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The Human Factor in AI Integration: How Cultural Orientation and Mindfulness Influence Autonomy and Creative Self- Efficacy in AI-Assisted Decision-Making

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List of Publications

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Abstract

Amid accelerating adoption of workplace artificial intelligence (AI), this dissertation investigates how AI integration reshapes employees' perceptions of job autonomy and creative self-efficacy (CSE) and identifies the cultural and individual factors that govern receptivity to AI advice. Three complementary studies (N = 1,456) combine cross-cultural, longitudinal and trait-interaction designs. Study 1 compares professionals in the United Kingdom (individualistic) and Mexico (collectivistic) and shows that first-time AI support slightly elevates perceived autonomy but leaves CSE unchanged overall, masking a modest male-specific CSE decline and a culturally driven CSE gain among collectivists. Study 2 tracks repeated AI use over several sessions: autonomy dips initially, especially for men, but rebounds as users acclimate, while collectivistic participants exhibit progressive CSE growth. Study 3, a within-person decision-revision experiment, demonstrates that advice taking depends on the interaction of mindfulness, CSE and gender-role orientation: highly mindful, low-CSE, communal-oriented individuals are most likely to follow AI recommendations, whereas confident, agentic users resist them. Collectively, the findings reveal that AI's human impact is dynamic, culturally contingent and trait-specific. The dissertation advances theory by integrating cross-cultural psychology and individual-difference frameworks into models of human–AI collaboration, and it offers actionable guidance for culturally sensitive, autonomy-preserving and user-adaptive AI design.

Kurzfassung

Vor dem Hintergrund der zunehmenden Integration von künstlicher Intelligenz (KI) am Arbeitsplatz untersucht diese Dissertation, wie die Einführung von KI die Wahrnehmung der Mitarbeitenden bezüglich ihrer Arbeitsautonomie und kreativen Selbstwirksamkeit (Creative Self-Efficacy, CSE) verändert, und identifiziert kulturelle und individuelle Faktoren, welche die Offenheit für KI-Empfehlungen beeinflussen. Drei komplementäre Studien (N = 1.456) verbinden interkulturelle, längsschnittliche und interaktive Designs. Studie 1 vergleicht Berufstätige aus dem Vereinigten Königreich (individualistisch) und Mexiko (kollektivistisch) und zeigt, dass die erstmalige Nutzung von KI-Unterstützung die wahrgenommene Autonomie leicht erhöht, die CSE jedoch insgesamt unverändert lässt. Diese Gesamtwirkung verdeckt einen moderaten Rückgang der CSE bei männlichen Teilnehmern sowie einen kulturell bedingten Anstieg der CSE bei kollektivistisch orientierten Teilnehmenden. Studie 2 verfolgt die wiederholte Nutzung von KI über mehrere Sitzungen: Die Autonomie sinkt zunächst, insbesondere bei Männern, erholt sich jedoch mit zunehmender Gewöhnung der Nutzer, während kollektivistisch geprägte Teilnehmende ein stetiges Wachstum ihrer CSE zeigen. Studie 3, ein intraindividuelles Entscheidungsexperiment, zeigt, dass die Annahme von KI-Ratschlägen von der Interaktion aus Achtsamkeit, CSE und geschlechtsspezifischer Rollenausrichtung abhängt: Besonders achtsame, gemeinschaftlich orientierte Personen mit geringer CSE folgen KI-Empfehlungen am ehesten, während selbstbewusste, agentische Nutzer diesen Empfehlungen widerstehen. Zusammengenommen verdeutlichen die Ergebnisse, dass die Auswirkungen von KI auf Menschen dynamisch, kulturell bedingt und traitspezifisch sind. Die Dissertation erweitert die Theorie, indem sie interkulturelle Psychologie und individuelle Differenzen in Modelle der Mensch-KI-Kollaboration integriert, und bietet praxisnahe Empfehlungen für ein kultursensitives, autonomieerhaltendes und nutzeradaptives KI-Design.

Chapter 1: Introduction (Preamble)

An expanding body of research now positions artificial intelligence (AI) not as a secondary concern but as a core focus within work and organizational psychology. Where early debates often treated AI as a technical or engineering problem, recent research emphasizes its socio-psychological consequences and transformative potential within the workplace. Major reference works such as *The Cambridge Handbook of Technology and Employee Behavior* (Landers, 2019) and *The Oxford Handbook of Ethics of Artificial Intelligence* (Dubber et al., 2020) foreground questions that are psychological at their core: how does AI reshape human motivation, cognition, and collaboration at work? Institutional voices now echo this call. The Society for Industrial and Organizational Psychology (SIOP), in its 2022 position statement, identifies AI-based hiring tools as both a strategic opportunity and an ethical risk, underscoring the need for psychological insight in system design and policy guidance. Likewise, McKinsey's 2025 report on the future of the workplace (Mayer et al., 2025) highlights not only the economic implications of AI adoption but its impact on employee creativity, equity, and autonomy. These sources emphasize a common priority: understanding how AI can promote human autonomy, creativity, and equity, while minimizing risks of algorithmic control and systemic bias.

Recent critical reviews position AI as the "existential test" for industrial–organisational (I-O) psychology (Deranty & Corbin, 2022). Russell and Norvig (2021) likewise call for a *machine-psychology* paradigm that unites computational and motivational science, while SIOP (2022) demands algorithmic audits equivalent to classic validation studies. This imperative is becoming ever more pressing as AI systems rapidly permeate the modern workplace. Across industries and regions, organizations are integrating artificial intelligence (AI) technologies to enhance efficiency, automate routine tasks, and augment human decision-making (Dwivedi et al., 2021; Makridakis, 2017). For example, AI-driven systems now support customer service via chatbots, streamline supply chain logistics, assist in medical diagnostics, and perform data analytics in finance (Kaplan & Haenlein, 2019). This widespread adoption of AI is *redefining the future of work* on a global scale (Brynjolfsson & McAfee, 2014). Yet, alongside promises of productivity and growth, AI integration raises critical questions about its impact on the human dimensions of work. As workplaces embrace AI, employees around the world are asking: *How will AI change my job, my autonomy, and my ability to be creative?* This dissertation confronts these questions by examining how AI integration in the workplace affects employees' perceptions and experiences, specifically their sense of job autonomy and their creative self-efficacy, across different cultural contexts and individual characteristics. In doing so, it aims to contribute to understanding the interplay between advanced technology and fundamental human work perceptions which is an issue of increasing global relevance and scholarly interest (Deranty & Corbin, 2024; Glikson & Woolley, 2020).

The core problem driving this research is the need to understand whether AI's integration into workplace tasks empowers employees or diminishes their agency and creative confidence. On one hand, AI tools can take over mundane duties, allowing employees greater freedom to focus on complex, innovative tasks, which could enhance feelings of autonomy and efficacy (Wilson & Daugherty, 2018; Gong et al., 2009). On the other hand, AI systems often introduce increased monitoring and algorithmic decision-making that might *undermine* employees' control over their work, potentially leading to reduced job autonomy and a stifling of creative initiative (Vredenburgh, 2022; Brougham & Haar, 2018; Ayyagari et al., 2011). Early evidence in the literature reflects this duality: some studies report that AI integration *promotes* flexibility, confidence, and autonomy in the workplace (Xavier & Korunka, 2025; Yin et al., 2024), while others caution that heavy reliance on automated systems can erode autonomy and negatively impact employee well-being (Tarafdar et al., 2019; Hülsheger et al., 2013). Similarly, AI's role in employee creativity is under debate. There is optimism that AI can serve as a cognitive aid that *boosts* employees' confidence in generating ideas (McGuire et al., 2024). Yet, there are also concerns that over-reliance on AI could cause employees to lose confidence in their own creative judgment (Dietvorst et al., 2015; Dietvorst et al., 2018). These conflicting perspectives point to a significant gap in our understanding: under what conditions does AI integration enhance, rather than hinder, employees' perceived autonomy and creative self-efficacy?

Compounding this uncertainty is the realization that employees' reactions to AI are not uniform; they may vary widely across different cultures and individual dispositions. Cultural values fundamentally shape how people perceive technology (Hofstede, 1984; Markus & Kitayama, 1991; Triandis & Gelfand, 2012). For instance, employees from more collectivistic cultures tend to view technological advancements favorably when they see AI as a tool for *collaboration and group benefit*, whereas those from individualistic cultures are more receptive to technologies that *improve personal efficiency and autonomy* (Brewer & Venaik, 2011; Ji et al., 2010; Zhong et al., 2016). Furthermore, individual traits likely influence AI perceptions: Do people who are more mindful or more confident in their creative abilities respond differently to AI advice? Does one's gender or associated gender-role orientation (e.g. a tendency toward cooperative versus independent traits) influence openness to working with AI? Prior research on technology adoption hints at these possibilities. For example, men and women have been found to sometimes differ in their attitudes toward new technologies due to social roles and design biases (Eagly & Wood, 2012; Diekman et al., 2010; Leavy, 2018), but these factors have seldom been examined in the context of AI-assisted work. Recognizing these gaps, this dissertation adopts a multifaceted approach, investigating not only the overall effects of AI integration on employee perceptions but also *how those effects differ across cultural contexts, time, and individual characteristics*.

Leadership style, reward systems, technostress, personality traits and many other variables predict how employees respond to workplace technology (Ayyagari et al., 2011; Dwivedi et al., 2021; Judge et al., 2020). Studying all of them simultaneously would dilute explanatory power. Instead, this thesis concentrates on four constructs with the strongest empirical and theoretical leverage: **job autonomy, creative self-efficacy (CSE), cultural orientation and mindfulness**. Job autonomy is the most robust work-design predictor of motivation and well-being (Humphrey et al., 2007). Similarly, CSE precisely explains creative output beyond general self-efficacy (Tierney & Farmer, 2002). Cultural orientation (individualism–collectivism) moderates technology acceptance across nations (Brewer & Venaik, 2011) and mindfulness reduces cognitive bias in technology-supported decisions (Hafenbrack et al., 2014). Together they form an explanatory set linking task design (autonomy), personal capability (CSE), socio-cultural meaning (culture) and self-regulation (mindfulness). All four have clear theoretical anchors: self-determination theory, social-cognitive theory and cross-cultural value models and, crucially, each can be modified by organizational action through work redesign, skills training or intercultural programs (Hornung, Rousseau, & Glaser, 2008; Brown & Ryan, 2003). Focusing on them therefore provides a coherent, high-leverage framework for analysing how AI reshapes both the structure of work and the human resources that translate that structure into behaviour.

Chapter 2: Literature Review & Theoretical Framework

This chapter provides the conceptual foundation for this dissertation by reviewing relevant literature and establishing the theoretical framework that guides the empirical investigations. Each section (2.1 to 2.7) synthesizes prior research, introduces key constructs, and outlines theoretical expectations that inform the design and hypotheses of the three empirical studies presented in Chapter 3.

2.1 AI Integration in the Workplace

AI technologies have become increasingly embedded in modern workplaces, prompting extensive scholarly attention to their implications for employees and organizations (Dwivedi et al., 2021; Deranty & Corbin, 2024). **AI integration** in the workplace can be defined as the systematic incorporation of AI-based systems (such as machine learning algorithms, intelligent assistants, and robotics) into organizational processes to enhance efficiency, decision-making, and innovation (Kaplan & Haenlein, 2019; Makridakis, 2017). This section reviews the current understanding of how AI integration reshapes work and the dual-edged effects it can have on employee experiences.

On one hand, AI offers considerable opportunities for improving work processes and outcomes. By automating repetitive and labor-intensive tasks, AI allows human workers to concentrate on more complex, creative, and value-added activities (Wilson & Daugherty, 2018; Brynjolfsson & McAfee, 2014). For example, AI chatbots can handle routine customer inquiries, freeing customer service employees to tackle complex issues requiring human empathy and problem-solving (Huang & Rust, 2020; Salo et al., 2020). In knowledge-based roles, AI systems can sift through vast data sets to provide insights or predictions (such as in supply chain disruptions or financial fraud detection), thereby supporting employees in making more informed decisions (Kaplan & Haenlein, 2019; Yin et al., 2024). This augmentation of human work by AI, sometimes referred to as "augmented intelligence", has been shown to improve performance in areas like data analysis and interpretation (Jeong & Jeong, 2024; McGuire et al., 2024). In this optimistic view, AI becomes a collaborative partner that can increase productivity and even open avenues for employees to develop new skills and exercise higher-level judgment (Tiwari et al., 2024; Beninger, 2019). Furthermore, comprehensive reviews of AI and employee well-being have identified that AI adoption can promote workplace flexibility and confidence, contributing to positive outcomes such as improved mental health (Hülsheger et al., 2013; Marsh et al., 2024; Pflügner et al., 2020). These findings paint AI integration as a potentially empowering force in the workplace, with the capacity to enhance both performance and personal growth.

On the other hand, however, lie significant challenges and concerns associated with AI in the workplace. A critical concern is that AI systems, if not implemented thoughtfully, can encroach on employee autonomy and heighten feelings of surveillance and control (Ayyagari et al., 2011; Tarafdar et al., 2019). AI-enabled monitoring tools can track employees' activities and performance metrics in real time, raising fears of an "algorithmic boss" that might reduce workers' discretion and increase stress (Vredenburgh, 2022; Danaher & Nyholm, 2021). The introduction of AI decision-making systems also brings about transparency and trust issues. Many AI models, especially complex machine learning algorithms, operate as "black boxes" that are not easily interpretable. Employees may find it difficult to trust AI recommendations if they do not understand the basis for those recommendations (Miller, 2019; Afroogh et al., 2024; Glikson & Woolley, 2020). In some cases, this has led to documented phenomena like **algorithm aversion**, where individuals prefer to rely on human judgment (or their own) over algorithmic advice, even when the algorithm is objectively more accurate (Dietvorst et al., 2018). Furthermore, AI integration can create a sense of job insecurity or threat. Awareness of *STARA* (Smart Technology, Artificial Intelligence, Robotics, and Algorithms) and their potential to replace human labor has been found to negatively impact employees' affective well-being (Brougham & Haar, 2018; Hinks, 2024). Essentially, if workers perceive that AI might render their roles obsolete, it can induce anxiety and lower morale. For instance, if an AI tool evaluates performance or screens job applicants, employees may worry about fairness and their own lack of control in such processes (Semuels, 2020; Costa & Ribas, 2019).

In summary, AI integration in the workplace presents a complex picture. It holds the promise of augmenting human potential but it also poses risks of alienating employees by reducing their agency. This ambivalence in AI's impact sets the stage for the focused constructs of this dissertation. Two constructs in particular: **job autonomy** and **creative self-efficacy**, are central to understanding employees' experiences with AI, as they capture the essence of employees' control and creative capability at work. The next sections review these constructs and examine how AI might influence each, thereby establishing the theoretical basis for investigating the research questions at hand.

2.2 Job Autonomy

In modern workplaces, artificial intelligence (AI) systems are increasingly used to monitor tasks and manage work schedules. Experimental data show that such algorithmic control lowers perceived autonomy compared with human oversight (Schlund & Zitek, 2024). These findings underscore the importance of autonomy as a cornerstone of the employee experience, and they raise concerns that AI oversight might undermine that cornerstone if not implemented carefully. **Job autonomy** or employee autonomy refers to the degree of control and discretion that an individual has over how they carry out their work tasks. In the classic Job Characteristics Model, autonomy is identified as a core job characteristic that contributes to critical psychological states and leads to higher motivation and performance (Hackman & Oldham, 1976). Self-determination theory similarly highlights autonomy as a basic psychological need essential for intrinsic motivation and optimal functioning (Deci & Ryan, 2000). High autonomy is typically associated with positive outcomes: greater job satisfaction, creativity, and well-being, because employees feel a sense of ownership and empowerment in their roles (Bakker & Demerouti, 2007; Xanthopoulou et al., 2007).

The increase of AI use in the workplace has raised relevant questions about its impact on job autonomy. Will AI diminish workers' autonomy by imposing machine-driven decisions and constant oversight, or might it *increase* autonomy by taking over menial chores and granting employees more control over meaningful work? The literature to date suggests there is no simple answer; rather, AI can affect autonomy in varying ways depending on how it is implemented and perceived (Ayyagari et al., 2011; Brougham & Haar, 2018).

The importance of autonomy is further illustrated by the concept of idiosyncratic deals (i-deals). I-deals are personalized work arrangements that employees negotiate with their employer, such as flexible schedules, remote-work options, or tailor-made responsibilities, that depart from standard policies to better suit individual needs. Research indicates that i-deals are often used to increase job autonomy and create a more rewarding work experience (Hornung & Glaser, 2010). Studies show that when employees successfully negotiate i-deals, they gain greater autonomy and experience a heightened sense of distributive justice, which in turn leads to higher job satisfaction (Hornung et al., 2010). This evidence points to an idiosyncratic-deal principle: providing employees with individualized control over their work tends to boost satisfaction and performance. Consequently, when organizations allow flexible, autonomous arrangements, even if that means bending rules on a case-by-case basis, employees typically respond with improved attitudes and outcomes. Conversely, any technology or management practice that restricts discretion runs counter to this principle; rigid AI systems that enforce one-size-fits-all rules or remove employee input risk undermining the proven benefits of autonomy. Maintaining high autonomy is therefore key to sustaining employee satisfaction and performance; even as companies adopt AI tools, they should strive to preserve autonomy to keep their workforce motivated and engaged (Hornung & Glaser, 2010).

On one hand, AI has the potential to enhance job autonomy. By automating routine tasks, AI can reduce employees' workload and time pressure, potentially giving them more latitude to choose how to allocate their time to complex tasks (Wilson & Daugherty, 2018). AI decision-support tools can equip employees with data and recommendations, enabling them to make choices with greater confidence and independence, rather than deferring to a human superior for guidance (Kaplan & Haenlein, 2019). In some studies, employees report that AI tools make them feel **more in control** of their work because they have better information and can accomplish tasks that would otherwise require intervention from others (Yin et al., 2024; Xavier & Korunka, 2025).

On the other hand, numerous scholars have cautioned that AI can erode job autonomy if not carefully managed (Tarafdar et al., 2019; Schlund & Zitek, 2024; Vredenburgh, 2022; Tarafdar et al., 2019). One mechanism is through **automated decision-making**: when algorithms start making decisions that were formerly made by employees, the latitude of those employees can shrink (Vredenburgh, 2022; Miller, 2019). If an AI recommends a solution that the organization expects the employee to follow (because "the data shows it's best"), the employee's discretion to dissent or try a different approach might be implicitly diminished. Another mechanism is **increased monitoring**. Research by Kinowska and Sienkiewicz (2022) found that algorithmic management practices significantly reduced employees' sense of autonomy, which had downstream negative effects on well-being (Tarafdar et al., 2019). Essentially, when every action is guided or evaluated by an AI, employees can experience a sense of techno-control, where the locus of control shifts from the individual to the system.

Considering the above literature, two theoretical expectations emerge: (a) AI integration can have a direct negative effect on perceived job autonomy if it is associated with reduced control or increased surveillance; but (b) this effect may be mitigated by factors like time (adaptation) and context (e.g., cultural norms valuing autonomy) Hofstede, 1984; Triandis & Gelfand, 2012). These expectations inform our empirical approach. Study 1 and Study 2 will specifically measure changes in perceived autonomy when employees perform tasks with versus without AI support and examine differences by culture and gender. Additionally, by capturing data across multiple time points, Study 2 provides insight into whether any autonomy-reducing effects of AI are temporary. Anticipating our findings, it will be shown that initial reductions in autonomy can indeed diminish as familiarity grows, an indication that the threat AI poses to autonomy might be manageable with proper introduction and training. The next section turns to *creative self-efficacy*, the second major employee perception of interest, which relates to employees' confidence in their creative abilities and is another crucial factor in this investigation.

2.3 Creative Self-Efficacy

High job autonomy not only fuels motivation, but it also strengthens employees' confidence that they can generate novel and useful ideas, a link replicated in cross-sectional, diary, and longitudinal studies (Chiang et al., 2022; Xavier et al., 2025; Kivrak et al., 2025). When people decide how, when, and in what order to perform their work, they accumulate mastery experiences and intrinsic motivation which are two ingredients that social-cognitive theory identifies as the basis of creative self-efficacy (Bandura, 1997; Ryan & Deci, 2000). **Creative self-efficacy (CSE)** is defined as an individual's belief in their capacity to generate creative ideas and solutions. Rooted in Bandura's social cognitive theory of self-efficacy, CSE is a domain-specific self-belief focusing on one's ability to think "outside the box" and produce novel, useful outcomes (Bandura, 1997). It was introduced by Tierney and Farmer (2002) as a construct to explain why some employees are more inclined to engage in creative efforts at work than others. High creative self-efficacy has been linked to greater creative performance, innovation, and persistence in the face of challenges (Gong et al., 2009). For example, employees with strong CSE are more willing to take risks and explore unconventional approaches because they are confident in navigating uncertain, complex problems. In contrast, those with low CSE may doubt their ability to contribute original ideas, which can lead to reduced creative engagement or quick deferment to others' ideas.

Within the context of AI-integrated workplaces, creative self-efficacy is a particularly relevant construct. AI can supply information, suggestions, or patterns that an employee might not have considered, thereby expanding the employee's problem-solving ability (McGuire et al., 2024). Bandura's theory of self-efficacy emphasizes mastery experiences and social modeling as sources of efficacy beliefs. Therefore, if AI assistance leads to successful outcomes (mastery) or if the AI serves as a model of idea generation that the human can emulate, the person's CSE may be sustained or improved.

Conversely, there is a plausible argument that heavy reliance on AI might diminish an employee's creative self-efficacy. If AI systems are perceived as more capable in certain domains (especially with the rise of generative AI that can produce art, text, code, etc.), employees might start to question the value or uniqueness of their own contributions. Some initial evidence of this comes from our Study 1 (and related literature) where a subset of participants experienced a **decrease** in creative self-efficacy after using an AI tool. One interpretation is that the AI's involvement made them feel less confident in their own creative ability, perhaps because it introduced a comparison point or because it changed their role from creator to evaluator.

As with autonomy, *how* the AI is used is critical. An AI that is positioned as a supportive tool might enhance CSE, whereas an AI that is positioned as an expert or replacement might undermine CSE. An individual's initial level of CSE could also play a role in how they react to AI. This interaction between personal efficacy and AI input is a focus of Study 3, where we examine advice-taking behavior: initial theorizing suggested that individuals with higher CSE would be less likely to revise their creative decisions based on AI advice.

2.4 Cultural Orientation: Individualism–Collectivism

Differences in job autonomy and creative self-efficacy across national samples have led scholars to argue that culture may be the key to resolving these inconsistencies. Meta-analytic reviews and large-scale experiments reveal that the strength and even direction of job autonomy and creative self-efficacy could fluctuate across cultural settings, signaling that they are culturally embedded rather than universal (Jan et al., 2024; Triandis & Gelfand, 2012; Ji et al., 2020). Cultural orientation plays a profound role not only in shaping how interpret autonomy and self-expression at work but also in how they interact with and make sense of technology in the workplace. Among the various cultural dimensions identified by cross-cultural psychology, **individualism–collectivism** is one of the most extensively studied and is highly relevant to AI integration (Hofstede, 1984; Triandis & Gelfand, 2012). In **individualistic** cultures, such as the UK, USA, or Austria, people are socialized to value personal autonomy, independence, self-reliance, and individual achievement. In **collectivistic** cultures, common in many Asian, African, and Latin American societies (e.g., Mexico, as represented in our studies), individuals tend to value group harmony, family or team success, cooperation, and adherence to group norms.

It is important to examine how individualism–collectivism might moderate the effects of AI in the workplace for several reasons. For instance, an AI system that emphasizes collaborative features might be more readily embraced in collectivist settings, whereas one that offers personal customization and control might appeal more in individualist settings (Ji et al., 2010).

Empirical studies have started to illuminate these differences. Ji et al. (2020) conducted research across diverse cultural samples and found that collectivistic employees tended to view new workplace technologies more favorably when they believed those technologies enhanced group collaboration, whereas individualistic employees showed a preference for technologies that enhanced their personal efficiency and control. In Study 1 we formulated hypotheses expecting that cultural moderation would occur: for instance, that any positive effect of AI on creative self-efficacy might be stronger for collectivists, who could interpret AI support as a form of social support or team augmentation.

We also acknowledged that the individualism–collectivism dimension not only applies between countries but also varies within populations. In our studies we measured individuals' cultural orientation at a personal level using validated questionnaires, acknowledging that not every person from the UK is highly individualistic nor every person from Mexico strictly collectivistic. This approach aligns with Triandis's concept of idiocentrism vs. allocentrism (individual differences in individualism–collectivism values within a culture).

To synthesize the theoretical expectation: **cultural orientation is expected to moderate employees' responses to AI integration**, such that individualistic orientations amplify concerns for autonomy and personal efficacy, while collectivistic orientations amplify considerations of collective benefit and shared efficacy.

2.5 Mindfulness

The previous sections have shown that job autonomy describes how much latitude employees have, creative self-efficacy (CSE) captures how confident they feel about contributing original ideas, and cultural orientation shapes the social meaning they ascribe to technology. Together, these factors explain a great deal about whether people can and want to benefit from AI at work. What they do not yet explain is how employees engage with AI systems is their capacity for self-regulation, particularly, the ability to stay attentive and open in uncertain or evolving situations. Over the past two decades, mindfulness has been widely studied in workplace settings for its benefits on stress reduction, focus, and adaptability under changing demands (Hafenbrack et al., 2014; Yao et al., 2024). **Mindfulness** or trait mindfulness refers to the disposition to be attentive to and aware of what is happening in the here and now, with an attitude of openness and acceptance (Brown & Ryan, 2003). From a theoretical standpoint, mindfulness is associated with enhanced metacognitive awareness and a reduction in cognitive biases. For example, Hafenbrack et al. (2014) has shown that individuals high in mindfulness are less susceptible to the sunk cost fallacy, that is, they can let go of prior investments when making decisions because they are more present-focused and less judgmental about "wasting" what was invested. Applying this to an AI context: suppose an employee made an initial decision or prediction, and then the AI provides a different recommendation. A mindful person might be more willing to *revise* their initial judgment considering the new evidence. We hypothesized in Study 3 that individuals high in mindfulness would show greater openness to modifying their decisions after receiving AI-generated advice.

Mindfulness has also been positively linked to creativity and self-efficacy in research. Studies find that practicing mindfulness can improve cognitive flexibility and encourage a mindset conducive to creative thinking (Hülsheger et al., 2013). Yao et al. (2024) found a direct positive effect of mindfulness on research creativity among students, with creative self-efficacy playing a mediating role. The literature on advice-taking and decision-making also provides a theoretical background. A mindful approach to decision-making involves being aware of one's cognitive processes and biases (Evans et al., 2008). Mindfulness encourages a pause between stimulus and response, a crucial space in which one can weigh an AI's advice rather than reacting on autopilot (Brown & Ryan, 2003). With the rise of algorithmic recommendations (in hiring, medical diagnostics, financial forecasting, etc.), having decision-makers who are mindful could lead to more balanced outcomes: they can override the AI when necessary (e.g., if they notice contextual factors the AI missed).

Despite these theoretical linkages, mindfulness had not been studied in the context of human–AI collaboration and advice-taking prior to our Study 3. Our work addresses this by including trait mindfulness as a key variable and examining its interaction with other traits in predicting receptivity to AI advice.

2.6 Gender and Gender-Role Traits

Gender as a factor has long been studied in organizational and technology research. For instance, some studies have found that male and female employees might perceive new technologies differently due to varying socialization, expectations, or domain experience (Barrett & Davidson, 2006). Costa and Ribas (2019) discussed how gender may influence attitudes toward technology adoption, with societal narratives sometimes portraying technology fields as male-dominated. However, in analyzing the human factors of AI integration, focusing solely on binary gender can be limiting. It risks reinforcing stereotypes and overlooks the variation within gender groups. A more nuanced approach is examining gender-role traits or orientations, essentially personality characteristics traditionally associated with masculinity or femininity, which can be present in any individual to varying degrees regardless of their biological sex (Bem, 1974; Eagly & Wood, 2012; Spence et al., 1973). This approach stems from social role theory, which conceptualized masculinity and femininity as two independent dimensions (often termed *agency* and *communion*, or agentic vs. communal orientations) that individuals can embody to different extents.

