AI Empowerment of Asian-Australian Migrant Workers: Progress, Potentials, and Patterns

Yingnan Shi
Centre for Business Data Analytics, Business School
University of Western Australia
Perth, Australia
Email: yingnan.shi@uwa.edu.au

Chao Ma
Research School of Management
Australian National University
Canberra, Australia

Abstract

As Artificial Intelligence (AI), particularly generative AI, becomes integral to organizational practices, its capacity to augment human capabilities presents opportunities and challenges. We focus on the integration of AI into the workplace, emphasizing its impact on Asian-Australian migrant workers—a group frequently transitioning from developing to developed economies and facing unique workplace challenges. We explore how AI may not only enhance job performance and integration by overcoming cultural and linguistic barriers but also influences perceptions of overqualification among these workers. Employing psychological empowerment theory and the information systems fusion framework, alongside time-lag surveys and K-means clustering, we introduce a novel AI empowerment scale and investigate the nuanced effects of AI on immigrant workers. Our findings reveal that while AI-driven psychological empowerment increases technology infusion use and overall job performance, it also underscores significant variations in how different demographic groups experience these benefits, offering new insights into the complex interplay between AI empowerment and employee perceptions. The study advances psychological empowerment and perceived overqualification research by revealing AI's varied impacts across workforce clusters. It underscores the need to manage AI carefully to avoid workplace inequalities and calls for further exploration of AI's dynamics in diverse settings.

Keywords: AI Empowerment, AI-human Collaboration, Artificial Intelligence, Migrant Workers, Technology Adoption.

1 Introduction

After years of hype and speculation, new generations of intelligence systems, especially generative AI software—as defined by Dwivedi et al. (2023) as advanced technologies capable of understanding and generating human natural language using large-scale machine learning models—has finally left the realm of science fiction to become a clear organizational priority (Ozturkcan & Gashi Nulleshi, 2024). In 2020, Schwartz et al. (2020) projected that, with its unprecedented computational power and efficiency, AI would add US$13 trillion to the global economy over the next decade, redefining job roles and operations across various sectors. Based on Precedence Research (2024), in 2024, the global artificial intelligence (AI) market was valued at USD 638.23 billion and is projected to grow to approximately USD 3,680.47 billion by 2034, reflecting a compound annual growth rate (CAGR) of 19.1% over this period. Its

Received on 15 April 2024, accepted on 18 November 2024 after 4 rounds of review with Karlheinz Kautz as accepting editor.

growing influence is particularly evident in Information Systems (IS), where AI's promise of augmenting human capabilities is being tested in real-world applications (Amankwah-Amoah et al., 2024; Dwivedi et al., 2023; Hughes et al., 2021). However, a thorough understanding of how AI applications can be effectively promoted to empower workers, especially in terms of inducing adequate behavioral responses, remains unclear (Enholm et al., 2022; Perifanis & Kitsios, 2023).

Addressing this challenge is crucial for harnessing the full potential of AI within diverse workforces, particularly among migrant workers. As Lindström et al. (2020) note, migrant workers transitioning from developing to developed economies find AI to be a crucial lever for economic, social, and environmental integration in their host countries. Among these migrant workers, AI's transformative opportunity is particularly significant for Asian workers. First, according to Hanson (2022), migrant workers, particularly ones born in East and South Asia, have contributed significantly to job growth in AI-related occupations since 2000, underscoring the technology's relevance for these migrant labourers. Second, recent studies demonstrate that Asian individuals exhibit a higher receptivity toward AI than other ethnic groups. For instance, Ho et al. (2023) found that Asian individuals place a higher level of trust in Emotional AI[1]—systems that read, classify, and interact with human emotions—compared to their Western counterparts. This trust suggests a smoother integration for Asian workers, marked by increased receptivity to AI-driven feedback and quicker adaptation to AI-human collaboration initiatives (Mantello et al., 2023). Given these cultural variations in relatedness, trust and receptivity, it is critical for AI designers to consider these preferences when developing tools that augment the capabilities of immigrant workers in AI-driven environments.

We have seen discussions suggesting that AI's advanced capabilities provide substantial benefits to migrant workers. These technologies, according to Hillmann (2022) and Hussain et al. (2024), help bridge language barriers, offer access to previously unreachable training programs, aid in navigating complex work and residency regulations, and capitalize on unique skills and experiences to boost job performance. As emphasized by Wang et al. (2023), AI-enabled technological supports are both functional and transformative, enabling immigrant workers to fully integrate and succeed in their new environments. Furthermore, AI is fostering empowerment beyond productivity and efficiency gains by encouraging organizational citizenship behaviors (OCBs) like constructive voicing, which are crucial for organizational adaptability and improvement (Karimikia, 2017; Karimikia et al., 2020).

We further argue AI-driven empowerment also reaches into the psychological domain, offering benefits beyond mere material enhancements of productivity and efficiency. To understand this empowerment, we applied Spreitzer (1995)'s framework of psychological empowerment, a motivational construct manifesting through four cognitions: meaning, competence, self-determination, and impact. This framework reflects an individual's

---

[1] *Emotional AI systems can dynamically adjust responses and interactions based on real-time emotion recognition, context awareness, and personalized feedback mechanisms, enhancing usability and effectiveness by tailoring the user experience to individual emotional states and thus improving user satisfaction across various applications and industries, see Ho, M. T., Mantello, P., & Ho, M. T. (2023). An analytical framework for studying attitude towards emotional AI: The three-pronged approach. MethodsX, 10, 102149. doi.org/https://doi.org/10.1016/j.mex.2023.102149 .*

perceptions of available resources and their active orientation toward their work role. We applied this construct to the context of workers' interactions with AI systems. This application helps us understand the nuanced empowerment journey AI provides: On one hand, as Eilers et al. (2022) suggest, psychological empowerment driven by AI can significantly enhance employee effectiveness, transforming not only workflows but also the psychological relationship between employees and organizations, fostering a more engaged and proactive workforce. As Hassandoust and Techatassanasoontorn (2022) also suggest, the psychologically empowered infusion use of new technologies may not only simplify routine tasks but also deepen engagement with and utilization of new technological applications, thereby enriching the work experience and facilitating more profound interactions with technology. On the other hand, while AI can significantly improve job performance and workplace integration, it may also lead to adverse effects. Some workers may feel inadequate in adapting to the changes brought by new intelligent systems (Chen et al., 2022), while others may experience overqualification, resulting the improvement in job performance could paradoxically lead reduced job satisfaction and cause related issues.

The above discussion reveals significant complexities in managing technological advancements to ensure they benefit rather than inadvertently harm those they are intended to aid: Despite the opportunities AI presents for enhancing the integration and effectiveness of migrant workers, careful management is necessary to avoid exacerbating disparities. To achieve this, a sufficient understanding of AI's empowerment effects on Asian immigrant workers is essential. Specifically, several research gaps remain unaddressed: there is a scarcity of research on how AI empowerment can trigger behavioral changes, such as infusion use, constructive voicing, job performance, and perceived overqualification. Additionally, there is limited research identifying how different groups respond differently to AI empowerment. Although research on AI empowerment is growing, the field still lacks a robust, validated AI empowerment scale. Finally, there is a shortage of research examining the micro-level impacts of AI on ethnic minorities, which impedes the development of practical implications for AI designers and developers. These gaps must be addressed to create more inclusive, empowering, and effective AI systems that can be applied in diverse workplace contexts.

Using an Australia-wide survey, we employ psychological empowerment theory and the IS fusion framework, alongside methodologies like three-wave time-lag surveys and K-means clustering, to uncover the complex dynamics of AI in workplace settings. Specifically, we address the research question: "How does psychological empowerment, facilitated by AI-enabled intelligent systems, influence the infusion use of AI, job performance, constructive voicing behaviors, and perceived overqualification among Asian-Australian migrant workers?" Our study also analyzes how demographic factors and job roles intersect with AI empowerment to produce varied outcomes among different worker clusters. This study thus significantly advances the literature on AI empowerment by validating a novel AI empowerment scale and exploring how AI influences behavioral changes, such as constructive voicing and job performance, as well as its nuanced effects on perceived overqualification. Additionally, we extend the discussion on how AI empowerment can shape the experiences of marginalized groups, particularly Asian Australian immigrants. Our research offers new insights into how AI ethics can promote diversity and inclusion, providing a framework for understanding AI's micro-level impacts on ethnic minorities in the workplace. Furthermore, we provide practical guidance for implementing AI empowerment in organizational IT strategies, highlighting the need for tailored support mechanisms to address the diverse reactions of employees to AI, ensuring it serves as a unifying rather than dividing tool. We also emphasize the importance of personalized managerial interventions for successful AI integration. For AI designers and developers, we underscore the importance of incorporating AI empowerment into UX design, in addition to technical functionalities, which have been overemphasized in current literature. By providing a foundational understanding of these interactions, this research sets the stage for further exploration of how AI strategies can be tailored to enhance inclusivity and effectiveness within diverse organizational contexts.

2 Literature review

Structured across three thematic sections, our review begins by exploring how AI, as part of intelligent systems, augments human capabilities, reshaping traditional work practices and decision-making processes. It then transitions to analyzing how psychological empowerment, catalyzed by AI, translates into various behavioral outcomes such as job performance and so on. Finally, it addresses the specific context of Asian Australian immigrants, evaluating how AI impacts their workplace experiences and intersects with issues of ethnic identity and cultural integration. This comprehensive review aims to delineate the multifaceted effects of AI on employee empowerment, behavior, and adaptation within diverse organizational settings.

2.1 Artificial Intelligence and psychological empowerment

We situate our study in the context of intelligent systems—in our case, Artificial Intelligence (AI)-enabled systems—in augmenting human capabilities and transforming human work behaviors. Intelligent systems are commonly defined as a computer-assisted system that uses computational tools such as learning algorithms and statistical models to provide knowledge for problem solving and decision making (Von Krogh, 2018). These systems, particularly those enhanced by AI, are now not merely tools for task execution but are capable of learning from and interacting with their environment in complex, often probabilistic ways that extend beyond traditional deterministic programming (Wu-Gehbauer & Rosenkranz, 2024). This positions these systems as active collaborators in the workplace, capable of augmenting human intelligence by managing complex and ambiguous problem-solving tasks traditionally handled by humans. This augmentation, where humans and machines collaborate closely to perform tasks (Jarrahi et al., 2023), ensures that humans retain responsibility for critical decision-making even when supported by AI systems (Chen et al., 2022; Cheng et al., 2022; Shi & Deng, 2024).

