Can artificial intelligence's limitations drive innovative work behaviour?

1. Introduction

Artificial Intelligence (AI) is increasingly taking over physical motion and performance activities, data processing and analysis, repetitive physical equipment management, and individual effective performance in workplaces (Chuang, 2020; Malik et al., 2021). One might, therefore, argue that workers engage in more innovative work behaviour (IWB) (Henkel et al., 2020; Jaiswal et al., 2021). But then, how will AI in a workplace make workers innovative? The answer seems to be more nuanced.

While the existing literature (Chuang, 2020; Klotz, 2018; Malik et al., 2021; Wilson & Daugherty, 2019) suggests that AI enhances workers' abilities (intuition, empathy, and imagination) by automating mundane, repetitive, and boring activities. In academic research, there is a debate on whether this enhancement in workers' abilities results from AI augmenting human intelligence and skills (Farrow, 2019; Klotz, 2018). Workplace AI that helps doctors diagnose disease and helps bankers detect fraud improves workers' detection abilities rather than innovative work behaviour. However, the use of AI in this context suggests that AI cannot act independently of human workers (Klotz, 2018; Wilson & Daugherty, 2019).

It is reasonable to imply that AI's limitations require human intelligence and abilities, for instance, to diagnose disease and detect fraud because current AI advancements cannot do so without humans (Klotz, 2018; Wilson & Daugherty, 2019). Workers, therefore, compensate for algorithmic flaws than relying on AI to enhance their creativity. While AI can influence workers' behaviour (Malik et al., 2021; Yam et al., 2020), it is unclear how it might enable innovative work behaviour.

The research question that guides this review is: how will AI make workers innovative in their work? Following a protocol, the analysis involved reviewing 65

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articles found in the Scopus database (Tranfield et al., 2003). Insights in the form of themes are obtained, along with propositions and prospective research areas, to highlight gaps in current knowledge and encourage further AI-enabled IWB research.

There are five sections to this study. The second section offers background for the two concepts. The third section describes the research method. Section four presents the research themes and propositions. The fifth section provides the concluding remarks, including discussion and conclusion, contributions, and study limits.

2. Background

2.1 Artificial Intelligence (AI) in the workplace. AI refers to computers' ability to learn from experience and perform human-like complex tasks, such as rational decision-making (Pomerol, 1997; P. Wang, 2019). A common trend emerging from AI definitions is that machines can perform complex human-like tasks based on algorithms and data in the workplace and society. AI's purpose is, therefore, to imitate human cognitive functions like perception, learning, reasoning, and decision-making (Holford, 2019; Lopes de Sousa Jabbour et al., 2018).

However, the performance of intelligent systems depends on the data fed into them (Farrow, 2019; Thesmar et al., 2019). Intelligent systems are unable to obtain missing parts of data. Therefore, data consistency and quantity are significant issues for AI applications in the workplace. Human intervention to support AI is required, as human intelligence and innovative behaviour are needed to find missing parts of data and categorise appropriate data for AI systems (Shute & Rahimi, 2021). Human intervention is also necessary to override or interpret the outputs of these 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). Many workers will lose their jobs to AI applications in the workplace (Balsmeier & Woerter, 2019). Consequently, the chances are high that the work performed by workplace AI would no longer need the workers' involvement (Holford, 2019; Wright & 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 advancement activates their innovative behaviour (Fügener et al., 2022; Klotz, 2018; Wilson & Daugherty, 2019). However, the reality is quite the opposite (Davenport, 2019; Gligor et al., 2021; Waterson, 2020a, 2020b). 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 themselves to engage in innovative behaviour to coexist with AI systems (Afsar et al., 2014; Jaiswal et al., 2021; Sousa & Wilks, 2018).

2.2 Innovative work behaviour (IWB). Scholarly research combines idea conception through completion under 'innovative behaviour' (Baer, 2012; Baer & Frese, 2003; Scott & Bruce, 1994; Somech & Drach-Zahavy, 2013). The generation and implementation of new and original ideas into newly designed goods, services, or ways of working are examples of innovative work behaviour (Baer, 2012; Perry-Smith & Mannucci, 2017).

Further, innovative behaviour is often associated with creative problem-solving in engineering literature (Anantrasirichai & Bull, 2021; Colin et al., 2016). AI technologies intend to enhance and support individuals' creativity in problem-solving.

In this literature, AI is a creative tool and can be a creator in its own right (Anantrasirichai & Bull, 2021; Colin et al., 2016). On the other hand, workers can use AI applications to demonstrate 'creativity in problem-solving' in the workplace. They could use AI to create something new, like a unique ice cream flavour. However, IWB is generally reactive rather than proactive in management literature, such as devising workarounds (Alter, 2014). Idea generation, elaboration, promotion, and implementation are parts of the process of developing workarounds (Alter, 2014; Perry-Smith & Mannucci, 2017). With AI's limits in perspective, innovative work behaviour serves as workarounds to compensate for AI limitations.

Moreover, as per engineering literature (Anantrasirichai & Bull, 2021; Colin et al., 2016), being creative is more about the creative process and an individual's intellect than the creative outcome and behaviour. Solving a problem through a dramatic shift in viewpoint by employing technology is vital in the creative process (Colin et al., 2016). As per management literature, innovative behaviour manifests in the creative product (the behaviour) through idea generation, elaboration, championing, and implementation (Alter, 2014; Perry-Smith & Mannucci, 2017). In this review, IWB is spontaneous activity to compensate for AI flaws or make sense of AI system outputs rather than a dramatic shift in an individual's perspective.

IWB necessitates deliberate workers' intervention in the workplace (Perry-Smith & Mannucci, 2017). It is thus IWB is the identification of issues, together with the generation, initiation, and implementation of new and original ideas, as well as the set of behaviours required to develop, initiate, and execute ideas with the intent of enhancing personal and business performance (Jong & Hartog, 2010).

The behavioural element is critical, which means the conception through completion of ideas is not enough to demonstrate IWB without workers' engagement

with others in this process (Perry-Smith & Mannucci, 2017). A worker collaborates with others to drive new ideas and determine feasibility (Perry-Smith & Mannucci, 2017). However, when a worker engages with others as part of IWB, groupthink is likely to kill an idea prematurely (Moorhead & Montanari, 1986). In addition, IWB reflects organisational contexts, which means ideation and the involvement of workers with others reflect the context of an organisation (Perry-Smith & Mannucci, 2017; Saether, 2019).