- **Agentic (Masculine-typed) traits** include assertiveness, independence, competitiveness, dominance, and a focus on personal achievement (Helgeson, 19994; Diekman et al., 2010). These traits emphasize *agency*, i.e., the capacity to act independently and make one's own free choices. In the context of work and decision-making, an agentic orientation would manifest as valuing autonomy, control, and individual efficacy. People high on agency often prioritize their own judgment and are motivated by mastery and achievement.

- **Communal (Feminine-typed) traits** include cooperativeness, empathy, warmth, nurturance, and a focus on others and relationships (Eagly & Wood, 2012). These traits emphasize *communion*, i.e., connection with others, collaboration, and harmony. In work and decision contexts, a communal orientation would involve valuing input from others, being receptive to advice or consensus, and prioritizing group goals or relationships over individual prerogative.

Applying this framework to the scenario of AI-generated advice in the workplace provides a compelling hypothesis: Communal-oriented individuals will be more receptive to AI advice, whereas agentic-oriented individuals will be less so, preferring their own judgment. Our Study 3 examined this by measuring participants' communal vs. agentic trait levels (through a standardized inventory) and testing interactions with mindfulness and CSE.

2.7 Research Gaps

Bringing together Sections 2.1 through 2.6, we can now outline the conceptual gaps each of the three studies aims to answer. The key research gaps based on the literature review:

- *Lack of cross-cultural, mixed-method evidence on AI's impact on job autonomy and creative self-efficacy.* Prior to Study 1, it was unclear whether employees in different cultural settings experience AI integration differently in terms of feeling autonomous or creatively efficacious. Theory suggested differences, but no experimental study had tested AI introduction in parallel samples across cultures. **Study 1** (a mixed method experiment in the UK and Mexico) addresses this by quantitatively measuring changes in autonomy and CSE with AI vs. non-AI task conditions. The study's results allow us to confirm, for example, whether the hypothesized cultural pattern (e.g., collectivists more receptive to AI, individualists emphasizing autonomy loss) appears.
- *Scarcity of longitudinal research on adaptation to AI and the role of demographics (culture, gender).* Before Study 2, we did not know how quickly employees might adapt to the presence of AI in their workflow. The literature review pointed to possible adaptation but needed empirical verification. **Study 2** implements a longitudinal experimental design with measurements over multiple time points of AI usage. It fills the gap by demonstrating that an initial decrease in autonomy was not sustained as participants adjusted to AI over a few sessions.
- *Limited understanding of how personal traits (mindfulness, creative self-efficacy, gender-role orientation) interact to influence receptivity to AI-generated advice.* Prior research on algorithmic advice-taking identified phenomena like algorithm aversion/appreciation generally but had not delved into how specific individual differences drive these outcomes. **Study 3** (a within-subject experiment in which professionals made decisions with and without AI suggestions) fills this gap. By measuring trait mindfulness, CSE, and communal/agentic orientation for each participant and analyzing their decision revisions, the study identifies interaction effects that clarify how these traits jointly affect behavior.

2.8 Research Objectives

Considering the above, this dissertation focuses on several interrelated objectives through three empirical studies, each with a more focused aim, as follows:

1. **Cross-Cultural Impact on Autonomy and CSE:** *To examine how AI integration influences perceived job autonomy and creative self-efficacy in different cultural contexts.* This objective is pursued by comparing an individualistic culture (the UK) and a collectivistic culture (Mexico). The study seeks to determine whether the introduction of AI in work tasks has distinct effects on employees' sense of autonomy and creative confidence across these cultural orientations, and how factors like cultural values and gender might moderate these effects.

2. **Longitudinal Impact on Autonomy and CSE:** *To investigate the longitudinal effects of AI integration on employee autonomy and creative self-efficacy, and test for moderation by culture and gender.* This objective involves observing employees' perceptions not just at a single moment, but across repeated interactions with AI over a relatively short period. The study asks whether initial impacts (positive or negative) on autonomy and CSE are sustained or whether employees adapt over time. It also examines whether cultural background or gender influences the trajectory of this adaptation.

3. **Individual Differences in Receptivity to AI:** *To determine how individual traits: specifically, trait mindfulness, creative self-efficacy, and gender-role (communal vs. agentic) orientations, affect an employee's receptivity to AI-generated advice in decision-making tasks.* This objective involves examining whether people accept or resist suggestions from an AI assistant. Additionally, it investigates how these tendencies are moderated by communal or agentic traits associated with gender roles, to see if a more relational (communal) orientation amplifies openness to outside help (including AI) relative to a more independent (agentic) orientation.

2.9 Contributions and Significance

This cumulative PhD dissertation makes several contributions to knowledge and practice. **First**, it provides *cross-cultural empirical evidence* on AI integration in the workplace, an area where prior research has been limited. By directly comparing responses from an individualistic context and a collectivistic context, the research highlights how cultural values influence the reception of AI at work. This contribution is timely as organizations deploy AI in multicultural environments; the findings can inform culturally sensitive AI implementation strategies. **Second**, the dissertation contributes one of the first *longitudinal experimental studies* on employees' adaptation to AI. Rather than assuming a static effect, it tracks changes in autonomy and CSE perceptions over time, revealing dynamic patterns such as initial decreases in autonomy that may attenuate as familiarity grows. **Third**, this work *integrates individual-differences psychology with AI research* by examining mindfulness and gender-role traits in an AI-assisted decision-making scenario. It extends theoretical frameworks of human–AI collaboration by identifying how attentional focus and self-perceived creative confidence jointly influence one's likelihood of following algorithmic advice. The novel finding of a three-way interplay (mindfulness × creative self-efficacy × communal/agentic traits) in shaping AI receptivity (as revealed in Study 3) breaks new ground in understanding person–technology fit. This insight has practical significance for designing *adaptive AI systems* – for example, interfaces that gauge a user's confidence and tailor how advice is presented. **Fourth**, the dissertation's methodological approach is noteworthy. It employs a mixed-methods cross-cultural experiment in Study 1, a controlled longitudinal design in Study 2, and a large-sample within-subject decision experiment in Study 3. By triangulating evidence from these approaches, the research offers a comprehensive report of the phenomena. **Finally**, parts of this work have been peer-reviewed and published – with Study 1 appearing in *PLOS One (2025)* with its earlier conference version receiving the *AOM Best Paper with International Implications Award (2024);* Study 2 published in *Computers in Human Behavior Reports (2024)*; and Study 3 currently under review at *Nature Scientific Reports.* Collectively, these milestones attest to this dissertation's scholarly value and contribution to multiple academic communities (e.g., occupational psychology, human–computer interaction, and organizational behavior).

Chapter 3: Synopses of Publications Included in the Thesis

Building on the literature review and theoretical framework outlined in Chapter 2, this chapter presents synopses of the three empirical studies that comprise this cumulative dissertation. Each of the following sections (3.1 to 3.3) corresponds to a research article included as part of the thesis. For each study, a full reference is provided followed by a narrative summary of its objectives, methodology, key findings, and its contribution to the research questions of the dissertation. The chapter concludes with a comparative summary table (Table 3.1) that highlights the key attributes of all three studies and how each contributes to the dissertation's research objectives.

3.1 Study 1: AI Integration and Workforce Development: Exploring Job Autonomy and Creative Self-Efficacy in a Global Context

Francis Xavier, D., Korunka, C., & Reiter-Palmon, R. (2025). *AI integration and workforce development: Exploring job autonomy and creative self-efficacy in a global context.* PLOS ONE, 20(6), e0319556. [Published, Impact Factor 3.2]. https://doi.org/10.1371/journal.pone.0319556

Francis Xavier, D., Korunka, C., & Reiter-Palmon, R. (2024). *The Impact of AI Integration on Job Autonomy and Creative Self-Efficacy: A Cultural Perspective.* Academy of Management Proceedings, 2024(1). https://doi.org/10.5465/AMPROC.2024.14489abstract

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Objectives: The first study aimed to examine the immediate impact of AI integration in the workplace on employees perceived job autonomy and creative self-efficacy, and to determine whether these effects differ across cultural contexts. This cross-cultural experiment was motivated by the question of how workers from individualistic versus collectivistic cultures respond to AI-based tools in terms of their sense of control over work tasks and confidence in their creative abilities. The study specifically compared participants from the United Kingdom and Mexico as representatives of individualistic and collectivistic cultural orientations. By investigating culture as a moderating factor, the study sought to provide initial empirical evidence on whether AI implementations might yield different psychological outcomes for employees in different cultural settings. In line with the dissertation's research questions, Study 1 addressed how AI-assisted work influences key employee perceptions and whether cultural background has an influence on these perceptions.

Methodology: A mixed-method experimental design was employed with a total of 480 working professionals between the UK and Mexico. Participants were randomly assigned to experience decision-making tasks with vs. without AI integration. Specifically, participants completed a business decision task (allocating a budget to a product based on sales data) twice: once independently and once with AI decision support providing data-driven insights. The order of AI vs. no-AI conditions was randomized to mitigate order effects. Before and after each task, participants filled out brief surveys measuring job autonomy (i.e. perceived control and discretion in one's work) and creative self-efficacy (confidence in one's ability to generate creative ideas). Demographic information (including gender and age) and a cultural orientation measure were also collected to verify each participant's alignment with individualistic or collectivistic values beyond just nationality. The primary analyses involved comparing pre- vs. post-task changes in autonomy and creative self-efficacy, using paired statistical tests and mixed-model analyses. Interaction effects were tested to see if changes in these outcomes differed by culture and gender, while controlling for age and other covariates in an ANCOVA framework. This approach allowed the researchers to isolate the effect of experiencing AI assistance on the two outcome measures and to observe any moderation by cultural background.

Key Findings: Job autonomy showed an increase after participants engaged with AI, indicating that, on average, employees felt a greater sense of control over their tasks when aided by AI tools. This finding was somewhat counterintuitive, as one might expect automation to reduce autonomy, but participants reported feeling more empowered, potentially because the AI offloaded routine aspects of the task, allowing them to focus on higher-level decision making. Culturally, the increase in autonomy was observed in both UK and Mexican samples; however, U.K. participants (individualistic culture) experienced a slightly larger increase in perceived autonomy than Mexican participants (collectivistic culture). In contrast, creative self-efficacy (CSE) did not uniformly increase with AI integration. Overall, there was no significant change in CSE after using AI assistance for the whole sample. However, the study uncovered differential effects by gender: male participants experienced a decrease in creative self-efficacy following AI-supported tasks (i.e. they became less confident in their creative abilities), whereas female participants' creative self-efficacy remained stable with AI use. This gender-specific impact was contrary to the initial expectation that AI support might improve creative confidence. Cultural orientation was a significant factor for CSE. Participants from the collectivistic culture (Mexico) showed a greater improvement in creative self-efficacy scores post-AI, compared to those from the individualistic culture. In other words, Mexican participants tend to become more confident in their creative thinking after receiving AI assistance.

Contribution to Dissertation: Study 1 provided foundational evidence that introducing AI into work tasks can change employees' perceived job autonomy and creative self-efficacy, and that these effects are influenced by cultural and gender factors. Moreover, it highlighted cultural context as a moderator: the positive perceptions of AI's impact were more pronounced in a collectivistic setting. Furthermore, because Study 1 was cross-sectional and focused on immediate effects, it raised additional questions about how these perceptions might evolve with continued or repeated AI use over time. These questions set the stage for *Study 2*, which examines short-term adaptation to AI over time in a longitudinal framework.

Academy of Management (AOM) Award: Study 1 gained further credibility when an earlier conference paper drawn from the same 480-participant UK–Mexico dataset, *"The Impact of AI Integration on Job Autonomy and Creative Self-Efficacy: A Cultural Perspective,"* won the **Academy of Management (AOM) 2024 "Best Paper with International Implications" Award** in the Organizational Behavior (OB) division.

3.2 Study 2: Integrating Artificial Intelligence Across Cultural Orientations – A Longitudinal Examination of Creative Self-Efficacy and Employee Autonomy

Francis Xavier, D., & Korunka, C. (2025). *Integrating artificial intelligence across cultural orientations: A longitudinal examination of creative self-efficacy and employee autonomy.* Computers in Human Behavior Reports, 18, 100623. [Published, Impact Factor 5.8]. https://doi.org/10.1016/j.chbr.2025.100623

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Objectives: The second study extended the inquiry of Study 1 by investigating how the effects of AI integration on employee perceptions change over time with repeated exposure to AI. While Study 1 provided a snapshot of immediate reactions to working with AI, Study 2 adopted a short-term longitudinal (repeated measures) design to capture adaptation dynamics. The study also continued to explore cross-cultural differences (United Kingdom vs. Mexico) and gender differences in these dynamics. The core objective was to determine whether the patterns observed in Study 1 hold over multiple interactions with AI or whether new trends emerge as users acclimate to AI assistance.

Methodology: A longitudinal experimental design was implemented, involving 427 participants drawn from professional sectors in the UK and Mexico. The experiment unfolded over multiple sessions in a short-term period to simulate an initial adaptation phase to AI integration. Participants engaged in a series of decision-making tasks similar to those in Study 1 (e.g., analyzing data and making business decisions), but this time tasks were alternated with and without AI support in successive rounds. For example, a participant might first perform a task without AI, then a similar task with AI assistance, and so on, across several iterations. This within-subject alternating pattern allowed each participant's change in perceptions to be tracked as they repeatedly encountered AI recommendations. The study collected measures of employee autonomy and creative self-efficacy at multiple time points (before and after each task on Day 1 and Day 3) to observe trends. Cultural orientation (UK vs. Mexico) and gender were recorded as between-subject factors. The analysis primarily used repeated-measures ANOVAs and growth-curve modeling to test for interaction effects between time (task rounds) and AI integration, and whether these effects differed by cultural group or gender.

Key Findings: The longitudinal results revealed a more complex picture of AI's impact on employee perceptions. In terms of creative self-efficacy, there was a significant interaction effect between AI exposure and cultural orientation: across the repeated tasks, participants from the collectivistic culture (Mexico) showed a greater improvement in creative self-efficacy over time with AI compared to those from the individualistic culture (UK). For employee autonomy, however, the study found an unexpected negative trend. Contrary to the initial study's one-time increase in autonomy, repeated interactions with AI were associated with a significant decline in perceived autonomy on average, in the overall sample. That is, over the course of the experiment, participants increasingly felt less autonomous in their work as they continued using the AI. Furthermore, gender differences surfaced in the longitudinal context with respect to autonomy. An exploratory analysis indicated that male participants experienced a more pronounced decrease in autonomy over repeated AI use than female participants. This gender divergence confirms the gender effect on creative self-efficacy seen in Study 1, and it further implies that men might be more sensitive to potential autonomy losses from algorithmic assistance.

Contribution to Dissertation: Study 2 contributed to the dissertation by examining how employee experiences with AI change over time. It showed that the effects of AI are not fixed. For example, a tool that increases perceived autonomy at first may later reduce it with continued use. This helps answer not only whether AI affects employee outcomes, but also how long these effects last and in what pattern they appear. The study also confirmed cultural differences in creative self-efficacy and revealed gender differences in how employees adapt over time. Finally, by identifying variation across cultures and genders, this study set the stage for Study 3, which explores how individual traits like mindfulness and communal-agentic orientations influences decision-making in response to AI advice.

3.3 Study 3: Mindfulness and Creative Self-Efficacy in Human–AI Decision-Making: Implications for Adaptive AI Design

Francis Xavier, D., Hughes, Z. D., & Korunka, C. (2025). *Mindfulness and creative self-efficacy in human–AI decision-making: Implications for adaptive AI design.* Manuscript under review at *Nature Scientific Reports*. [Under Review, Impact Factor 5.8].

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Objectives: The third study focused on individual psychological traits and how they affect employee responses to AI-generated advice in decision-making. Building on Studies 1 and 2, which showed that culture and gender influence reactions to AI, Study 3 explored why these differences occur by examining deeper traits. Specifically, it investigated mindfulness (awareness of the present moment) and creative self-efficacy (confidence in one's creative ability), along with communal and agentic gender-role traits. These traits reflect a person's orientation toward qualities like empathy and cooperation (communal) or assertiveness and independence (agentic), moving beyond broader categories like male versus female or national culture. By addressing this, Study 3 supports the overall objective of the dissertation to identify human factors that influence collaboration with AI.

Methodology: This study employed a within-subject decision-revision experiment involving professional employees (N = 549) in the United Kingdom. Each participant was tasked with making a series of decisions (similar to Study 1 and 2, analyzing and interpreting data) without AI assistance initially, and then was presented with an AI-generated recommendation or advice for the same decision. Participants then had the opportunity to revise their initial decision after considering the AI's input. This design allowed the researchers to observe directly whether individuals change their decisions in the direction of the AI's suggestion, thereby operationalizing receptivity to AI advice. The AI advice was systematically generated to be of high quality (to simulate a competent decision aid) while not being "perfect", thus leaving room for participants to either agree or disagree with it. All participants completed standardized questionnaires assessing their trait mindfulness, creative self-efficacy, and communal/agentic orientation. The data were analyzed using multinomial logistic regression models to predict decision outcomes, categorizing each trial's outcome as either maintaining the original decision or revising the decision in line with the AI's suggestion. Interaction terms were included in the regression to test whether mindfulness and CSE jointly influence advice-taking, and whether this relationship is further moderated by communal vs. agentic orientation (a three-way interaction).

Key Findings: The results showed a clear interaction between mindfulness and creative self-efficacy in predicting whether participants revised their decisions after receiving AI advice. Among those with high mindfulness, individuals with low creative self-efficacy were the most likely to change their decisions to align with the AI's suggestion. This suggests that mindful individuals who lack confidence in their creative judgment are more open to external input and more willing to accept AI guidance. In contrast, those who were both highly mindful and highly confident in their creative ability tended to stick with their original decisions. A three-way interaction also emerged, involving communal traits. The pattern of high mindfulness and low self-efficacy leading to greater AI advice-taking was strongest among individuals with a communal orientation. By contrast, participants with strongly agentic traits were less likely to follow the AI's advice, particularly when they also had high creative self-efficacy. These findings align with social role theory, which suggests that people with communal traits are more receptive to help and collaboration, while those with agentic traits prefer to rely on their own judgment.

Table 3.1 below presents a comparative summary of key attributes of the three studies, including their design, samples, focal constructs, AI task context, analytical approaches, publication status, and how each study's findings contribute to the overall research questions of the dissertation.

Table 3.1. Comparative Summary of Studies 1–3

Attribute	Study 1 (PLOS ONE)	Study 2 (CHB Reports)	Study 3 (Nature)
Research Design	Cross-cultural experiment (mixed design: between-subjects culture (UK vs. Mexico); within-subjects AI vs. no-AI condition)	Longitudinal experiment (short-term repeated measures with alternating AI vs. no-AI tasks; cross-cultural comparison between UK and Mexico)	Within-subject decision revision experiment (each participant makes initial decisions and then can revise after AI advice)
Sample & Context	N = 480 working adults (professional sectors) in UK and Mexico	N = 427 working professionals in UK and Mexico	N = 549 professionals in the UK
Constructs Measured	Job autonomy; Creative self-efficacy (CSE); Culture; Gender	Employee autonomy; Creative self-efficacy; Time (adaptation); Culture; Gender	Trait mindfulness; Creative self-efficacy; Communal-agentic orientation; Decision revision outcome
Type of AI Task	Decision task with & without AI analytics support	Series of decision tasks alternating AI support to model short-term adaptation	Advisory decision-support scenario with opportunity to accept/reject AI recommendation
Analytical Approach	Mixed ANOVA/ANCOVA (AI × Culture; exploratory AI × Gender)	Repeated-measures ANOVA & growth-curve modelling (Time × AI; moderation by Culture & Gender)	Multinomial logistic regression with two- and three-way interactions (Mindfulness × CSE × Communal/Agentic)
Publication Status	Published (2025)	Published (2025)	Under review (submitted 2025)
Contribution to Research Questions	Shows AI alters autonomy & CSE; underscores cultural & gender effects	Reveals dynamic shifts over time; autonomy declines with repeated AI; culture & gender moderate impact	Identifies psychological profiles for AI advice receptivity; highlights mindfulness-CSE-gender-role interaction

Chapter 4: Discussion

This chapter synthesizes the findings from all three studies to address the dissertation's central research questions. It integrates cross-study insights to clarify how timing, identity, and context influence human–AI collaboration. Rather than reviewing each study in isolation, the discussion is structured thematically around the three research questions, drawing comparisons across studies to articulate coherent theoretical and practical implications. Through this integration, the chapter offers a grounded interpretation of how AI changes the psychological experience of work, and what conditions enable that change to be empowering rather than constraining.

Research Question 1: AI Integration and Perceived Job Autonomy

RQ1: How does the integration of AI into the workplace impact employees' perceived job autonomy, and do these effects differ across contexts (e.g., cultural orientations)?

This question was primarily addressed by Study 1 (a cross-cultural experiment) and Study 2 (a longitudinal study), which both examined job autonomy as a key outcome of AI integration. Here, we compare their findings drawing on the theoretical perspectives introduced earlier.

First, the effect of AI integration on perceived job autonomy was not consistently negative or stable across studies. Study 1 found a general increase in autonomy, particularly when AI was introduced after manual task completion, while Study 2 showed an initial autonomy decline that recovered over time. These contrasting patterns are partially explained by differences in task sequencing and repetition. Both studies used controlled task environments, but while Study 1 involved a single-session exposure to AI, Study 2 included repeated sessions, which likely made participants more aware of AI's persistent presence and influence. Initially, AI may have been perceived as intrusive or evaluative in Study 2, triggering concerns about control (Ayyagari et al., 2011). In contrast, Study 1's delayed AI introduction may have reinforced a sense of human primacy in the task, framing AI as an optional support. Over time, however, participants in Study 2 appeared to reframe the AI as a helpful, non-coercive assistant, which helped restore a sense of control. These results show that autonomy perceptions are time-sensitive and strongly influenced by the timing and framing of AI within task sequences (Wilson & Daugherty, 2018; Miller, 2019).

Second, gender differences were evident in early reactions to AI, with male participants reporting sharper declines in autonomy. This pattern may reflect a higher sensitivity to control and status threats among men, especially in task settings involving performance evaluation (Eagley & Wood, 2012). Social role theory and technology adoption research suggest that men may feel more ego-threatened by ceding control to AI, whereas women, possibly due to communal orientations or different expectations in tech contexts, maintained more stable autonomy perceptions (Barrett & Davidson, 2006). These differences converged over time as all participants adapted, pointing to the importance of initial psychological orientation and its influence on short-term responses.

Third, cultural orientation had a more pronounced effect on creative self-efficacy than on autonomy. While Study 1 hypothesized that individualistic cultures would show greater sensitivity to autonomy changes, only UK participants showed a marked autonomy increase. Mexican participants, by contrast, displayed smaller changes, possibly because collectivistic values involve greater acceptance of shared control (Triandis & Gelfand, 2012). Study 2 found no significant cultural difference in autonomy trends over time, suggesting that early cultural effects may level out as AI becomes part of the routine. This convergence supports the idea that cultural values influences initial expectations, but lived experience with the technology tends to override these predispositions. It also aligns with the finding that agentic orientations (linked to individualism and masculinity) are more reactive to autonomy shifts, while communal orientations (linked to collectivism and femininity) may buffer against perceived loss of control.

Research Question 2: AI Integration and Creative Self-Efficacy

RQ2: How does AI integration influence employees' creative self-efficacy (CSE) and how do these effects vary across time, cultural contexts, and gender?

This question is closely tied to RQ1 but focuses on **creative self-efficacy** as the outcome of interest. Studies 1 and 2 both measured CSE before and after AI exposure (with Study 2 adding a longitudinal perspective), while Study 3 considered CSE in a different way: as a stable trait influencing behavior. Studies 1 and 2 investigated CSE as a dynamic outcome affected by AI integration, while Study 3 treated it as a moderating trait that shapes how employees respond to AI-generated input. Together, these studies offer a layered understanding of how CSE is influenced by both the presence of AI and the user's context and characteristics.

Study 1, a cross-cultural experiment, found no overall change in CSE following a single instance of AI-supported decision-making. However, a closer look revealed two important interaction effects. First, there was a culturally contingent pattern: participants from the collectivistic culture (Mexico) experienced modest gains in CSE after using AI, while participants from the individualistic culture (UK) showed no improvement. This suggests that collectivistic norms, which emphasize shared success and interdependence, may predispose individuals to interpret AI assistance as a legitimate resource for improving performance thus reinforcing rather than threatening their self-belief. Second, gender differences emerged: male participants experienced a decline in CSE following AI use, whereas female participants maintained stable levels. This finding is noteworthy given the stereotype-consistent expectation that men tend to exhibit higher baseline technological self-confidence. It may be that the presence of an automated system encroached on men's self-concept as independent problem-solvers, thus leading to a subtle erosion in perceived creative ability. Conversely, women, perhaps more accustomed to collaborative or mediated input, were less threatened by the AI's suggestions.

Study 2 extended these findings by introducing a longitudinal component. It examined how CSE evolves over multiple exposures to AI in a short-term adaptation window. The study confirmed that collectivistic participants exhibited gradual gains in CSE across repeated AI-assisted tasks, suggesting a cumulative process of confidence-building facilitated by continued success and perceived support from the AI system. This pattern aligns with Bandura's theory of guided mastery: repeated positive outcomes in a challenging domain, especially when assisted by competent tools, can strengthen self-efficacy beliefs. Notably, the longitudinal design revealed that these gains were not evident immediately but emerged over time, reinforcing the idea that CSE is context-sensitive and develops through interaction. In contrast, participants from individualistic cultures did not exhibit the same upward trajectory in CSE. Their creative confidence remained largely unchanged, and in some cases, declined slightly across sessions. This may reflect a more evaluative or competitive frame through which AI input was perceived perhaps as a rival rather than a partner. As with Study 1, gender patterns were also observed: male participants again showed flatter or declining CSE trajectories, whereas female participants displayed greater stability.

Study 3 adopted a different lens by conceptualizing CSE as a moderator rather than an outcome. Here, creative self-efficacy interacted with mindfulness and communal-agentic orientation to predict advice-taking behavior. The results confirmed that individuals with high CSE were less likely to revise their decisions based on AI advice, especially when they also endorsed agentic traits. This suggests that confident individuals may interpret AI input as unnecessary or even intrusive, preferring to rely on their own judgment. In contrast, participants with low CSE were more receptive to AI guidance—but only if they also scored high on mindfulness and communal orientation. This three-way interaction illuminates the conditions under which low self-belief does not lead to disengagement but instead facilitates learning from external input. In effect, CSE's influence on AI receptivity is not linear but contingent: low CSE can either hinder or enhance AI uptake depending on whether the individual is open (mindful) and socially oriented (communal).

Taken together, the three studies indicate that AI integration has no uniform effect on creative self-efficacy. Whether AI boosts, diminishes, or has no impact on CSE depends on a constellation of factors: cultural norms, gender roles, task repetition, and individual traits. From a theoretical standpoint, this underscores the need to distinguish between trait-level and state-level interpretations of CSE. While the construct is often treated as stable, it is also susceptible to moment-to-moment recalibration depending on perceived success, social comparison, and the framing of AI's role (collaborator vs. evaluator). Moreover, cultural and gendered self-constructs shape the interpretive lens through which AI is perceived. For collectivists and communal-oriented individuals, AI may act as a source of support that validates and scaffolds creative thinking. For individualists and agentic individuals, it may be experienced as a threat to personal authorship or competence.

From a theoretical standpoint, our findings on CSE and AI highlight the tension between two possible outcomes that was foreshadowed in Chapter 2's frameworks. Augmentation theory and Bandura's concept of guided mastery would predict that AI support can elevate self-efficacy by enabling success in challenging tasks (Bandura, 1997). Additionally, consistent gender differences point to underlying social-cognitive factors: it may be that societal stereotypes (e.g. about technology or creativity) and self-construal (agentic vs communal) mediate how AI influences one's self-perception.

Research Question 3: Individual Differences in Receptivity to AI Advice

RQ3: What individual difference factors (traits or orientations) predict whether an employee will revise their decisions based on AI advice?