Granted, using AI to augment human capabilities across various industries exemplifies a dual narrative of opportunities for enhancement and adaptation challenges. For instance, Benbya et al. (2020) illustrate how AI-based systems enhance diagnostic accuracy by aiding physicians in interpreting complex digital images. Despite these advances, there remains a significant learning curve as medical professionals reconcile these new tools with conventional microscope-based diagnostics. Furthermore, IBM (2023) reports that AI facilitates a shift in business processes by simplifying routine tasks, thereby allowing employees to engage in more strategic activities that enhance business efficiency. Nonetheless, this shift requires employees to develop new skills and adapt to changing roles within AI-enhanced workflows. Among these cases, as Sarker et al. (2024) argue, AI has the potential to augment human intellectual capacities, promoting effective collaboration within teams. Yet, the integration of AI into daily operations involves adjustments in decision-making processes and team dynamics, presenting both a strategic advantage and a challenge, which underscores the complex interaction between AI's transformative potential and the need for adaptive strategies in its practical implementation.

We attempt to understand this adaptation by borrowing and appropriating Spreitzer (1995)'s "psychological empowerment" construct framework. This construct was conceptualized as an employee's experienced psychological state based on cognitions about themselves in relation to their work role. It is a motivational construct manifested in four key cognitions: meaning, competence, self-determination, and impact. Together, these dimensions create an overall sense of empowerment that reflects an individual's orientation to their work role. Specifically, *Meaning* refers to the value that an individual attaches to their work, based on their own standards and ideals. This concept was originally initiated by Thomas and Velthouse (1990). When employees find their work meaningful, they are more likely to be engaged and committed. Developed from Gist (1987) and Bandura (1990)'s self-efficacy, *competence* is the belief in one's ability to perform tasks skillfully. This belief in personal capability is crucial for taking on challenges and persisting in the face of difficulties. *Self-Determination* was adapted from Deci and Ryan (2008) and reflects the degree of autonomy and freedom employees feel they have in their work. It involves having control over how tasks are carried out and the ability to make decisions regarding one's work. *Impact* refers to the extent to which an individual feel they can influence organizational outcomes (i.e., employees who feel their actions make a difference are more likely to be proactive and involved in their work and thus be more empowered). It is adapted from Ashforth (1989)'s research regarding experience of powerlessness and Martinko and Gardner (1982)'s research about learned helplessness. We appropriated this construct for a specific and increasingly important context—employees, particularly Asian Australian migrant workers, using intelligence systems (especially with the recent AI boom) in their workplace. Our construct also examines this motivational perspective and adapted the aforesaid four dimensions[2]. Moreover, structurally, this construct, as outlined by Spreitzer (1995), is a second-order construct, meaning that psychological empowerment is not directly measured but is instead understood through four underlying dimensions. Spreitzer (1995) also offers a structured validation process for later researchers to follow. These guidelines help subsequent researchers, like us, extend, evolve, adapt, and develop the construct, and we have seen many good instances in recent years. For instance, Seibert et al.

---

[2] *Particularly, the meaningfulness dimension captures the extent to which the AI system's knowledge is perceived as personally significant and relevant to the worker's tasks. For Asian-Australian immigration workers, our research suggests that the AI system provides crucial insights that are highly relevant to their work, especially in areas like decision-making, case analysis, and improving human-AI collaboration in immigration processes. Competence refers to the workers' belief in their ability to use the AI system effectively to enhance their research or job-related tasks. Specifically, for immigration workers, this includes feeling confident in using AI to navigate complex immigration issues and applying AI-driven insights to make informed decisions. The self-determination dimension reflects the autonomy and freedom workers experience when using AI systems. In our research on Asian-Australian immigration workers, this involves having the freedom to choose how they integrate AI into their workflows, including deciding on methodologies and approaches that best suit their tasks. Impact refers to the perceived influence that the AI system's knowledge has on the worker's ability to affect outcomes in their work environment. In our context, this means how the AI system helps workers better understand human-AI collaboration dynamics, control the analysis process, and influence decisions that shape immigration policies or case outcomes.*

(2004) introduced the concept of an "empowerment climate" as a higher-level construct that transformed the individual-level construct of psychological empowerment. Many of these studies are in the information systems field. For instance, Kim and Gupta (2014) explore the role of psychological empowerment in the successful infusion of information systems into users' work lives. Hassandoust and Techatassanasoontorn (2022) operationalized psychological empowerment within the IS context, relating it specifically to IT usage. Notably, their research involved end-users of CRM systems from organizations in New Zealand, with all measures adapted to fit the CRM context. Oetting (2009) adapted Spreitzer (1995)'s psychological empowerment construct to the context of consumer marketing processes, establishing a new construct called Empowered Involvement (EmI). Ng and Kim (2009) reinterpreted psychological empowerment by introducing the concept of "user empowerment," which reflects an individual's orientation towards system usage. Chen et al. (2022) appropriated the concept of psychological empowerment by adapting it to the knowledge context, resulting in a new construct called Intelligent System Knowledge Empowerment. Albrecht et al. (2021) introduced the concept of "Pro-Environmental Meaningful Work" (PEMW), and they tested how it acts as a mediator between corporate environmental responsibility and pro-environmental employee outcomes in the workplace. Zaza and Junglas (2016) established a new construct called "IT Empowerment," focusing on how employees engage with technology in the workplace. We referenced these prior studies when implementing our appropriation of the construct.

Notably we also separated our constructs from other potentially similar constructs, such as AI use, AI integration, AI collaboration, and AI transformation. Relevant details are provided in Appendix 5 to ensure a smooth reading experience.

2.2 Behavioral outcomes of empowerment: Infusion use, Job Performance, Perceived Overqualification, and Constructive Voicing

Psychological empowerment leads to behavioral changes in the workplace. Research has consistently shown that empowered individuals are more likely to demonstrate persistence and resourcefulness, facilitating easier adaptation during the implementation of intelligent systems. These systems tend to introduce significant shifts in business processes and employee routines (Beaudry & Pinsonneault, 2005), and AI-enabled systems are not an exception (Afiouni & Pinsonneault, 2023). While AI augmentation presents opportunities for upskilling, it also necessitates substantial changes as employees must adapt to new technologies and integrate them into their daily workflows (Jaiswal et al., 2022).

One significant outcome is the infusion use of information systems, which is defined by Schwarz (2003) as the extent to which a system's capabilities are fully utilized, seamlessly integrated into work processes, and maximized to enhance job performance. Employees are more inclined to fully utilize complex systems, such as enterprise systems, when they are confident in their skills and have autonomy in determining how to comprehensively use the system (Kim & Gupta, 2014). Sehgal (2007) notes that when users perceive the system's usage as aligning with their personal needs and desires, they consider such use important and personally relevant. This alignment motivates users to engage deeply with the system, utilizing its features extensively to perform tasks (Hsieh & Wang, 2007).

Achieving optimal job performance is also a critical goal in management information systems research. According to Methot et al. (2016), job performance is defined by the effectiveness and productivity with which an individual completes specific tasks and responsibilities associated with their role. Empowerment not only reflects an employee's beliefs based on meaning, competence, self-determination, and impact but also captures the interplay between technology and work, which includes the belief an employee holds about their work role and their motivation to engage in behaviors that enhance job performance (Ng & Kim, 2009). Strong beliefs in competence can enhance employees' confidence in managing changes and viewing challenging tasks as attainable (Herold et al., 2007; Vardaman et al., 2012). Similarly, as Bankins et al. (2024) summarize, the integration of AI systems into organizational practices can empower employees by providing new tools and resources, reducing work demands, and enhancing job satisfaction, ultimately leading to psychological empowerment that increases job performance

Constructive voice, according to Krefft et al. (2024), consists of workers' voluntary expressions of specific, constructive-intended, and future-change-oriented messages in the workplace. By viewing challenges as surmountable, employees become more involved with their colleagues, reducing the likelihood of discrepancies with their role expectations and minimizing role conflict. Reduced role conflict alleviates psychological strain, allowing employees to focus more on problem-solving and decision-making for work objectives (Keith & Frese, 2005; Muraven & Baumeister, 2000). A robust sense of empowerment encourages employees to anticipate and address issues proactively and cooperatively, fostering organizational citizenship behaviors such as voicing behaviors, which are crucial for organizational adaptability and improvement (Karimikia, 2017; Karimikia et al., 2020).

Notably, the aforementioned four dimensions of psychological empowerment—meaning, competence, self-determination, and impact—could significantly influence behavioral outcomes like job performance and constructive voicing. While Spreitzer describes these dimensions as "collectively" fostering an overall sense of empowerment, each aspect of AI psychological empowerment plays a unique role in shaping employee engagement with tasks and interactions with AI systems, thereby driving improvements in performance and voicing behaviors: First, since the meaning dimension refers to how perceivably valuable or relevant an employee finds their work in relation to their ideals or standards, when AI systems provide perceivably meaningful insights, employees are more likely to engage deeply with the technology and view its integration into their workflow as purposeful. As employees find greater meaning in their work, they become more motivated to invest effort, thus enhancing job performance, particularly during a digital transformation process (Yildiz et al., 2024). In AI-augmented environments, where the system's outputs could directly influence decision-making and problem-solving, employees who attach high personal value to these systems may be more inclined to maximize their utility, leading to infusion use which, in turn, leads to better job outcomes as employees are more thorough and effective in their work. Constructive voicing could be similarly impacted by meaning, as employees who perceive their work as meaningful are more likely to feel a sense of responsibility to improve processes, provide feedback, and engage in change-oriented behaviors that benefit the organization. This pathway aligns with Hwang et al. (2023), who found that coaching leadership can promote employees' sense of meaningfulness in their work, though our focus here is on how AI systems facilitate this sense of purpose. Second, the sense of compentency, once heightened, could promote job performance, as employees become more resilient, willing to experiment with AI tools, and capable of navigating complex tasks. Immigrant workers often face various career barriers, such as social and political pressures, economic constraints, and the stress of cultural differences between their home and host countries (Schultheiss, 2015). Enhanced perceived competence may help them address these barriers. When immigrant workers feel capable, they are also more likely to engage in voicing behaviors (Gardner, 2010), making this a key area where large language models can particularly exert a beneficial effect. Third, in AI-augmented environments, the self-determination dimension plays a critical role in empowering employees to decide how and when to use AI tools. When employees have the freedom to integrate AI into their workflows as they see fit, they experience greater satisfaction and engagement (Kim & Gupta, 2014), which improves performance. Furthermore, self-determination can positively influence constructive voicing; employees with greater autonomy feel empowered to suggest process improvements and contribute to decision-making, fostering a work environment where they feel free to express ideas. Finally, the impact dimension relates to employees' belief that they can influence organizational outcomes (Spreitzer, 1995), which is essential for fostering proactive behaviors. Management literature generally agrees that employees' self-assessment of impact significantly influences constructive voicing behaviors (Burris et al., 2013): When employees feel that their input matters—and assuming other factors, such as employee-supervisor alignment, are met—they are more likely to speak up. An increased sense of impact also enhances job performance, as employees observe the direct effects of their contributions on organizational success. Prior Management research supports this pathway. For instance, a sense of impact, often linked to positive emotional affect, improves job performance (Côté, 1999). For another, job satisfaction and organizational commitment are shown to correlate with work engagement and performance, indicating that employees' sense of impact significantly enhances their performance (Tadampali & Hadi, 2017). Our research adopts a new angle by examining AI empowerment, with a consideration of the impact dimension within this empowerment.