While workers identify potential problems and initiate behaviours that allow sharing of knowledge and insights (Chatterjee et al., 2021), IWB is expected to produce innovative output (Farrow, 2019). It is, therefore, reasonable to suggest that IWB is a worker's deliberate action of ideation and adopting new ideas, goods, processes, and procedures to their tasks, unit, department, or organisation (Jong & Hartog, 2010). In this analysis, IWB examples include supporting the design, implementation, introduction and use of AI applications in the workplace (Desouza et al., 2020), implementing AI-related technologies (Choi et al., 2019), and proposing ways of achieving goals and executing work tasks using AI technologies (Mahroof, 2019). However, this is not an exhaustive list; any behaviour in an organisation with an 'innovative' element falls under IWB (Jong & Hartog, 2010).

3. Research method

The researcher formulated the research question, determined the keywords, and identified, collected, analysed and synthesised the relevant literature (Klein & Potosky, 2019; Tranfield et al., 2003). The research began with a review of relevant literature on 'artificial intelligence' and 'innovative work behaviour.' The review question – how will AI in a workplace make workers innovative in their work? –

allowed for a 'concept-centric' approach to the review, as mentioned in Method 1

below (Rousseau et al., 2008).

Three stages were followed to find studies on 'artificial intelligence' and

'innovative behaviour': First, a manual search was performed in Google Scholar using

a combination of the two concepts. This search aimed to delve into the potential

keywords for the data collection. Second, a search was performed in the electronic

and multidisciplinary database of Scopus using a combination of the

keywords: ALL(("artificial intelligence" OR "augmented

intelligence" OR robot*) AND ("human innovati*" OR "human

creativ*" OR "innovative work behavi?r"))

Previous literature (e.g., Bos-Nehles et al., 2017; Charlwood & Guenole, 2021;

Farrow, 2019) has used these keywords. Also, Truncation and Wildcards techniques

were used to optimise the search string. Truncation and Wildcards are 'search string

broadening strategies' to include various word endings and spellings. For example, in

"innovative work behavi?r", the Truncation symbol "?" in "behavi?r" was used to force

the search string to return the British and American spellings of "innovative work

behaviour." The search string used the Scopus field code 'ALL()' rather than 'TITLE-

ABS-KEY()' to search document contents for the combination of the keywords. The

search string returned documents that included the combination of the keywords in

the entire body of the documents and the title, abstract, and keywords.

Figure 1

The final list of articles was retrieved from the Scopus database. The breadth of

publications was prioritised over the depth. The Scopus database provides this, as it

covers peer-reviewed journals published by major publishing houses and goes beyond only influential journals (Ballew, 2009; Burnham, 2006; Sharma et al., 2020). Further, due to the nature of 'artificial intelligence' and 'innovative behaviour' concepts, an interdisciplinary field coverage was chosen, a strength of the Scoups database compared to other databases such as the Web of Science. While Google Scholar could have provided such interdisciplinary field coverage, compared to Scopus, it has significant drawbacks, including difficulty narrowing down search results, limited sorting options, questionable content quality, and difficulties accurately extracting meta-data from PDF files, to highlight a few.

When the Scopus database was searched, the returned results were limited to the last ten years (Figure 2), articles in the English language, journal as a source type, articles as a document type, articles of ABS ranking, articles in the following subject areas: Business, Management, and Accounting; Social Sciences; Psychology; Arts and Humanities; and Decision Sciences.

Table 1

The Scopus field code EXACTSRCTITLE () was used to limit the returned results to ABS-listed journals (Table 1). This field code was supplied with a list of ABS-ranked journals. Then, manual checking of journal titles was performed to verify the quality of the returned data to ABS-rated journals. A graphic representation of the process is shown in Figure 1.

A further reduction of the list was made by reviewing the abstracts of the articles in stage 2 above (Di Vaio et al., 2020). Articles had to satisfy thematic requirements to be included in the review. Articles that addressed the relationship

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between artificial intelligence and innovative work behaviour were retained for analysis. A careful reading of the articles' abstracts helped create an excel table highlighting the relevance of each article to the topic (Di Vaio et al., 2020).

Then, in the third stage, to identify articles not returned by the Scopus search string in the second stage, a review of the reference lists of the recent articles, among the articles returned by the Scopus database, was performed (Di Vaio et al., 2020). Following the exclusion and inclusion criteria, 65 studies matching the criteria were combined for this analysis.

Figure 2

The objective of the data analysis stage was to understand the selected list of articles (Tranfield et al., 2003). The data were organised into themes in an Excel spreadsheet (Braun & Clarke, 2006).

The analysis adopted 'Reflexive Thematic Analysis' (Braun & Clarke, 2019, 2022). 'Reflexive' in this context highlights the role of the researcher in generating the themes (Braun & Clarke, 2022; Terry & Hayfield, 2020). This analysis method relies on the researcher's interpretation and active engagement with the data considering the research question (Braun & Clarke, 2022; Byrne, 2022; Terry & Hayfield, 2020).

Using reflexive thematic analysis, a researcher can offer deeper levels of meaning and significance, analyse hidden interpretations and assumptions, and explore the implications of meaning (Braun & Clarke, 2022; Byrne, 2022). In the reflexive thematic analysis, themes are hence patterns of meaning anchored by a shared idea or concept (Terry & Hayfield, 2020). They are generated, explored, and refined throughout iterative rounds rather than simply emerging from the data (Braun

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& Clarke, 2022; Byrne, 2022; Terry & Hayfield, 2020). They are meaningful entities from codes that capture the essence of meanings from data rather than clusters of data, classifications, or summaries (Braun & Clarke, 2022; Terry & Hayfield, 2020).