While Research Questions 1 and 2 focused on how AI integration alters employees' perceptions of autonomy and creative self-efficacy, the third question shifts the emphasis toward the likelihood that individuals will accept or reject AI-generated advice in decision-making tasks. This question reflects a growing concern in human–AI interaction research: not merely whether employees feel supported or constrained by AI, but how they respond when the system offers a recommendation that differs from their initial judgment. Study 3 was designed to address this question by identifying which psychological traits make employees more (or less) receptive to algorithmic input.

The findings from Study 3 align with prior research on algorithm aversion and advice-taking (Dietvorst et al., 2015; Logg et al., 2019). For instance, **algorithm aversion** literature has noted that many people prefer human judgment over algorithms even when the latter are more accurate. Our results indicate that such aversion might be especially characteristic of individuals high in creative self-confidence and strongly agentic. Conversely, **algorithm appreciation** is likely higher among individuals who are less confident in the given domain, more mindful, and higher in communal orientation (Brown & Ryan, 2003). The results also revealed a nuanced three-way interaction. First, individuals high in mindfulness and low in creative self-efficacy were the most likely to revise their decisions in the direction of the AI recommendation. This pattern suggests that mindfulness fosters a present-focused, non-defensive mindset that makes individuals more willing to reconsider their choices particularly when they are unsure of their own abilities. Second, this receptivity was magnified among individuals who endorsed communal traits. That is, highly mindful, low-CSE individuals who were also more communal in their self-construal were most likely to treat the AI as a helpful partner and adjust their decision accordingly. Conversely, those with a more agentic orientation were less likely to revise their decisions, especially when they also had high CSE. These individuals may have viewed AI input as a challenge to their authority or self-sufficiency and thus were more inclined to stick with their initial choices.

Links between Studies 1, 2 and 3: While Studies 1 and 2 did not explicitly test personality traits, they shed light on two major individual-difference factors, culture and gender, which conceptually tie into the communal–agentic dimension studied in Study 3. Bringing this perspective in, the results from Studies 1 and 2 resonate with Study 3's findings:

1. **Collectivistic (communal) participants were more receptive to AI overall**; they integrated AI into their work without decrease in autonomy (Study 2) and they experienced gains in creative self-efficacy with AI support (Studies 1 and 2). A communal, mindful person low in initial self-belief would be most likely to consider AI guidance constructively. This could explain why in Mexico (collectivistic context) we saw participants benefiting from AI (in terms of CSE increases).
2. **Individualistic (agentic) participants were comparatively less receptive or more guarded**; they showed either smaller benefits or even negative reactions (e.g., UK males' drop in CSE, initial autonomy drop) to AI. This aligns with agentic individuals' tendency to prioritize their own agency and potentially view AI suggestions as intrusions or challenges to their expertise. In Study 3 terms, these would be the high-CSE, low- or average-mindfulness, high-agentic participants who are the least likely to follow AI advice. Encouraging reflective pauses before dismissing AI suggestions may lessen this resistance.
3. **Gender patterns** map onto these orientations too. The fact that male participants were less inclined to benefit from AI (and more likely to feel threatened in autonomy or creative confidence), whereas female participants were generally more stable or accepting, can be understood beyond just biological sex: it reflects underlying trait differences. Study 3's finding that communal-oriented individuals were most inclined to incorporate AI advice maps onto the idea that many female participants (especially those endorsing communal traits) would accept AI input if it seems useful, whereas many male participants (especially those with agentic leanings) would stick to their own path.

Chapter 5: Conclusion and Future Directions

Building on the findings of the dissertation, several future directions emerge for both research and practice in work and organizational psychology. As AI technologies advance and proliferate, understanding their long-term effects on employees, teams, and organizations will be crucial. Below, we outline key areas where future research and organizational strategies should focus, emphasizing that technological change must be examined in tandem with human and cultural factors. While the dissertation primarily examined AI **decision-support systems**, future research should explore a wider array of AI applications in the workplace. This includes generative AI tools that **create content**, autonomous robots performing physical tasks, and predictive analytics guiding strategic decisions. Different types of AI may influence employees in distinct ways. For example, a **creative AI assistant** that co-produces ideas might affect creative self-efficacy differently than an **automated decision-maker** that autonomously allocates tasks. The *role* an AI system plays – whether as an assistant, a collaborator, or an automator – is likely to moderate its impact on human autonomy and confidence. Researchers should compare outcomes with **high-autonomy AI** (systems that make decisions with minimal human input) versus **collaborative AI** (systems that co-create or require human confirmation). Such comparisons can reveal how each mode affects employees' sense of control and contribution. Expanding the scope beyond knowledge work, investigations into AI in service roles or manual labor (via robotics) will also be valuable to see if similar psychological dynamics hold in those contexts. In short, broadening the technological contexts studied will test whether the dissertation's findings generalize across a richer variety of AI systems and job domains, or whether new patterns of human–AI interaction emerge.

A clear implication of current findings is that **one-size-fits-all AI implementations are suboptimal**. Future work should therefore delve into adaptive collaboration styles between humans and AI. Not all employees respond to AI the same way – some may thrive with high automation, while others feel disempowered. Design science research can investigate interfaces that allow users to **modulate the AI's level of control** in their tasks, effectively giving employees a dial for how autonomous or assistive the AI should be. Such *adaptive interfaces* could monitor user comfort and performance, and dynamically adjust AI autonomy: for instance, stepping in with more guidance for a novice but ceding control to an expert user. This aligns with emerging ideas of *contextual autonomy*, where AI systems are flexible in role depending on the user's needs. Additionally, future experiments might examine **explainable AI features** – e.g. interactive explanations or feedback – to see if they increase users' sense of mastery and trust in the AI's suggestions. Early evidence suggests that AI teammates combining **proactive support with clear explanations** foster the most robust human trust and learning. Thus, research should continue to prototype and test AI systems that can **negotiate control** with users through dialog and transparency. The goal is to find collaboration patterns where AI augments human capabilities without unduly eroding human agency, and these patterns may differ by task type or individual preference.

The dissertation's studies spanned only two national cultures, highlighting a need to broaden cultural perspectives in future research. Cultural values and norms can strongly shape how AI is perceived and adopted. For instance, evidence suggests that individuals in **individualistic cultures** (common in Western contexts) often view AI as an external agent that could threaten their uniqueness or autonomy, whereas those in **collectivistic cultures** may see AI as an *extension of the self* that supports group consensus and goals. One recent review found that Western individualists tend to interpret AI features as infringing on their autonomy and privacy, while collectivists are more open to AI facilitating harmony and responding to communal needs. This insight dovetails with the dissertation's finding that creative self-belief grew in team-oriented cultures but faltered in prestige-driven ones. Moving forward, researchers should include cultures with varying values – not just individualism vs. collectivism, but also dimensions like **power distance, uncertainty avoidance, and long-term orientation**. These could yield valuable nuances: for example, **power distance** (acceptance of hierarchy) might affect whether employees welcome AI decisions. Initial evidence is mixed – one study found that people with high power-distance values showed *more* negative attitudes toward AI's social influence yet were paradoxically *more* accepting of AI in workplace roles, perhaps due to deference to organizational decisions. Such complex findings underscore that cultural context fundamentally alters the human–AI dynamic. Future research should use cross-cultural field studies and experiments to examine, for example, if high power-distance environments prefer less "explainability" (trusting authority of the AI), or if high **uncertainty avoidance** cultures demand more AI transparency to feel secure. By expanding the cultural scope, we can discover whether the dissertation's results hold universally or vary across different cultural **work schemas**. This will be critical as AI systems are deployed in globally diverse workforces.

Integrating AI into organizational decision-making raises pressing **ethical questions** that future research must address. One key concern is **algorithmic bias** – whether AI systems inadvertently encode or even amplify biases present in historical data. The dissertation touched on users' perceptions of fairness when algorithms make high-stakes decisions (like hiring or promotions). Going forward, more direct investigation is needed into AI-driven inequities. Studies should examine if AI recommendations systematically disadvantage certain demographic or social groups, and if so, how to mitigate it. Importantly, evidence so far shows a dual potential: AI *can* reduce human bias in some cases (for example, by ignoring sensitive attributes like race or gender in decision models), but if the training data or algorithms themselves are biased, they can just as easily **perpetuate or even exacerbate inequities**. For instance, if an AI hiring tool is trained on data from a company that historically under-hired women or minorities, it may continue that pattern unless explicitly corrected. On the other hand, an AI system calibrated to focus purely on meritocratic criteria (and audited for bias) could make fairer decisions than biased human managers. Future research should thus test interventions like bias auditing, algorithmic transparency, and inclusion of fairness constraints in AI models. *Field experiments* could be especially insightful: e.g. deploying an AI decision aid in different conditions – one with "blind" processing of sensitive data vs. one without such safeguards – to see how outcomes differ for protected groups. Moreover, **employee perceptions** of fairness need study: when do workers see an AI decision as more impartial than a human's? Some studies suggest that in environments where human managers are viewed with suspicion or favoritism, employees might prefer a "neutral" algorithm, particularly in cultures valuing group harmony. However, if the algorithm's workings are opaque, it could undermine trust. To maintain **dignity and justice** in AI-supported workplaces, future scholarship should develop best practices for *algorithmic governance* – such as regular bias audits, transparent criteria, and a way for employees to contest or appeal AI-driven decisions. Ensuring that AI integration is **ethical and inclusive** will not only be a research priority but also a moral imperative for organizations.

The trajectory of AI adoption in workplaces has revealed an evolution in employee mindsets – from early excitement to more cautious skepticism as AI's limitations are exposed. Thus, **trust** in AI systems (and in organizations deploying them) has become a central concern. Future research should continue to explore how to foster appropriate trust: enough trust that employees can rely on AI assistance, but not so much that they become complacent or over-dependent. One promising avenue is increasing **transparency and explainability** of AI. When users understand *why* an AI made a recommendation, they are more likely to trust its outputs and feel empowered to collaborate with it . Recent syntheses indicate that transparency and explainability are among the most important factors for building trust in AI across domains. For example, in a dynamic with a decision-support AI, providing clear explanations for its suggestions can avert overtrust and help users maintain an active role. Future studies should test different transparency techniques (from simple rule-based explanations to visualizations of an AI's reasoning) to see which best sustain user trust and learning over time. Another key aspect is **organizational accountability**. Trust is not built on technology features alone, but on the broader context of how AI is implemented. Companies that establish **Responsible AI policies** – including regular algorithmic audits, ethics boards, and channels for employees to report AI errors or biases – may cultivate higher trust among their workforces. Empirical research can examine this by comparing organizations or departments with strong AI governance versus those without, measuring employee trust levels and technology acceptance. Early industry reports underscore that having clear AI accountability mechanisms significantly improves employee confidence in AI. In fact, global surveys show that while workers are using AI more frequently, they express greater trust in *their own* company's AI usage when they know oversight and fairness checks are in place. Future research might also explore **training interventions** to build what we might call *mindful AI users*. Training that improves AI literacy – teaching employees about an AI system's capabilities and limits – could reduce both unrealistic expectations and undue fears. Ultimately, trust in AI is **dynamic**, and scholars should adopt longitudinal approaches to see how trust evolves with prolonged AI interaction and how interventions (like transparency features or policy changes) can recalibrate trust to an optimal level (neither distrustful nor blindly trusting).

Translating these insights into practice, designers and managers are advised to adopt more **adaptive, human-centric strategies** when rolling out AI in the workplace. Rather than imposing AI systems uniformly, future implementations should consider employees' psychological needs for autonomy, competence, and relatedness. Several best practices are emerging from current research and industry analyses (including our findings, recent reviews, and reports like the McKinsey 2025 workplace study):

- **Phased Introductions with Support:** Instead of a sudden overhaul, introduce AI tools gradually. Early phases can focus on AI assisting in low-stakes tasks, with *extensive training and coaching* for employees. This phased approach gives workers time to adjust and to **renegotiate their role** alongside the AI, mitigating "AI-nxiety" (anxiety about AI). For example, an employee might first observe the AI's recommendations, then start making decisions with AI input, and finally trust the AI for autonomous decisions once confidence is built. Training should be **autonomy-supportive**, highlighting how employees retain control and can override or question the AI, so that they feel **empowered rather than replaced** during the transition.

- **Adaptive User Interfaces:** Invest in AI interfaces that offer **explanations** for their suggestions and allow user control. As noted, an AI system could have adjustable settings (from manual to auto mode), letting users decide how much they want the AI to do. Additionally, UI features like explainability toggles (e.g., "Why did the AI suggest this?" prompts) and confidence indicators can help users calibrate their reliance. Such features increase perceived transparency and give users a sense of command over the AI, enhancing their perceived autonomy. Over time, the interface might learn the user's preferences – providing more detail or less, stepping in only when needed – thus creating a personalized collaboration style.

- **Dialogic Framing and Communication:** How AI is introduced and talked about in the organization makes a big difference. Future implementation should frame the AI as a *collaborative partner* or tool **open to feedback**, not as an infallible authority or a human replacement. Managers should encourage a **dialogue** around the AI: for instance, inviting employees to share where the AI is helpful versus where it hampers their work. By presenting AI as *negotiable* and emphasizing its role as supporting human expertise ("the AI brings speed, you bring judgment"), employees are more likely to embrace it without feeling their identity or creativity is threatened. This kind of framing fosters a **collective orientation**, where AI's successes are celebrated as **shared achievements** rather than attributing all credit (or blame) to the machine. Industry best practices note that when workers see AI as enhancing their team's performance (and not undermining their individual contribution), acceptance and creative use of the AI increase.

All these strategies aim to align AI integration with human psychology, recognizing that sustainable adoption comes from employees feeling **in control, valued, and secure** in their work alongside AI. Future case studies in organizations that implement such human-centric approaches would be extremely valuable to document outcomes like productivity, employee well-being, and innovation levels.

Another important direction for both researchers and practitioners are to understand how human **skills and job roles** evolve in response to AI augmentation. The dissertation found that AI can liberate workers from routine tasks, potentially enabling them to focus on higher-level skills. Future research should examine over longer time horizons what new **competencies** become crucial when AI takes over certain job aspects. Early perspectives suggest that as AI handles more data-driven and repetitive work, uniquely human skills increase in importance. Complex **problem-solving, critical thinking, ethical reasoning, interpersonal communication, and emotional intelligence** are likely to be the cornerstone of human contribution in AI-rich workplaces. For example, an AI system might generate a detailed analytical report, but a human manager will be needed to interpret nuanced implications, make judgment calls aligned with company values, and communicate decisions empathetically to the team. Huang and Rust (2018) argue that "*softer*" skills – intuitive, empathetic, and creative abilities – will remain the most **enduring areas of advantage** for human workers, even as AI grows more capable. Empirical research can test this by tracking employees whose work has been partially automated: Do their roles shift toward roles of **strategy, oversight, and collaboration**? And correspondingly, what training or development do they need to excel in those areas? Some longitudinal studies could involve partnering with companies to measure skill utilization before and after an AI introduction. We might find, for instance, that an accountant freed from routine number-crunching by AI now spends more time on financial planning and client relations – tasks requiring insight, creativity, and human trust. Rather than AI causing widespread job loss, it is more likely to **reshape jobs**. This echoes the notion of **"augmentation"**: AI complements and extends human capabilities instead of replacing them. Indeed, surveys of companies that have adopted AI show that new job categories often emerge (e.g., AI explainers, AI ethicists, human-AI team facilitators) even as certain tasks are automated. Future research should catalogue these emerging roles and identify best practices for workforce transition – how organizations can reskill or upskill employees to thrive in partnership with AI. By clarifying the evolving human role, we also address employees' existential anxieties about AI. The message from research and thought leaders is that **human creativity, leadership, and empathy will be irreplaceable**, and organizations should cultivate these in tandem with AI deployment.

AI's integration into work doesn't just influence practice – it also opens new frontiers for **organizational research methods**. Future research can leverage the **digital trace data** generated by AI-human interactions to gain unprecedented insights into workplace behavior. Traditionally, work and organizational psychology has relied on surveys, interviews, and observations which provide snapshots of attitudes or performance. In contrast, AI systems (from collaboration platforms to decision tools) often log rich, moment-to-moment data: **interaction logs, decision records, communication patterns, response times**, and more. These data can fuel *longitudinal, process-oriented research* at a scale and granularity never before possible. For example, consider a team working with an AI project management assistant – every suggestion the AI makes and every human response (accepted, overridden, modified) could be logged and analyzed. Researchers could model how teams gradually learn to use the AI, how trust builds or erodes with each interaction, and what communication behaviors lead to the best human–AI performance synergy. By applying techniques from data science and network analysis, organizational scholars can observe **learning curves and adaptation processes** in real time, rather than inferring them retroactively. This approach aligns with calls for a new "machine psychology" or computational organizational science. Of course, harnessing such data comes with challenges – privacy must be protected, and data usage must be ethical. Future research should also tackle questions of data governance: how to use AI-collected data to benefit employees (e.g., personalized training or well-being interventions) without crossing the line into surveillance. Nonetheless, if used responsibly, these digital traces can help validate and refine classic theories under the novel conditions of AI-rich work environments. For instance, theories of **motivation and feedback** can be revisited: AI systems often provide instantaneous feedback on performance, so researchers could investigate how that affects motivation compared to human-delivered feedback. Similarly, concepts like team cohesion and leadership might play out differently when an "algorithmic teammate" is part of the team. The ability to analyze such situations with granular data may confirm, extend, or challenge longstanding principles in organizational psychology. In short, AI is **not only a subject of study but also a tool for discovery** in this field, enabling a more **data-driven, dynamic science** of work behavior.

In conclusion, the integration of AI into the workplace is an ongoing journey – one that will define work and organizational psychology for years to come. The future directions outlined above stress that technological advancement cannot be divorced from human and cultural contexts. **Sustained benefits from AI** will emerge only when systems are designed and implemented in harmony with core human values and needs: autonomy, fairness, competence, creativity, and social connection. This means future research must remain interdisciplinary, marrying technical understanding of AI with deep insights into human behavior, culture, and ethics. Long-term field studies across diverse settings will be especially valuable to capture the *full trajectory* of adaptation: initial excitement, potential mid-course disenchantment, and hopefully eventual effective integration where AI's strengths and humans' strengths are optimally combined. Future research should boldly test the boundaries of this vision: for example, identifying where **algorithmic autonomy** genuinely enhances human potential and where it hinders it, examining how AI can contribute to **well-being and diversity** in workplaces, and devising governance frameworks that keep AI systems accountable to human stakeholders. The coming decade will no doubt bring more sophisticated AI and with it, new challenges and opportunities. By keeping **human values at the center** of AI integration, we can ensure the future of work is not only more efficient, but also more **empowering, equitable, and creatively fulfilling** for all. The frontier of AI in organizational life is expansive, but with adaptive and ethical guidance informed by research, it is a future we can approach with cautious optimism and purpose.

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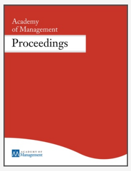
The Impact of AI Integration on Job Autonomy and Creative Self-Efficacy: A Cultural Perspective

Deeviya Francis Xavier, Christian Korunka and Roni Reiter-Palmon

Tools Share

Abstract

This paper explores the relationship between Artificial Intelligence (AI) integration in the workplace, cultural orientation and its impact on job autonomy and creative self-efficacy. Our study employs a mixed-method experimental design across 480 individuals from different cultural backgrounds, specifically individualistic (United Kingdom) and collectivistic (Mexico) cultures. We evaluate how they perceive AI's role in their professional lives. We focus on two key aspects: job autonomy, the level of control and discretion employees have over their tasks, and creative self-efficacy, the confidence in one's ability to generate innovative ideas. Our findings revealed a significant decrease in job autonomy following AI integration across all participants. Interestingly, this decrease was more pronounced in the individualistic participants. Regarding creative self-efficacy, we found gender-specific impacts, with male participants experiencing a decrease, contrary to our expectations. Finally, our results supported the hypothesis that cultural orientation influences perceptions of AI, with collectivistic participants being more receptive to AI integration. These findings have significant implications for organizations integrating AI in multicultural environments. They highlight the importance of considering cultural differences in AI deployment strategies and suggest a need for culturally sensitive AI systems. The study also opens avenues for future research, particularly in exploring the role of other cultural dimensions, conducting longitudinal studies, and investigating ethical and bias-related aspects of AI in the workplace.



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RESEARCH ARTICLE

AI integration and workforce development: Exploring job autonomy and creative self-efficacy in a global context

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Abstract

This paper explores the relationship between Artificial Intelligence (AI) integration in the workplace, cultural orientation, and its impact on job autonomy and creative self-efficacy. Our study employs a mixed-method experimental design across 480 individuals from different cultural backgrounds, specifically individualistic (United Kingdom) and collectivistic (Mexico) cultures. We evaluate how they perceive AI's role in their professional lives. We focus on two key aspects: job autonomy, the level of control and discretion employees have over their tasks, and creative self-efficacy, the confidence in one's ability to generate innovative ideas. Our findings revealed a significant increase in job autonomy following AI integration across all participants. Interestingly, this increase was more pronounced in the individualistic participants. Regarding creative self-efficacy, we found gender-specific impacts, with male participants experiencing a decrease, contrary to our expectations. Finally, our results supported the hypothesis that cultural orientation influences perceptions of AI, with collectivistic participants being more receptive to AI integration. These findings have significant implications for organizations integrating AI in multicultural environments. They highlight the importance of considering cultural differences in AI deployment strategies and suggest a need for culturally sensitive AI systems. The study also opens avenues for future research, particularly in exploring the role of other cultural dimensions, conducting longitudinal studies, and investigating ethical and bias-related aspects of AI in the workplace.

Introduction

Artificial Intelligence (hereafter, AI) has undergone a profound transformation across various industries, marking an era of advanced technological integration and unparalleled operational efficiency. The integration of AI into workplaces to automate mundane tasks has not only heightened efficiency but also redirected human workers towards intricate and creative endeavors [1,2,3]. For example, in customer service, AI chatbots adeptly manage routine inquiries, enabling human agents to address more complex issues [4]. In supply chain management, AI has transcended basic inventory tracking to predict disruptions and optimize logistics [5]. In the healthcare sector, AI algorithms have assumed a pivotal role in diagnostics

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and personalized treatment planning [6]. Meanwhile, the manufacturing sector relies on AI for predictive maintenance, reducing downtime and costs, and the finance industry utilizes AI for fraud detection and personalized banking services [7]. In terms of decision-making, AI provides unparalleled data-driven insights, particularly in marketing, where it is employed to analyze consumer data, tailor marketing strategies, and forecast trends [8].

In this study, we address the core research question: How does AI integration influence employees' perceptions of job autonomy and creative self-efficacy, and do these effects differ by cultural orientation (individualistic versus collectivistic)? By focusing on Mexico and the United Kingdom, we capture meaningful contrasts in cultural orientations that allow us to examine how AI deployment might vary across these national contexts.

Initially, AI was confined to automating repetitive tasks. However, advancements in machine learning and deep learning have allowed AI systems to learn from data, refine algorithms, and make increasingly complex decisions [9, 10]. This evolution—from basic automation to advanced support systems—stands as a testament to AI integration's growing significance across diverse sectors. Studies have shown that while AI could automate certain tasks, it also creates new tasks and roles, leading to a transformation of jobs rather than their elimination [11,12]. Bessen's historical analysis of technological change in the workplace revealed that new technologies often require new skill sets, thus changing the nature of jobs rather than eradicating it [13]. Similarly, a study by Davenport and Ronanki focused on the concept of "augmented intelligence," where they emphasized the potential for AI to improve employee performance, particularly in areas requiring data analysis and interpretation [14].

In exploring the intersection of technology and cultural differences, Ji and colleagues delved into how employees from diverse cultural backgrounds perceive technology's role in the workplace [15]. Their research revealed that individuals from collectivistic cultures tend to view technology advancements more favorably when it is seen as enhancing group collaboration. In contrast, those from individualistic cultures showed a preference for technology applications that bolster personal efficiency and autonomy.

The theories of individualism and collectivism, central to Hofstede's cultural dimensions, offer a comparative lens to understand these variances in values, beliefs, and behaviors [16]. Individualism, with its emphasis on personal achievements, autonomy, and self-reliance, is predominant in societies like the United States and Western Europe, where personal goals and independence are highly valued. Conversely, collectivism emphasizes group goals, community ties, and collective well-being, a characteristic of many Asian and Latin American cultures, where the group's needs and goals often supersede individual desires [17]. This dichotomy significantly impacts technology adoption and workplace behavior. In individualistic cultures, the drive for technology adoption is often linked to enhancing personal efficiency, innovation, and gaining a competitive edge [18]. Employees in these cultures may favor technologies that improve individual performance and offer avenues for personal and career development [19]. AI is often perceived as a tool to boost personal productivity and decision-making autonomy, with a keen interest in how it can facilitate independent work and skill development [4]. On the other hand, collectivistic cultures may approach technology adoption with a group-centric focus, valuing technologies that promote communication, collaboration, and group cohesion [20].

While existing research offers insights into the broader impacts of AI on technology adoption, there's a lack of depth in exploring how these variables intersect and influence key dimensions of cultural orientations, employee well-being and productivity, namely job autonomy and creative self-efficacy [21]. Job autonomy was chosen as a central variable to reflect perceptions of AI integration because it is a well-established measure of employees' sense of control and decision-making power in their roles, particularly within individualistic cultures where personal autonomy is highly valued [12,4,21,22,23]. Theoretical foundations for job autonomy, rooted in self-determination theory, suggest that autonomy is a critical factor for job satisfaction, motivation, and performance [21]. Autonomy in the workplace refers to the degree of control and discretion employees have over their tasks and the way they perform them [12]. In the context of AI integration, there is a concern that increased automation and decision-making by AI systems could undermine this sense of autonomy, particularly in individualistic cultures where personal control and independence are highly valued [4].

Creative self-efficacy, deeply rooted in Bandura's social cognitive theory, is an essential variable for understanding the true effects of AI integration on employee behaviour, particularly in decision-making abilities [24]. According to Bandura, this concept relates to an individual's belief in their capacity to produce creative outcomes [25]. In the workplace, this translates into the confidence employees have in their ability to generate innovative and effective solutions, a critical aspect of modern professional environments where adaptability and innovation are highly valued [19]. Individuals with high creative self-efficacy are more likely to take risks, explore unconventional approaches and persist against challenges, enhancing their performance in problem-solving and decision-making tasks [26,27]. The integration of AI in the workplace has a significant potential to enhance creative self-efficacy through AI's ability to identify patterns and insights that might not be immediately apparent to human analysis, leading to more informed and innovative decisions [19].

However, the intersection of AI, job autonomy, and creative self-efficacy becomes even more complex and relevant when considered within different cultural contexts. Cultural factors play a crucial role in shaping these variables [17,28]. For instance, in collectivistic cultures, AI might be seen as a tool that enhances group collaboration and collective creative efforts, positively influencing self-efficacy in creative tasks. Conversely, in individualistic cultures, AI might be viewed as a means to bolster individual performance and decision-making capabilities [29, 18]. Therefore, assessing changes in creative self-efficacy in response to AI integration can provide valuable insights into how AI tools are influencing employee decision-making abilities. If AI integration correlates with an increase in creative self-efficacy, it suggests that AI tools are being effectively utilized to enhance these abilities. In contrast, a decrease in creative self-efficacy post-AI integration could indicate an over-reliance on AI, possibly undermining individuals' confidence in their own decision-making skills.

This manuscript aims to investigate the complex interplay between AI integration and its impact on job autonomy and creative self-efficacy across diverse cultural contexts. Such an inquiry is essential, as it delves into the significant, though insufficiently explored, effects of AI on workplace dynamics across different cultural landscapes. Specifically, job autonomy and creative self-efficacy are chosen as key variables because they are deeply influenced by cultural contexts, making them ideal for examining the intersection of AI integration and cultural orientations [21,23]. Therefore, we propose the following hypotheses:

1. **AI Integration and Job Autonomy**: AI integration negatively influence perceived job autonomy.
2. **AI Integration and Creative Self-Efficacy**: AI integration positively influences creative self-efficacy.
3. **Cultural Orientation and Perception of AI Integration**: Individuals from collectivistic cultures are more likely to be receptive to AI integration compared to those from individualistic cultures.