Perceived overqualification refers to a subjective appraisal where individuals consider themselves to possess more education, experience, or skills than required by their jobs (Ma et al., 2020). Research has shown that many highly educated immigrant workers often find themselves in entry-level positions or are forced to pursue new career paths upon relocating, leading to the phenomenon of overqualification (Dolan et al., 2022; Mackey et al., 2022). This places immigrant workers in a situation where they feel their skills and qualifications exceed the demands of their jobs. As AI technology becomes more sophisticated, workers who experience higher levels of psychological empowerment—feeling more competent, impactful, and autonomous in their roles—are more likely to let AI enable them to take on more complex tasks, fostering a sense of mastery and meaningful contribution to their work, and offering these technologies that enhance perceived competence, impact, and autonomy allows workers to reshape their roles to better align with their strengths, motivations, and passions. As Demir et al. (2024) suggest, this can help employees feel more adequately challenged and aligned with their job responsibilities, thereby reducing the perception of overqualification. In this sense, AI becomes a tool for workers to reclaim a sense of value and fulfillment in their roles, mitigating the negative effects of overqualification. Conversely, recent reports highlight a rise in AI-induced overconfidence (Sison et al., 2023; Underwood, 2024), where individuals feel overly capable due to substantial assistance from advanced intelligence systems, which could be particularly problematic when those with limited AI knowledge or experience overestimate their understanding of AI's capabilities in augmenting their work (Horowitz & Kahn, 2024; Zhang, 2023). Furthermore, as AI increasingly takes over both routine and complex tasks previously managed by employees (Huang & Rust, 2018), some workers may develop a sense of insecurity and underutilization (Dou, 2023). Witnessing AI's ability to handle these tasks can amplify the perception that their own skills and qualifications are no longer fully utilized, thereby increasing feelings of overqualification. This dual effect highlights the critical need for thoughtful AI implementation, as it has the potential to either empower workers or exacerbate feelings of underutilization, depending on the specific tasks involved.

2.3 Behavioral outcomes in Asian Australian Context and ethnic identity

Asian Australian immigrants face unique challenges in the workplace, often viewed through the lens of the "invisible model minority" stereotype (Yip et al., 2021). Some researchers and practitioners use the term 'bamboo ceiling,' first introduced by Hyun (2005) in her book *Breaking the Bamboo Ceiling: Career Strategies for Asians*, to describe the invisible barriers that prevent qualified Asian individuals from attaining leadership positions in the U.S., analogous to the 'glass ceiling' that impedes the advancement of women. Some researchers have given the 'bamboo ceiling' a narrower definition: Lu (2023) describes it as a phenomenon where, despite notable educational and economic achievements, Asians, particularly East Asian migrants, are disproportionately underrepresented in leadership roles. This underrepresentation is often attributed to pervasive stereotypes that East Asians lack creativity, which is deemed essential for leadership in U.S. culture. The 'bamboo ceiling' thus encapsulates the barriers and subtle biases that prevent Asians from reaching the highest ranks of professional leadership, despite their competence and qualifications. However, as Ho (2020) and Sum et al. (2023) have noted, this phenomenon is not exclusive to America nor limited to East Asian communities. In fact, the impact of the 'bamboo ceiling' on Asian-Australians in the professional realm is also evident but remains poorly understood. For instance, Evans (2019) noted that although Asian-Australians constitute 12% of the population, they hold only about 3% of senior leadership positions in public institutions and major corporations, a disparity that is exacerbated by racial discrimination, cultural stereotypes, and a lack of institutional commitment to cultural diversity. These figures contrast with 7% and 6% in the U.S., as reported by Hemmige et al. (2023) and Ruiz et al. (2023), respectively. Liu et al. (2024) provide a detailed analysis of these nuances through the lens of "precarious multiculturalism," which illuminates the intermittent and conditional nature of racial inclusion in Australia. As Morris (2008) suggests that while the stereotype (e.g., the "model minority"—quiet, hardworking, studious, and compliant) has been praised for demonstrating the success of Asian communities, it also masks a variety of difficulties including navigating cultural differences and confronting career stagnation. Despite the perception of Asians excelling academically and professionally, they remain underrepresented in leadership roles due to cultural stereotypes and racial discrimination (Ruiz et al., 2023).

Notably, AI has the potential to significantly influence immigrant workers by helping them overcome these cultural barriers and triggering beneficial work behavioral changes. Studies by Sumi et al. (2024) and Rude and Giesing (2022) demonstrate how AI aids immigrants in utilizing their unique skills, leading to better integration. Additionally, Yan and Grossman (2023) discuss the role of ICTs in building social capital among immigrants, facilitating their adaptation and integration by enhancing communication and building networks. Such technological support is crucial as it not only helps immigrants integrate into new environments but also maximizes their potential to contribute effectively within their workplaces.

Adding to the complexity is the notion of ethnic identity, which is defined as increasing an individual's receptivity to social influence from members of the same ethnic group while decreasing their receptivity to social influence from non-group members (Hekman et al., 2009). Some research highlights that high ethnic identity among employees can foster positive behavioral outcomes such as self-affirmation values and psychological empowerment, influencing how immigrant workers perceive and control their environment, including their interaction with technology (Henze et al., 2002; Molix & Bettencourt, 2010). Workers who feel a strong connection to their ethnic identity may derive confidence and empowered feelings, perceive a higher status, and are empowered to engage more proactively with technological tools, overcome adaptation challenges, and enact more inter-ethnic group and in-group helping behaviors (Abad Merino, 2014).

Overall, the empowerment afforded by AI warrants thorough investigation due to its nuanced distinctions, which remain underexplored in systematic and detailed research. AI's role in the workplace is evolving, and its impact on psychological empowerment and infusion use needs deeper examination, particularly as it relates to job performance, organizational citizenship behaviors (OCBs), such as constructive voicing behaviors, and perceived overqualification. The role of AI in the workplace is still a complex interplay of enhancing capabilities while also potentially reinforcing existing inequalities, requiring a nuanced understanding and proactive management to harness its benefits while mitigating its challenges.

3 Method

3.1 Participants

In partnership with Octopus Group, a reputable Australian survey firm, we secured a participant pool validated through the following mechanisms, ensuring reliability for our data collection: First, Octopus Group's dedicated team and systematic recruitment processes guarantee that participants meet the required demographic and psychographic criteria. They mandate Australian-based mobile numbers for participation and require SMS and email confirmation, ensuring the authenticity of responses. Second, their high reward rates attract a large and diverse panel, resulting in balanced representation across age, gender, education, and ethnicity. Moreover, to further ensure data quality, we implemented several filtering methods. We screened out subjects who did not complete all three waves of our study and those who completed the survey in less than two minutes. Additionally, we included a question regarding participants' interaction with AI, derived from the study by Sowa et al. (2021), which defines human-AI interaction across four tiers. At the basic Level 1, the interaction between humans and AI is minimal, where human operators either compete against or operate separately from AI. In Level 2, described as Complementary Collaboration, humans and AI each handle tasks suited to their specific strengths. At Level 3, termed Dependent Collaboration, there is a symbiotic relationship where AI sometimes relies on human input for making decisions. Level 4, termed as Hybrid Collaboration, sees AI as an integral part of human cognitive processes, working in unison in what is referred to as a 'centaur' setup. We introduced an initial Level 0 (i.e., individuals who do not engage with AI at all); Participant who chose "Level 0" were not included in our analysis. Detailed procedure checks were included in Appendix 4.

We issued 600 questionnaires and, following screening and participant drop-off, ended up with 525 valid responses, equating to a retention rate of 87.5%. This sample size is sufficiently larger than other recent similar research by Chen et al. (2022) and Hassandoust and

Techatassanasoontorn (2022). All respondents were Asian migrant workers at a company based in Australia.

Demographic Factor	Mean	Range	Coding
Age	2.51	[0, 6]	1 = less than 21; 2 = 22 – 30; 3 = 31 – 40; 4 = 41 – 50; 5 = more than 50.
Gender	-0.13	[-1, 1]	-1 = Female, 0 = Others (including "prefer not to say"), 1 = Male.
Education	3.02	[0, 5]	0 = high school and lower; 1 = diploma; 2 = bachelor's degree; 3 = master's degree; 4 = doctoral degree.
Tenure	41.17	[0, 390]	Measured in months.

Table 1 Demographics statistics

3.2 Procedure

We employed a three-wave time-lag survey design in this research. This design has the potential to provide causal insights that are comparable to those derived from experimental designs. As Wang et al. (2017) explains, the time lag between measurements is crucial for addressing the "issues of causality" (if the lags are neither too long nor too short), similar to how experimental designs utilize time precedence to strengthen causal inferences. Additionally, this design facilitated the tracking of trends over time (Cohen et al., 2013) and helped mitigate common method bias (Hedman, 1972; Maynard et al., 2014; Podsakoff et al., 2003; Vomberg & Klarmann, 2022). Collaborating with Octopus, we acquired data from a diverse and Australian nationwide sample. There was an approximate one-month interval between each wave of data collection. This time interval strikes a critical balance by being far enough separated to reduce common method bias but close enough to maximize retention of participants. And it has been adopted by prior studies in both Management and Information Systems fields, such as Y. Li et al. (2022), Fiori et al. (2015), Gorostiaga Manterola et al. (2022), and Bhattacherjee and Premkumar (2004).

Our sample exhibited considerable diversity in terms of their demographic characteristics (see Table 1). The timing for distributing the key measurements can be found in Table 3. Demographic variables were collected across the three time points.

Note that we tolerated a certain level of missing data, and, when that happens to a numeric variable, we imputed them with its mean.