When reviewing the selected articles, the researcher allowed the six phases of thematic analysis (Braun et al., 2019; Braun & Clarke, 2006) to guide theming and anchoring data to themes. First, the researcher immersed himself in the selected articles by re-reading them to familiarise himself with the data. During this phase, by being curious, the researcher made casual notes of interesting statements, such as "tasks robots will dominate" (Wirtz et al., 2018), "robot-related up-skilling" (Lu et al., 2020), "robots often make mistakes" (Yam et al., 2020), etc. In the second phase, the researcher started anchoring statements from the selected articles to interesting codes such as "robot mistake", "replacement fear", etc. In the third phase, constructing themes, themes were "built, molded, and given meaning" (Braun & Clarke, 2019, p. 854), and they were the analytic output of an immersion process and deep engagement (Braun & Clarke, 2022). The researcher explored latent meanings, connections, and possible interpretations such as "tasks robots will dominate" (Wirtz et al., 2018) and the uncertainties around robot-human tasks distribution, or "robot-related up-skilling" (Lu et al., 2020) and the perpetual race of upskilling and reskilling, or "robots often make mistakes" (Yam et al., 2020) and the idea of worker's finding workarounds, etc. The researcher reviewed the candidate themes in the fourth and fifth phases and revised and defined them. Themes that were substantiated using the reviewed articles and were related to one another and the research question were kept (Braun & Clarke, 2022). The researcher also shared the themes in research circles to enhance reflexivity and interpretative depth (Braun & Clarke, 2022; Dwivedi et al., 2019). After that, in the sixth phase, the researcher used an iterative approach

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to report the themes with supporting references from the list of selected articles and relate the analysis to the research question (Braun & Clarke, 2022). The researcher also presented the themes at the 37th EGOS Colloquium 2021. The researcher benefited from the participants' feedback to further enhance reflexivity and interpretative depth (Braun & Clarke, 2022; Dwivedi et al., 2019).

The development of a coding book, intercoder reliability, and reproducibility are inconsistent with reflexive thematic analysis (Braun & Clarke, 2022). Furthermore, multiple analyses are possible; however, the researcher selected and developed the themes most pertinent to the research question (Terry & Hayfield, 2020).

Therefore, the process of thematic analysis was interpretive, intending to identify themes and highlight links (Tranfield et al., 2003). The analysis began with a manual text study. Themes were developed inductively (Braun & Clarke, 2006). They were linked iteratively, meaning that the analysis process entailed continual forward and backward movement in terms of constructing and refining themes (Braun & Clarke, 2006).

4. Analysis and interpretation

The analysis suggested several themes in terms of how AI might drive IWB. A tabular presentation of the themes and supporting references is shown in Table 2.

Table 2

These themes are discussed in this section. Propositions are also included after each theme to encourage future research into the role of AI in driving IWB.

4.1 Robots make mistakes, and such mistakes stimulate workers' IWB

In this context, 'robots' refers to any intelligent systems in a workplace that emulate workers' intelligence and abilities (Yam et al., 2020). To increase efficiency, organisations rely on robots (Yam et al., 2020). For instance, robots generated non-structured agreements in greater numbers than humans (Druckman et al., 2021). Negotiators working with a robotic platform were more pleased with the results and had more favourable views of the mediation experience (Druckman et al., 2021). These algorithmic approaches reduce human knowledge and meaning in the workplace (Holford, 2019). However, different cultures can have different perspectives on robots. Americans, for example, were more critical of AI-generated content than the Chinese (Wu et al., 2020).

One might argue that robots in a workplace interact with workers who may not be adequately trained to interact with them. Therefore robots need to relate to inexperienced instructions and feel normal to workers even in unstructured interactions (Scheutz & Malle, 2018). However, autonomy and flexibility expose robots to a plethora of ways in which they can make mistakes, disregard a worker's expectations and the ethical code of a workplace, or create physical or psychological harm to a worker (Scheutz & Malle, 2018).

A robot in an Amazon warehouse mistakenly ripped a can of bear repellent spray, resulting in the hospitalisation of 24 workers (Parker, 2018). Microsoft's robot editor used a photo of the wrong mixed-race member of a band to illustrate a news article about racism (Waterson, 2020b). An AI robot camera, which was meant to monitor the football during a game, instead tracked the assistant referee's head, resulting in sudden camera movements towards the referee and repeated switching

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between the referee's head and the actual football (HT Tech, 2020). Although organisations increasingly depend on robots to improve efficiency, they frequently make mistakes, adversely affecting workers and their organisations (Yam et al., 2020). Also, algorithmic approaches fail to understand the distinct characteristics of human creativity and the tacit knowledge that goes with it (Chatterjee et al., 2021; Holford, 2019).

Therefore, an observation in the literature (Li et al., 2019; Wilson & Daugherty, 2019) is evident in favour of workers shaping an organisation's service innovation performance more than robots. Although this can come as a surprise, since robots are supposed to make fewer errors, workers' IWB may benefit from robots' mistakes (Choi et al., 2019; Yam et al., 2020). Delivery drivers, for example, can drive in real traffic while predicting events for a robotic autopilot (Grahn et al., 2020). Although robotic autopilot can manage predicted events in this scenario, workers can deal with uncertainty and related adaptive and social behaviours in specific, highly congested traffic conditions and environments (Grahn et al., 2020).

If robots frequently fail to provide the expected service, workers would be pushed to think outside the box to eliminate robot mistakes. In this case, the role of robots in the workplace stimulates workers' ability to think and innovate to overcome robot limitations (Klotz, 2018; Wilson & Daugherty, 2019). Manual assembly, for example, would place high demands on workers' cognitive processing in a robotic-enabled workplace (Van Acker et al., 2021).

If robots make mistakes (or due to the diverse nature of services), they will likely continue to stimulate workers' IWB. Therefore, robots in the workplace (particularly in knowledge work) must prioritise collaborative approaches in which workers and robots collaborate closely (Fügener et al., 2022; Sowa et al., 2021).

The interpretation of this theme is summed up in Proposition 1. Table 3 proposes relevant questions to investigate this proposition further.

Proposition 1: Robots make mistakes, and such mistakes stimulate workers' IWB**.**

4.2 AI triggers 'fear' in workers, and this 'fear' stimulates workers' IWB

AI technologies in the workplace can reshape tasks and the definition of work across businesses (Braganza et al., 2020). This reshaping eliminates certain jobs or parts of an automated job (Braganza et al., 2020). As a result, algorithmic approaches aim to reduce various forms of human involvement and interpretation in the workplace (Holford, 2019). Self-service technology (SST) and the Wizard-of-Oz (WOZ) experiment, for example, can demonstrate that the contribution of workers to services that incorporate these technologies has been reduced (Costello & Donnellan, 2007).