By exploring these hypotheses, this study aims to deepen the understanding of how AI integration intersects with cultural orientation to impact job autonomy and creative self-efficacy.

Materials and methods

Study design

For the study design, we employed a methodological framework that integrates both between-subjects and within-subjects components. The between-subjects component of our study entailed the comparison of participants hailing from two culturally distinct backgrounds: the United Kingdom (hereafter, UK) and Mexico. The selection of Mexico and the UK for this study was strategically based on their respective scores on Hofstede's Individualism index, which assesses individualism across 102 countries [30,17]. Mexico, with a score of 34, ranks among the lowest for individualism, aligning it closely with collectivist cultures. In contrast, the UK, scoring 76, ranks among the highest, positioning it firmly within individualistic cultures. It is noteworthy that both countries have recognized the importance of AI at the national policy level. The United Kingdom, for example, introduced its National AI Strategy – AI Action Plan, released in July 2022, which emphasizes responsible AI development and outlines initiatives for accelerating AI adoption [31]. Meanwhile, Mexico's National AI Agenda, released in May 2024, details strategies to identify AI opportunities and address societal needs, indicating a growing commitment to incorporating AI into its economic landscape [32]. These differing national priorities may further shape employees' attitudes toward AI integration in the workplace. By conducting separate analyses for each cultural group, we aimed to unveil overarching cultural differences in how AI integration is perceived and how it impacts job autonomy and creative self-efficacy. This approach allowed us to explore the macro-level variations that cultural orientation may introduce into these domains. Concurrently, the within-subjects component of our design delved into the effect of AI integration at the micro-level, focusing on job autonomy and creative self-efficacy within each cultural group. By employing a within-subjects design, we were able to assess how individual participants' perceptions and attitudes were influenced when exposed to AI-integrated scenarios compared to non-AI-integrated ones. To ensure the integrity of our data, randomization was implemented to assign task scenarios to participants. This strategy minimized order effects and sequence biases, allowing each participant to encounter both scenarios—AI-integrated and non-AI-integrated. This approach prevents any potential bias that could arise from the order in which tasks are presented, thereby ensuring the reliability of our findings [33].

Demographics of participants

In this section, we provide a more detailed description of the participants, highlighting the demographic characteristics that shed light on the diversity of our sample. The study engaged a total of 480 participants were evenly distributed between two culturally distinct groups: UK and Mexico, across the following sectors: Accounts and Finance, Business Strategy, Customer and Client Handling, Hiring, Marketing and Advertising, Operations and Production, People Management, Research and Development, and Supply Chain and Logistics. This deliberate focus on business roles underscores the relevance of the sample to our research objectives, which aim to explore AI's implications in environments where its application is both critical and transformative. In the UK cohort, comprising 258 individuals, there was a balanced representation of genders, with 130 males and 128 females. The age range of participants in the UK spanned from 18 to 65 years, with a mean age (M) of 40.76 and a standard deviation (SD) of 10.95. Meanwhile the Mexican group, consisting of 222 participants, featured 121 males and 101 females. The age range of participants from Mexico was between 18 and 54 years, with a mean age (M) of 29.82 and a standard deviation (SD) of 6.14. (Fig 1) shows a visual representation of the demographics of the participants by country and gender.

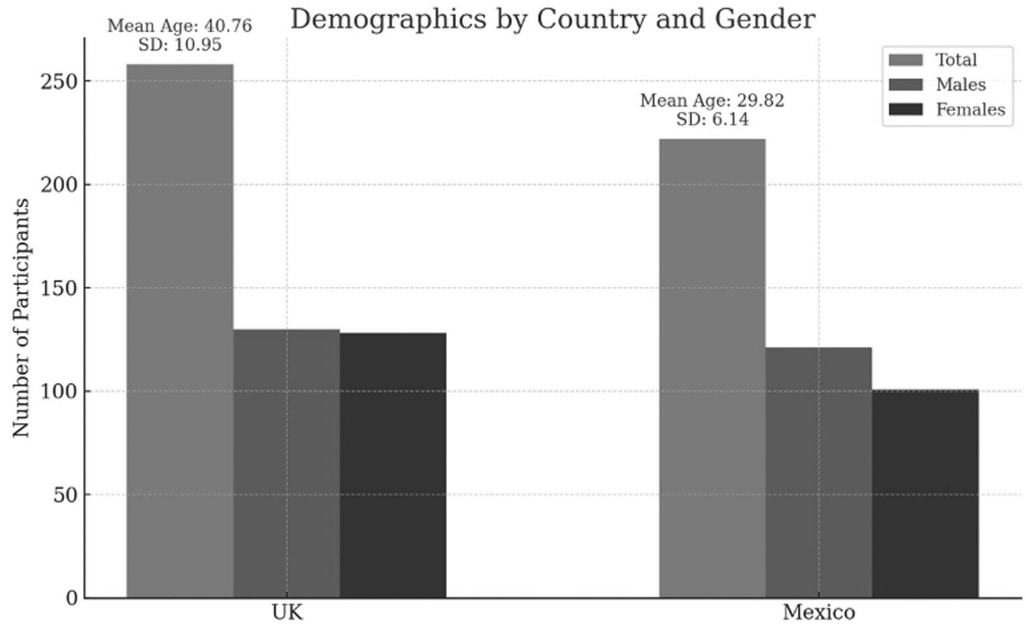

Fig 1. Demographics by Country and Gender.

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Data collection

Data collection was planned to align with the highest scientific standards and ethical considerations. The Institutional Review Board (IRB) of the Department of Applied Psychology: Work, Education, Economy at the University of Vienna granted approval (Approval Number: 2019/A/002), ensuring all procedures were ethically sound. Participant recruitment was conducted via Prolific. Upon confirming eligibility, participants were provided with detailed information about the study, titled "Decision-making Training," which was deliberately named to obscure the true objective of examining how cultural orientations influence AI-integrated scenarios. This precaution was taken to avoid introducing bias into the participants' responses. They were informed that the activity would involve participating in decision-making exercises and completing brief surveys before and after these exercises, with a reassurance that no sensitive personal information would be collected. Participants were also asked if they agreed with the conditions, and if they clicked 'Disagree,' the survey was set to end automatically. The total expected time commitment was outlined as approximately 20 minutes. Data collection commenced and concluded on November 13, 2023.

Participants were required to meet specific criteria: be 18 years or older, have a reliable internet connection, use a computer desktop, and reside in either the UK or Mexico. Consent was secured through Qualtrics, which was configured to terminate the survey for those who did not consent, thus upholding the principle of voluntary participation. Subsequent to obtaining consent, demographic questionnaires were administered to collect data on age, gender and professional background. This facilitated a thorough characterization of the sample's diversity. Participants were then assessed using a cultural orientation scale to ensure accurate classification into cultural groups based on their individual scores, rather than mere geographical origin [28]. This ensured a precise alignment of participants with either collectivist or individualist orientations. Following this classification, participants were then randomly assigned to various decision-making scenarios, both with and without AI integration. Their decision outcomes and reflections on autonomy and creative self-efficacy were recorded. Upon survey completion, participants were debriefed and thanked for their contributions.

AI integration exercise

The study included a two-part exercise to evaluate decision-making processes involving AI integration:

1. **Without AI Integration**: Participants analysed sales data and bar charts for four products, deciding on the allocation of an increased marketing budget to one product without the aid of AI. Their decisions were recorded for later analysis.
2. **With AI Integration**: Participants engaged in a similar task, but this time with AI-generated insights informing their decisions. These insights were provided by a text-based AI simulation using OpenAI's ChatGPT, embedded within the Qualtrics survey platform. The AI, functioning as a language model, was programmed to analyse and interpret sales data presented in chart form and generate strategic recommendations. This setup allowed participants to directly compare their decision-making processes with and without AI assistance.

Survey instruments

In addition to the experimental manipulation of AI integration, we employed the following survey scales to measure our key constructs. Participants completed these scales both before and after the decision-making exercises, enabling us to assess changes in job autonomy and creative self-efficacy.

- **AI Integration** was manipulated experimentally through two separate tasks: one without AI support and one with AI support. This design allowed us to assess changes in job autonomy and creative self-efficacy between non-AI and AI-assisted tasks, rather than relying on a self-report scale to gauge AI perceptions.
- **Cultural orientation** was assessed once at the beginning of the survey using a reduced version of the horizontal and vertical individualism and collectivism scale originally adapted from Hofstede's model and further developed by Sivadas and colleagues. (Sample item for individualism: 'I enjoy being unique and different from others in many ways.'. Sample item for collectivism: 'I usually sacrifice my self-interest for the benefit of my group.') [16,28].
- **Job Autonomy** was assessed using a modified version of the Job Autonomy Scale, originally proposed by Breaugh and Becker [12]. This scale has been extensively validated and employed in various organizational research studies. (Sample item: 'I have considerable opportunity for independence and freedom in how I do my job'). Cronbach's α = .89.
- **Creative Self-Efficacy** was measured using the Creative Self-Efficacy Scale, as developed by Tierney and colleagues [24]. This scale was chosen for its psychometric properties and its ability to discern the self-perceived creative capabilities of individuals. (Sample item: 'I feel confident in my ability to propose novel ideas.'). Cronbach's α = .91.

Results

In this section, we present the findings of our study aimed at exploring the multifaceted impact of AI integration in the workplace.

Hypothesis 1: AI integration and job autonomy

- **Original Hypothesis**: AI integration may negatively influence perceived job autonomy.
- **Overall Results**: Contrary to the original hypothesis, there was a **significant increase** in job autonomy after AI integration, with a t-statistic of **2.91**, p-value of **0.004**, and an **effect size** (Cohen's d = **0.12**). The 95% confidence interval (CI) for the effect size ranged from **0.04 to 0.20**.
- **Exploratory Analysis Results**: Due to randomization of task order, participants were divided into two groups. The first group (referred to as the "Initial AI Integration" group) experienced AI integration in their workflow before switching to a non-AI workflow. The second group, the "Delayed AI Integration" group, started without AI and later integrated AI into their workflow.
    - **Initial AI Integration Group**: No significant change in job autonomy was observed (**t = 1.11, p = 0.27, d = 0.06**), with a CI of **-0.13 to 0.25**.
    - **Delayed AI Integration Group**: A **significant increase** in job autonomy post-AI integration was found (**t = 2.94, p = 0.004, d = 0.17**), with a CI of **-0.02 to 0.36**.
- Gender Differences.
    - **Male Participants**: A **significant increase** in job autonomy was observed (**t = 2.92, p = 0.004, d = 0.17**), with a CI of **-0.02 to 0.35**.
    - **Female Participants**: No significant change in job autonomy was detected (**t = 1.06, p = 0.29, d = 0.06**), with a CI of **-0.13 to 0.25**.
- **ANCOVA**: After controlling for gender, cultural orientation, and age, AI integration still had a significant effect on job autonomy (**F = 5.95, p = 0.02, η^2 = 0.012**), indicating that AI integration explained a small portion of the variance in job autonomy beyond the control variables.
- Repeated Measures ANOVA: A significant main effect of AI integration on job autonomy was found (F = 5.06, p = 0.03, ges = 0.002). However, the main effect of cultural orientation was not significant (F = 1.77, p = 0.18, ges = 0.003.
- **Interpretation**: Overall, AI integration had a **positive impact** on job autonomy, contrary to the original hypothesis. The **Delayed AI Integration group** showed a significant increase in job autonomy after AI was introduced, suggesting that delayed exposure to AI might lead to greater perceived autonomy. However, the **Initial AI Integration group** did not experience a significant change, indicating that initial exposure to AI may not have a marked effect on autonomy perception.

Fig 2 presents a heat map summarizing the t-statistics, p-values, and effect sizes for all subgroups under Hypothesis 1.

Hypothesis 2: AI integration and creative self-efficacy

- **Original Hypothesis**: AI integration positively influences creative self-efficacy.
- **Overall Results**: Across all participants, there was **no significant change** in creative self-efficacy after AI integration (**t = 0.67, p = 0.50, d = 0.02**), with a CI of **-0.11 to 0.16**.
- **Exploratory Analysis Results**: Further analysis revealed gender-specific effects:

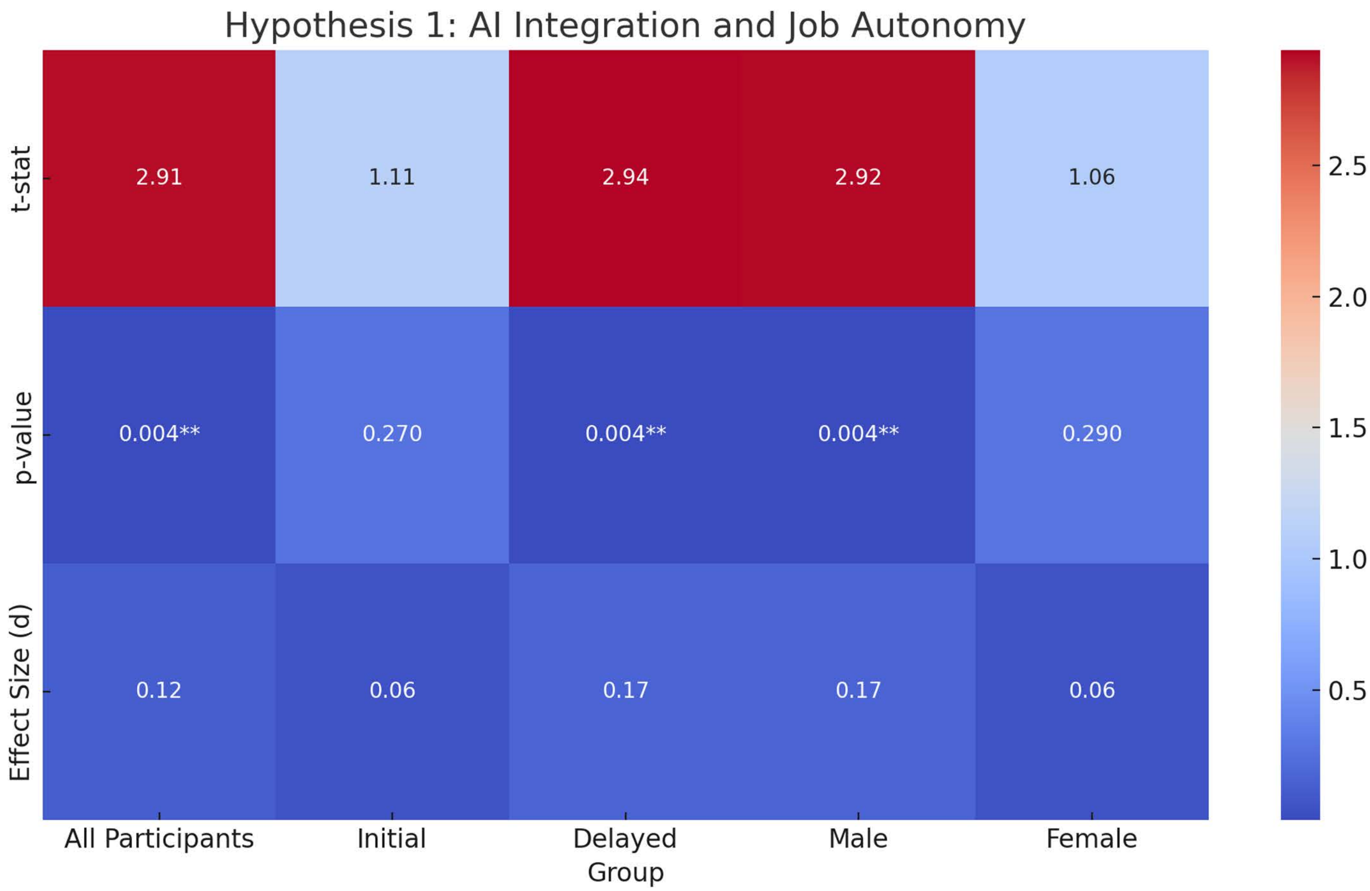

Fig 2. Heat Map of Hypothesis 1 (AI Integration and Job Autonomy) Results. This heat map illustrates the t-statistics (top row), p-values (middle row), and effect sizes (bottom row) for each subgroup tested under Hypothesis 1. The color scale ranges from – 1 (dark blue) to + 3 (bright red), with p < .05 indicated by double asterisks. Warmer colors correspond to larger positive values, cooler colors to smaller or negative values.

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- Male Participants: A marginally significant decrease in creative self-efficacy post-AI integration was found (t = 1.74, p = 0.08, d = 0.08), with a CI of -0.10 to 0.27.
- **Female Participants**: No significant change in creative self-efficacy post-AI integration (**t = -0.90, p = 0.37, d = -0.04**), with a CI of **-0.23 to 0.16**.

- **ANCOVA**: After controlling for gender, cultural orientation, and age, AI integration had a marginal effect on creative self-efficacy (**F = 3.70, p = 0.06, η^2 = 0.002**).
- **Repeated Measures ANOVA**: There was **no significant main effect** of time (pre/post-AI) on creative self-efficacy (**F = 1.36, p = 0.24, ges = 0.000**). However, the **main effect of cultural orientation** was significant (**F = 13.78, p = 0.000, ges = 0.028**), suggesting that cultural orientation influences creative self-efficacy post-AI.
- **Interpretation**: The results suggest that **AI integration does not significantly improve creative self-efficacy** across all participants, contrary to the hypothesis. However, the findings highlight a gender-based difference, with male participants showing a marginal decrease in creative self-efficacy, whereas female participants remained unaffected.

Fig 3 presents a heat map summarizing the t-statistics, p-values, and effect sizes for all subgroups under Hypothesis 2.

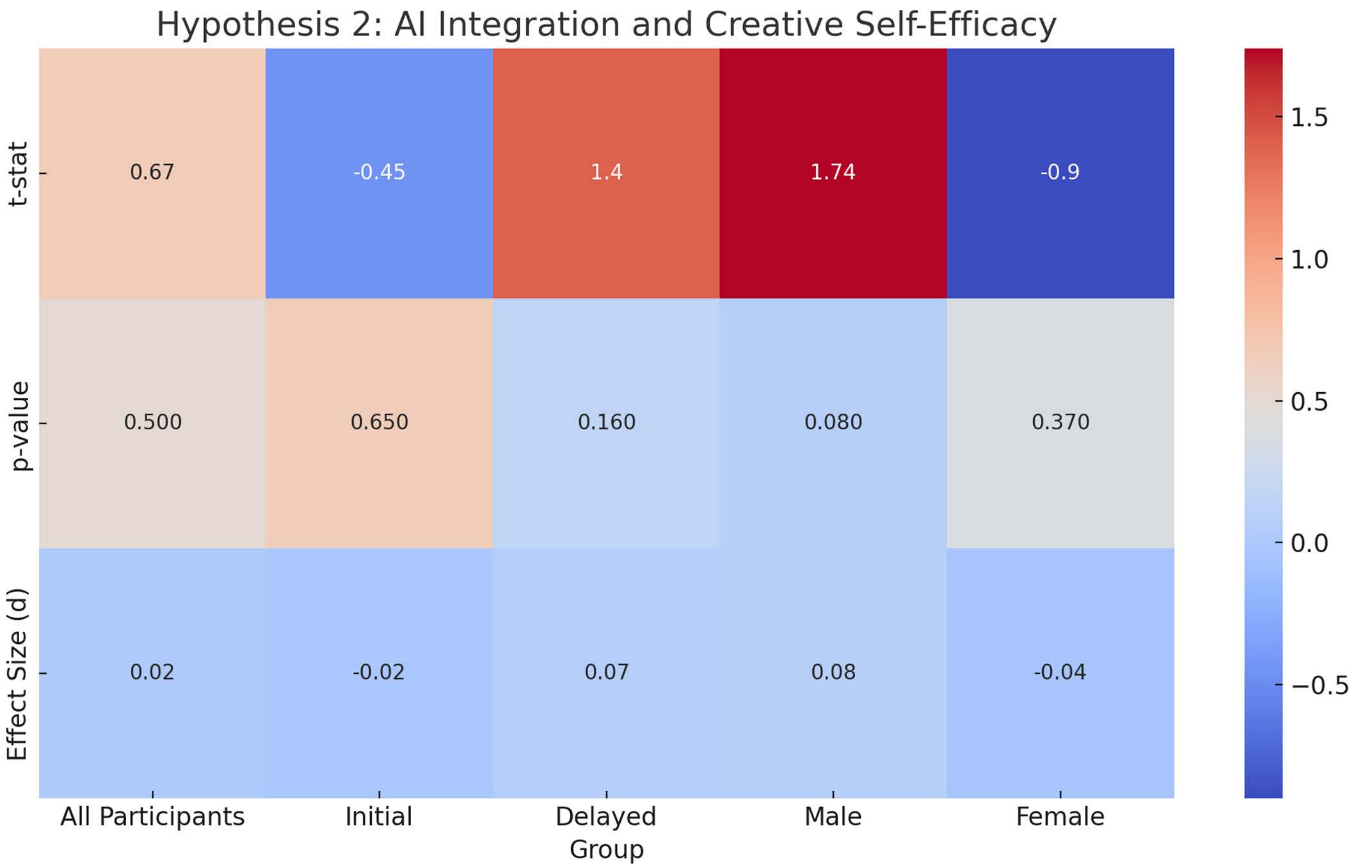

Fig 3. Heat Map of Hypothesis 2 (AI Integration and Creative Self-Efficacy) Results. This heat map illustrates the t-statistics (top row), p-values (middle row), and effect sizes (bottom row) for each subgroup tested under Hypothesis 2. The color scale ranges from – 1 (dark blue) to + 3 (bright red). Warmer colors correspond to larger positive values, cooler colors to smaller or negative values.

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Hypothesis 3: cultural orientation and AI integration

- **Original Hypothesis**: Individuals from collectivistic cultures are more receptive to AI integration compared to those from individualistic cultures.
- **Results**:
    - **Job Autonomy**: There was **no significant difference** between individualistic and collectivistic cultures in terms of job autonomy after AI integration (**$t = -1.04$, $p = 0.30$, $d = -0.10$**), with a CI of **-0.30 to 0.09**.
    - **Creative Self-Efficacy**: A **significant difference** was found between individualistic and collectivistic cultures post-AI integration (**$t = 3.77$, $p = 0.000$, $d = 0.36$**), with a CI of **0.17 to 0.55**. Collectivistic cultures showed greater gains in creative self-efficacy.
- **ANCOVA**: After controlling for gender and age, cultural orientation had a **significant effect** on both job autonomy (**$F = 4.42$, $p = 0.04$**) and creative self-efficacy (**$F = 13.89$, $p = 0.000$**).
- **Repeated Measures ANOVA**: There was a marginal interaction between culture and time for job autonomy (**$F = 3.51$, $p = 0.07$, ges $= 0.001$**), but no significant interaction for creative self-efficacy (**$F = 1.18$, $p = 0.28$, ges $= 0.000$**).

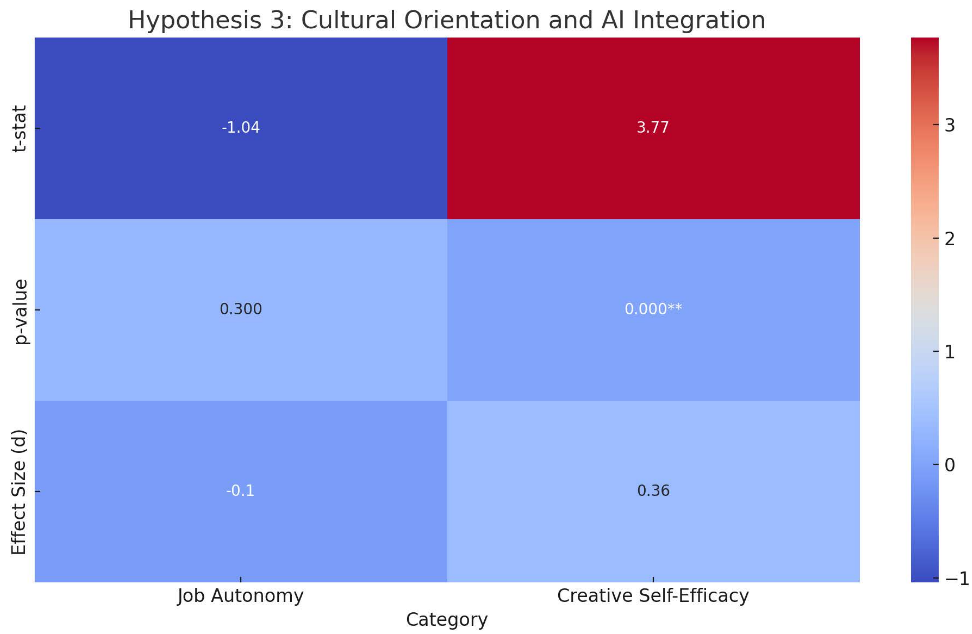

Fig 4. Heat Map of Hypothesis 3 (Cultural Orientation and AI Integration) Results. This heat map illustrates the t-statistics (top row), p-values (middle row), and effect sizes (bottom row) for each subgroup tested under Hypothesis 3. The color scale ranges from − 1 (dark blue) to + 3 (bright red), with p < .05 indicated by double asterisks. Warmer colors correspond to larger positive values, cooler colors to smaller or negative values.

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- **Interpretation**: The results indicate that **cultural orientation** influences perceptions of AI integration, especially in the case of **creative self-efficacy**, where participants from collectivistic cultures experienced a more substantial improvement. However, the impact of AI integration on **job autonomy** did not differ significantly between individualistic and collectivistic cultures.

Fig 4 presents a heat map summarizing the t-statistics, p-values, and effect sizes for all subgroups under Hypothesis 3.
Table 1 further summarizes the main statistical findings for all hypotheses, including effect sizes and confidence intervals, offering a consolidated view of how AI integration impacted job autonomy and creative self-efficacy across cultural orientations.

Discussion

In this section, we will discuss the findings of our study in five key points: the relationship between AI integration and job autonomy, the influence of AI integration on creative self-efficacy, the impact of cultural orientation on perceptions of AI integration, gender-specific effects of AI integration, and the effects of the order of AI integration.

Contrary to Hypothesis 1, which posited that AI integration would negatively influence perceived job autonomy, our findings demonstrated a significant increase in job autonomy following AI integration. This suggests that AI, rather than undermining autonomy, may provide employees with greater discretion over high-level tasks by automating routine or mundane activities [34,35]. The exploratory analysis further revealed that the Delayed AI Integration group experienced a significant increase in job autonomy post-AI. However, the Initial AI Integration group did not show a significant change, indicating that exposure to AI early in the workflow might not have as profound an effect on perceived autonomy.

Table 1. Summary of statistical analyses for the effects of AI integration on job autonomy and creative self-efficacy including exploratory analyses.