3.3 Measures

Prior to elaborating on our primary metrics, we ascertained the reliability and validity of the core variable, "AI Empowerment (AIEMP)," through the utilization of Python (Version 3.9), with the aid of the factor_analyzer and semopy packages. For this construct, we adapted the psychological empowerment framework developed by Spreitzer (1995) to suit the context of AI empowerment. The original framework, which comprises four dimensions, has seen widespread application across numerous pertinent studies within the field of management information systems. Initially, we conducted a Kaiser-Meyer-Olkin (KMO) test on our data, yielding an adequacy value of 0.9469. Based on criteria posited by Shrestha and Statistics (2021), this is adequate.

We then tested the Cronbach's α values for all dimensions of our adapted construct and found they all were high, exceeding 0.86 (Meaningfulness: 0.864; Competence: 0.907; Self-Determination: 0.889; Impact: 0.900): All well above the recommended threshold of 0.707 as suggested by Nunnally (1978). We subsequently used an Exploratory Factor Analysis (EFA) to further explore the adapted construct. Specifically, we used the oblique version of Geomin rotation with Minimum Residual methods. We chose these methods is because our data did not pass normality tests (see Appendix 2) and these methods do not assume normality and can be more robust in smaller samples compared to other methods such as Maximum Likelihood and Maximum Likelihood Estimation. Four components collectively accounted for 80.71% of the total variance. All items loaded more highly on their own constructs than on other constructs, supporting a four-factor solution for AIEmp. Overall, the results suggest adequate psychometric properties for measurement of the dimensions. We reported the loadings for the proposed four factors in Table 2.

We further conducted a two-step EFA to explore the hierarchical factor structure underlying the AIEmp items. We calculated the average score for items under each dimension and performed EFA again. A single overarching component emerged that explains 78.02% of the variance in the scores derived from the second-step EFA components, supporting that a second-order structure for overarching construct (i.e., AIEMP).

Variable	Factor 1	Factor 2	Factor 3	Factor 4
AIEMP_Meaningfulness_1	**0.699**	0.093	0.105	0.016
AIEMP_Meaningfulness_2	**0.719**	0.121	0.081	0.096
AIEMP_Meaningfulness_3	**0.536**	0.184	0.037	0.160
AIEMP_Competence_1	0.220	**0.574**	0.201	0.033
AIEMP_Competence_2	0.116	**0.738**	0.087	0.099
AIEMP_Competence_3	0.079	**0.518**	0.095	0.310
AIEMP_SD_1	0.103	0.249	0.228	**0.402**
AIEMP_SD_2	0.087	0.053	0.121	**0.718**
AIEMP_SD_3	0.031	0.174	0.288	**0.528**
AIEMP_Impact_1	0.096	0.142	**0.596**	0.193
AIEMP_Impact_2	0.069	0.092	**0.711**	0.114
AIEMP_Impact_3	0.111	0.084	**0.451**	0.332
Note: N = 525, missing variables (N=6) were imputed with mean.				

Table 2 Cross-loadings of the AIemp items

We summarised the factors in Table 3. Note that, besides AI Empowerment, other measurements that we employed in this study had been used in prior management and information system researches, including Jones et al. (2002), Schwarz (2003), Sundaram et al. (2007), Norton et al. (2015) and Babalola et al. (2019).

Factor	Description	Adapted from
AI Empowerment (AIEMP) [Time 1]	AI Empowerment (AIEMP) is measured on a two-level scale, with a set of items assessing how fully individuals utilize AI to enhance their job performance, integrate AI into their work processes, and maximize the potential of AI to support and enhance their work activities (i.e., the four dimensions, including Meaningfulness, Competence, Self Determination, and Impact).	Spreitzer (1995)
Ethnic Identity (EI) [Time 1]	Ethnic Identity refers to an individual's sense of belonging, attachment, and identification with a specific ethnocultural group (Hekman et al., 2009) and is measured through five items that explore personal identification with Asian ethnicity, assessing how criticism or praise of Asians feels personal, the use of inclusive language when referring to Asians, a shared sense of achievement with other Asians, and feelings of embarrassment in response to negative media portrayal of Asians.	Besco (2015) and Mael and Tetrick (1992)
Infusion Use (IU) [Time 2]	Infusion Use is the extent to which individuals utilize the system's capabilities to their fullest potential, seamlessly integrate it into their work processes, and maximize its potential to support and enhance their job performance. There were 3 items used to measure this capability.	Chen et al. (2022), Sundaram et al. (2007) and Schwarz (2003)
Job Performance (JP) [Time 3]	Job performance is defined as the effectiveness and productivity with which an individual completes the specific tasks and responsibilities associated with their work role. It is measured using self-reported ratings of five items that assess task-focused contributions, including the completion of assigned duties and the fulfillment of responsibilities specified in the job description. These items are designed to evaluate both the quality and quantity of work performed, reflecting how well an employee aligns with and contributes to organizational goals.	Methot et al. (2016)
Perceived Overqualification (PO) [Time 3]	Perceived Overqualification is a subjective appraisals where individuals consider themselves possessing more education, experience, or skills than required by their jobs (Ma et al., 2020). Perceived overqualification was measured with the nine-item scale and has been used frequently in various overqualification research studies (Liu et al., 2015). Sample item includes "My job requires less education than I have."	Maynard et al. (2006)
Constructive Voicing (CV) [Time 3]	Constructive voice is defined as the voluntary expression of specific, constructive-intended and future-change-oriented messages in workplaces; there are 5 items and, similarly, all the items are measured on a 7-point Likert scale.	Krefft et al. (2024)

Table 3 Measurement summary

3.4 Analyses & Results

The clustering method that we used in this study was based on K-means clustering algorithm. Recent advancements in data analysis and clustering algorithms have significantly impacted various scientific and industrial fields by enabling more sophisticated data handling and decision-making processes. Among the various clustering algorithms, the K-means clustering algorithm stands out due to its simplicity, efficiency, and broad applicability, and the sample size also makes this study be suitable for conducting a K-mean clustering analysis (Ikotun et al., 2023).

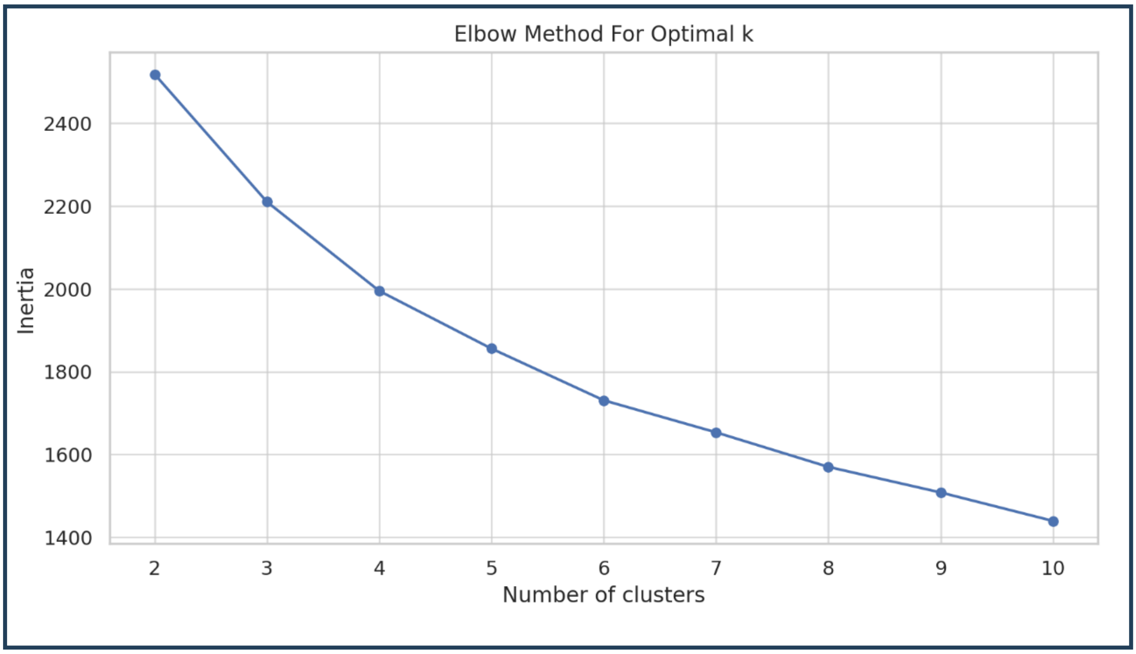


Figure 1 The Elbow Method plot

We firstly adhered to the traditional approach (D'Silva & Sharma, 2020) by generating an Elbow Method plot. As observed in Figure 2, the plot illustrates the inertia scores for various numbers of clusters, ranging from 1 to 10. The "elbow point," where the curve begins to flatten, appears around 3, 4, 5, or 6 clusters. Subsequently, we compared the Silhouette Scores among these configurations and identified that clusters 3, 4, and 6 were potentially viable. After a more detailed examination of the Principal Component Analysis (PCA) processed scatter plots for these three options (refer to Appendix 1), we determined that the 6-cluster solution was the most logical choice.

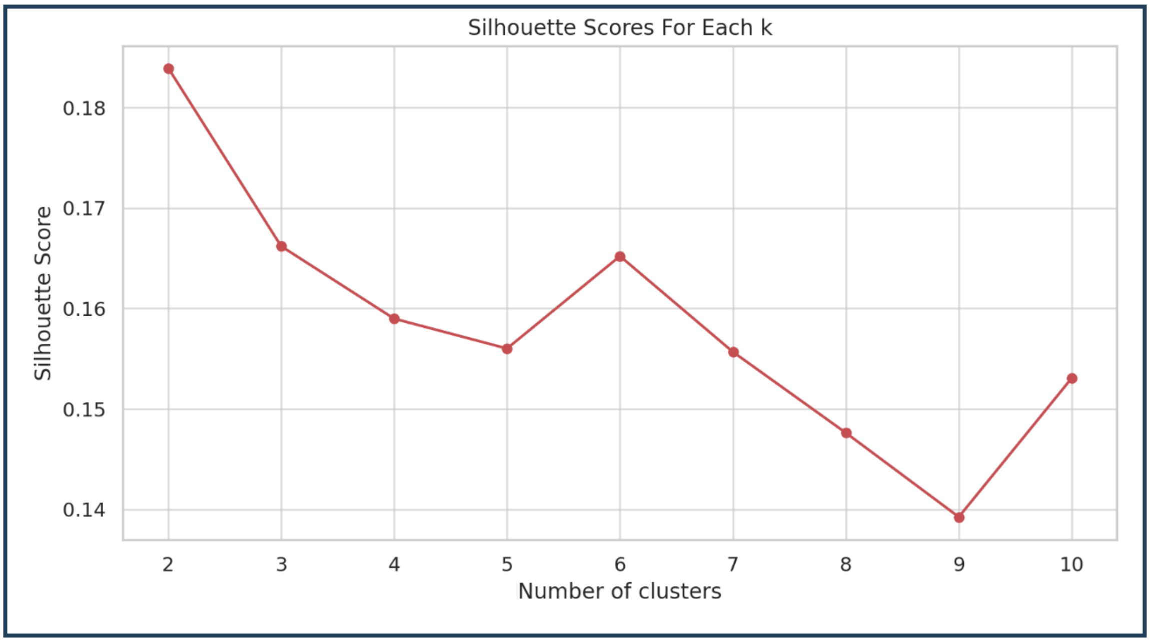


Figure 2 Silhouette Scores Comparisons among 1-10 Clusters

We calculated and presented the distances between cluster centres and the ANOVA results across clusters in Table 4 and Table 5, respectively. The ANOVA results show significant differences in the clustering variables across the clusters models, indicating that the clusters are distinct in terms of the variables used.

