the 'life-need' category of tasks.

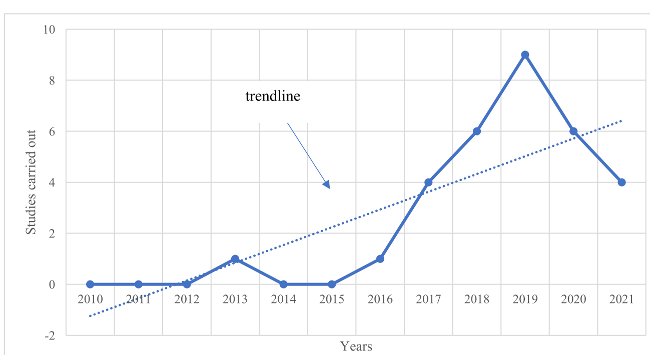
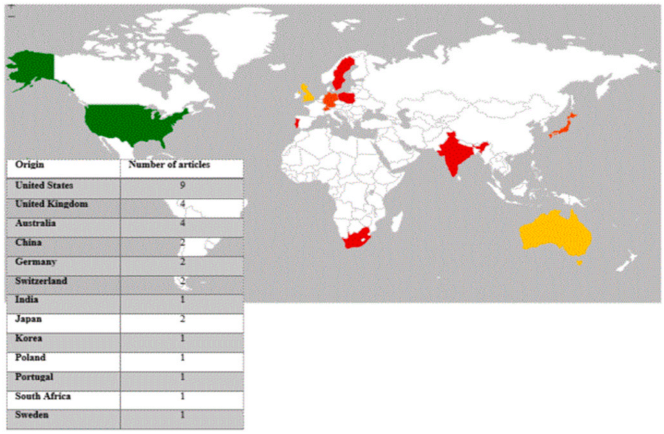


Figure A2Publication trend



Origin	Number of articles
United States	9
United Kingdom	4
Australia	4
China	2
Germany	2
Switzerland	2
India	1
Japan	2
Korea	1
Poland	1
Portugal	1
South Africa	1
Sweden	1

Fig. A3. Geographical distribution of research

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