Hypothesis	Analysis	t/F	p	d/η²/ges	95% CI	M(SD), Pre AI	M(SD), Post AI
Hypothesis 1: AI Integration and Job Autonomy							
Post vs Pre AI Integration (All Participants)	T-test *(Overall)*	t = 2.91	0.004**	d = 0.12	[0.04, 0.20]	3.73(0.84)	3.83(0.76)
Post vs Pre AI Integration (Initial)	T-test *(Initial)*	t = 1.11	0.27	d = 0.06	[-0.13, 0.25]	3.80(0.81)	3.85(0.74)
Post vs Pre AI Integration (Delayed)	T-test *(Delayed)*	t = 2.94	0.004**	d = 0.17	[-0.02, 0.36]	3.67(0.87)	3.81(0.77)
Post vs Pre AI Integration (Male)	T-test *(Male)*	t = 2.92	0.004**	d = 0.17	[-0.02, 035]	3.71(0.85)	3.85(0.80)
Post vs Pre AI Integration (Female)	T-test *(Female)*	t = 1.06	0.29	d = 0.06	[-0.13, 0.25]	3.76(0.84)	3.80(0.72)
Controlling for cultural orientation, gender and age	ANCOVA *(Overall)*	F = 5.95	0.02*	η^2 = 0.012	–	–	–
Main Effect of AI Integration	Repeated Measures ANOVA	F = 5.06	0.03*	ges = 0.002	–	–	–
Main Effect of Cultural Orientation	Repeated Measures ANOVA	F = 1.77	0.18	ges = 0.003	–	–	–
Hypothesis 2: AI Integration and Creative Self-Efficacy							
Post vs Pre AI Integration (All Participants)	T-test *(Overall)*	t = 0.67	0.50	d = 0.02	[-0.11, 0.16]	4.07(0.72)	4.08(0.78)
Post vs Pre AI Integration (Initial)	T-test *(Initial)*	t = -0.45	0.65	d = -0.02	[-0.21, 0.17]	4.01(0.76)	4.00(0.81)
Post vs Pre AI Integration (Delayed)	T-test *(Delayed)*	t = 1.40	0.16	d = 0.07	[-0.12, 0.26]	4.12(0.68)	4.17(0.74)
Post vs Pre AI Integration (Male)	T-test *(Male)*	t = 1.74	0.08	d = 0.08	[-0.10, 0.27]	4.12(0.70)	4.18(0.72)
Post vs Pre AI Integration (Female)	T-test *(Female)*	t = -0.90	0.37	d = -0.04	[-0.23, 0.16]	4.01(0.75)	3.98(0.83)
Controlling for cultural orientation, gender and age	ANCOVA *(Overall)*	F = 3.70	0.06	η^2 = 0.002	–	–	–
Main Effect of AI Integration	Repeated Measures ANOVA	F = 1.36	0.24	ges = 0.000	–	–	–
Main Effect of Cultural Orientation	Repeated Measures ANOVA	F = 13.78	0.000***	ges = 0.028	–	–	–
Hypothesis 3: Cultural Orientation and Perception of AI Integration							
Individualistic vs Collectivistic	T-test *(Job Autonomy)*	t = -1.04	0.30	d = -0.10	[-0.30, 0.09]	†3.81(0.80), ‡3.62(0.89)	†3.86(0.72), ‡3.78(0.81)
Individualistic vs Collectivistic	T-test *(Creative Self-Efficacy)*	t = 3.77	0.000***	d = 0.36	[0.17, 0.55]	†4.01(0.71), ‡4.15(0.73)	†3.97(0.82), ‡4.24(0.70)
Controlling for gender and age	ANCOVA *(Job Autonomy)*	F = 4.42	0.04*	η^2 = 0.001	–	–	–
Controlling for gender and age	ANCOVA *(Creative Self-Efficacy)*	F = 13.89	0.000***	η^2 = 0.021	–	–	–
Cultural Orientation x AI Integration (Interaction)	Repeated Measures ANOVA *(Job Autonomy)*	F = 3.51	0.07	ges = 0.001	–	–	–
Cultural Orientation x AI Integration (Interaction)	Repeated Measures ANOVA *(Creative Self-Efficacy)*	F = 1.18	0.28	ges = 0.000	–	–	–

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This suggests that the sequence in which AI is introduced plays a critical role in shaping its perceived impact [11,36]. The contrast effect could explain why the Delayed AI group felt a more pronounced increase in autonomy, as the shift from a non-AI environment to an AI-enhanced one may highlight the advantages of AI [21]. Additionally, after controlling for gender, cultural orientation, and age, AI integration continued to have a significant effect on job autonomy, suggesting that even when these variables are accounted for, AI's influence on autonomy remains. These findings point to the complexity of AI's impact, emphasizing the importance of context, timing, and user familiarity.

Hypothesis 2 suggested that AI integration would positively influence creative self-efficacy. However, across all participants, no significant change in creative self-efficacy was observed post-AI integration. This aligns with literature suggesting that simply introducing AI may not be enough to enhance creative self-efficacy; organizational practices that foster innovation are essential for maximizing the benefits of AI [19]. Our exploratory analysis uncovered gender-specific effects. Male participants experienced a marginal decrease in creative self-efficacy following AI integration. In contrast, female participants did not exhibit any significant change. These findings indicate that AI may have a differential impact on creative self-efficacy based on gender. While the effects observed among males were small, the marginal significance suggests that further investigation is warranted. One possible explanation is that societal norms around control and independence may lead men to feel that AI undermines their creative confidence by automating decision-making tasks traditionally seen as markers of competence [24].

Hypothesis 3 posited that individuals from collectivistic cultures would be more receptive to AI integration than those from individualistic cultures. While our results showed no significant difference in job autonomy between individualistic and collectivistic cultures, there was a significant difference in creative self-efficacy, with collectivistic cultures showing a more substantial improvement post-AI. These findings suggest that cultural orientation plays a more prominent role in shaping perceptions of creative self-efficacy than job autonomy. In collectivistic cultures, where group collaboration and interdependence are highly valued, AI may be viewed as a tool that enhances collective creativity [30]. This contrasts with individualistic cultures, where AI's role in supporting autonomy may be less pronounced [15]. However, the lack of a significant cultural difference in job autonomy suggests that AI's perceived impact on autonomy may transcend cultural boundaries, potentially due to its role in augmenting decision-making regardless of individual or collective orientations [26,24].

Our exploratory analysis revealed a significant impact of AI integration on creative self-efficacy among male participants but not among female participants. This observation could be attributed to prevailing gender norms that emphasize control and independence more strongly in men than in women [37]. Such norms may predispose men to perceive the introduction of AI integration—a technology that automates tasks and can make decisions—as a more direct threat to their professional autonomy [22,38]. On the other hand, female participants did not exhibit significant changes in their perception of autonomy. This difference might be linked to gender-specific expectations and socialization processes, where women might either view technological aids in a less threatening manner or have different expectations about employee autonomy and control in the workplace [37]. Moreover, the relative stability in women's perceptions from the outset suggests that their response to AI integration could be less about a perceived loss of autonomy and more about how these tools can be utilized to enhance job performance without undermining their role [22].

The order of AI integration in the workflow significantly affected job autonomy. Participants initially experiencing a work environment without AI showed a more pronounced decrease in perceived autonomy when AI was later introduced. This can be explained by the contrast effect—a psychological phenomenon where introducing a new factor is more starkly felt against the backdrop of a previous condition without that factor [38]. In contrast, participants starting with AI in their workflows and later experiencing its removal did not exhibit significant changes in their perceptions. This group's initial adaptation to AI might have moderated their perceptions from the outset, setting a different baseline where AI's presence was normative [8]. The removal of AI might not have been perceived as an enhancement of autonomy but rather as a return to a less preferred state without the assistance of AI. This suggests that initial exposure to AI may help to establish familiarity and comfort with the technology, making subsequent changes less disruptive. Familiarity with AI plays a crucial role in shaping perceptions and attitudes toward its integration. Research indicates that familiarity can reduce perceived threats and increase acceptance of new technologies [34]. When employees are introduced to AI from the start and gradually build their understanding and skills around its usage, they are more likely to see it as a supportive tool rather than an intrusive one [4]. This progressive exposure leads to smoother transitions and higher comfort levels with AI, mitigating negative perceptions related to autonomy and control [14].

Limitations and future research

Our study has provided valuable insights into the complex relationship between cultural orientation, AI integration, job autonomy, and creative self-efficacy. However, it is essential to acknowledge the limitations of our research and propose areas for future research that can build upon these findings. In this section, we will discuss the limitations and recommendations in six key points.

First, a primary limitation in our study is the small effect sizes observed, which might stem from the controlled experimental setting. Such environments often fail to fully capture the complexities of real-world workplaces, potentially limiting our ability to observe the extensive impacts of AI integration on employee perceptions [19]. To address this and enhance the generalizability of our findings, future research should consider conducting real-life field studies that observe participants in their everyday work environments over extended periods. These studies could provide ecologically valid insights into the long-term effects of AI on job autonomy and creative self-efficacy, allowing for a better understanding of how AI integration interacts with the dynamic and multifaceted nature of real-world work settings. Additionally, expanding the scope to include a broader range of fields—such as manufacturing, healthcare, and education—would allow researchers to explore how attitudes towards AI and autonomy might vary across different occupational contexts. This broader approach could help identify specific factors that influence the effectiveness of AI integration and provide more actionable recommendations for implementing AI across diverse workplace environments.

Second, although our research focused on the UK and Mexico, providing insights into specific cultural contexts, it also limits the breadth of cultural perspectives explored. Expanding future research to include comparative studies across a broader range of countries and cultures could help identify cross-cultural patterns and variations in AI perceptions. It is also crucial to include diverse demographic factors within these studies, such as age and gender, to assess how these variables interact with cultural orientations in shaping AI adoption and its impacts. For instance, different age groups and genders may have varying degrees of receptivity towards AI, influenced by cultural norms and personal experiences [19]. A global comparative analysis that accounts for these factors might assess regional or national differences in AI adoption and how cultural orientations, alongside economic, regulatory, and technological factors, shape these trends [17]. This would enhance our understanding of how different cultural contexts affect AI integration and how demographic factors further modulate these effects.

Third, our study's participant age ranges were carefully chosen to represent the workforce demographics of Mexico and the UK, reflecting each country's typical labour force. In Mexico, with its younger workforce and early job market entry, the 18-54 year age range aligns with national statistics [17]. In contrast, the UK workforce, characterized by a significant proportion of older employees and longer career spans, is represented by the broader 18-65 year age range. Exploring additional age brackets or career stages is crucial for understanding how AI impacts might impact different stages of a career. A more diverse age sample could reveal differences in how various age groups experience and adapt to AI, thereby offering a more comprehensive view of its effects on employee perceptions.

Fourth, while our quantitative approach provided structured insights, integrating qualitative research methods such as in-depth interviews or focus group discussions could offer a deeper understanding of the cultural factors influencing AI integration. These qualitative methods would allow participants to express their perspectives and experiences more freely, revealing personal narratives and group dynamics that might remain hidden in survey data. This approach would enrich our understanding of cultural facilitators or barriers to AI adoption and inform more culturally sensitive and inclusive AI integration strategies.

Fifth, our study did not extensively explore alternative methods of measuring receptivity to AI, such as trust in AI systems. Future research should investigate how biases embedded within AI systems could perpetuate or exacerbate workplace inequalities, influencing employee trust and acceptance of these technologies [39]. Additionally, building trust in AI technologies through transparent communication about AI functionalities, decision-making processes, and protective measures for employee data is crucial [40]. Exploring these aspects can provide a more comprehensive understanding of employees' receptivity to AI, beyond job autonomy and creative self-efficacy, and help organizations implement AI in ways that foster trust and minimize resistance.

Finally, considering the dynamic nature of technology and work environments, longitudinal studies tracking the evolution of AI integration over time would be beneficial. These studies could observe how perceptions and impacts change as employees become more accustomed to AI in their workflows, paying attention to how these changes differ over time. Additionally, researching and testing interventions or best practices for culturally sensitive AI implementation could guide organizations in optimizing AI strategies within diverse workforces. Such research could also explore how interventions can address specific concerns related to gender differences or masculinity-femininity traits and their impact on the acceptance and effectiveness of AI technologies [37].

By addressing these limitations and exploring the proposed areas for future research, subsequent studies can advance our understanding of how AI technologies interact with cultural and demographic dynamics in the workplace. This ongoing research is crucial for developing effective strategies that leverage AI's potential while accommodating the diverse needs and perspectives of the global workforce.

Conclusion

This study provides crucial insights into the multifaceted impacts of AI integration on job autonomy and creative self-efficacy, influenced by cultural orientation. First, we observed a significant overall decrease in job autonomy following AI integration, supporting our initial hypothesis that AI could negatively impact perceived autonomy. These results suggest that AI's role in standardizing and automating tasks may lead to a perceived loss of control and discretion in work-related activities. Second, contrary to our hypothesis that AI would enhance creative self-efficacy, our findings revealed no overall improvement in creative self-efficacy post-AI integration. Notably, gender-specific analyses revealed that male participants experienced a significant decrease in creative self-efficacy following AI integration, whereas female participants' perceptions remained largely unchanged. This suggests that while AI may not uniformly boost creative abilities, it could have a detrimental impact on male employees' perceived creative self-efficacy, highlighting the importance of considering gender differences in evaluating technological impacts. Third, our study confirmed that cultural orientation significantly affects perceptions of AI integration, particularly regarding job autonomy. Participants from individualistic cultures, such as those in the UK, reported a more pronounced decrease in job autonomy compared to those from collectivistic cultures like Mexico. This supports our hypothesis that cultural attitudes toward technology and collaboration shape how AI is perceived and experienced in terms of autonomy. Although the effect on creative self-efficacy was not statistically significant, there was a trend indicating that collectivistic cultures might perceive some enhancement in creative self-efficacy, suggesting a potentially positive view of AI's role in supporting collective success. Overall, these findings illustrate the intricate and variable impacts of AI integration on different cultural and demographic groups. The study's limitations, including small effect sizes and the controlled experimental environment, highlight the need for further research in real-world settings.

Supporting Information

S1 File. Study Data.
(XLSX)

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Integrating Artificial Intelligence across cultural orientations: A longitudinal examination of creative self-efficacy and employee autonomy

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ABSTRACT

In a world where Artificial Intelligence (AI) is increasingly prevalent, a growing discussion persists on how AI integration could affect one's beliefs and degree of control in executing specific tasks. This is especially relevant at the workplace, where psychological and cultural implications of technology integration can significantly influence employee behavior and overall organizational dynamics. In response to this issue, our longitudinal experimental study aims to explore the impact of AI integration and cultural orientation on perceived employee autonomy and creative self-efficacy. We formulated and tested four hypotheses to analyze the relationship between AI integration and employee perceptions within different cultural contexts—specifically individualistic cultures, represented by the United Kingdom, and collectivistic cultures, represented by Mexico. A total of 427 participants from professional sectors participated in this study that alternated tasks with and without AI integration, resulting in an analysis of changes in employee perceptions over time. The empirical findings revealed a positive interactive impact of AI integration on creative self-efficacy, particularly pronounced among participants from collectivistic cultures. Furthermore, reports on employee autonomy revealed a significant negative impact of AI integration in the overall sample. An exploratory gender-specific analysis further revealed significant differences in the impact of AI integration on employee autonomy, with male participants experiencing a more pronounced decrease than female participants. Our findings provide quantitative evidence on how AI integration impacts diverse employee groups, making a significant contribution to the research on ethical and societal considerations in the deployment of AI.

1. Introduction

"How will Artificial Intelligence (hereafter, AI) change the way I do my work?" Such questions are becoming increasingly common among employees who are facing rapidly changing workplace settings due to the deployment of AI technologies at work (Danaher & Nyholm, 2021; Semuels, 2020). AI technologies at the workplace include automating tasks and providing analytics for strategic decisions, with their degree varying from basic automation to sophisticated uses like predictive analytics and customer service via chatbots, are fundamentally transforming job roles, enhancing productivity, and reshaping decision-making processes across various sectors (Glikson & Woolley, 2020; Hu et al., 2019; Wilson & Daugherty, 2018). This shift towards AI-driven operations underscores a pivotal transition in the labor market and corporate ecosystems, necessitating a deeper empirical understanding of AI's role in modifying traditional employment and productivity paradigms. While there is a broad understanding of what AI integration entails, we define AI integration in the workplace as the systematic incorporation of AI technologies into various organizational processes and functions to enhance operational efficiency, decision-making, and innovation. This definition frames our investigation and aligns with the established perspectives on technological integration in organizational settings (Hinks, 2024).

While AI promises to automate routine tasks and boost efficiency, it also introduces challenges such as increased monitoring and automated decision-making, potentially undermining employee autonomy and leading to decreased job satisfaction and stifled creativity (Huang & Rust, 2020; Vredenburgh, 2022; Yin et al., 2024). These concerns are magnified by the broader cultural and societal implications of AI integration. For instance, discussions around AI, such as those presented by Gill (2024), highlight the potential of AI to commodify human creativity and influence the richness of the creative struggle, essential to the human spirit and mutual human connection. These insights remind us of the need to consider not only the operational but also the societal

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impacts of AI on the workplace. Moreover, understanding these impacts requires examining how AI integration is perceived across different cultural contexts, emphasizing the importance of a culturally sensitive lens to fully grasp its implications. For example, diversity in cultural orientations could lead some (i.e., collectivistic cultures) to perceive AI integration as a promise to a better world with improvements beneficial for humanity while leading others (i.e., individualistic cultures) to believe that AI integration is a threat, possibly an existential threat, that needs to be controlled strictly (Danaher & Nyholm, 2021; Goffi & Momcilovic, 2022). These contrasting perceptions can substantially influence how AI technologies are adopted and their consequent impact on the increasingly global workplace.

Furthermore, we included an exploratory focus on gender-specific impacts of AI integration. Existing studies on technology adoption indicate that men and women may hold differing perceptions of, and respond differently to, new technologies—differences often linked to social roles and the presence of biases within technological design (Barret & Davidson, 2006; Costa & Ribas, 2019). By recognizing this potential divergence, we sought to understand whether AI integration might influence creative self-efficacy and employee autonomy in distinct ways according to gender. This exploratory angle enriches our primary investigation by considering demographic factors that could significantly shape employees' perceptions of AI integration at work.

Despite the importance, empirical evidence on the interactive effects of AI integration and cultural orientation remains sparse, with limited longitudinal evidence on how AI integration affects employee perceptions (Arias-Pérez & Vélez-Jaramillo, 2022; Jin et al., 2016; Verma & Singh, 2022). Given the rapid pace of AI integration and globalization, understanding and addressing the complexities of maintaining employee well-being amidst these developments is crucial for both researchers and organizations. This research significantly contributes to the existing body of scientific knowledge by exploring the complex effects of AI integration in workplace environments. We introduce a conceptual framework designed to empirically investigate the interactions between AI technologies and cultural orientations, addressing a notable gap in the literature, particularly concerning longitudinal and empirical data on how AI impacts employee perceptions, particularly creative self-efficacy and employee autonomy. These variables were chosen because they encapsulate both the innovative potential and the perceived control employees have in their work—two critical dimensions when introducing AI-driven tools that can both augment and automate tasks (Huang & Rust, 2020; Tiwari et al., 2024). Additionally, this study is among the first to assess how cultural differences affect the adoption and outcomes of AI in workplace settings. By developing and applying this conceptual framework, we aim to provide a more comprehensive view of the dynamics at play between AI integration and cultural orientation in workplace settings.

1.1. Creative self-efficacy

We introduce creative self-efficacy, defined as the belief in one's ability to produce original and creative outcomes, as our first dependent variable. This variable is rooted in Bandura's social cognitive theory and emphasizes the confidence individuals have in their ability to "think outside the box" and devise innovative solutions, which are crucial for daily work tasks such as decision-making and problem-solving (Bandura, 1997; Tierney & Farmer, 2002, 2011). Unlike other forms of self-efficacy, creative self-efficacy specifically focuses on an individual's belief in their capacity to generate novel and useful ideas (Güngör et al., 2014; Haase et al., 2018). This belief is essential because it directly influences the likelihood of successfully engaging in creative endeavors, improving overall performance (Gong et al., 2009). When employees have high creative self-efficacy, they are more willing to take risks, explore unconventional approaches, and persist in the face of challenges (Mathisen, 2011; Teng et al., 2019). AI integration in the workplace, according to Bandura's theory, may play a significant role in enhancing creative self-efficacy. With their algorithmic precision and ability to process vast amounts of data, AI systems can encourage individuals, support well-informed decision-making, and reduce the risk of error (Chang et al., 2019). Furthermore, in the domain of digital art, Rani et al. (2024) illustrates how AI, through the use of generative adversarial networks, empowers artists to create unique works, thereby reshaping perceptions of creativity and authorship. This parallels the potential of AI to augment human creativity in organizational settings, facilitating innovative problem-solving by leveraging technological capabilities. By providing employees with advanced tools and resources, AI can bolster their confidence in their creative abilities and encourage them to engage more deeply in innovative activities. Therefore, building on Bandura's social cognitive theory, we propose that AI integration can significantly enhance employees' creative self-efficacy.

Hypothesis 1. AI integration positively affects perceived creative self-efficacy.

1.2. Employee autonomy

We introduce employee autonomy as the second dependent variable. Employee autonomy refers to the degree of control and discretion employees feel they have over their work tasks and decisions (Lartey, 2021). This concept is rooted in self-determination theory, which posits that autonomy is a fundamental psychological need that supports intrinsic motivation, well-being, and optimal functioning (Deci & Ryan, 2000). Meanwhile, employee autonomy is defined as the ability to decide on various aspects of work, including the place, time, and manner in which tasks are completed (Burcharth et al., 2017). AI integration, while primarily viewed as a tool to automate tasks and enhance operational efficiency, poses significant challenges to employee autonomy. Koenig (2024) provides a comprehensive framework that categorizes AI acceptance into user acceptance, delegation acceptance, and societal adoption acceptance, each offering distinct insights into how different groups perceive and accept AI technology (Koenig, 2024) For example, the automation and monitoring capabilities of AI systems can lead to a perceived loss of control among employees. When AI systems take over decision-making processes or dictate the methods by which tasks are performed, employees may feel that their professional discretion is undermined (Huang & Rust, 2020). This sense of being monitored or controlled by AI can negatively impact their perception of autonomy, leading to feelings of disenfranchisement and decreased job satisfaction (Hu et al., 2019). The concern here is that AI integration, if not managed carefully, could transform workplaces into environments where employees feel more like passive operators rather than active agents, which could erode their sense of ownership and responsibility over their work. The potential reduction in autonomy due to AI integration could thus have far-reaching implications, not only for individual employees' job performance and mental health but also for overall organizational productivity and innovation. Therefore, supported by the self-determination theory, we propose the following hypothesis based on the assumption that when AI is integrated into work tasks, employees would perceive a lower degree of autonomy over their work tasks and decisions.

Hypothesis 2. AI integration negatively affects perceived employee autonomy.

1.3. Cultural moderation

Cultural values and norms profoundly influence individuals' perceptions and interactions with technology, including AI integration. Research reveals that individuals from collectivistic cultures tend to view technological advancements as tools that enhance group collaboration, while those from individualistic cultures often favor technologies that bolster personal efficiency and autonomy (Ji et al., 2010). Building on Hofstede's cultural dimensions theory, which outlines a dichotomic perspective of culture between individualism and collectivism, this study considers cultural orientation as a moderator (Hofstede, 1984). In individualistic cultures, typically prevalent in Western societies, the emphasis is on self-reliance and independence. Conversely, in collectivistic cultures, predominant in many Asian and Latin American regions, the focus is on group goals, harmony, and the interdependence of members within the community (Woldu et al., 2013; Zhong et al., 2016). AI integration in collectivistic settings might not only enhance group processes but could also significantly boost the creative self-efficacy of team members, as the technology supports shared creative expression and problem-solving. Furthermore, AI-driven platforms could facilitate brainstorming and project management within teams, potentially enhancing the group's creative output and, consequently, the creative self-efficacy of individuals within that community setting (Mooij & Hofstede, 2010; Yu et al., 2016). Therefore, based on these considerations, we propose:

Hypothesis 3. The positive impact of AI integration on creative self-efficacy will be more pronounced for individuals from collectivistic cultures than those from individualistic cultures.

In individualistic cultures, where there is a strong emphasis on personal freedom and independence, the integration of AI into the workplace may introduce significantly different changes to traditional roles and expectations. As AI technologies take over decision-making processes or creative tasks, individuals from individualistic cultures may feel a sense of dispossession regarding their professional autonomy and a fear that their individual discretion in decision-making is being undermined (Brewer & Venaik, 2011). Such concerns are often exacerbated by fears of increased surveillance and control, where AI's capabilities for data collection and analysis could potentially be used to monitor and evaluate employee performance continuously (Acikdeniz et al., 2024). The perceived encroachment on personal autonomy and the erosion of private decision-making spaces may foster resistance among employees, prompting a critical reassessment of AI's role and value in enhancing workplace dynamics (Zhong et al., 2016). Therefore, we propose our fourth hypothesis based on the assumption that in individualistic cultures, where personal autonomy and independence are highly valued, the integration of AI could be perceived as a direct threat to their values.

Hypothesis 4. The negative impact of AI integration on employee autonomy will be more pronounced for individuals from individualistic cultures than those from collectivistic cultures.

The four hypotheses outlined explore the differential impacts of AI integration based on cultural settings, aiming to provide a comprehensive understanding of how diversity influences technological integration within professional environments. Through this analysis, the study seeks to offer insights that could help organizations tailor their technological strategies to the cultural contexts of their global workforce, thus ensuring that AI integration enhances rather than impedes employee engagement and innovation. This approach underpins the conceptual framework illustrated in Fig. 1, which provides a structured visual pathway for investigating these complex interactions.

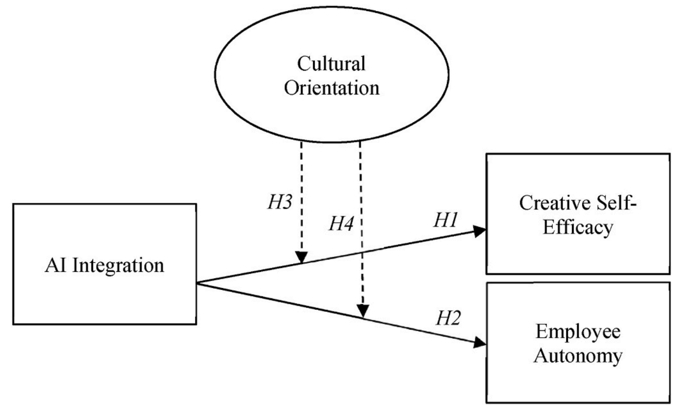

Fig. 1. Conceptual Framework.
*Hypothesis is denoted by 'H' in the diagram.

2. Study design

Our study investigates the effects of AI integration and cultural orientation on creative self-efficacy and employee autonomy using an experimental longitudinal design. We employed a combined between-subjects and within-subjects approach, categorizing participants by cultural orientation—collectivistic (Mexico) and individualistic (United Kingdom; hereafter, UK)—with final classification confirmed through scores on the cultural orientation scale. This setup allowed for more accurate analyses of cultural influences on responses to AI integration. A longitudinal design is particularly critical in this context because AI integration often triggers rapid, yet dynamic, shifts in employee perceptions (Hasgall & Ahituv, 2018). While single-point measurements might capture only an initial snapshot, collecting data at multiple points—in this case, across Day 1 and Day 3—helps us detect whether early reactions (such as dips in autonomy or enhancements in creative self-efficacy) stabilize, intensify, or dissipate over a short period. This approach aligns with evidence that user attitudes toward new technologies can evolve significantly even within a few days of first exposure, reflecting both 'shock' and 'adaptation' phases (Autor, 2015; Brynjolfsson & McAfee, 2014). Data were collected at four points: before and after AI integration on Day 1 and similarly on Day 3. The AI integration exercises were repeated on Day 3 with a randomized task order to control for sequence biases. Consequently, participants experienced the exercises in either the same sequence as Day 1 or in a reversed order, providing a balanced design to detect potential learning or adaptation effects. Although these conditions are somewhat laboratory-like, this brief longitudinal window was chosen to capture immediate perception changes rather than long-term organizational shifts. Moreover, this timeframe helps mitigate attrition risks, as prolonged studies can lead to participant fatigue and skewed results (Zhou & Fishbach, 2016). We also employed randomization to assign task scenarios, minimizing order effects and ensuring that our findings were not influenced by the sequence of AI vs. non-AI tasks (Field, 2013). This methodologically sound approach allowed us to track whether initial dips in autonomy or boosts in creative self-efficacy would persist or diminish, thereby offering a thorough understanding of how AI integration impacts employee perceptions in diverse cultural contexts. The subsequent subsections detail our data collection protocols, AI integration exercises, and the survey instruments used in this study.