Cluster	0	1	2	3	4	5	N
0	0.00						114
1	2.68	0.00					99
2	2.96	2.90	0.00				104
3	3.83	4.15	3.06	0.00			68
4	2.95	3.24	2.03	2.64	0.00		106
5	2.34	2.53	2.28	2.73	2.35	0.00	34

Table 4 Distances Between Final Cluster Centers

Factor	SS	t	P-value
AIEMP	214.89	66.43	<0.001
EI	221.76	80.27	<0.001
IU	317.17	78.89	<0.001
PO	352.43	72.14	<0.001
PE	257.51	133.79	<0.001
CV	356.91	85.27	<0.001
Note: N =525; Degree of Freedom=5; SS = Sum of Square; AIIMP = AI Empowerment, EI = Ethnic Identity, IU = Infusion Use, PO = Perceived Overqualification, JP = Job Performance, CV = Constructive Voicing			

Table 5 ANOVA results

Cluster	AIEMP	EI	IU	PO	JP	CV	AGE	GENDER	EDUCATION	TENURE
0	4.93	5.45	4.92	5.64	6.19	5.50	2.58	-0.08	3.16	35.71
1	5.23	5.22	5.20	3.02	6.26	5.79	2.51	-0.16	3.04	37.66
2	4.44	4.66	4.14	3.95	4.45	4.30	2.25	-0.09	2.96	38.05
3	2.91	4.16	2.38	4.29	6.30	4.68	3.02	0.04	2.81	63.21
4	4.13	4.80	4.12	4.24	6.13	3.26	2.49	-0.32	3.00	41.85
5	4.33	3.57	4.56	4.47	6.12	5.18	2.44	-0.12	3.04	41.08

Table 6 Means of 6-Cluster Model

We reported the results of the clustering analysis in Table 6, in which the model delineates profiles of Asian immigrant workers in terms of their responses to AI empowerment and its perceived impact on their work lives. With this model, we observe a complex landscape where AI-related variables and self-perceptions vary significantly across clusters. The clusters illuminate differences in perceived overqualification, AI empowerment, and behavioral outcomes, indicating that the relationship between AI integration and worker perception is multifaceted.

In **Cluster 0,** these individuals perceive a relatively high level of overqualification and moderate AI empowerment. Their use of technology and performance are quite high, suggesting they are successfully adapting and utilizing AI in their work. They engage actively in constructive voicing, indicative of a proactive workplace attitude. Their ethnic identity is strongly felt, which might contribute to their confidence and status, empowering them further. They are younger on average, with a slight female skew, well-educated, and have moderate tenure.

Per **Cluster 1,** this group reports a high levels of AI empowerment, infusion use, and constructive voicing behaviors, suggesting that they may feel very enabled by AI to enhance their work roles, leading to high performance. Their relatively strong ethnic identity could also be providing a significant sense of empowerment. They are relatively younger, more likely to be female and have also a moderate tenure, similar to Cluster 0 but with a significantly lower perceived overqualification.

Per **Cluster 2,** members of this cluster show relatively low level of perceived overqualification, AI empowerment, and infusion use, paired with relatively lower performance and constructive voicing behaviors. This suggests a less proactive engagement with AI tools or possible adaptation challenges. Their ethnic identity is strongly felt, which may influence their work experience and adaptation process. They tend to be slightly less educated and have a lower gender skew towards females compared to Clusters 0 and 1, with similar age and tenure.

Individuals in **Cluster 3**, which is a small-size group, show moderate levels of perceived overqualification, the lowest AI empowerment, and infusion use among all clusters, yet their performance is quite high. Their engagement in constructive voicing is strong, suggesting that while they may not feel as empowered by AI, they still perform well and contribute to the workplace. They have the highest average age and tenure, which could indicate more experience in the workforce or possibly a resistance or refrain from AI adaptation. Their ethnic identity is also felt less strongly compared to other clusters.

Per **Cluster 4,** This cluster has moderate perceived overqualification and AI empowerment, with average infusion use and performance. However, their constructive voicing behaviors are lower, indicating a potential hesitance or barriers to fully engaging in workplace dialogue or technology adaptation. They are the oldest group on average, have a notable female presence, are well-educated, and possess the highest tenure, suggesting a matured workforce.

Cluster 5 has the lowest number of members. It exhibits moderate perceived overqualification and AI empowerment, good infusion use, and very high performance. Their constructive voicing is also high, reflecting effective workplace communication and engagement with AI. They have a moderate age and tenure and are likely to be educated, with a balanced gender distribution.

The six clusters reflect a spectrum of adaptation and empowerment experiences among Asian immigrant workers, influenced by their interaction with AI tools, their sense of ethnic identity, and control variables such as age, gender, education, and tenure. These findings could guide targeted interventions and supports to enhance AI integration and overall satisfaction in the workplace.

We believe conducting post-hoc analysis is a crucial step in exploring and understanding the differences between clusters. This method validates the initial clusters and provides deeper insights into the variability within the data that may not be apparent from the primary clustering. By examining these differences, researchers can confirm the distinctiveness of clusters, uncover hidden patterns, and draw more informed conclusions. This approach is commonly used in empirical studies, such as those by Balaban et al. (2023) and Stewart et al.

(2006), who utilized post-hoc analysis to identify meaningful groupings and inform future research directions.

3.5 *Post-hoc* analysis

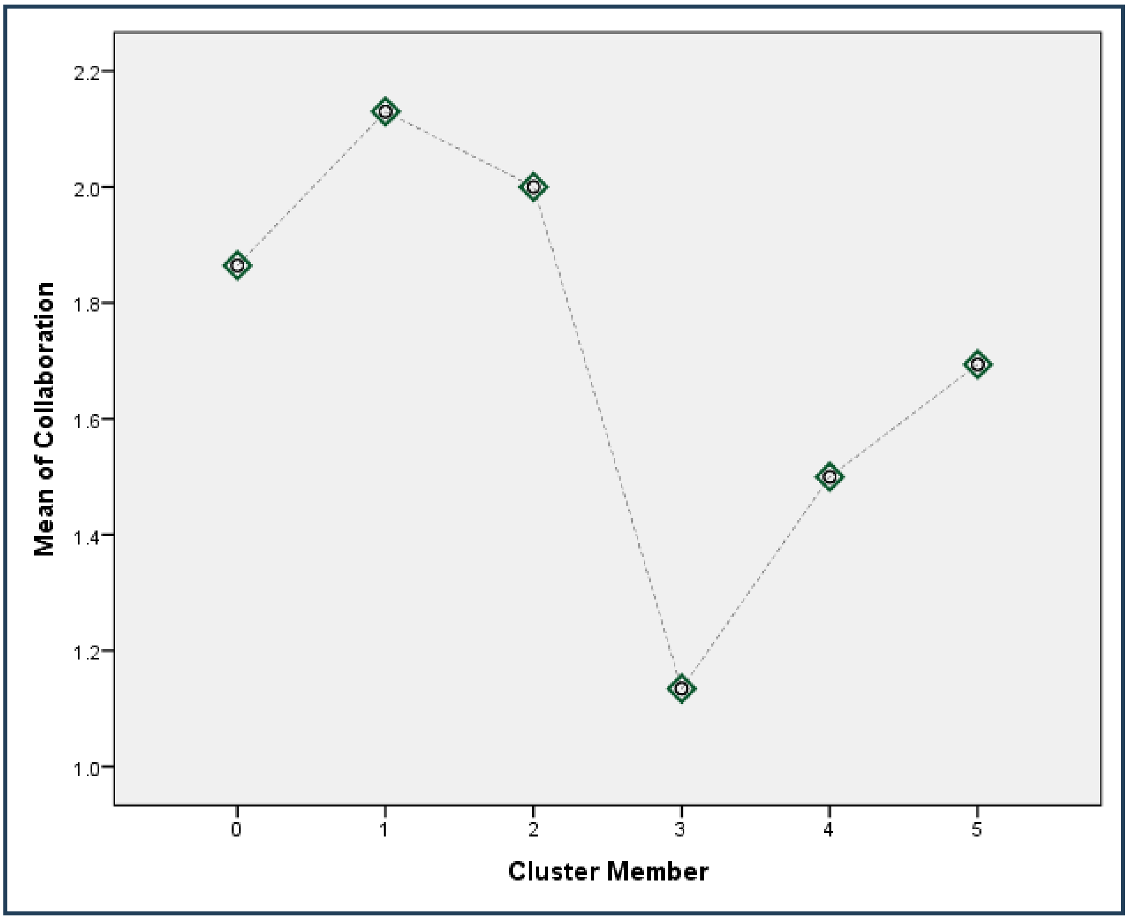


Figure 3 Means of AI-Human Collaboration levels according to clusters

In the first post hoc analysis, we tried to find a further explanation on the nuanced difference between Cluster 0 and 1. Although the key variables that we used for clustering and the demographical variables of the two cluster groups were very similar, significant variations were observed between the two identified clusters regarding their AI-Human collaboration levels at Time 1, which have been categorized into four stages as defined by Sowa et al. (2021)[3]. A one-way ANOVA test was conducted to compare the AI-Human collaboration levels between the clusters, revealing a statistically significant difference (Mean Difference = 0.027, $p = 0.019$). This analysis suggests that individuals in Cluster 0 predominantly engage in lower levels of AI-human collaboration, where the role of AI is less integral. Interestingly, this relatively superficial level of AI interaction tends to coincide with a stronger perception of overqualification. Conversely, individuals in Cluster 1, who experience enhanced levels of AI-human collaboration, heightened AI empowerment, more effective technology infusion, and superior self-reported job performance, exhibit a lower level of perceived overqualification. This correlation may be attributed to several factors. Firstly, the enhanced AI empowerment in Cluster 1 likely results in more positive performance feedback. Such feedback can affirm an

[3] *Please note that the attention-checking choice (level 0) is not considered a formal level in this test.*

employee's perception of the suitability of their role and the adequacy of their skill utilization. The positive reinforcement and tangible outcomes of their efforts serve to align their skills with job demands more closely.