Moreover, rather than directly influencing worker productivity, AI technologies indirectly influence the development of new, modified, or unmodified worker routines (Giudice et al., 2021). Therefore, it is generally accepted that workplace AI threatens the continuity and security of workers' jobs (Rampersad, 2020). It is also projected that AI applications will take over full-time and permanent jobs while workers will be hired for short-term assignments (Braganza et al., 2020). Therefore, considering the adoption of technological transformation, uncertainty about the employment of workers appears to be an integrated feature of AI systems (Costello & Donnellan, 2007). This threat is genuine for jobs requiring repetitive motion, data management and analysis, repeated physical equipment control, and individual evaluative interaction (Chuang, 2020; Lloyd & Payne, 2022).

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This argument, however, does have limitations. Although there is a persistent fear of job loss (Sousa & Wilks, 2018), the academic literature (e.g., Jaiswal et al., 2021; Wilson & Daugherty, 2019) suggests a drive toward a more symbiotic synthesis of human-machine competencies. This drive takes a more proactive approach to AI adoption in the workplace, encouraging businesses to be cautious in treating their workers (Li et al., 2019). This body of literature also argues that businesses should actively protect workers' interests and cautiously implement technology that supports rather than replaces them (Li et al., 2019).

What can be suggested is that this line of thinking implies uncertainty about future employment for workers (Li et al., 2019). This uncertainty, however, may encourage workers to actively engage in service innovation (Li et al., 2019). And if an organisation can afford AI solutions, it is suggested that their workers' IWB be enhanced by training (Klotz, 2018; Wilson & Daugherty, 2019). While AI systems help workers in innovation (Candi & Beltagui, 2019; Verganti et al., 2020), the 'fear' factor may trigger IWB in workers. This factor theoretically benefits workers in their quest for a long-term career and assists organisations in surviving through the transition time by safeguarding the interests of their workers (Haefner et al., 2021; Li et al., 2019).

To stay relevant in a workplace where AI is reshaping human employment, workers must enhance their IWB (Klotz, 2018; Rampersad, 2020; Sousa & Wilks, 2018). To coexist with intelligence systems, workers can capitalise on critical thinking, problem-solving, communication and teamwork (Rampersad, 2020; Sousa & Wilks, 2018). Therefore, workplace AI can stimulate IWB in workers because of improved workplace technology and the uncertainty and insecurity of jobs it brings to workers (L. Jiang et al., 2020; Nam, 2019). 'Fear' of being replaced by robots or

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artificial intelligence, or 'aliennational psychological contacts' may trigger IWB in workers rather than the actual technology (Braganza et al., 2020; Kim et al., 2017). This discussion may also suggest that developments in AI systems, regardless of industry or context, stimulate IWB in workers if workers perceive a threat from these systems.

However, when discussing the 'fear' of being replaced, the human culture's underlying position on workplace technology should be considered (Shujahat et al., 2019). How workers perceive AI in the workplace through a cultural lens could indicate how much the 'fear' factor is perceived (Wu et al., 2020). For example, perceived wider family support might help alleviate the 'fear' factor (Tu et al., 2021).

Though tailored approaches to mitigate the 'fear' factor of AI technologies and to put workers at the centre of workplace technologies are advised (Kim et al., 2017; Palumbo, 2021), artificial intelligence is increasingly being adopted by organisations without careful consideration of the workers who will be working alongside it. Uncertainty regarding the employment of workers continues to be an inherent feature of AI systems being adopted (Costello & Donnellan, 2007). Proposition 2 summarises this understanding. Table 3 proposes relevant research questions to investigate this proposition further.

Proposition 2: Workplace AI triggers 'fear' in workers, and this 'fear' stimulates IWB in workers as a means of staying relevant in the workplace.

4.3 Workers are reskilled and upskilled to compensate for AI shortcomings

By rendering processes more scalable, broadening the scope of operations across boundaries, and enhancing workers' learning abilities and flexibility, AI technologies

enable organisations to transcend the limitations of human-intensive processes (Verganti et al., 2020). As per this interpretation, AI technologies encourage a people-centred and iterative approach (Henkel et al., 2020; Verganti et al., 2020). However, one might argue that AI supports human-based approaches to user-centred solutions by requiring workers to reskill and upskill (Verganti et al., 2020; Wilson & Daugherty, 2019). Therefore, while AI technologies can potentially reshape working arrangements, they can also facilitate workers' reskilling and upskilling (Kim et al., 2017; Palumbo, 2021).

Further, human oversight of AI applications can encourage reskilling and upskilling of workers (Brunetti et al., 2020; Xu & Wang, 2019). Human supervision is often needed with AI applications to ensure that biases are not propagated (Sowa et al., 2021). For instance, although AI robot lawyers can perform certain tasks, such as answering legal questions, it has been argued that working with human lawyers ensures nuanced issues are adequately handled (Xu & Wang, 2019). As a result, the human-AI collaboration focuses on situations in which humans and AI collaborate closely (Sowa et al., 2021; Wilson & Daugherty, 2019). This interpretation explains that "algorithmic approaches," which aim to reduce human intervention in processes, could mean that while mundane and manual skills are delegated to robots, workers hone skills through reskilling and upskilling that robots still lack (Holford, 2019; Kim et al., 2017).

Workers, therefore, can reskill and upskill themselves because of the introduction of AI in the workplace (Jaiswal et al., 2021). When upskilling and reskilling combine data with human intuition to make the most of AI technological advances, algorithms can positively impact workers' work and discretionary power (Criadoa et al., 2020; Jaiswal et al., 2021). However, not only practical and technical

knowledge and skills are necessary for that purpose, but also creativity-focused skills such as managing uncertainty, critical thinking, problem-solving, exploring possibilities, tolerating ambiguity, exhibiting self-efficacy, teamwork, and effective communication (Cropley, 2020; Rampersad, 2020). Recent literature (Jaiswal et al., 2021) also includes data analysis, digital, complex cognitive, decision-making, continuous learning skills, and creativity-focused skills.