2.1. Data collection

The study's data collection was carefully designed to achieve research objectives while adhering to best scientific practices. This study was approved for ethical considerations by the Institutional Review Board (IRB) of the Department of Applied Psychology: Work, Education, Economy at the University of Vienna (Approval Number: 2019/A/002). After obtaining IRB approval, data collection began with the recruitment of participants via Prolific, targeting a balanced sample comprising 509 individuals to ensure we obtain at least 400 participants after filtering for ineligibility during analysis (Prolific, 2024). The minimum number of participants was decided by conducting an a priori power analysis using F-test for ANOVA with repeated measures, specifically assessing the within-between interaction effects (Faul et al., 2007). Participants were recruited specifically from the UK and Mexico across sectors requiring decision-making tasks and the use of AI software or technologies in their work. Specifically, they worked in corporate operations (research and development teams), business management, and market engagement (advertising and sales). To ensure participants genuinely engaged in decision-making tasks and regularly used AI or analytics tools in their work, we implemented two additional screening steps using Prolific's built-in screening feature, allowing only those who self-reported meeting these criteria to access the study. This approach ensured participants possessed real-world experience with AI-driven or data-focused decision-making processes, thereby enhancing the study's ecological validity. First, individuals had to endorse an item confirming that their primary roles involved at least moderate use of data analytics software, AI platforms, or comparable decision-support technologies. Second, participants had to self-report having taken part in at least one workplace task in the last three months that used an AI-based tool (e.g., predictive analytics, chatbot-based customer support, or machine learning applications for marketing). Only respondents meeting both conditions proceeded in our study. Upon establishing eligibility, participants were provided with detailed study information, including the purpose, confidentiality measures, and the expected time commitment. Consent was obtained through Qualtrics, with surveys set to terminate if consent was not given, ensuring participation was voluntary and informed (Qualtrics, 2024). Following that, we administered demographic questionnaires, collecting data on age, gender, professional background, and frequency of AI use to characterize the sample's diversity. Participants then underwent random assignment to decision-making task scenarios, some involving AI integration and others not, to evenly distribute experiences and minimize bias. Their decisions were recorded, and participants reflected on their experience by rating their perceptions of autonomy and creative self-efficacy. After completing the surveys, participants were debriefed and thanked for their contributions.

2.2. AI integration exercise

The AI integration exercise was structured into two distinct parts to thoroughly evaluate the decision-making processes of participants under different conditions:

- *Without AI Integration:* In this part of the exercise, participants were presented with sales data and bar charts for four products. They were required to analyze this data manually, without any AI assistance, and make decisions regarding which product should receive an increased marketing budget. This task aimed to assess their baseline decision-making capabilities and provide a control scenario for comparison.
- *With AI Integration:* Contrasting the previous part, this segment of the exercise introduced AI-generated insights to aid the participants. The AI system provided enhanced analytics, including strategic recommendations, based on the same sales data. Participants then reconsidered their decisions on the marketing budget allocation with this additional information.

Participants were instructed to complete the tasks using only the data and tools provided within the study's interface (Qualtrics). This restriction allowed us to isolate the effect of our experimental AI feature without contamination from other technologies. While we could not enforce this absolutely, we filtered out suspicious responses (e.g., unreasonably fast completion times or contradictory inputs). Although our AI integration exercise centered on a specific budget-allocation scenario—arguably narrower than the full complexity of real-world roles—it was deliberately designed to involve skills such as interpreting raw data, weighing trade-offs, and making resource-allocation decisions, thereby activating creative and strategic thinking (Tierney & Farmer, 2011). Thus, even in a structured budget context, the task prompted participants to demonstrate and to perceive themselves as capable of innovative problem-solving, linking both task creativity and creative self-efficacy to the ways they integrated AI into their decision-making. Because the data provided (e.g., sales figures, bar charts for four products) did not point to one single 'correct' solution, participants engaged in both divergent (generating multiple potential allocation strategies) and convergent (selecting and justifying a final budget decision) thinking. In line with (Gong et al., 2009; Shin & Zhou, 2003), we found that such open-ended tasks—requiring cost–benefit analysis, interpretation of ambiguous data, and integration of personal judgment—can effectively capture one's confidence in generating innovative solutions, i.e., creative self-efficacy. In the 'With AI Integration' condition, the AI system offered strategic recommendations that participants could accept or reject, thus providing an opportunity to exhibit (or strengthen) their creative decision-making skills while simultaneously manipulating the sense of autonomy. No formal human-to-human collaboration was included, so participants operated independently, making decisions without group input. However, to capture cultural influences on decision-making, we assessed participants' cultural orientation (Sivadas et al., 2008) to examine whether collectivistic or individualistic tendencies might moderate reactions to the AI's outputs. For example, participants from collectivistic cultures might emphasize collaboration, whereas individualistic participants might adopt a more self- or competition-focused decision process. After completing each condition, participants then filled out measures of creative self-efficacy and employee autonomy, allowing us to observe how these cultural and cognitive factors influenced participants' perceptions of AI support.

2.3. Survey instruments

Prior to the experimental tasks, we assessed each participant's tendency toward individualism or collectivism using a revised scale adapted from Sivadas et al. (2008). The scale comprises statements reflecting both individualistic (e.g., "Competition is the law of nature") and collectivistic (e.g., "Group welfare is more important than individual rewards") values. Participants indicated their agreement on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Higher scores on individualistic items correspond to a more individualistic orientation, while higher scores on collectivistic items correspond to a more collectivistic orientation. This assessment allowed us to explore whether cultural predispositions moderated the impact of AI on creative self-efficacy and autonomy in later tasks (Hofstede, 1984; Sivadas et al., 2008). Our primary outcome measures were creative self-efficacy and employee autonomy, both administered before and after participants completed each condition (i.e., with and without AI).

Creative Self-Efficacy (CSE). To assess employees' confidence in generating innovative ideas and solutions, we utilized the Creative Self-Efficacy Scale (Tierney & Farmer, 2011). Participants rated each statement on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Higher scores indicate stronger beliefs in one's creative capacity. We reasoned that if participants felt AI intruded on their creative process, their CSE might decrease (reflecting a threat perception), whereas if AI provided a supportive boost, CSE might remain stable or increase (suggesting a facilitative perception). Sample items included:

- "I have confidence in my ability to solve problems creatively."
- "I feel that I am good at generating novel ideas."

Employee Autonomy. Perceived autonomy was measured using a modified version of Breaugh's Work Autonomy Scales (Breaugh, 1999). Like CSE, these items were rated on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Higher scores reflect a greater sense of freedom and self-direction in one's job. If AI was seen as constraining or dominating decision-making, we expected autonomy scores to drop; conversely, if AI offloaded mundane tasks and thereby expanded participants' sense of control, autonomy scores would be maintained or enhanced. Representative items included:

- "I have the freedom to choose the methods to use in carrying out my work."

- "I have a great deal of control over the sequence in which I perform my tasks."

Although employees may perceive AI as either a potential 'threat' or a 'facilitative' tool, we reasoned that changes in creative self-efficacy and autonomy inherently capture these dynamics. Decreases in either measure would reflect a more threatening or intrusive view of AI, while stable or rising scores would suggest an enabling or empowering perception (Deci & Ryan, 2000; Huang & Rust, 2020). By concentrating on these two well-established constructs, we obtain a clear, outcome-focused window into how AI integration affects critical employee experiences across diverse cultural orientations.

3. Results

In this section, we present our findings of our study through subsections discussing each hypothesis followed by an exploratory analysis on gender-specific impacts.

3.1. Participant demographics

Initiating our analysis, we used cultural orientation scores to confirm that participants from both the UK and Mexico reflected their expected cultural values. To ensure accurate classification, we employed the horizontal and vertical individualism and collectivism scale (Sivadas et al., 2008). UK participants were confirmed as individualistic if they scored an average of at least 7 out of 10 on individualism items (with reverse scoring) and below five on collectivism items. Conversely, Mexican participants were confirmed as collectivistic if they scored an average of at least 7 out of 10 on collectivism items and below five on individualism items (with reverse scoring). These measures ensured strong alignment with their respective cultural orientations, providing an accurate foundation for analyzing the cultural influence on the interaction of AI integration on creative self-efficacy and employee autonomy. Additionally, we introduced additional filtering criteria to remove outliers and improve the validity of responses. The criteria included (1) ensuring that all mandatory survey questions were answered, (2) verifying that responses were completed within a reasonable time frame to avoid rushed or incomplete answers, and (3) checking for response consistency by identifying patterns that suggested inattentiveness or random answering, such as selecting the same option for all questions regardless of content. Applying this stringent criterion resulted in a final sample of 427 participants out of the initial recruitment of 509 participants. This final sample included 247 individuals from the UK and 180 from Mexico, with a balanced gender distribution. As the study progressed from Day 1 to Day 3, only one participant from the UK dropped out, leading to an overall participant count of 426 (246 from the UK and 180 from Mexico). The minimal dropout rate ($n = 1$, $<1\%$), did not significantly impact the overall integrity of our data. The balanced gender distribution within our sample facilitated a comprehensive examination of each hypothesis, as outlined in the following subsections.

3.2. AI integration on creative self-efficacy and employee autonomy (hypothesis 1 and 2)

The statistical analysis conducted to assess the effect of AI integration on creative self-efficacy and employee autonomy involved several robust methods: t-tests were used to determine the differences in means between two groups, p-values were calculated to assess the statistical significance of these differences, and Cohen's d was employed to measure the effect size, providing a quantitative measure of the impact of AI integration on the studied variables (Cohen, 1988; Field, 2013). In our study, the two groups represent the scenarios before and after AI integration. The statistical analysis for Hypothesis 1 investigating the influence of AI integration on creative self-efficacy revealed significant results on Day 1, with a t-value of 0.67 and a corresponding p-value of 0.50. Additionally, Cohen's d value was calculated to be 0.02. These statistical measures indicate that AI integration had no significant effect on creative self-efficacy at this early stage of the study. In other words, the mean scores for creative self-efficacy before and after AI integration did not differ significantly from each other. As the study progressed to Day 3, a similar trend was observed. The t-value obtained was 1.28, accompanied by a p-value of 0.20. The Cohen's d value for Day 3 was calculated to be 0.04. These results suggest that similar to Day 1, AI integration had only a minimal effect on creative self-efficacy by Day 3. Once again, the mean scores before and after AI integration did not exhibit significant differences.

The statistical analysis for Hypothesis 2 investigating the influence of AI integration on employee autonomy revealed significant results on Day 1, with a t-value of 2.91 and a corresponding p-value of 0.04. This indicates a decrease in perceived autonomy shortly after the introduction of AI integration. Participants reported feeling less autonomous in their work following the integration of AI technology. However, by Day 3, the effect was no longer statistically significant. The t-value obtained was 1.49, with a p-value of 0.14. This suggests that the initial decrease in employee autonomy was not sustained over time. Instead, perceptions regarding autonomy appeared to stabilize as participants adjusted to the presence of AI in the workplace.

3.3. AI integration and cultural orientation on creative self-efficacy and employee autonomy (hypothesis 3 and 4)

The interaction between AI integration and cultural orientation on creative self-efficacy and employee autonomy was investigated using a two-way ANOVA. A two-way ANOVA is particularly effective for simultaneously examining the effects of two factors, in this instance, AI integration and cultural orientation. F-values, p-values, and eta-squared values were used to assess the magnitude and significance of the effects, providing a comprehensive analysis of the data (Hays, 1994; Tabachnick & Fidell, 2018). The statistical analysis for Hypothesis 3 investigating the interactive influence of AI integration and cultural orientation on creative self-efficacy revealed significant differences, as evidenced by the F-values obtained ($F = 7.07$, $p < 0.05$; $F = 11.60$, $p < 0.05$), which confirms the presence of significant interactions over time. Furthermore, to visually represent the creative self-efficacy scores between participants from the UK and Mexico before and after AI integration over time, box plot charts were utilized. These charts, depicted in Fig. 2, provide a graphical representation of the data through 8 box plots offering a visualization of creative self-efficacy scores of participants from Mexico and the UK, both before and after the integration of AI, measured on Day 1 and Day 3. Before AI integration, the box plots show that Mexican participants generally reported higher creative self-efficacy scores compared to UK participants. After AI integration, the box plots reveal improvements in creative self-efficacy scores for both groups, especially by Day 3. Specifically, for Mexican participants, the median score on Day 1 was lower at four but increased to 4.50 by Day 3, with reduced variability. This suggests a positive impact of AI integration on their creative self-efficacy. UK participants showed a similar trend, with a consistent median of 3.75 on Day 1 and an increase to 4.00 by Day 3 after AI integration. These visual findings align with the statistical results of the two-way ANOVA, confirming that AI integration positively influenced creative self-efficacy, with a more pronounced effect observed among Mexican participants.

The statistical analysis for Hypothesis 4 investigating the interactive influence of AI integration and cultural orientation on employee autonomy revealed no significant interactions, as indicated by the obtained F-values ($F = 0.68$, $p = 0.41$; $F = 0.39$, $p = 0.53$ over time). This suggests that the impact of AI on autonomy did not vary significantly between cultural orientation groups. Fig. 3 presents box plot charts to visually represent the employee autonomy scores between UK and Mexico participants before and after AI integration over time. Before AI

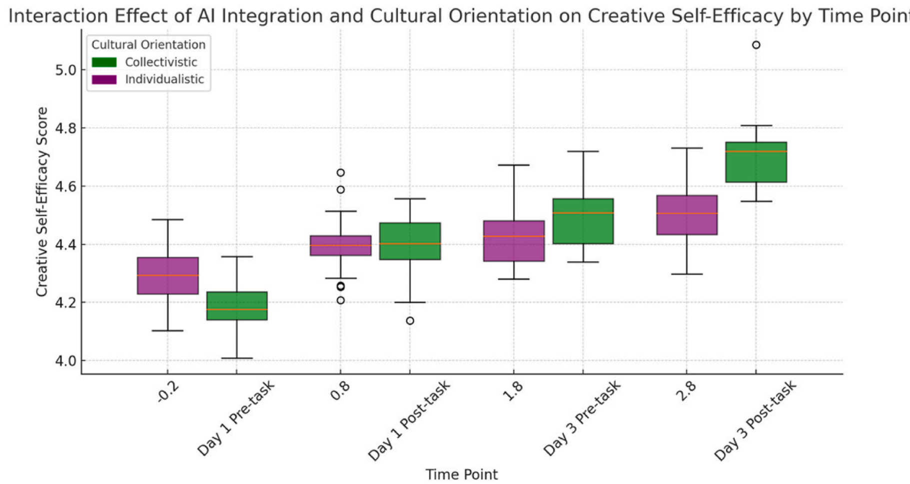

Fig. 2. Box plot chart summarizing creative self-efficacy scores between individualistic and collectivistic orientations over time.

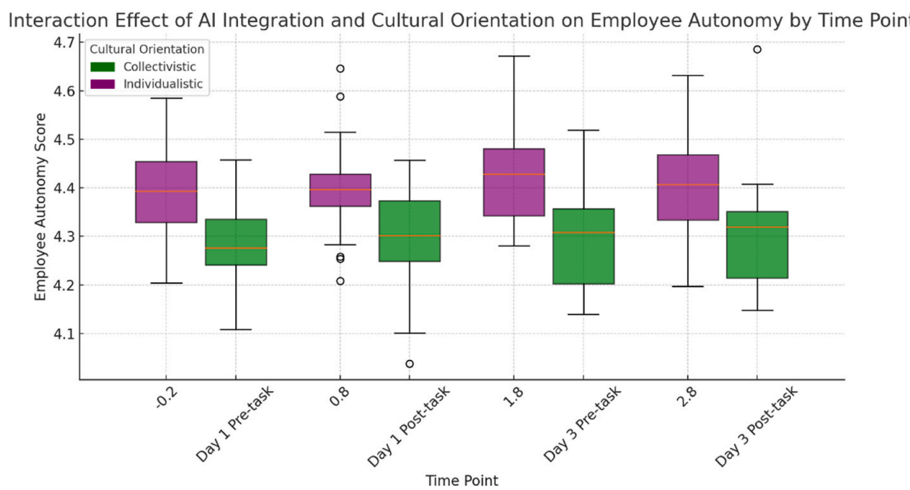

Fig. 3. Box plot chart summarizing employee autonomy scores between individualistic and collectivistic orientations over time.

integration, the box plots show that both Mexican and UK participants had similar distributions of employee autonomy scores. After AI integration, the box plots reveal little change in employee autonomy scores for both groups. By Day 3 after AI integration, the median scores for both groups remained consistent with their pre-integration levels. Overall, these findings suggest that AI integration had a minimal impact on employee autonomy perceptions, with no significant differences observed between the cultural orientations of Mexican and UK participants.

3.4. Exploratory analysis: gender-specific effects

In this study, we conducted an exploratory analysis of gender-specific effects to account for the substantial influence of gender differences on responses to technological changes. Prior research has highlighted that gender differences can significantly shape how individuals perceive and adapt to new technologies, impacting their responses in various workplace contexts (Barret & Davidson, 2006; Costa & Ribas, 2019; Eagly & Wood, 2012). Furthermore, gender bias in AI is a critical concern, as AI systems can perpetuate and even exacerbate existing biases if they are trained on data that reflects societal inequities. These biases can manifest in various ways, such as differences in how AI tools are designed, deployed, and utilized by different genders. For example, men and women may experience different levels of trust in AI systems, with women potentially exhibiting higher levels of skepticism due to historical underrepresentation in technology development and biases in AI outputs (Beninger, 2019; Leavy, 2018). Additionally, AI systems used for hiring or performance evaluations might favor characteristics more commonly associated with male employees, further entrenching gender disparities in the workplace (West et al., 2019).

Our analysis aimed to identify whether AI integration affects men and women differently in terms of employee autonomy and creative self-efficacy. By accounting for gender-specific effects, we hope to provide a better understanding of how AI integration can be managed to mitigate biases and promote an inclusive work environment. Therefore, we explored these possible effects, starting with Hypothesis 1, which examined the interaction between AI integration and creative self-efficacy. Our analysis revealed no significant gender-specific effects for either gender across both days. However, both male and female participants exhibited stability in their creative self-efficacy perceptions, indicating a consistent response to AI integration regardless of gender. Fig. 4 illustrates the distribution of creative self-efficacy scores by gender for Day 1 pre-task vs. post-task and Day 3 pre-task vs. post-task. Significant findings emerged in Hypothesis 2, which evaluated the impact of AI integration on employee autonomy. Among male participants, there was an initial decrease in perceived autonomy on Day 1, with a significant decrease in mean scores. In contrast, female participants did not exhibit any significant changes in perceived autonomy throughout the study, revealing a gender-specific difference in the impact of AI on autonomy. As shown in Fig. 5, male autonomy scores

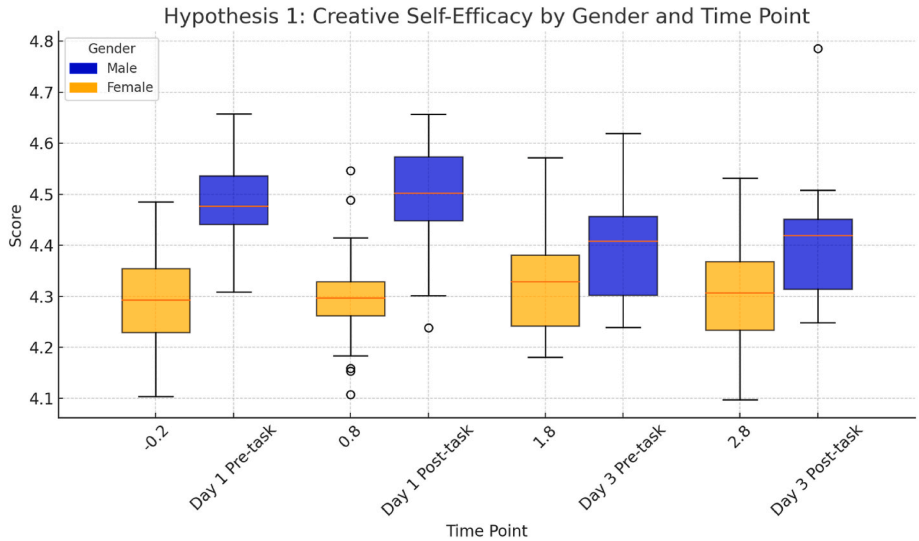

Fig. 4. Box plot chart summarizing creative self-efficacy by gender across day 1 and day 3 (Hypothesis 1).

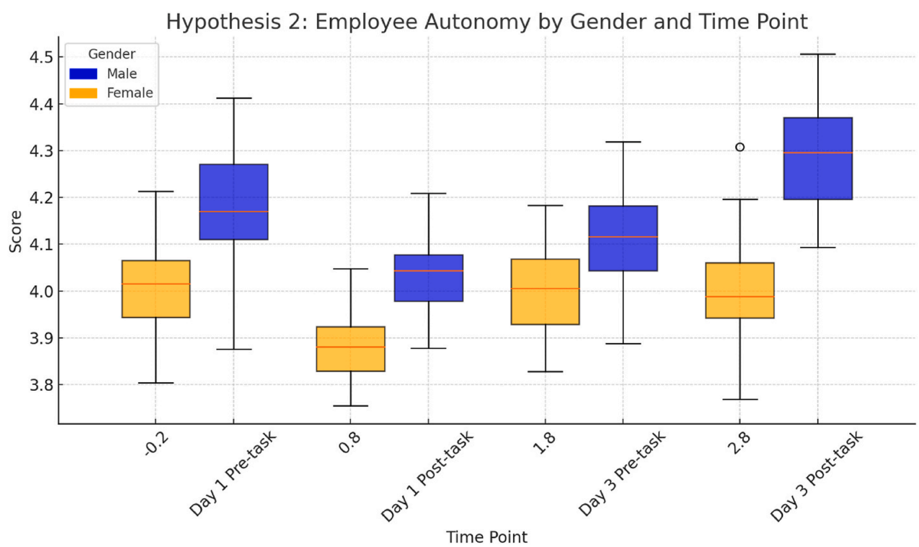

Fig. 5. Box plot chart summarizing employee autonomy by gender across day 1 and day 3 (Hypothesis 2).

dropped more sharply post-task on Day 1, suggesting a possible perception of AI as limiting their control. When exploring the interaction of cultural orientation and AI on creative self-efficacy in Hypothesis 3, significant results were noted over time for male participants in collectivistic settings. Female participants, however, showed no significant changes in creative self-efficacy, suggesting potential gender-specific differences in the relationship between cultural orientation, AI integration, and creative self-efficacy. Fig. 6 provides a visual breakdown of how these scores varied by gender and time point. Similarly, Hypothesis 4, regarding the interaction between AI integration and cultural orientation on employee autonomy, showed no significant changes for either male or female participants. In Fig. 7, we illustrate how autonomy scores evolved for male and female particpants across cultural orientations on Day 1 and Day 3. Overall, the main findings from our exploratory analysis indicate that while creative self-efficacy remained stable across genders, male participants experienced a significant decrease in perceived autonomy with AI integration, whereas female participants did not. This exploratory analysis confirms the necessity of considering gender-specific effects when examining the impact of AI integration. Table 1 summarizes the overall results of each hypothesis, including gender-specific effects.

4. Discussion

In this section, we delve deeper into the interpretations of our findings on the integration of AI within workplace dynamics, particularly focusing on creative self-efficacy and employee autonomy across different cultural orientations. The minimal impact of AI integration on enhancing creative self-efficacy, as observed in our study, could be explained with prior research, which posits that technological tools alone are insufficient to significantly enhance creative self-efficacy without the support of conducive organizational practices (Deranty & Corbin, 2024). This finding emphasizes the necessity for a holistic approach to implementing AI, one that not only introduces new technologies but also incorporates organizational structures and practices that could actively foster creative self-efficacy. Furthermore, the continuation of minimal effects throughout the study period suggests that both the duration of exposure to AI integration and the specific nature of its applications might need to be strategically designed to achieve more pronounced effects on employee perceptions (Chang et al., 2019). This might involve long-term integration strategies with continuous adaptations and feedback loops to tailor AI functionalities that directly support work tasks.

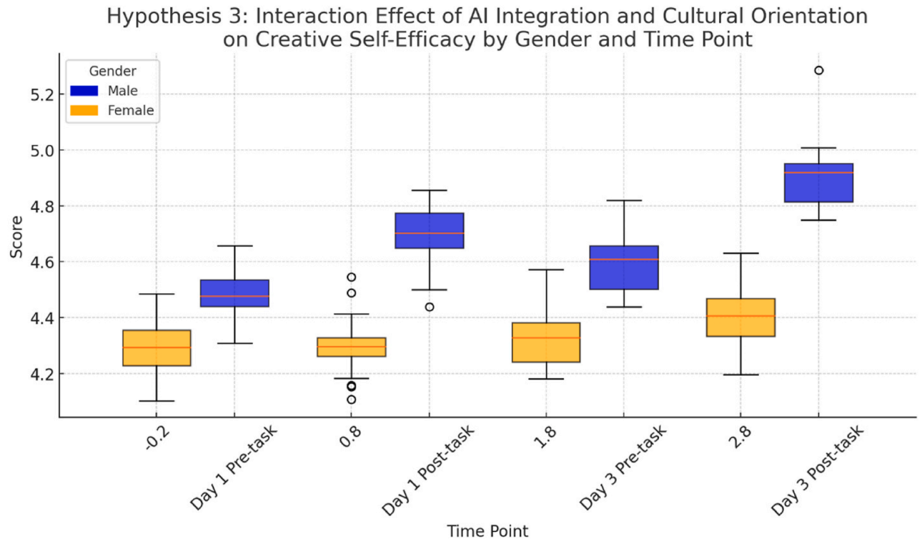

Fig. 6. Box plot chart summarizing the interaction of AI integration and cultural orientation on creative self-efficacy by gender (Hypothesis 3).

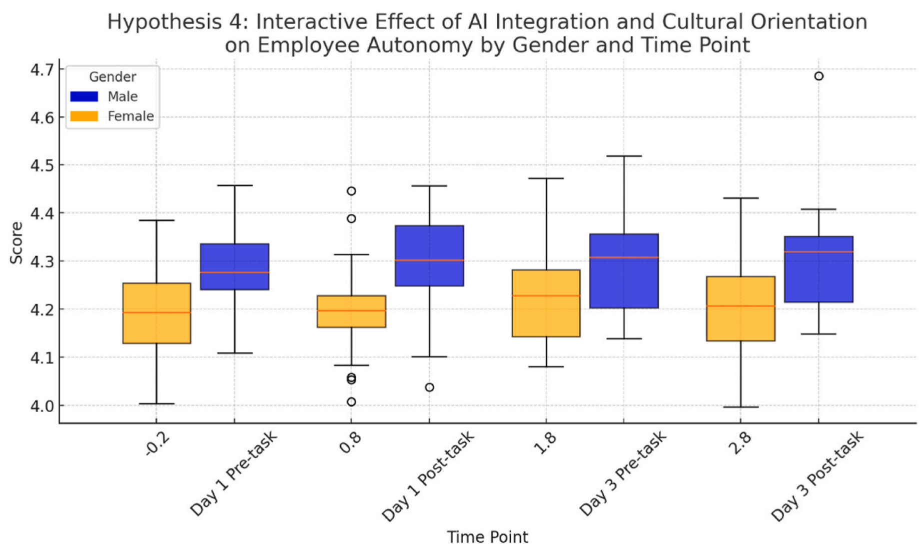

Fig. 7. Box plot chart summarizing the interaction of AI integration and cultural orientation on employee autonomy by gender (Hypothesis 4).

Concerning employee autonomy, the initial decline noted post-AI integration resonates with research suggesting that new technologies can be perceived as intrusive, especially when they enable extensive monitoring or automated decision-making (Lee & See, 2004; Gilkson and Woolley 2018). However, our findings indicate that this effect was temporary: as participants became more accustomed to the AI, they recognized that its recommendations were optional rather than mandated, allowing them to maintain final decision-making authority. This practical realization helped reframe AI from a threat to a facilitative tool—one that offloaded repetitive tasks and freed participants to focus on more strategic or creative aspects of their work (Tiwari et al., 2024). By Day 3, participants reported a diminished sense of being "controlled" by the system, suggesting that perceived autonomy recovered once they established personalized ways of integrating AI suggestions into their workflow. In line with self-determination theory (Deci & Ryan, 2000), this shift underscores the importance of fulfilling autonomy needs by offering employees choice and control in using AI. It highlights the dynamic nature of technology adoption: initial resistance can quickly evolve into acceptance and positive adaptation as employees discover how to leverage AI without relinquishing their sense of ownership over the process.