Additionally, heightened AI empowerment may imply that employees are not merely users of AI tools but are actively involved in their development, optimization, or detailed interaction. This deep engagement may increase their perception of being integral to critical aspects of organizational operations and innovation, enhancing their sense of skill utilization and ongoing development, thereby mitigating feelings of overqualification.

This distinguished from Cluster 3 which presents a unique case wherein moderate levels of perceived overqualification are observed, despite the lowest levels of AI empowerment and infusion use among all clusters. This cluster also displays the lowest level of AI-Human collaboration and is characterized by the highest average age and tenure. These attributes may suggest a greater amount of workforce experience, which could concurrently indicate a potential resistance to, or a slower adaptation of, AI technologies. Additionally, the less strongly felt ethnic identity in this cluster could influence their integration and interaction within the technological and social fabric of the organization, potentially impacting their engagement with AI technologies.

Overall, the advanced integration of AI in Cluster 1 appears to create a work environment where employees perceive their roles as adequately challenging and commensurate with their skills, thus reducing the incidence of perceived overqualification. This dynamic underscores the importance of strategic AI deployment in aligning job demands with employee capabilities, fostering job satisfaction, and enhancing organizational performance.

4 Discussion

AI empowerment is increasingly becoming a focal point of discussion within both academic and industrial circles. This shift is propelled by the advancements in new waves of AI applications, especially generative AI technologies, that have reached a threshold where their potential for mass and effective collaboration with humans in general tasks unveils new vistas of efficiency and possibility (Benbya et al., 2024; Kanbach et al., 2023; Shi & Deng, 2024). The interplay of AI's prowess in automation and data analytics with human creativity and intuition offers fertile ground for innovation. Through AI collaboration, the streamlining of workflows, acceleration of creative processes, and amplification of productivity in creative professions are feasible (Amankwah-Amoah et al., 2024). However, the potential of AI to automate tasks within these industries also brings into sharp focus the risks of job displacement and necessitates a thorough exploration of how human roles can evolve to work symbiotically with AI technologies (Mogaji et al., 2024). As echoed by scholars like Shukla (2023), Davenport and Miller (2022), and Ghaffari et al. (2024), the field is currently fraught with uncertainties, including the balance of automation with the human touch, ethical use, and the impact on job roles (Amankwah-Amoah et al., 2024). This study, therefore, contributes a timely exploratory discussion to this burgeoning discourse.

Adding to the importance of our research is the focus on the cohort of Asian Australian immigrants. Despite being considered a model minority with a significant representation in STEM and computing and algorithmic-related areas (Rude & Giesing, 2022; Yan & Grossman, 2023), Asian Australian immigrant workers often encounter the 'bamboo ceiling' phenomenon (Hwang & Beauregard, 2022; Lee & Zhou, 2015; Lu, 2022; Yip et al., 2021). They are susceptible to becoming the invisible workforce within their professional environments (Jun et al., 2023). The psychological empowerment afforded by AI has the potential to assist these workers in breaking through the transparent glass barriers, especially when these barriers are entrenched in domains where AI, notably generative AI, excels (Sumi et al., 2024). Nonetheless, there exists the possibility that while job performance improves, employees might concurrently experience a sense of perceived overqualification. This perception can engender job dissatisfaction (Kaymakcı et al., 2022), among other subsequent issues. Should this be true, such a phenomenon deserves our vigilant attention.

Underpinned by the psychological empowerment theory, the IS fusion framework, and utilizing time-lag surveys alongside K-means clustering methods, our exploratory study ventures into these significant discussion points. We first extended the classical psychological empowerment scale to formulate our novel AI empowerment scale, which we have rigorously tested for validity and reliability. Subsequent to our time-lagged survey, we validated the classical resource-based view that AI-enabled psychological empowerment can incite infusion use among Asian Australian migrant workers. The data, segmented through time-lag research, revealed that groups with higher AI-enabled psychological empowerment also reported higher infusion use, and vice versa. Similarly, we confirmed the anticipated effect of infusion use on job performance. On another note, our findings uncovered a potential link between perceived overqualification and the diversity in AI empowerment. Our data revealed two distinct clusters of participants who were comparable in various dimensions (age, education level, AI empowerment, high infusion use levels, and significant job performance), yet one cluster felt overqualified, while the other did not report heightened overqualification-related perception. Further scrutiny suggests that the differential in AI-human collaboration levels could explain the reasonable differences in perceived overqualification observed. Moreover, we identified a smaller-sized cluster of individuals predisposed to stronger perceived overqualification tendencies alongside higher self-reported job performance, independent of AI-enabled empowerment. Our results also indicated that these individuals tend to be older, predominantly male, and relatively less educated. Intriguingly, they also reported higher levels of constructive voicing behavior, which we speculate may be associated with the specific industries they are concentrated in.

By contrast, Cluster 2 and Cluster 4 present varied profiles. Cluster 2, with the youngest average age across all clusters, reported moderate AI empowerment levels but did not exhibit high job performance or perceived overqualification. Cluster 4 reported relatively higher job performance, yet their voicing behaviors were markedly lower, and Cluster 4 comprised a higher proportion of female members. This also attracts future further research.

Lastly, the connection between ethnic identity and the three outcome variables measured at time 3 (i.e., job performance, constructive voicing, perceived overqualification) appeared to be complex. This suggests that ethnic identity may have a negligible impact, or there may exist intricate moderated mediation effects, which warrant further empirical investigation.

4.1 Theoretical contributions

This study makes a significant contribution to the literature on empowerment, particularly AI empowerment, by validating a potentially widely-applicable scale that clarifies the nuanced roles AI can play in enhancing the capabilities of the human workforce. While AI empowerment is an emerging research area, and recent studies have explored this concept, we identified certain gaps that our study addresses. For example, T. J.-J. Li et al. (2022)

examined AI empowerment in the context of gig workers, proposing a bottom-up approach where AI-enabled intelligent assistants empower workers with task planning and decision-making. Although their study offers valuable insights into AI-driven empowerment, it does not establish a measurable construct for AI empowerment, nor does it delve into the psychological foundations of empowerment. For another, Reis et al. (2021) introduced "AI-based User Empowerment" in the context of visual Big Data analysis, aiming to enhance system usability and boost users' self-confidence through adaptive interfaces. While their focus on interface design is important, their research lacks an explicit framework to quantitatively capture empowerment. Our paper expands on these ideas in a more theoretically robust manner by adding a more systematic, empirically-valid research paradigm. This study also breaks new ground by linking AI empowerment to higher levels of job performance in different ways, suggesting that empowerment goes beyond subjective perception and has tangible impacts on operational outcomes.

Our research extends the literature on empowerment-induced behavioral change in two keyways. First, we confirm prior studies, such as Hassandoust and Techatassanasoontorn (2022), which demonstrate the effect of psychological empowerment on information system infusion use and job performance, and show that AI empowerment can similarly induce comparable behavioral changes. Moreover, we offer a nuanced discovery by exploring how micro-level interactions with AI technologies influence perceptions of overqualification. Previous studies in this field have primarily focused on macro-level factors leading to overqualification (Liu et al., 2022; Sparreboom & Tarvid, 2016; Syed, 2008). However, as highlighted by Liao et al. (2024) research on overqualification is evolving to recognize that it is not only caused by macro-level misfits but also shaped by the day-to-day technological empowerment of employees. In line with this, our findings suggest that individuals'AI empowerment plays a pivotal role in shaping perceptions of overqualification, following two distinct paths: some workers felt overqualified while reporting higher-than-average job performance, while others reported lower perceptions of overqualification. This aligns with theoretical literature: one stream suggests AI can enable workers to take on more complex tasks, fostering a sense of mastery and meaningful contribution to their work. Technologies that enhance perceived competence, impact, and autonomy allow workers to reshape their roles to better align with their strengths, motivations, and passions, as suggested by Demir et al. (2024); some may indeed experience AI-induced overconfidence (Sison et al., 2023; Underwood, 2024), and thus they perceive more overqualification. Furthermore, our results revealed the group of respondents who experience higher-than-average levels of perceived overqualification tends to be older, predominantly male, and relatively less educated. Interestingly, they also reported higher levels of constructive voicing behavior. We speculate that this behavior may be influenced by underlying factors such as cultural norms, which foster environments where speaking up and providing input are encouraged for such Asian migrant workers as pre-described, regardless of formal qualifications. These individuals may come from sectors where proactive communication and engagement are highly valued, motivating them to voice their opinions—an area that remains underexplored in the existing literature. Our empirical results also suggest employees' current level of AI-human collaborations, as measured by Sowa et al. (2021)'s framework, may also have a critical role on affecting the perceived overqualification, thus we also introduce another promising theoretical direction to link a hot information system topic with a promising human resource topic organically together.

Third, with the literature on AI ethics in ethnic research, our study made two key advances. First, AI empowerment, through its transformative capabilities, holds significant potential in promoting diversity and inclusion. Our research extends this stream of work, such as Almufareh et al. (2024) (AI-enabled inclusive technologies), Austin and Holloway (2022) (AI-enabled Assistive technologies), and Pritiprada et al. (2024) (the role of new technologies, including AI, Blockchain, and the Metaverse, in empowerment of promoting diversity), by showing how AI can help move Asian Australian immigrants from marginalized "invisible" actors and break through the "bamboo ceiling." In this regard, we believe our study serves as a starting point for a deeper understanding of how AI, while functioning as a tool for inclusion, also poses ethical dilemmas that could further marginalize already 'invisible' groups. Thus, we build on Chi et al. (2021)'s work by offering new insights into how AI ethics is being reconfigured to make diversity and inclusion more actionable for practitioners, ensuring that marginalized ethnic groups are not sidelined. Moreover, we observed the complex nature of AI's role in the workplace empowerment of Asian Australians. Not all cohorts benefit equally and fairly from the advances in newer generations of AI systems. Some individuals, as we also observed, may be significantly left behind, which, as Lin and Chen (2022) also noted, suggests that AI can function both as a tool for empowerment and as a source of potential marginalization. This dual perspective contributes to the ongoing discourse on AI ethics, as our results demonstrate the nuance that, while AI has the capacity to enhance the roles of some marginalized ethnic groups, its benefits are not equally experienced. Although certain groups may gain empowerment, there is a danger that others may remain excluded or further marginalized. Furthermore, another stream of research (Preminger, 2020), has expressed concerns that AI systems may mask underlying ethnic hierarchies and deny collective rights, further marginalizing already disadvantaged groups. Our findings help to mitigate this fear to some extent, as we observed that AI empowerment, particularly in a large cluster of young Asian migrant workers, triggers positive behavioral changes in the workplace (e.g., voicing behaviors). This may help these workers break the invisible ceiling and counter stereotypes of being quiet, passive, and non-confrontational (Ruttiman, 2009). Our research places a spotlight on the ethical imperative for inclusivity within AI development and implementation. Thus, this theoretical advancement bridges a gap in the current literature by emphasizing the micro-level impact of AI on ethnic minorities, particularly in how it may enhance or diminish their visibility and agency in service sectors.