The necessary skill set for upskilling and reskilling can fall into three categories: technical, human, and conceptual skills (Northouse, 2018). Also, one might argue that upskilling and reskilling might mean workers are given AI-related short-term assignments when full-time and permanent assignments transfer to AI applications (Braganza et al., 2020). This discussion may also mean that to stay relevant, workers would go through a cycle of upskilling and reskilling, with the required skills evolving (Gratton, 2020; Ransbotham, 2020).

Workers must also be challenged and empowered to generate and implement new ideas (Auernhammer & Hall, 2014). Therefore, though workplace AI requires upskilling and reskilling (Braganza et al., 2020), workplace AI places high demands on workers' cognitive processing (Van Acker et al., 2021). Gamification and simulations help workers understand the feasibility of ideas by collaborating in cross-functional teams and being involved in the active development and auditing processes of AI applications (Anjali & Priyanka, 2020; Criadoa et al., 2020). Consequently, human-AI collaboration is needed to overcome AI limitations in the workplace. For human workers to stay relevant in such human-AI collaboration, they need to upskill and reskill. Proposition 3 summarises this understanding. Table 3 proposes relevant research questions to investigate this proposition further.

Proposition 3: Workers can be reskilled and upskilled because of human-AI shortcomings in the workplace.

4.4 AI interface stimulates worker engagement

When AI technologies take a people-centred approach, there are indications in the literature (e.g., Wilson & Daugherty, 2019) that the interface of AI systems can stimulate IWB in workers rather than the frequent errors of service robots (Yam et al., 2020). Earlier scholars (e.g., Davis, 1998) agree that the interface design of technologies provides users with a means to interact with such technologies. For instance, Wilson & Daugherty (2019) report that medical professionals became medical coders in training workplace AI when the interface was user-friendly. The software interface, in this example, allowed medical coders to work with workplace AI and be involved in the AI solution's much-needed training (Wilson & Daugherty, 2019).

However, it is essential to mention that usability and interface design requirements may change from one worker to another (Massey et al., 2007). It is also possible to infer that high-skilled workers are better at interacting with AI systems (Shute & Rahimi, 2021). Therefore, a high-skilled worker may have different expectations from an AI system's interface design regarding usability and responsiveness than a low-skilled worker (Garnett, 2018; Krzywdzinski, 2017). While a 'responsive' and 'usable' interface is proposed to stimulate IWB in workers, the judgement of a 'responsive' and 'usable' interface is impacted by complex interactions (Garnett, 2018; Massey et al., 2007).

The current research (Massey et al., 2007; Wilson & Daugherty, 2019) suggests that a 'responsive' and 'usable' interface, for example, to enter data into AI-

systems, requires workers' perspective on interface design. In the workplace, recent research (Beane & Brynjolfsson, 2020; Yam et al., 2020) also suggests that when robots are human-like—capable of thinking and feeling—workers evaluate them more favourably. This favourable perception can be explained by the fact that workers like assisting others and sharing their knowledge (Lo & Tian, 2020; Yam et al., 2020). Human-like robots may offer humans such feelings (Giudice et al., 2021; Lo & Tian, 2020).

However, the interface must meet workers' sensory and functional needs (Massey et al., 2007). Therefore, designing such interfaces for workplace AI requires workers' perspectives and understanding (Massey et al., 2007). While this extends beyond the interface design of an AI system (Massey et al., 2007), it suggests that intelligent systems can only encourage innovative behaviour if workers feel linked to them (Wilson & Daugherty, 2019; Yam et al., 2020). This line of argument is extended further by proposing that a 'responsive' and 'usable' interface allows workers to conveniently enter data into an AI system and make sense of the systems' outputs through such interface design (Verganti et al., 2020).

The interface should clarify which issues need to be addressed and how the outputs should be used (Verganti et al., 2020). If workers can make informed decisions using such an interface, the interface may encourage IWB (Verganti et al., 2020). If AI systems have 'friendly' interface designs, responsive and usable, one may conclude that workplace AI stimulates IWB in workers. This understanding is summed up in Proposition 4. Table 3 proposes relevant research questions to investigate this proposition further.

Proposition 4: When workplace AI has a user-friendly interface design, it encourages workers to generate and implement ideas.

4.5 Algorithmic bias requires innovative behaviour

Algorithmic bias may come from institutionalising existing human biases or introducing new ones (Albrecht et al., 2021). Implementing a machine learning model, for example, might be pitched to improve the satisfaction of employees and consumers. However, how do you define 'satisfaction' specifies the algorithm's inner workings and the desired output (Akter et al., 2021; Stahl et al., 2020). And when AI technologies inform (or make) a decision that affects a human being (i.e. a worker), such bias has a detrimental effect, resulting in discrimination and unfairness (Akter et al., 2021).

For instance, based on data obtained from male CVs, Amazon's AI recruitment system did not rate candidates gender-neutrally (BBC, 2018). Facebook's Ad algorithm allowed advertisers to target users based on gender, race, and religion, all of which are protected classes (Hern, 2018). An algorithm the UK's Home Office used in visa decisions was dubbed "racist"; the algorithm focused on an applicant's nationality (BBC, 2020).

Hence, although organisations are increasingly using AI systems and algorithms, the accessibility and interpretability of algorithms (algorithmic transparency) have drawn attention to the organisation's algorithmic footprint (Criadoa et al., 2020). As a result, innovative behaviour in the workplace entails addressing the ethical, social, economic, and legal aspects of AI applications (Di Vaio et al., 2020).

While workers may still use discretion to override AI systems, biases in datasets and ambiguous algorithms force workers to rely on IWB to help AI systems make choices (Criadoa et al., 2020). Therefore, targeted human interventions are required to resolve the limitations of biases in a dataset and ambiguous algorithms (Palumbo, 2021). Proposition 5 summarises this theme. Table 3 proposes relevant research questions to investigate this proposition further.

Proposition 5: Algorithmic bias necessitates innovative behaviour to overcome the limitations of biases in a dataset and ambiguous algorithms.