Furthermore, the observed cultural differences in how AI integration impacts creative self-efficacy underscore a critical dimension of workplace technology integration: the alignment of technological tools with cultural values. In collectivistic cultures, where the community's needs and goals are prioritized over individual desires, the introduction of AI integration that bolsters communal success or enhances group-based tasks is particularly impactful. This heightened impact on creative self-efficacy within collectivistic settings may stem from a cultural predisposition to value technological enhancements more when they are perceived as benefiting the group or community (Chang et al., 2019; Hofstede, 1984; Markus & Kitayama, 1991). Such predispositions can make collaborative AI tools—those that facilitate group brainstorming, collective problem-solving, and shared project management—especially resonant and effective, enhancing the group's creative output and thereby boosting individual members' creative self-efficacy within that group context. In contrast, the uniformity of responses regarding employee autonomy across cultural backgrounds suggests that perceptions of autonomy in relation to AI integration might be influenced more by universal aspects of human-technology interaction rather than cultural specificities. This finding aligns with previous research indicating that reactions to certain technological functionalities—such as

Table 1
Summary of results including exploratory analysis.

Category	Statistical Tests	Subcategory	Day 1 Statistics	Day 3 Statistics	Interpretation
Hypothesis 1: AI Integration and Creative Self-Efficacy	*Paired t-test*	Overall	$t = 0.67, p = 0.50, d = 0.02$	$t = 1.28\ p = 0.20, d = 0.04$	No significant change.
		Male Participants	$t = 1.74, p = 0.08, d = 0.09$	$t = 1.71, p = 0.09, d = 0.08$	No significant change.
		Female Participants	$t = -0.90, p = 0.37, d = 0.04$	$t = 0.05, p = 0.96, d = 0.00$	No significant change.
Hypothesis 2: AI Integration and Employee Autonomy	*Paired t-test*	Overall	$t = 2.91, p < 0.05, d = 0.12$	$t = 1.50\ p = 0.14, d = 0.04$	Overall significant decrease, which improved over time.
		Male Participants	$t = 2.92, p < 0.05, d = 0.17$	$t = 1.58, p = 0.12, d = 0.07$	Significant decrease for male participants, which improved over time.
		Female Participants	$t = 1.06, p = 0.29, d = 0.06$	$t = 0.38, p = 0.71, d = 0.01$	No significant change.
Hypothesis 3: Cultural Orientation and AI on Creative Self-Efficacy	*Two-Way ANOVA*	Overall	$F = 7.01, p < 0.05, \eta^2 < 0.01$	$F = 11.60, p < 0.05, \eta^2 < 0.01$	Overall significant increase for collectivistic cultures over time.
		Male Participants	$F = 1.00, p = 0.32, \eta^2 = 0.01$	$F = 8.41, p < 0.01, \eta^2 = 0.01$	Significant increase for male participants over time.
		Female Participants	$F = 0.69, p = 0.41, \eta^2 < 0.01$	$F = 2.31, p = 0.13, \eta^2 < 0.01$	No significant change.
Hypothesis 4: Cultural Orientation and AI on Employee Autonomy	*Two-Way ANOVA*	Overall	$F = 0.01, p = 0.91, \eta^2 < 0.01$	$F = 0.29, p = 0.59, \eta^2 < 0.01$	No significant change.
		Male Participants	$F = 0.18, p = 0.67, \eta^2 < 0.01$	$F = 0.00, p = 0.96, \eta^2 < 0.01$	No significant change.
		Female Participants	$F = 0.90, p = 0.34, \eta^2 < 0.01$	$F = 0.79, p = 0.38, \eta^2 < 0.01$	No significant change.

*Note: Statistical values in the table have been rounded off to two decimal points as recommended by the American Psychological Association (APA) guidelines (APA, 2020).
t: t-value, the ratio of the mean difference to variability within groups.
p: p-value, probability that results are due to chance under the null hypothesis.
Cohen's d: Effect size indicating the standardized difference between means.
F: F-value, the ratio of the variance between groups to variance within groups in ANOVA.
η^2 (Eta Squared): Proportion of variance explained by an effect in ANOVA.

automation and control—may elicit similar responses across different cultural landscapes (Triandis & Gelfand, 2012).

For multinational organizations, this implies that while it is critical to tailor aspects of AI integration to align with cultural preferences or sensitivities, particularly those affecting collaborative and creative capacities, the strategies for addressing autonomy-related concerns might not require rigorous customization. Instead, organizations could focus on universally applicable strategies that address common concerns about employee autonomy loss, such as ensuring transparency in how AI systems make decisions or involving employees in the development and deployment phases of AI projects. This duality—where cultural differences significantly influence certain perceptions and reactions to AI integration (i.e., creative self-efficacy) while showing minimal effect on others (i.e., employee autonomy)—highlights the complexity of designing and implementing AI integration systems in culturally diverse workplaces. It underscores the need for an approach that considers both the universal and culture-specific implications of AI technologies. Such an approach not only facilitates smoother integration of AI across diverse teams but also enhances the overall effectiveness and acceptance of technological systems, ensuring they are seen as augmentative rather than disruptive.

The gender-specific results from our exploratory study provide a deeper layer of insight into how AI integration impacts the workforce, unveiling distinct initial reactions between male and female participants, particularly concerning employee autonomy. Specifically, male participants reported a more pronounced decrease in perceived employee autonomy shortly after AI integration. This observation could be attributed to prevailing gender norms that emphasize control and independence more strongly in men than in women. Such norms may predispose men to perceive the introduction of AI integration—a technology that automates tasks and can make decisions—as a more direct threat to their professional autonomy (Eagly & Wood, 2012; Leavy, 2018). On the other hand, female participants did not exhibit significant changes in their perception of autonomy. This difference might be linked to gender-specific expectations and socialization processes, where women might either view technological aids in a less threatening manner or have different expectations about employee autonomy and control in the workplace (West et al., 2019). Moreover, the relative stability in women's perceptions from the outset suggests that their response to AI integration could be less about a perceived loss of autonomy and more about how these tools can be utilized to enhance job performance without undermining their role. Moreover, as the study progressed to Day 3, the significant differences in perceptions of employee autonomy between genders began to diminish, suggesting a normalization of attitudes towards AI integration as both male and female participants adjusted to its integration. This convergence indicates a potential adaptation process where initial fears or reservations about AI are overcome as employees become more familiar with its capabilities and limitations. It's possible that as both genders recognize that AI can coexist with and even augment their roles without usurping their autonomy, their perceptions adjust accordingly (Barret & Davidson, 2006; Beninger, 2019). This gradual stabilization of autonomy perceptions over time underscores the importance of considering the temporal dynamics of adopting new technologies in the workplace. It suggests that while immediate reactions to AI integration can vary significantly between genders, these perceptions may become more aligned as the novelty of the technology wanes and its practical applications and implications are better understood.

5. Limitations and future research

In this section, we will discuss six key points regarding the limitations of our study and propose avenues for future research to address these limitations and expand upon our findings. First, a primary limitation in our study is the observed small effect sizes, which could be partly attributed to the controlled experimental setting that does not fully replicate the complexities of real-world work environments. Our use of a specific budget-allocation task—though deliberately designed to prompt data analysis and decision-making—does not necessarily mirror the entire range of responsibilities participants face in their respective roles (e.g., R&D, business management, or market engagement). This may have constrained our ability to capture the full extent of the effects of AI integration on employee perceptions. Consequently, observed effect sizes in creative self-efficacy and autonomy might be smaller than those that could emerge in more realistic or long-term contexts, reducing the ecological validity of our findings. Future research could consider conducting real-life field studies, where participants engage with AI tools in their actual workplaces over longer spans (e.g., a full workweek or month), to address the limitation of small effect sizes and improve the generalizability of our findings. Real-life field studies would allow for the examination of various contextual factors, such as organizational culture, team dynamics, and individual differences. Furthermore, field studies would offer more ecologically valid insights into the long-term effects of AI integration on employee autonomy and creative self-efficacy in actual workplace settings by observing participants in their everyday work environments over an extended period—potentially spanning a full workday or multiple workdays. By doing so, researchers can produce larger effect sizes and yield a more accurate and comprehensive insight of how AI integration truly impacts employee behaviors and perceptions.

Second, our study focused on the United Kingdom (individualistic) and Mexico (collectivistic) to examine cross-cultural differences in AI integration, representing specific nationalities and cultural backgrounds. However, this binary cultural lens may overlook rich variations across other regions and subcultures. Although we screened participants for roles involving decision-making and AI usage, these categories were necessarily broad, raising questions about whether each participant's actual job context aligned perfectly with our experimental task. Future research could expand to additional countries and include stricter screening to ensure a tighter match between participants' real-world responsibilities and the AI tasks under study. A more global, nuanced comparative analysis might assess how factors such as regulatory environments, economic conditions, or cultural traits (e.g., masculinity–femininity, uncertainty avoidance) influence AI perceptions. In parallel, researchers should also consider gender intersections with cultural orientation—examining how traditional gender roles interact with AI usage across diverse global workforces—potentially revealing how cultural norms amplify or attenuate gender-based differences in AI integration.

Third, while our between- and within-subjects design provided valuable quantitative data on creative self-efficacy and autonomy, it did not capture deeper, context-specific nuances—particularly how participants personally interpret AI's role in their unique professional settings. Qualitative methods such as in-depth interviews or focus group discussions could allow participants to express their perspectives and experiences more freely. For example, in-depth interviews could uncover personal narratives that highlight specific cultural facilitators or barriers to AI adoption that remain invisible to standardized scales (e.g., unwritten norms around deference to authority in collectivistic contexts). Similarly, focus groups could provide a platform for diverse cultural groups to discuss their collective views on AI integration, revealing consensus points and divergent opinions that might influence group norms and workplace dynamics. Future research integrating mixed methods—both quantitative and qualitative—would offer a more holistic view of AI integration, allowing scholars to triangulate numerical changes in self-efficacy and autonomy with employee narratives about trust, fear, or enthusiasm. Such an approach would enhance cultural sensitivity in AI implementations, enabling more tailored strategies for diverse teams and organizational contexts.

Fourth, AI systems can inadvertently perpetuate workplace inequalities, especially if their underlying algorithms are trained on biased data, reinforcing stereotypes or excluding minority perspectives. Addressing these biases necessitates transparent model development, continuous oversight, and the active involvement of end-users. In the short term, trust in AI can be undermined by opaque decision processes or privacy concerns; in the long term, distrust may erode employee engagement and autonomy. Thus, future investigations should focus on how biases and trust-building measures shape employee adoption of AI, possibly examining how team-based training, explainable AI, or employee co-design can mitigate perceived threats. Studying these elements across different cultural and gender groups would clarify whether interventions aimed at reducing bias and increasing transparency vary in effectiveness based on cultural orientation or gender norms.

Fifth, our study deliberately focused on creative self-efficacy (Tierney & Farmer, 2011) and employee autonomy (Breaugh, 1999) to provide a clear, outcome-focused lens on AI's impact. However, we did not employ specific items gauging whether participants perceived AI as inherently threatening or facilitative (Huang & Rust, 2020). As a result, while shifts in autonomy and creative self-efficacy can indirectly reflect threat vs. facilitation, we cannot confirm whether some participants framed AI use primarily as constraining or enabling. Future work could incorporate targeted scales measuring employees' threat perceptions (e.g., fear of automation, job displacement) versus facilitative perceptions (e.g., enhanced task efficiency, creativity support). Doing so would complement standard measures of autonomy and self-efficacy, yielding a more multi-dimensional understanding of how employees interpret AI's role in their workflow—and how these interpretations might shape behaviors, performance, and well-being.

Finally, our study design focused on individual participants interacting with an AI system, which does not fully capture the potential of human–AI collaboration as practiced in many modern workplaces. While we allowed participants to accept or reject AI recommendations, the task did not reflect continuous, real-time collaboration where employees and AI co-create solutions, learn from each other, or share responsibilities dynamically. Future research should investigate cooperative or team-based AI scenarios that more closely mirror real-world settings, such as project teams incorporating AI-driven analytics, or joint decision-making platforms where humans and AI 'negotiate' outcomes. Examining how trust, accountability, and control evolve in these deeper forms of collaboration—particularly across diverse cultural and gender groups—could yield valuable insights into how organizations can foster effective human–AI partnerships without compromising employee autonomy or creative potential.

6. Conclusion

In conclusion, this study provides novel and important findings on the intersections of AI integration, cultural orientations, and employee perceptions. Through rigorous quantitative analysis, we demonstrated how cultural orientations significantly shape perceptions of AI's impact on creative self-efficacy and employee autonomy. Specifically, our results reveal that individuals from individualistic cultures tend to experience a more pronounced decrease in perceived employee autonomy due to AI integration, often viewing these technologies as an infringement on their independence and control at work. Conversely, individuals from collectivistic cultures often perceive an improvement in their creative self-efficacy following AI integration, likely viewing AI as a facilitator of cohesion and collective success. Additionally, our exploratory analysis of gender-specific effects shed light on the significant influence of gender differences in responses to technological changes. Our findings indicate that while creative self-efficacy remained stable across genders, male participants reported a significant decrease in perceived autonomy with AI integration, a trend not observed among female participants. This suggests that gender may play a crucial role in how AI integration is perceived and can affect workplace dynamics differently based on gender. Overall, our findings illustrate the complex and multifaceted impact of AI integration on various demographic groups, underscoring the necessity for organizations to consider cultural and demographic factors when implementing AI technologies in the workplace. While our findings contribute significant insights, they also come with limitations that suggest avenues for further research. The small effect sizes and the controlled environment in our experimental study call for future field studies in real-life settings to validate and expand upon our findings. Such studies could provide a more comprehensive understanding of AI's long-term impacts on employee behavior and perceptions in diverse work environments. Moreover, extending this research to a wider global reach could help delineate cross-cultural patterns and enhance organizational strategies for AI integration, tailoring approaches to varied cultural and demographic contexts. Future research should also delve deeper into the qualitative aspects of AI integration, exploring personal and group narratives that could offer richer insights into the cultural and ethical dimensions of AI in the workplace. Ultimately, this study underscores the necessity for organizations to consider cultural, demographic, and ethical factors when implementing AI technologies, advocating for inclusive strategies that ensure AI serves as an enhancer of workplace dynamics rather than a disruptor. By fostering an understanding of AI's diverse impacts, we can better navigate the ethical challenges and opportunities it presents, aiming to create a more equitable and productive future in the evolving landscape of work.

CRediT authorship contribution statement

Deeviya Francis Xavier: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Christian Korunka:** Writing – review & editing, Validation, Supervision, Conceptualization.

Statements and declarations

The authors have no competing interests to declare relevant to the content of this article. The authors did not receive support from any organization for the submitted work.

Ethics approval

This study was approved for ethical considerations by the Institutional Review Board (IRB) of the Department of Occupational, Economic, and Social Psychology at the University of Vienna, Austria, with Approval Number: 2019/A/002.

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Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Deeviya Francis Xavier reports article publishing charges was provided by University of Vienna. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The data supporting the results and analysis in this study are available in the Harvard Dataverse repository. Access to the published files is restricted to protect individual privacy. To use the restricted files, a request must be submitted for access via the Harvard Dataverse platform. Access will be granted based on the relevance of the research purpose and compliance with the study's data usage policies.

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Mindfulness and creative self-efficacy shape human–AI decision-making: Implications for adaptive AI design

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Abstract

Human decision-making is increasingly augmented by artificial intelligence (AI) systems, yet individuals vary in whether they revise their judgments based on AI-generated suggestions. This study provides a timely contribution to the understanding of human factors in AI decision-making, specifically on how two psychological traits i.e. trait mindfulness and creative self-efficacy (CSE), interact with communal-agentic personality orientations to influence decision revision after AI input. Using multinomial logistic regression, we analyzed data from 549 professionals in the United Kingdom to determine whether participants maintained or adjusted their initial decisions following AI advice. Results revealed a significant interaction between mindfulness and CSE. Individuals with high mindfulness and low CSE were more likely to revise their decisions in the direction of AI recommendations, while those high in both traits tended to maintain their original choices. A three-way interaction further showed that this mindfulness–CSE dynamic was most pronounced among individuals scoring high on communal-femininity traits. These findings highlight how attentional focus (mindfulness), perceived creative competence (CSE), and gender-role orientation jointly shape receptivity to AI suggestions. We discuss implications for advancing theory on individual differences in human–AI collaboration and for designing adaptive AI systems tailored to users' psychological profiles.

Introduction

Artificial intelligence (AI) systems are increasingly integrated into human decision-making processes across domains such as healthcare, finance, and creative work[1,3,12,17]. While AI recommendations can improve decision accuracy and consistency, individuals show substantial variability in whether they accept, modify, or reject such advice[1]. Previous studies have documented *algorithm aversion*[1,44,46], where people tend to prefer human over algorithmic recommendations, even when the latter performs better[2]. However, *algorithm appreciation* i.e. the tendency to favor AI input, emerges when algorithms are perceived as highly accurate[3,32], tasks are objective or high-stakes[4], users lack confidence in their own judgment[5], or when AI outputs are transparent and explainable[6]. These opposing tendencies highlight a fundamental question in human–AI interaction: which psychological characteristics predict openness to AI-generated advice?

Understanding the individual differences that shape receptivity to AI input is critical for both theory and application[45]. From a theoretical perspective, identifying the cognitive and personality mechanisms that underlie advice-taking can inform models of adaptive decision-making in human–machine systems[4,11,46]. From a design perspective, such insights can guide the development of AI interfaces that dynamically adjust their recommendations to users' cognitive styles and confidence levels[3,7,12].

In the present study, we focus on two individual-difference variables: **mindfulness** and **creative self-efficacy (CSE)**, as predictors of decision revision following AI suggestions. This extends prior work on trait-based predictors of decision quality and adaptive behavior[3,4,5,16,25]. **Mindfulness** is defined as a dispositional tendency to attend to present-moment experience in a nonjudgmental and accepting manner[7]. It has been associated with enhanced metacognitive awareness, reduced reliance on heuristics, and improved cognitive flexibility[8]. Theoretically, mindfulness may support more deliberate and context-sensitive processing of external information, including algorithmic input. For example, mindful individuals have been shown to be less prone to decision biases such as the sunk-cost fallacy[9], suggesting a greater willingness to revise prior judgments in response to new evidence. Based on this, we hypothesize that individuals high in mindfulness will exhibit greater openness to modifying their initial decisions following AI-generated advice.

Creative self-efficacy (CSE) refers to an individual's belief in their ability to generate creative ideas and solutions[7,39]. Rooted in Bandura's self-efficacy theory[8], CSE captures domain-specific confidence in navigating tasks that require originality, insight, or innovation. While general self-efficacy reflects a broad sense of personal competence, CSE is more directly relevant in contexts requiring adaptive thinking under uncertainty such as evaluating algorithmic recommendations[3,12,37]. Individuals high in CSE are more likely to trust their own creative judgment and persist in solving problems autonomously[7,8]. In contrast, those low in CSE may doubt the quality of their ideas and seek external guidance, including that provided by AI[3,12]. We therefore hypothesize that individuals with higher CSE will reflect greater reliance on internal judgement and less likely to revise their decisions following AI advice.

We propose that mindfulness and CSE interact in shaping advice-taking behavior. Drawing on interactionist personality frameworks i.e. the cognitive-affective processing system[4,5,11], we argue that mindfulness may moderate the influence of self-efficacy on openness to AI input. For example, individuals low in CSE may be more receptive to AI advice when they are also high in mindfulness, as mindful awareness could enhance recognition of their uncertainty and increase thoughtful engagement with external input[5,6]. Conversely, among high-CSE individuals, mindfulness may reinforce selective engagement with AI, leading them to consider the recommendation without necessarily adopting it[7]. We hypothesize that mindfulness will increase the likelihood of decision revision among low-CSE individuals but have limited influence on those with high CSE.

In addition to these cognitive traits, we examine the potential moderating role of **gender-linked personality orientations**, conceptualized using the communal–agentic framework[9,10,30]. Drawing on social role theory[14], we distinguish between **communal traits** (e.g., warmth, empathy, cooperativeness), traditionally associated with femininity, and **agentic traits** (e.g., assertiveness, independence, dominance), traditionally associated with masculinity. This dimensional approach enables the study of gender-role orientations as continuous psychological dispositions, offering a more precise account of behavioural differences rather than binary sex-based comparisons[9,10,14,]. This interpretation is in line with Bakan's agency-communion framework which describes agency as striving for individuality and mastery, and communion as striving for connection and sharing[9,13]. Prior research suggests that individuals higher in communal traits are more receptive to external perspectives, while those higher in agentic traits prioritize autonomy and self-direction[9,10,15]. These traits have also been shown to influence how individuals process persuasive messages and social cues, particularly in cognitively demanding contexts[15].

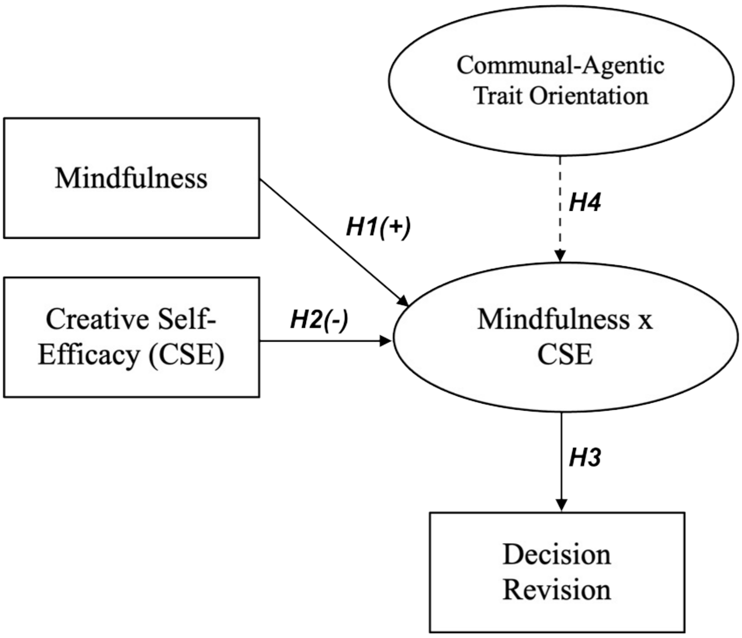
Related cross-cultural findings further suggest that individuals from collectivistic (communal) cultures report greater increases in decision confidence and creative self-efficacy when supported by AI, compared to individuals from individualistic (agentic) cultures[17]. This supports the broader premise that social-motivational orientations shape how algorithmic input is interpreted and applied. However, the interaction of gender-linked trait orientations with mindfulness and CSE in AI-assisted decision-making remains unexplored[11]. We hypothesize that communal-agentic orientations will moderate the mindfulness × CSE interaction with an amplified effect among communal-oriented individuals especially when they are both mindful and lower in CSE.

Hypotheses

- **H1**: Higher mindfulness will increase likelihood of revising decisions based on AI suggestions.
- **H2**: Higher CSE will decrease likelihood of revising decisions based on AI suggestions.
- **H3**: Mindfulness and CSE will interact to predict decision revision, such that mindfulness will increase likelihood of decision revision among individuals low in CSE.
- **H4**: The interaction between mindfulness and CSE will be moderated by communal-agentic trait orientation. Specifically, the mindfulness × CSE effect will be stronger among individuals higher in communal traits.

Figure 1 presents the conceptual framework summarizing the hypothesized relationships among mindfulness, creative self-efficacy, gender-linked trait orientation, and decision revision following AI input.

Figure 1
Conceptual framework.



Results

To examine the conditions under which individuals revise their decisions in response to AI-generated suggestions, we analyzed the effects of mindfulness, creative self-efficacy (CSE), and gender-role traits on response change. Below, we report the descriptive statistics, primary regression analyses, and interaction effects that tested our four hypotheses. Overall, the results support **H1** (mindfulness predicts openness to AI), **H3** (mindfulness and CSE interact), and **H4** (gender traits moderate this effect). **H2** (main effect of CSE) was not supported.

Descriptive Statistics and Initial Response Patterns

A total of 549 participants completed the study with the majority (393 participants, 71.6%) showing no change in their response after receiving AI input, while 65 participants (11.8%) increased and 91 participants (16.6%) decreased their ratings. Descriptive statistics for these variables are presented in Table 1.

Table 1
Descriptive Statistics of Main Variables

Variable	*M*	*SD*	Min	Max
Mindfulness	3.86	0.84	1.73	6.00
CSE	8.82	1.10	6.00	10.00
First response	2.69	2.69	1.00	4.00

Second response	2.59	0.78	1.00	4.00

A McNemar's test confirmed significant changes between the first and second responses, $\chi 2(6) = 44.28$, $p < .001$, indicating that the distribution of changes across response categories was not uniform, and therefore validating response change as the dependent variable.

Main Effects of Mindfulness and Creative Self-Efficacy

A multinomial logistic regression was conducted to assess the impact of mindfulness and CSE on the likelihood of changes (Increase or Decrease), with "No Change" as the reference category. We found that neither mindfulness nor CSE alone significantly predicted response change. The model converged with a residual deviance of 861.76 and an AIC of 873.76. Key results are summarized in Table 2.

Table 2

Multinomial Logistic Regression Predicting Change

Predictor	Coefficient	*SE*	*z*	*p*
(Intercept)	0.09	1.43	0.16	.310
CSE	-0.19	0.17	-1.19	.370
Mindfulness	-0.03	0.16	-0.22	.640

Interaction Effects: Mindfulness x CSE

Introducing an interaction term between mindfulness and CSE improved model fit (AIC = 869.18). The interaction was significant ($p = .041$), as was mindfulness ($p = .046$), indicating moderation (Table 3).

Table 3

Multinomial Logistic Regression Predicting Change with Interaction Term

Predictor	Coefficient	*SE*	*z*	*p*
(Intercept)	-14.84	7.13	-2.02	.066
CSE	1.50	0.81	1.81	.097
Mindfulness	3.91	1.83	2.09	.046*
CSE x Mindfulness	-0.45	0.21	-2.12	.041*

Note: $*p < 0.05$ indicates statistical significance.

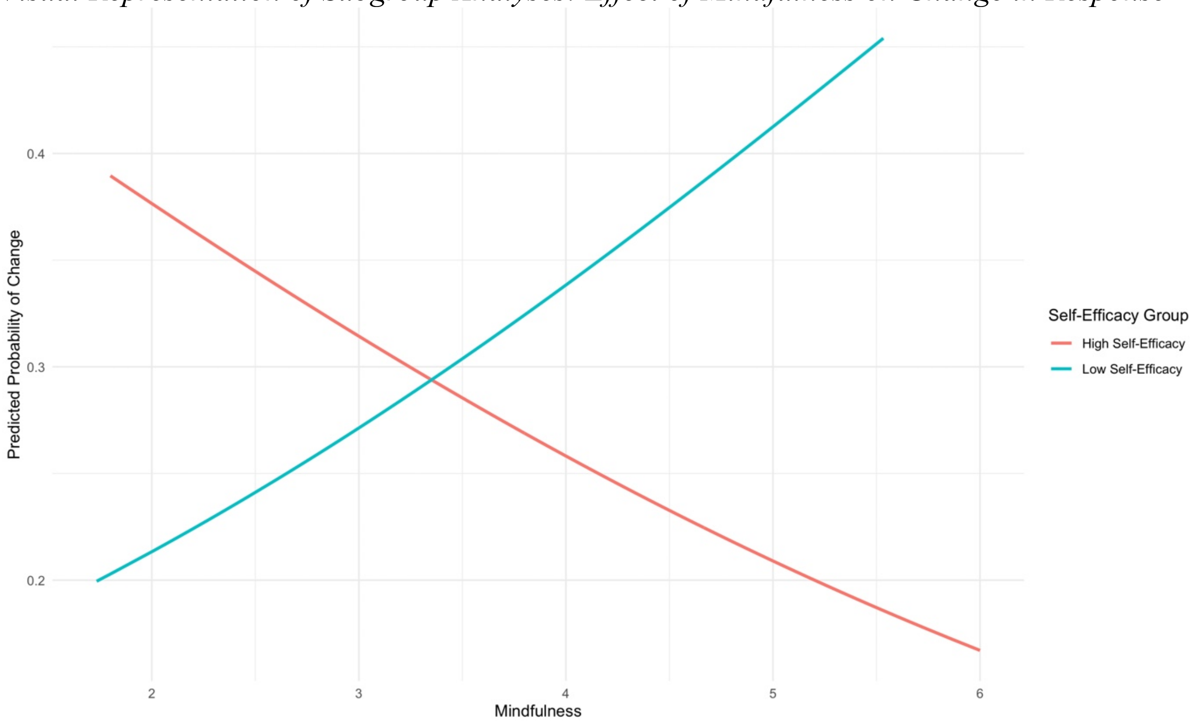
These results show that mindfulness alone significantly predicted changes in responses ($p = .046$), suggesting that individuals with higher mindfulness were more likely to experience a response change when AI input was provided. The interaction between CSE and mindfulness was also significant ($p = .041$).