4.2 Practical contributions

The first practical contribution of this study is our study helps the introduction of AI empowerment in designing organizational IT strategies that effectively promote AI applications. Prior research by Monod et al. (2024), Reis et al. (2021), Gladden et al. (2022) and Usmani et al. (2023) has already emphasized the importance of incorporating empowerment in practice. However, our research goes further by offering companies a concrete AI implementation framework. Specifically, to promote AI empowerment, four key components should be prioritized: meaningfulness, competence, self-determination, and impact. Additionally, our findings suggest that the success of such AI empowerment strategies depends on the specific cohort of individuals it targets and how the AI implementation project is introduced and supported. This underscores the need for personalized support paths and psychological mechanisms to ensure employees feel empowered by AI, rather than alienated by its integration, as Mittal et al. (2023) emphasize.

Second, employees' behavioral reactions to AI empowerment are diverse, and distinct clusters exhibiting different reactions are likely to emerge as new AI strategies are implemented. Due to this high degree of variability, companies should tailor their strategies and provide not only technical but also psychological support mechanisms to help employees feel more empowered by AI. Current research often focuses on the role of managers in fostering AI-Human collaboration by conducting needs analyses and offering tailored technical AI literacy training (Dixit & Maurya, 2021). Our study further argues that incorporating a tailored psychological empowerment approach can help mitigate the risk of creating segments within the company where AI becomes a dividing factor rather than a unifying and empowering tool.

Building on the initial point about the necessity for a strategic approach to AI promotion, it becomes clear that merely adopting new technologies does not guarantee an augmentation of IT-Human collaboration. This is corroborated by prior *Management Information Systems* literature (Harper et al., 2004) and is clearly applicable to AI applications. In fact, as demonstrated by Sowa et al. (2021) and also the empirical results of this study, low levels of AI-Human collaboration might lead to unintended side-effects. Therefore, appropriate managerial intervention becomes critical, and this intervention, as Sowa et al. (2021) introduce, should focus on several key areas, such as adequate training, user experience (UX) design, etc., to foster effective AI-Human collaboration. Beyond the aforementioned training program designs, an AI-empowerment-driven IT strategy can also guide user-centric design approaches. Our AI empowerment framework can thus be also applied to participatory approaches, leading to the creation of user-friendly interfaces that align with employees' specific needs and workflows. This approach recommends that future generations of workplace AI tools significantly enhance users'—particularly migrant workers'—perceived meaningfulness, competence, self-determination, and impact on their work.

Moreover, interventions should consider the emotional and psychological aspects of AI integration. As Gladden et al. (2022) and Ghaffari et al. (2024) argue, we suggest managers can introduce change management strategies that address the common fears and misconceptions about AI, such as job displacement and loss of control. They should emphasize the value of AI as a tool that enhances employee capabilities and productivity rather than a replacement for human intelligence. To minimize the AI divide within a company, managers should also develop differentiated strategies that cater to the diverse reactions and readiness levels across employee clusters. This may include personalized support paths, such as mentoring for those less comfortable with AI and advanced projects for those who are more tech-savvy.

Finally, management should establish clear guidelines and ethical standards for AI use to ensure that the technology is applied responsibly and inclusively, considering the impact on all stakeholders. Regular assessments of AI's impact on job roles and organizational structure will help to identify areas where human roles can evolve alongside AI advancements, thereby promoting a culture of continuous learning and adaptation (Ibrahim & Rashad, 2024; Wilson & Daugherty, 2018). In this regard, our study also provides a foundation for understanding the complex interplay between AI advancements and the inclusivity of ethnic minorities, highlighting the need for digital corporate responsibility. It calls for service organizations to actively engage in ethical decision-making processes that recognize the dignity and rights of all employees, particularly those who are at risk of remaining 'invisible' in rapidly digitizing environments.

4.3 Limitation and Future Suggestions

A potential limitation of our study is the exclusive reliance on self-reported measures for all variables. Since our research focused specifically on Asian racial employees rather than a broader employee sample across business organizations, we employed a self-report approach to data collection. This method was chosen due to the nature of our participants and the longitudinal design of our study, which aimed to minimize participant dropout over multiple timepoints. Although our analysis indicated that common method bias was not a major issue, we recognize that future research could benefit from a multi-source design to gain a deeper understanding of the studied constructs. For example, adding evaluations from immediate supervisors regarding performance outcomes could help offset the biases inherent in self-report methods and enhance the validity of our findings. Employing such a multi-source approach in future studies could provide a more thorough evaluation of the relationships between variables and reduce the limitations tied to sole reliance on self-reported data. Additionally, while our research model outlines general mechanisms by which AI empowerment supports employees' adaptation, leading to enhanced performance and organizational citizenship behaviors (OCBs), we acknowledge that the effectiveness of these constructs may vary across different contexts. Higher-level factors and constructs could play a significant role as well. Although we employed empowerment as an individual-level construct in alignment with its original design, we believe that future research should explore high-level constructs, such as empowerment climate—a group-level adaptation of empowerment proposed by researchers such as Seibert (2004) to establish further investigation and contextualization of empowerment-related constructs.

Recently more and more studies have begun to illuminate that perceived overqualification, traditionally seen as a disadvantageous condition for both employees and organizations, may actually hold positive implications under certain circumstances (Liao et al., 2024). These findings suggest that overqualification does not solely lead to dissatisfaction and turnover intentions as previously thought. Instead, it can potentially drive employees to pursue further personal development and innovation within their roles, contributing to organizational growth and adaptability. This emerging perspective warrants deeper investigation, particularly in how organizations might harness the potential of overqualified employees. Further research should explore the conditions under which perceived overqualification leads to positive outcomes, such as enhanced creativity, greater organizational commitment, or proactive engagement in tasks beyond assigned roles. Moreover, it is crucial to understand the specific organizational cultures, leadership styles, and job design factors that can convert the challenges associated with overqualification into valuable opportunities. While the aim of our exploratory research is to generate new insights rather than to formulate formal hypotheses, we suggest that future studies should focus on developing precise hypotheses for empirical testing. These hypotheses can then be employed to investigate the long-term impacts of perceived overqualification on career trajectories and organizational outcomes. Such investigations may lead to a reevaluation of hiring and management practices, facilitating a more effective integration and utilization of the skills and potential of overqualified employees.

Despite its popularity, the K-means algorithm that we primarily used in this study is not without limitations. The need to pre-specify the number of clusters and the sensitivity to initial centroid placement can lead to suboptimal clustering performance, particularly with complex or high-dimensional datasets (Ikotun et al., 2023). Additionally, the traditional implementation of K-means struggles with scalability issues in the era of big data, where datasets are not only large but also often come from diverse data sources and contain noise and outliers. This will not be an issue for this study as the sample is reasonably small. However, in the future, if a population-wide or multi-centered survey to be conducted, this issue embedded in K-means algorithm may become a series issues. In this regard, we suggest using improved initialization techniques, such as K-means++, and adaptations that allow for better handling of outliers and noisy data, are among the key developments that enhance the robustness and accuracy of the clustering results (Ailon et al., 2009; Liu et al., 2023).

Lastly, many researchers have expanded the concept, psychological empowerment, from individual to group-level constructs. For instance, Seibert et al. (2004) appropriated the original psychological empowerment construct and introduced an "empowerment climate", characterized by information sharing, autonomy, and team responsibility. While our research continues to employ empowerment at the individual level, we recognize the potential of these higher-level constructs and suggest further exploration in diverse contexts.

References

Abad Merino, S. (2014). *Dynamics of prosocial behaviour: Subtle bias toward racial and gender groups*. Universidad de Córdoba.

Afiouni, R., & Pinsonneault, A. (2023, December 10-13). Human-in-Control: A human-centered model of adaptation to AI augmentation. In *Proceedings of the 45th International Conference on Information Systems* (ICIS), Hyderabad, India.

Ailon, N., Jaiswal, R., & Monteleoni, C. (2009). Streaming k-means approximation. In *Proceedings of the 22nd International Conference on Neural Information Processing Systems* (NeurIPS), Vancouver, Canada.

Alabed, A., Javornik, A., & Gregory-Smith, D. (2022). AI anthropomorphism and its effect on users' self-congruence and self–AI integration: A theoretical framework and research agenda. *Technological Forecasting and Social Change, 182*, 121786. doi.org/10.1016/j.techfore.2022.121786

Albrecht, S. L., Bocks, A., Dalton, J., Lorigan, A., & Smith, A. (2021). Pro-environmental employee engagement: The influence of pro-environmental organizational, job, and personal resources. *Sustainability, 14*(1), 43. doi.org/10.3390/su14010043

Almaiah, M. A., Alfaisal, R., Salloum, S. A., Hajjej, F., Shishakly, R., Lutfi, A., Alrawad, M., Al Mulhem, A., Alkhdour, T., & Al-Maroof, R. S. (2022). Measuring institutions' adoption of artificial intelligence applications in online learning environments: Integrating the innovation diffusion theory with technology adoption rate. *Electronics, 11*(20), 3291. doi.org/10.3390/electronics11203291

Almufareh, M. F., Kausar, S., Humayun, M., & Tehsin, S. (2024). A conceptual model for inclusive technology: Advancing disability inclusion through artificial intelligence. *Journal of Disability Research, 3*(1), 20230060. doi.org/10.57197/jdr-2023-0060

Amankwah-Amoah, J., Abdalla, S., Mogaji, E., Elbanna, A., & Dwivedi, Y. K. (2024). The impending disruption of creative industries by generative AI: Opportunities, challenges, and research agenda. *International Journal of Information Management*, 102759. doi.org/10.1016/j.ijinfomgt.2024.102759

Ashforth, B. E. (1989). The experience of powerlessness in organizations. *Organizational Behavior and Human Decision Processes, 43*(2), 207–242. doi.org/10.1016/0749-5978(89)90051-4

Austin, V., & Holloway, C. (2022). Assistive technology (AT), for what? *Societies, 12*(6), 169. doi.org/10.3390/soc12060169