4.6 AI as a general-purpose tool for innovative behaviour

AI-assisted technologies can encourage curiosity-questioning, systematic thinking, trial and error, reasoning, and elaboration (Güss et al., 2021). A recently published preprint (T. T. Wang et al., 2022) shares how curiosity might encourage humans to use AI's 'blind spots.' The underlying argument is that AI-enabled systems encourage workers to reach wide and deep into their knowledge bases, resulting in novel ideas (Althuizen & Reichel, 2016). Therefore, AI acts as a tool to transcend the limitations of human-intensive processes by allowing workers to generate ideas and assess their feasibility, thereby entering a cycle of learning iterations that is constantly updated (Verganti et al., 2020).

Even if AI-enabled solutions act as a general tool for innovation, workers still need to share expertise (Chatterjee et al., 2021). However, knowledge sharing appears to be challenging in this context as digital technologies reshape working arrangements and the organisational social climate (Palumbo, 2021). Inadvertently, these technologies may create high-skilled vs low-skilled groupings of workplace

workers (Garnett, 2018; Krzywdzinski, 2017). Workplace design, training, and organisational culture, on the other hand, may also impact knowledge sharing in this context and, as a result, help AI-assisted technologies enable innovative behaviour (Aureli et al., 2019).

Further, rather than serving as a general-purpose tool for innovation, AI-enabled solutions may create time and space for innovative behaviour (Beltagui et al., 2021; Candi & Beltagui, 2019). Intelligent systems perform routine tasks, relieving workers to be more innovative (Jaiswal et al., 2021). Instead of 3D printing being a tool for innovation (Beltagui et al., 2021; Candi & Beltagui, 2019), it will relieve workers from work they have traditionally done (Greenhalgh, 2016). Workers will have more opportunities to plan on innovative aspects of their jobs.

While AI technologies can create time and space for idea generation, workers react to these opportunities differently (Kronblad, 2020). It is also interesting that workers' perceptions differ across cultures regarding AI-generated content (Wu et al., 2020). Besides, procedural and distributive justice and the manager-employee relationship may impact how innovative work behaviour can be improved in a workplace (Perry-Smith & Mannucci, 2017; Potter, 2021).

Furthermore, intuition commonly guides innovative behaviour and relies on workers' perception, knowledge, and value judgment (Stierand et al., 2014). Even so, AI technologies can create additional time and space for workers to engage in idea generation and deliberation (Nevo et al., 2020), 'willingness to innovate,' as exhibited by experimenting with ideas, plays a critical role in innovative behaviour (Auernhammer & Hall, 2014).

AI technologies can overcome design process limitations and improve the ability of workers to learn and adapt (Verganti et al., 2020). These technologies

provide patterns and products to workers critical for innovative behaviour: idea conception through completion (Nevo et al., 2020; Perry-Smith & Mannucci, 2017). AI systems open new avenues for innovative thinking (Townsend & Hunt, 2019). Proposition 6 summarises this theme, and table 3 proposes relevant research questions to investigate this proposition further.

Proposition 6: AI facilitates innovative behaviour by serving as a general-purpose tool for innovation, providing space and time for innovation, and providing patterns and products that workers can engage with.

5. Concluding remarks

This section discusses the themes, concludes the review, and highlights the study's contributions and limitations.

5.1 Discussion and conclusion

The relationship between artificial intelligence and innovative work behaviour is explored in this review, and several themes are developed. Per the analysis, artificial intelligence's flaws in the workplace can stimulate innovative work behaviour. However, this review does not dispute the advancement of artificial intelligence and how it helps workers, workplaces, and organisations (Shrestha et al., 2021; Sowa et al., 2021). It does, however, attempt to draw attention to artificial intelligence's limits and how these limitations may drive innovative behaviour (Braganza et al., 2020; Stahl et al., 2020).

The first theme suggested that intelligent robots in the workplace make mistakes (Yam et al., 2020). While developers attempt to consider multiple scenarios,

they cannot anticipate all scenarios when an intelligent robot interacts with an untrained human (Scheutz & Malle, 2018). Intelligent robots may make mistakes even when not interacting with untrained humans since they cannot make sense of specific information or situations (Yam et al., 2020). Humans in the workplace should be innovative to compensate for such flaws in intelligent robots. However, rather than the technology's ability to drive innovative behaviour, it appears that the technology's shortcomings are doing so.

A worker may feel at ease delegating simple tasks to robots while keeping social and creative tasks (Van Looy, 2022). The nature of the social and creative tasks that human workers reserve for themselves, as opposed to the mistakes made by robots, might drive innovative work behaviour. Although this is reasonable, it does not explain why workers are sceptical about robots performing social and creative tasks (Van Looy, 2022). Therefore, the idea that robots make mistakes may explain why human workers delegate simple tasks to robots (Van Looy, 2022). In this process, human workers do social and creative tasks which require innovative work behaviour.

The second theme focuses on the 'fear' factor associated with integrating intelligent systems in the workplace (Li et al., 2019; Rampersad, 2020). AI will take over routine and manual tasks from humans, allowing humans to focus on tasks, for instance, that involve critical thinking and creativity (Rampersad, 2020; Sousa & Wilks, 2018). While this insight appears to be positive, it also brings a fear factor into the workplace (Braganza et al., 2020). Workers will eventually worry if such intelligent systems will replace them. Therefore, while AI provides narrow intelligence that exceeds human abilities, one may argue that it does not create jobs for itself but instead takes human jobs (Chuang, 2020). The "fear" factor drives innovative

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behaviour as individuals attempt to remain relevant in a workplace where intelligent technologies are expected to take over existing tasks.

Recent studies (Chowdhury et al., 2022; Shin, 2021) suggest that there may be another explanation for what drives innovative work behaviour other than the fear of intelligent systems. According to this line of research, when humans and AI collaborate, they can outperform an AI system alone (Fügener et al., 2022). Therefore, rather than the "fear" factor, a worker's understanding of how an AI system decides, predicts, and performs tasks, as well as the limitations of an AI decision and its rationale, could drive innovative work behaviour (Chowdhury et al., 2022; Shin, 2021). This course of research is still evolving; therefore, it is unclear whether workers' understanding of how an AI system decides, predicts, and fulfils tasks reduces the likely fear that workers will be replaced by the system (Plumwongrot & Pholphirul, 2022).