To further investigate the significant interaction between CSE and mindfulness, a subgroup analysis was conducted. The self-efficacy measure was split into two subgroups: high CSE and low CSE, based on the median CSE score. A logistic regression model was applied to both subgroups to assess the effect of mindfulness on the likelihood of change.

The model showed that mindfulness did not significantly predict change in the low self-efficacy group (beta = 0.317, SE = 0.199, z = 1.592, p = 0.111). Although the estimate suggested a positive relationship, the lack of statistical significance indicates that for individuals with low self-efficacy, mindfulness did not have a meaningful impact on their likelihood of exhibiting a change in response. However, the analysis indicated a marginally significant inverse relationship between mindfulness and change for the high self-efficacy group (beta = -0.276, SE = 0.151, z = -1.820, p = 0.069). This suggests that for individuals with high self-efficacy, increased mindfulness was associated with a slight reduction in the likelihood of change, though the effect did not reach the conventional threshold for statistical significance ($p < 0.05$). The negative coefficient implies that mindfulness may have a suppressive effect on response change for this subgroup.

A visual representation of the interaction is displayed in Figure 2. For individuals with high self-efficacy, mindfulness seems to have a negative effect on the likelihood of change: as mindfulness increases, likelihood of change decreases. For individuals with low self-efficacy, mindfulness had a positive effect on the likelihood of change: as mindfulness increases, their likelihood of response change increases, and people are more receptive to input from AI.

Figure 2
Visual Representation of Subgroup Analyses: Effect of Mindfulness on Change in Response



Main Effects of Gender-Linked Traits

To examine how gender-linked personality traits influence openness to AI recommendations, we incorporated trait scores derived from the Personal Attributes Questionnaire (PAQ)[18]. This instrument captures self-perceived agentic-masculine and communal-feminine attributes along orthogonal dimensions[9,10,18,19]. Participants were not grouped categorically but instead scored along three continuous subscales: Agentic-Masculinity (PAQ_M), Communal-Femininity (PAQ_F), and Balanced (PAQ_MF), based on validated item groupings[20,21].

Univariate logistic regressions with PAQ subscales revealed no significant main effects (Table 4). Communal-Femininity (PAQ_F) showed an upward trend (Figure 3).

Table 4

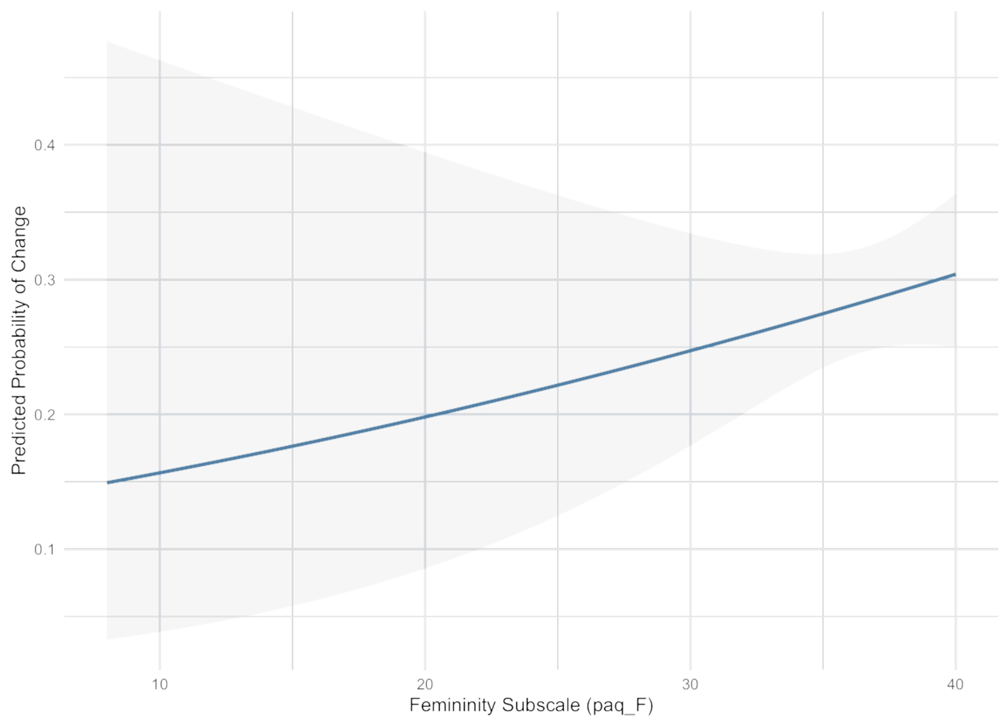
Univariate Logistic Regression Results for Gender Traits (PAQ) Subscales

Predictor	Estimate	Std. Error	z-value	p-value	Odds Ratio	95% CI
PAQ_M	0.03	0.03	0.79	0.432	1.021	(0.97, 1.08)
PAQ_F	-0.03	0.03	-1.30	0.192	1.035	(0.98, 1.09)
PAQ_MF	0.00	0.02	0.18	0.858	1.004	(0.96, 1.05)

Note: *$p < 0.05$ indicates statistical significance.

Figure 3

Effect of Communal-Femininity Traits on Change in Response



Interaction Effects: Mindfulness x Communal Traits

Including Mindfulness and PAQ_F (Communal-Femininity) and their interaction significantly improved prediction (Table 5). The PAQ_F × Mindfulness term was significant ($p = .0295$), showing that mindfulness enhanced the effect of communal traits on change likelihood. Figure 4 displays the predicted probability of response change as a function of Communal-Femininity scores.

Table 5

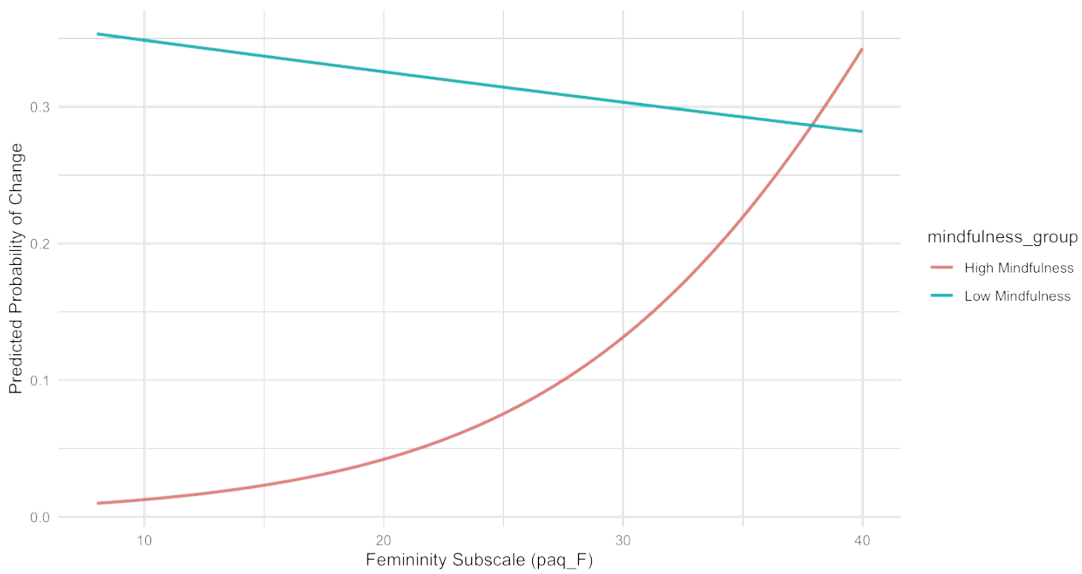
Interaction Model: Communal-Femininity and Mindfulness as Predictors of Change

Predictor	Estimate	Std. Error	z-value	p-value	Odds Ratio	95% CI
PAQ_F	-0.26	0.14	-1.89	0.058	0.7711	(0.59, 1.01)
Mindfulness	-3.11	1.39	-2.24	0.025*	0.0448	(0.00, 0.63)
PAQ_F x Mindfulness	0.08	0.04	2.18	0.030*	1.0085	(1.01, 1.17)

Note. $p < 0.05$ indicates statistical significance.

Figure 4

Visual Representation of Interactive Effects: Communal-Femininity and Mindfulness on Change in Response



Interaction Effects: Mindfulness x Communal Traits x CSE

Finally, we tested a three-way interaction among Communal-Feminity Traits (PAQ_F), Mindfulness, and CSE. As shown in Table 6, several terms approached significance (e.g., $p \approx .04–.07$). In particular, the interaction between communal traits and mindfulness remained significant, and the highest-order three-way term trended toward significance (p = .0662). Figure 5 illustrates these three-way effects, showing separate lines for low vs. high mindfulness and low vs. high CSE.

Table 6

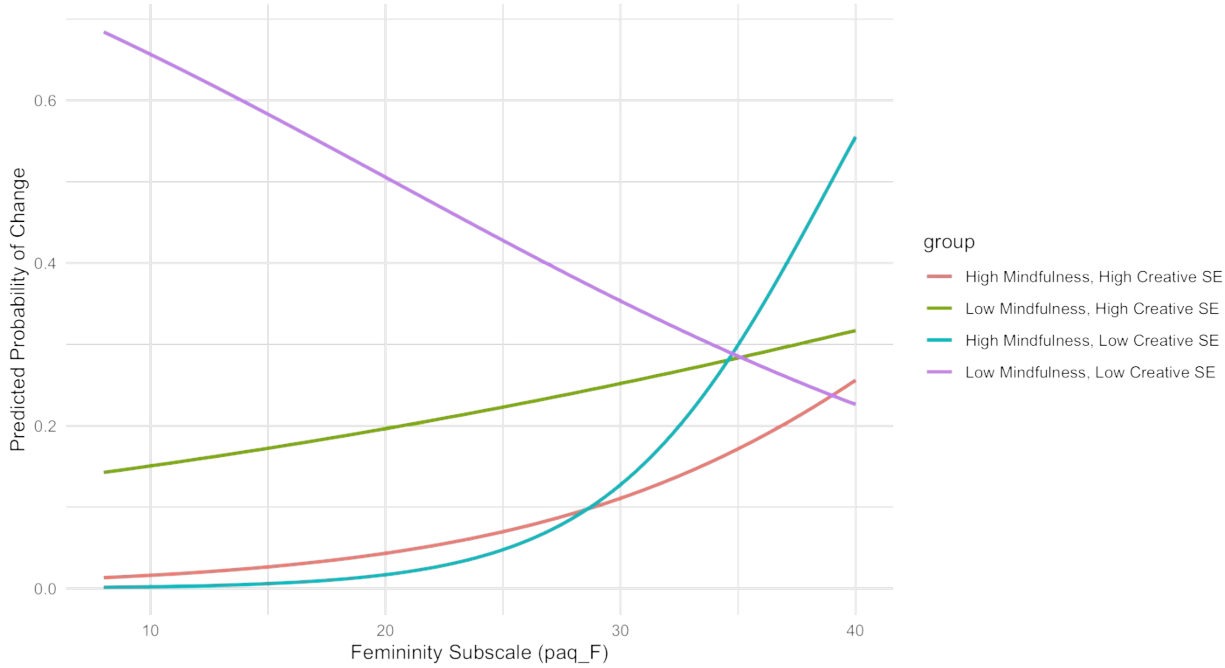
Three-Way Interaction Model: Femininity, Mindfulness and Creative Self-Efficacy as Predictors of Change

Predictor	Estimate	Std. Error	z-value	p-value	Odds Ratio	95% CI
PAQ_F x Mindfulness	0.97	0.48	2.04	0.042*	2.6401	(1.02, 6.42)
PAQ_F x CSE	0.37	0.20	1.84	0.066	1.4458	(0.97, 2.11)
Mindfulness x CSE	3.07	1.91	1.61	0.107	21.5465	(0.45, 664.96)
PAQ_F x Mindfulness x CSE	-0.10	0.05	-1.84	0.066	0.9073	(0.82, 1.01)

Note. $p < 0.05$ indicates statistical significance.

Figure 5

Visual Representation of Three-Way Interaction Plot: Femininity, Mindfulness and Creative Self-Efficacy as Predictors of Change



Discussion

Mindfulness and Openness to AI Suggestions

Our findings indicate that higher trait mindfulness is associated with greater openness to AI-generated suggestions, supporting H1. Participants who scored higher on mindfulness were more willing to revise their initial decisions after receiving input from the AI system. This suggests that mindful individuals process algorithmic advice in a receptive, less judgmental manner[5,6]. Prior research similarly shows that mindfulness reduces cognitive biases and automatic thinking, effectively "debiasing" decision processes[6,34]. Thus, consistent with dual-process models, mindfulness may engage more deliberative System 2 thinking i.e. analytical evaluation of the AI's suggestion, rather than defaulting to System 1 i.e. intuition or habit[4,44]. This capacity explains why more mindful individuals in our study were amenable to the AI's advice instead of dismissing it outright. Notably, mindfulness has been linked to greater openness and creativity in past work[5,44], and our results extend this notion to openness toward AI-generated input.

Creative Self-Efficacy and Resistance to AI Advice

We also found evidence for H2: higher CSE was associated with a lower likelihood of revising one's decisions based on AI suggestions. In other words, individuals who are more confident in their own creative judgment were less inclined to incorporate the AI's input. This inverse relationship aligns with research on advice-taking and overconfidence[12,17,38]. Decision-makers with strong confidence in their abilities tend to discount or undervalue external advice[8,12,39]. Our results suggest that such confidence may lead to a form of *egocentric advice discounting*[12]: those high in CSE appeared to trust their initial ideas over the AI's suggestions. This finding is consistent with prior work showing that people with greater self-assuredness in a task domain give less weight to others' input[7,38]. Thus, while creative self-efficacy is generally linked to improved creative performance[7,39], it may have the unintended effect of making individuals more rigid or autonomous in their decision-making, thereby diminishing their responsiveness to potentially useful AI recommendations[16,39,43]. This effect underscores the role of self-related beliefs in human–AI collaboration i.e. a rational AI suggestion might be ignored if the human user's self-efficacy is very high and unchecked by situational factors[12,39].

Interactive Effects of Mindfulness and Creative Self-Efficacy

Beyond these main effects, we observed a significant interaction between mindfulness and creative self-efficacy in predicting decision revision behavior, as hypothesized in H3. In our data, mindfulness particularly increased openness to AI input among individuals low in creative self-efficacy. Low-CSE individuals who were more mindful showed substantially higher likelihood of revising their decisions with AI input than low-CSE individuals who were less mindful[5,34]. In contrast, among those with high creative self-efficacy, mindfulness made little difference – highly efficacious people tended to resist AI advice regardless of mindfulness level[11,39]. This pattern supports H3 and suggests a compensatory mechanism: mindfulness appears to buffer or counteract some of the reluctance that low-CSE individuals might have in using external help[5,13,34]. One explanation is that mindfulness, through its emphasis on non-judgmental awareness and acceptance, helps low-CSE individuals regulate the insecurity or ego-threat that can arise when receiving suggestions[5,35,44]. Lacking confidence in one's creativity might normally induce anxiety or defensiveness (e.g., fear of being judged or of losing autonomy), which could either lead to outright rejection of advice or conversely over-reliance in an unproductive way[11,12,38]. Mindfulness likely enables a balanced approach: low-CSE individuals high in mindfulness can acknowledge their initial idea's fallibility without self-criticism and are calmly open to alternatives[34,36]. This interpretation aligns with self-regulation theories – mindfulness strengthens self-regulatory capacity to manage negative emotions and ego involvement[5,13,34,47]. Thus, a mindful low-CSE person can engage with the AI suggestion more thoughtfully rather than either defensively dismissing it or uncritically accepting it out of self-doubt.

Moderating Role of Communal vs. Agentic Orientation

Our final hypothesis, H4, proposed that the above mindfulness–CSE interaction would itself be moderated by individuals' communal vs. agentic trait orientation. The results confirmed this three-way interaction: the influence of mindfulness on openness to AI suggestions (especially for low-CSE individuals) was strongest for those high in communal orientation[9,14,15]. In contrast, the interactive benefits of mindfulness were diminished for those with a more agentic orientation[10,18,20]. This finding supports H4 and highlights the importance of personality orientations in technology-related behaviors[9,13]. Our results suggest that a communal person who is mindful and low in self-efficacy is especially likely to treat the AI as a collaborative partner and incorporate its suggestions, because doing so aligns with their intrinsic orientation toward cooperation and openness to others' contributions[9,14,21]. In contrast, a strongly agentic person may feel an internal drive to maintain control and originate ideas autonomously even when mindful, which could dampen their willingness to adopt an external suggestion[10,14,20]. By confirming our hypothesis, we prove that user traits related to social orientation substantially shape human–AI interaction patterns[25,27]. Communal, team-oriented users – especially if mindful and not overconfident in their own creativity – stand to benefit the most from AI decision support, whereas agentic users may require different approaches to engage them with AI[14,15,21].

Psychological Theoretical Implications

From a **dual-process perspective**, our findings suggest that mindfulness shifts users from intuitive, heuristic processing to more reflective, analytical evaluation when interacting with AI[4,6]. This aligns with evidence that mindfulness counters cognitive biases and promotes deliberate (System 2) thinking over impulsive (System 1) responses[4,6,34]. Mindful users, especially those low in self-efficacy, were more open to AI advice because mindfulness curbs ego-driven or anxious reactions and enhances attention to external input[5,34,44]. In line with **self-regulation theory**, mindfulness also appears to help users manage emotional responses to conflicting input[5,13,47]. A mindful low-CSE individual may experience doubt when contradicted by AI but remain receptive instead of shutting down or overreacting[12,34,35]. This self-regulation helps avoid both overconfidence and underconfidence, supporting more balanced decisions[13,36,47].

Another implication concerns **trust in AI and human–automation interaction**. Openness to AI suggestions can reflect trust or at least serious consideration of its input[12,26,29]. Our findings show that such trust depends not just on system transparency or performance, but also on user traits[12,26,33]. High CSE and agentic users showed lower willingness to revise their decisions, suggesting greater reliance on their own judgment. In contrast, mindfulness and communal orientation were linked to greater openness, indicative of higher trust[5,9,15]. This supports existing models of calibrated trust: optimal reliance on automation occurs when users adjust their confidence in AI relative to self-assurance. Prior work on algorithm aversion shows people often avoid AI input after errors[1,2]; our data refine this by identifying who is most prone (self-confident, agentic individuals) and who remains receptive (mindful, communal individuals)[5,9,25]. Trust-building may thus require targeting internal states: reducing ego defensiveness (via mindfulness or design) and framing AI as a collaborator[26,36,38].

Practical Implications for AI Adoption and Design

Our findings offer important practical implications for organizations implementing AI decision-support tools and for designers developing such systems[24,28]. **For AI adoption**, our results suggest that promoting a mindful mindset in end-users could enhance their openness to algorithmic assistance[5,34,36]. Companies could integrate mindfulness training or interventions into broader change management strategies when introducing AI technologies[35]. Our findings also highlight that users high in creative self-efficacy and agentic orientation may be natural resisters to AI input[7,10,39] – these are often experienced experts or highly independent thinkers whose intuition might conflict with algorithmic advice[12,25]. For these users, organizations could include involving them in the AI implementation process (increasing their sense of control and buy-in) and emphasizing the AI's role as augmentative (not replacing their expertise)[26,27].

For AI system design, the moderated effects we found suggest the value of adaptive, user-aware AI interfaces[22,24,26]. Systems could be designed to detect or allow input of user traits and then adjust how advice is presented[29,30,31]. For example, an AI assistant might provide more explanatory context or confidence metrics to a user identified as high CSE/agentic, to earn their trust and justify the suggestion while respecting their autonomy[12,23,38]. Conversely, users lower in self-efficacy or higher in communal orientation may respond better to a more collaborative and encouraging tone, where suggestions are framed as shared improvements rather than corrections[14,21,25,45]. In conclusion, a one-size-fits-all approach to AI advice may be suboptimal – our results argue for personalization in human-AI interaction, considering user mindfulness, confidence, and social orientation to improve both adoption and user satisfaction in human–AI interactions[12,24,37].

Limitations and Future Research

While this study provides novel insights, several limitations must be acknowledged, which also open avenues for future research.

First, the scope of context. Our experiment focused on decision revision within a specific task using AI-generated suggestions. It remains to be seen whether these findings generalize to different types of decisions (e.g., high-stakes versus low-stakes, creative versus analytical domains) or to other AI formats such as predictive versus prescriptive tools[22,24]. **Second**, issues of causality and measurement. Mindfulness, creative self-efficacy, and trait orientation were measured rather than manipulated. Future research using experimental manipulations such as mindfulness inductions or self-efficacy priming could establish directionality more clearly[34,35]. Additionally, our binary outcome (i.e., decision revision vs. no revision) captures limited process-level information. Complementary methods such as interaction logging could offer deeper insights into how traits shape engagement with AI[36,38]. **Third**, we did not systematically examine demographic or cultural variables, which may moderate or interact with the psychological traits studied. Communal versus agentic orientations are culturally influenced and testing our model across different cultural contexts or organizational settings could enhance generalizability[17,25]. Likewise, age and technological familiarity may shape trust in AI. For example, younger users may exhibit lower baseline algorithm aversion and may engage with AI differently[45]. **Fourth**, the AI system used in our study functioned as a black-box advisor with assumed reliability. In practice, user receptivity depends not only on internal traits but also on system transparency, error rates, and the quality of explanation[23,26,45]. Future research could explore how individual traits interact with AI performance variability. For instance, would a mindful user remain open to suggestions after witnessing AI errors? Understanding how trust in AI evolves over time in response to system performance could be an important contribution. **Fifth**, we did not examine longitudinal trajectories of user behavior. It remains unclear whether the observed influences of mindfulness, self-efficacy, and social orientation are stable over time or subject to adaptation through repeated interaction with AI systems[17,24]. Longitudinal and adaptive research designs are needed to map how user–AI relationships evolve and whether openness to AI can be cultivated, sustained, or undermined over time.

Methods

Study Design and Preregistration

This study employed a within-subject experimental design to investigate how individual traits, namely mindfulness, creative self-efficacy (CSE), and gender-role orientation, influence receptivity to AI-generated advice in a decision-making context. The design included both AI-absent and AI-present conditions, allowing direct assessment of decision change after AI input. The study was preregistered on the Open Science Framework (OSF; *link blinded for peer review*) and received ethical approval from the Institutional Review Board of the Department of Applied Psychology: Work, Education, Economy at the University of Vienna (Approval Number: 2019/A/002).

Participants and Procedure

Participants were recruited via the online platform Prolific, targeting professionals based in the United Kingdom with occupational exposure to AI systems or decision-making technologies. Eligibility screening ensured that respondents were currently employed in sectors such as business analytics, R&D, sales, or marketing, domains where AI-assisted decision-making is increasingly prevalent.

A total of 549 participants (after quality control and screening) completed the full survey hosted on Qualtrics. All participants provided informed consent electronically before beginning the study. The survey included embedded logic to terminate participation if consent was not granted. Compensation was provided in line with Prolific's ethical payment guidelines.

After providing demographic data, participants completed trait-level measures of mindfulness, creative self-efficacy, and gender-role traits. They were then randomly assigned to a sequence of decision-making scenarios designed to test baseline judgments (without AI input) and response shifts after receiving AI-generated advice, with scenario order counterbalanced to mitigate sequence effects.

In the non-AI condition, participants reviewed sales data and bar charts for four products and were asked to allocate a marketing budget based solely on their independent analysis. In the AI-assisted condition, they were shown the same data along with an AI-generated recommendation regarding optimal budget allocation and given the opportunity to revise their original decision. This design enabled us to observe whether, and how, participants' decisions changed in response to AI input. The survey concluded with a final assessment of creative self-efficacy and a full debrief.

Measures

Mindfulness was assessed using the 15-item Mindful Attention Awareness Scale (MAAS)[5]. Items (e.g., "I find myself doing things without paying attention") were rated on a 6-point Likert scale. The scale showed excellent internal consistency ($\alpha = .90$). Higher MAAS scores reflect greater dispositional mindfulness, capturing attentional awareness and reduced automaticity.

Creative Self-Efficacy (CSE) was measured using the 3-item Creative Self-Efficacy scale[7] and 6-item subscale of the Short Scale of Creative Self (SSCS)[45]. Participants rated items such as "I trust my creative thinking skills" on a 5-point Likert scale. The subscale demonstrated good reliability ($\alpha = .85$). While the full SSCS includes a Creative Personal Identity subscale, only the CSE component was used in this study to capture confidence in generating novel solutions.

Gender-Role Traits i.e. communal and agentic traits were measured using the Personal Attributes Questionnaire (PAQ)[18]. The communal-femininity (PAQ_F) and agentic-masculinity (PAQ_M) subscales each consist of 8 bipolar adjective pairs (e.g., "Not at all sympathetic – Very sympathetic" for PAQ_F; "Not at all independent – Very independent" for PAQ_M). Subscale reliabilities were acceptable ($\alpha = .78$ for PAQ_F, $\alpha = .75$ for PAQ_M). The two dimensions were orthogonal, allowing for independent and interactional modeling of trait orientations[19].

Decision Change After AI Input was measured as the primary outcome variable. We recorded whether participants revised their decision between the non-AI and AI-supported phases. This outcome was categorized into:

- **Change**: The participant changed their response following AI recommendations.
- **No Change**: The decision remained unchanged.

Statistical Analysis

To examine how individual traits influence decision revision in response to AI-generated advice, we employed **multinomial logistic regression (MNL) models** using R (version 4.2, nnet package). The dependent variable was a categorical outcome reflecting direction of change between initial and final decisions: **Change**, or **No Change** (reference category). This outcome structure reflects our interest in whether participants updated their decisions in either direction following AI input, and it captures directional nuance relevant to the psychological mechanisms proposed in our hypotheses (e.g., openness vs. resistance to AI suggestions).

All continuous predictor variables: **mindfulness**, **CSE**, and **gender-role** traits, were standardized (z-scores) prior to analysis to allow accurate interpretation of main and interaction effects. Our analysis followed a nested model-building approach to systematically test Hypotheses H1 through H4:

- **Model 1: Main Effects (H1 & H2):** Included mindfulness, CSE, PAQ_F (communal-femininity), and PAQ_M (agentic-masculinity) as predictors to assess whether these traits individually predicted likelihood of decision change.
- **Model 2: Two-Way Trait Interaction (H3):** Added the **mindfulness × CSE** interaction to test whether mindfulness moderated the relationship between CSE and decision revision.
- **Model 3: Trait Orientation (Extension of H2 & H3):** Included the full set of gender-role traits (PAQ_F, PAQ_M, PAQ_MF) to examine how personality orientation contributed to openness or resistance.
- **Model 4: Moderated Trait Interactions (Part of H4):** Introduced two-way interactions between **mindfulness × PAQ_F** and **CSE × PAQ_F** to explore whether communal orientation influenced the individual effects of mindfulness and CSE.
- **Model 5: Three-Way Interaction (H4):** Tested the hypothesized **mindfulness × CSE × PAQ_F** interaction to determine whether the combined influence of mindfulness and CSE on decision revision was amplified among individuals higher in communal-femininity traits.

All models evaluated using **Akaike Information Criterion (AIC)** and **likelihood ratio tests** to assess improvements in model fit. Odds ratios (OR) and 95% confidence intervals (CI) are reported to aid interpretability. To probe significant interactions, we conducted **simple slopes analyses** and **plotted predicted probabilities** at ±1 SD of the interacting variables (Figures 1–4).

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Author Contributions

Deeviya Francis Xavier, Zoe Danielle Hughes and Christian Korunka contributed equally to study conceptualization and methodology design. DFX drafted and wrote the manuscript. DFX and ZDH led the data collection, statistical analyses and data interpretation. CK and ZDH provided critical revisions and theoretical framing.

Competing Interests

The authors declare no competing interests.