The third theme suggests that workers would need to be reskilled and upskilled to compensate for AI's shortcomings (Cropley, 2020; Rampersad, 2020). Consequently, existing worker skills may become obsolete as these systems advance (Sousa & Wilks, 2018). Whether workers enter a loop of becoming low-skilled and needing reskilling and upskilling as the weaknesses of AI systems are addressed is an interesting issue to explore. However, it is essential to highlight that such reskilling and upskilling do not appear to be motivated by the need for workers to remain relevant - instead, they seem to be driven by the desire to improve workers' abilities to help AI systems in the workplace (Choi et al., 2019; Kim et al., 2017). It appears to be about exploiting humans to assist AI systems with existing flaws (Choi et al., 2019; Sousa & Wilks, 2018). It is, therefore, reasonable to imagine that once AI flaws in an area are addressed, reskilling and upskilling of required skills to address

flaws will cease. While AI systems would be predicted to replace human-only skills like creativity (Holford, 2019), such predictions have yet to be realised. Furthermore, this interpretation does not consider how different personality traits among workers may drive innovative work in different ways (X. Jiang et al., 2022), or how using AI would lower the quality of work even after workers have been retrained and upskilled (Charlwood & Guenole, 2021).

The fourth theme suggests that artificial intelligence interface is driving innovative behaviour. Workers will engage with AI systems in the workplace if the interface is designed human-friendly (Wilson & Daugherty, 2019). However, it is worth noting that AI's weakness needs such an interface to operate with humans (Sowa et al., 2021; Wilson & Daugherty, 2019). Also, this theme has yet to clarify whether worker personality traits would affect how innovative they are when interacting with a user-friendly AI interface or whether doing so requires technical expertise above and beyond basic digital skills (X. Jiang et al., 2022; Lloyd & Payne, 2022). Alternatively, if AI systems had progressed to general intelligence (human level), no such interface would have been required (Holford, 2019). While creating such an interface implies that humans can collaborate with AI systems (Fügener et al., 2022), this collaboration is primarily about providing AI systems with additional data to work with or reinforcing AI learnings (Sowa et al., 2021; Wilson & Daugherty, 2019). Therefore, AI's flaws need the development of a friendly interface that allows humans to improve such systems.

The fifth theme argues that AI bias necessitates innovative work behaviour (Criadoa et al., 2020). AI systems use the data that has been fed to them (Albrecht et al., 2021). While humans give data and models that aid AI systems in learning from the data, the data and models may contain algorithmic bias (Vereycken et al., 2021).

AI systems have yet to make sense of data beyond applying models. Human ingenuity is essential to assist AI systems in identifying and correcting bias in data or algorithms. Workers are, therefore, more likely to use their knowledge and training through innovative work behaviour to improve an AI system when moral violations are not involved (Wilson & Daugherty, 2019).

The sixth theme suggests that AI can be used as a general-purpose innovation tool (Chan et al., 2018). AI applications in the workplace encourage curiosity-questioning, thinking, trial and error, reasoning, and elaboration (Güss et al., 2021). Thus, AI in the workplace creates new tools, time and space for innovation and new patterns for workers to engage with (Cebollada et al., 2021). But this might be because workers are still hesitant about how well AI systems can perform creative and social tasks (Castañé et al., 2022; Van Looy, 2022). It can be argued that AI is a general-purpose tool for innovative behaviour because the technology has yet to innovate without humans' help (Wilson & Daugherty, 2019). While it is predicted that the technology will have this capability in the distant future (Holford, 2019), workers with innovative behaviour will be required to make sense of the AI systems' elements or use the system ingeniously.

5.2 Contributions

Recent reviews have delved into the use of AI in the workplace. These include AI to reshape innovation management (Haefner et al., 2021), artificial intelligence and business models (Di Vaio et al., 2020), electronic brainstorming for idea generation (Maaravi 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. On the other hand, these reviews focus

on the apparent transformational strengths of new technologies such as AI. It is, however, not always the case with AI, which has limitations and weaknesses. For example, skilled personnel must fix errors made by service robots so that customers are not dissatisfied and their organisation is not adversely affected (Yam et al., 2020).

In contrast to prior reviews, the present one identifies AI weaknesses before suggesting that these flaws, rather than AI's strengths, could also drive innovative work behaviour. This positioning suggests that AI flaws should be embraced in the workplace, enabling worker ingenuity. Innovative work behaviour, therefore, compensates for AI flaws. However, a further implication of this positioning is whether AI adoption in the workplace would reduce innovative behaviour when AI advances or worker ingenuity overcome existing AI limitations (Chuang, 2020; Rampersad, 2020). This further implication does not appear favourable to workers, let alone motivation to adopt AI in the workplace (Chuang, 2020; Rampersad, 2020). Is it not a reason to avoid adopting AI in the workplace? Or that AI may be programmed to stimulate innovative behaviour? Or should we appreciate AI's flaws since they allow workers to exhibit their ingenuity? Holford (2019, p. 143) argues that future AI advancement that minimises the human element will fail to recognise "the unique and inimitable characteristics of human creativity and its associated tacit knowledge." Accordingly, advances in AI and minimizing AI limitations are less likely to reduce the demand for innovative work behaviour. While intelligent robots may be less likely to make mistakes in the future, innovative behaviour will still be required, for example, to understand AI system outputs.

Further, although Rogers' innovation theory (2003) groups adopters into five groups based on their adoption rate, the theory does not explain how AI applications

in the workplace might help adopters realise their IWB. In conclusion, this review suggests several potential research lines regarding AI and workers' IWB, hoping to extend this theory.

There are also implications for practice. AI technologies stimulate innovative work behaviour (Liu et al., 2022; Odugbesan et al., 2022). Therefore, organisations should foster an environment where workers and AI technologies can coexist (Sowa et al., 2021; Wilson & Daugherty, 2019). However, how an organisation fosters such an environment is critical. While integrating intelligent robots and systems into a workplace helps workers to seek workarounds and enhance areas where such intelligence systems have limitations, such integration should not create an environment of fear (Chuang, 2020; Hasija & Esper, 2022).

The fear of losing one's job to intelligent systems may drive innovative work behaviour, but the existing intelligent systems cannot thrive without human involvement (Grimpe et al., 2022; Plumwongrot & Pholphirul, 2022). Therefore, the fear factor may drive workers to restrict such systems from reaching their full potential.

But how can an organisation minimise this fear factor? One way is by outlining the "real" reason for incorporating intelligent systems at work (Liu et al., 2022). Another way is carefully contemplating how humans and AI systems can coexist (Berkers et al., 2022; Plumwongrot & Pholphirul, 2022). While organisations' understanding of manual jobs and those that require human elements is evolving, it seems that even if AI technologies can perform certain tasks like providing warmth and empathy, consumers prefer to interact with real people for that purpose (Beeler et al., 2022; Modliński et al., 2022; Peng et al., 2022).

Organisations might look at training options that help workers get along with AI systems. By retraining and upskilling workers, such training programmes can enable workers to overcome the limitations of intelligent systems. Such retraining and upskilling can enable workers to lessen algorithmic bias in workplace intelligent systems (Tilmes, 2022). Additionally, such retraining and upskilling can allow employees to use intelligent systems to augment their innovative work behaviour (Odugbesan et al., 2022; Peng et al., 2022). Therefore, while AI's limitations may drive innovative work behaviour, a meaningful coexistence that involves retraining and upskilling workers allow AI and humans to augment one another's strengths.

This review has policy implications too. Suppose workers' interaction with AI is intended to compensate for AI flaws. 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 benefits primarily from interactions with workers rather than workers directly benefiting from such interactions. Therefore, policymakers should explore how AI may continue to be a human partner (Sowa et al., 2021; Wilson & Daugherty, 2019) rather than a rival (Chuang, 2020; Rampersad, 2020), as AI advancements may overcome the weaknesses highlighted in this review.

5.3 Limitations

The analysis is limited to ABS-ranked peer-reviewed journal articles, excluding non-peer-reviewed or non-ABS ranking papers, books and book chapters, and practitioner research.

Also, the search string may not have located relevant scholarly publications outside the Scopus database. The articles were retrieved from the Scopus database because of the breadth of publications it offers. The systematic search employed the ABS ranking to limit the returned articles to ABS-ranked journals. However, as one of the reviewers advised, the WoS database only indexes high-quality journals in each academic discipline. Future reviews on AI and innovative work behaviour can, therefore, source articles from the WoS database considering the quality aspect of the database.

Further, while the used keywords were derived from related papers, they may not have returned all relevant articles. When limiting the scope of the study, the researcher used the concept of 'artificial intelligence' as a keyword to mean "a collection of technologies" rather than referring to subset fields or other contributing concepts. Therefore, the search string did not include the search keywords such as "big data", "machine learning", "deep learning", "digital transformation", "recommender system", or "natural language processing". These keywords can be used in a future bibliometric analysis, along with the 'artificial intelligence' keyword, to explore further how AI limitations drive innovative work behaviour in the workplace.

Furthermore, later revisions excluded two themes from the manuscript: "AI accelerates knowledge creation and sharing" and "AI fosters open innovation, which involves workers' IWB in a supply chain." The researcher concluded that other themes had already covered these two themes. The researcher also recognised the need for additional research in the supply chain context about 'AI fosters open innovation, which involves workers' IWB in a supply chain'. This decision was taken following Braun & Clarke's guideline that "[...] the researcher needs to decide on and develop the particular themes that work best for their project—recognizing that the

aims and purpose of the analysis [...]" (2022, p. 10). Future studies utilising different analytical techniques can explore whether such themes can be developed independently.

In addition, while acknowledging the choices made in the study's research design to limit the scope, the researcher understands that documents outside the inclusion criteria and alternative analytical methods may have added additional themes about AI and innovative work behaviour. Perhaps "AI's explainability and causality to encourage innovative work behaviour" was one of these themes. Explainable AI describes how an AI system decides, predicts, and performs tasks (Rai, 2020), enabling a worker to understand the limitations of an AI decision, its rationale, and preferred patterns of action (Chowdhury et al., 2022; Shin, 2021). Therefore, it makes sense to infer that such themes might exist. According to recent research, explainable AI increases user trust and emotional confidence in the technology (Shin, 2021). When workers know how AI makes decisions, along with the AI system, they can surpass an AI system on its own (Fügener et al., 2022). Therefore, it is intriguing to explore explainable AI with innovative work behaviour in future studies, for instance, to determine whether user trust and emotional confidence in AI would lead to innovative work behaviour among workers.

Finally, the researcher's active role in theme generation is also acknowledged. The researcher adopted the reflexive thematic analysis method (Braun & Clarke, 2022). The analysis adhered to "Big Q qualitative paradigms" (Braun & Clarke, 2022; Kidder & Fine, 1987). Therefore, the analysis and the themes need to be viewed through the 10-point core assumptions of reflective thematic analysis (Braun & Clarke, 2022, pp. 8–9). With this approach, a researcher can generate intriguing and unique themes by blending the data, subjectivity, theoretical and conceptual

understanding, and training and experience (Braun & Clarke, 2022). The researcher chose this form of analysis to engage with compelling, insightful, thoughtful, complex, and deep meanings from the texts reviewed for this study (Braun & Clarke, 2022) and in line with the existing literature that suggests subjectivity is a resource for research than an issue to be managed (Gough & Madill, 2012, as cited in Braun & Clarke, 2022). However, this analysis method is inconsistent with the objectivity and reproducibility of themes (Braun & Clarke, 2022; Byrne, 2022; Terry & Hayfield, 2020). The researcher understands that the inherent subjectivity in reflexive thematic analysis and the researcher's active role did not adhere to what scholars refer to as "Small q qualitative paradigms" (Braun & Clarke, 2022; Kidder & Fine, 1987). Future studies can adopt analytic approaches of "Small q qualitative paradigms" to control for subjectivity and the researcher's active role. Future research can use other analytical methods like content analysis (Seuring, 2012) and bibliometric analysis (Ellegaard & Wallin, 2015). While generating reproducible research, such alternative analytical methods can also advance our understanding of other themes and the recurrent nature of the themes identified in this reflexive thematic analysis.

While acknowledging these limitations, the purpose of this work is to encourage further research into exploring and expanding our understanding of AI-driven innovative work behaviour.

Table 3

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