Babalola, M. T., Ren, S., Kobinah, T., Qu, Y. E., Garba, O. A., & Guo, L. (2019). Negative workplace gossip: Its impact on customer service performance and moderating roles of trait mindfulness and forgiveness. *International Journal of Hospitality Management, 80*, 136–143. doi.org/10.1016/j.ijhm.2019.02.007

Balaban, I., Filipović, D., & Zlatović, M. (2023). Post hoc identification of student groups: Combining user modeling with cluster analysis. *Education and Information Technologies, 28*(6), 7265–7290. doi.org/10.1007/s10639-022-11468-9

Bandura, A. (1990). Perceived self-efficacy in the exercise of control over AIDS infection. *Evaluation and Program Planning, 13*(1), 9–17. doi.org/10.1016/0149-7189(90)90004-G

Bankins, S., Ocampo, A. C., Marrone, M., Restubog, S. L. D., & Woo, S. E. (2024). A multilevel review of artificial intelligence in organizations: Implications for organizational behavior research and practice. *Journal of Organizational Behavior, 45*(2), 159–182. doi.org/10.1002/job.2735

Beaudry, A., & Pinsonneault, A. (2005). Understanding user responses to information technology: A coping model of user adaptation. *MIS Quarterly, 29*(3), 493–524. doi.org/10.2307/25148693

Benbya, H., Davenport, T. H., & Pachidi, S. (2020). Artificial intelligence in organizations: Current state and future opportunities. *MIS Quarterly Executive, 19*(4). doi.org/10.2139/ssrn.3741983

Benbya, H., Strich, F., & Tamm, T. (2024). Navigating generative artificial intelligence: Promises and perils for knowledge and creative work. *Journal of the Association for Information Systems, 25*(1), 23–36. doi.org/10.17705/1jais.00872

Besco, R. (2015). Rainbow coalitions or inter-minority conflict? Racial affinity and diverse minority voters. *Canadian Journal of Political Science/Revue canadienne de science politique, 48*(2), 305–328. doi.org/10.1017/S0008423915000396

Bhattacherjee, A., & Premkumar, G. (2004). Understanding changes in belief and attitude toward information technology usage: A theoretical model and longitudinal test. *MIS Quarterly, 28*(2), 229–254. doi.org/10.2307/25148634

Burris, E. R., Detert, J. R., & Romney, A. C. (2013). Speaking up vs. being heard: The disagreement around and outcomes of employee voice. *Organization Science, 24*(1), 22–38. doi.org/10.1287/orsc.1110.0732

Chen, F. F., Sousa, K. H., & West, S. G. (2005). Teacher's corner: Testing measurement invariance of second-order factor models. *Structural Equation Modeling: A Multidisciplinary Journal, 12*(3), 471–492. doi.org/10.1207/s15328007sem1203_7

Chen, L., Hsieh, J. P.-A., & Rai, A. (2022). How does intelligent system knowledge empowerment yield payoffs? Uncovering the adaptation mechanisms and contingency role of work experience. *Information Systems Research, 33*(3), 1042–1071. doi.org/10.1287/isre.2021.1097

Cheng, X. S., Zhang, X. P., Cohen, J., & Mou, J. (2022). Human vs. AI: Understanding the impact of anthropomorphism on consumer response to chatbots from the perspective of trust and relationship norms. *Information Processing & Management, 59*(3), 102940. doi.org/10.1016/j.ipm.2022.102940

Chi, N., Lurie, E., & Mulligan, D. K. (2021). Reconfiguring diversity and inclusion for AI ethics. In *Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society*, Virtual Event, USA. doi.org/10.1145/3461702.3462622

Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2013). *Applied multiple regression/correlation analysis for the behavioral sciences* (3rd ed.). Routledge. doi.org/10.4324/9780203774441

Côté, S. (1999). Affect and performance in organizational settings. *Current Directions in Psychological Science, 8*(2), 65–68. doi.org/10.1111/1467-8721.00016

Czarnitzki, D., Fernández, G. P., & Rammer, C. (2023). Artificial intelligence and firm-level productivity. *Journal of Economic Behavior & Organization, 211*, 188–205. doi.org/10.1016/j.jebo.2023.05.008

D'Silva, J., & Sharma, U. (2020). Unsupervised automatic text summarization of Konkani texts using K-means with Elbow method. *International Journal of Engineering Research and Technology, 13*(9), 2380–2384. doi.org/10.37624/IJERT/13.9.2020.2380-2384

Davenport, T. H., & Miller, S. M. (2022). *Working with AI: Real stories of human-machine collaboration*. MIT Press. doi.org/10.7551/mitpress/12127.001.0001

Deci, E. L., & Ryan, R. M. (2008). Self-determination theory: A macrotheory of human motivation, development, and health. *Canadian Psychology/Psychologie Canadienne, 49*(3), 182–185. doi.org/10.1037/a0012801

Demir, M., Dalgıç, A., & Yaşar, E. (2024). How perceived overqualification affects task performance and proactive behavior: The role of digital competencies and job crafting. *International Journal of Hospitality & Tourism Administration, 25*(3), 552–574. doi.org/10.1080/15256480.2022.2135665

Dixit, S., & Maurya, M. (2021, February 17–19). Equilibrating emotional intelligence and AI-driven leadership for transnational organizations. In *Proceedings of the 2021 International Conference on Innovative Practices in Technology and Management* (ICIPTM), Uttar Pradesh, India.

Dolan, M., Epstein, A., Lipson, R., & Winiski, E. (2022). Building the new high road: Immigrants and workforce development. *Labor Markets & Employment*. https://www.pw.hks.harvard.edu/post/new-high-road

Dou, Y. (2023). Does the application of artificial intelligence technology affect employees' turnover intention? In *Proceedings of the 2023 6th International Conference on Information Management and Management Science* (IMMS), Chengdu, China. doi.org/10.1145/3625469.3625488

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., & Ahuja, M. (2023). "So what if ChatGPT wrote it?"

Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management, 71*, 102642. doi.org/10.1016/j.ijinfomgt.2023.102642

Eilers, K., Peters, C., & Leimeister, J. M. (2022). Why the agile mindset matters. *Technological Forecasting and Social Change, 179*, 121650. doi.org/10.5465/ambpp.2021.13110abstract

Enholm, I. M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2022). Artificial intelligence and business value: A literature review. *Information Systems Frontiers, 24*(5), 1709–1734. doi.org/10.1007/s10796-021-10186-w

Evans, G. (2019). The 'bamboo ceiling' in Australia is real. *The Sydney Morning Herald*. https://www.gevans.org/opeds/oped208.html

Fiori, M., Bollmann, G., & Rossier, J. (2015). Exploring the path through which career adaptability increases job satisfaction and lowers job stress: The role of affect. *Journal of Vocational Behavior, 91*, 113–121. doi.org/10.1016/j.jvb.2015.08.010

Gardner, K., & Liu, R. (2010). Claiming their voice: Sociolinguistic factors affecting immigrant workers' ability to speak up. *The CATESOL Journal, 21*(1), 45–65.

Ghaffari, S., Yousefimehr, B., & Ghatee, M. (2024). Generative-AI in e-commerce: Use-cases and implementations. In *Proceedings of the 20th CSI International Symposium on Artificial Intelligence and Signal Processing* (AISP), Babol, Iran.

Gist, M. E. (1987). Self-efficacy: Implications for organizational behavior and human resource management. *Academy of Management Review, 12*(3), 472–485. doi.org/10.5465/amr.1987.4306562

Gladden, M., Fortuna, P., & Modliński, A. (2022). The empowerment of artificial intelligence in post-digital organizations: Exploring human interactions with supervisory AI. *Human Technology, 18*(2), 98–121. doi.org/10.14254/1795-6889.2022.18-2.2

Gorostiaga Manterola, M. A., Balluerka Lasa, M. N., & Rodríguez López, A. (2022). Assessment of adaptive performance and its role as a moderator of the relationship between person-organization fit and organizational citizenship behaviors. *Psicothema*. doi.org/10.7334/psicothema2021.310

Hair, J. F., Anderson, R. E., Tatham, R. L., & Black, W. C. (2006). *Multivariate data analysis with readings* (6th ed.). Pearson Prentice Hall.

Hanson, G. (2022). Immigration and regional specialization in AI. In *Robots and AI* (pp. 180–231). Routledge. doi.org/10.4324/9781003275534

Harper, L. D., Gertner, A. S., & Guilder, J. A. V. (2004). Perceptive assistive agents in team spaces. In *Proceedings of the 9th International Conference on Intelligent User Interfaces* (IUI), Funchal, Madeira, Portugal. doi.org/10.1145/964442.964496

Hassandoust, F., & Techatassanasoontorn, A. (2022). Antecedents of IS infusion behaviours: An integrated IT identity and empowerment perspective. *Behaviour & Information Technology, 41*(11), 2390–2414. doi.org/10.1080/0144929X.2021.1928287

Hekman, D. R., Steensma, H. K., Bigley, G. A., & Hereford, J. F. (2009). Effects of organizational and professional identification on the relationship between administrators' social influence and professional employees' adoption of new work behavior. *Journal of Applied Psychology, 94*(5), 1325–1335. doi.org/10.1037/a0015315

Hemmige, H., Ellison, R., & Chen, A. (2023). How companies can bring more Asian Americans into the C-suite. *Boston Consulting Group*. https://www.bcg.com/publications/2023/how-companies-can-promote-asian-american-executives

Henze, R., Norte, E., Sather, S. E., Walker, E., & Katz, A. (2002). *Leading for diversity: How school leaders promote positive interethnic relations*. Corwin Press.

Herold, D. M., Fedor, D. B., & Caldwell, S. D. (2007). Beyond change management: A multilevel investigation of contextual and personal influences on employees' commitment to change. *Journal of Applied Psychology, 92*(4), 942–951. doi.org/10.1037/0021-9010.92.4.942

Hillmann, F. (2022). New technologies, migration and the future of work. *Journal of Culture, Politics and Innovation, 2022*(3), 2283–7949. doi.org/10.12893/gjcpi.2022.3.7

Ho, C. (2020). *Aspiration and anxiety: Asian migrants and Australian schooling*. Melbourne University Publishing.

Ho, M.-T., Mantello, P., & Ho, M.-T. (2023). An analytical framework for studying attitude towards emotional AI: The three-pronged approach. *MethodsX, 10*, 102149. doi.org/10.1016/j.mex.2023.102149

Holmström, J. (2022). From AI to digital transformation: The AI readiness framework. *Business Horizons, 65*(3), 329–339. doi.org/10.1016/j.bushor.2021.03.006

Horowitz, M. C., & Kahn, L. (2024). Bending the automation bias curve: A study of human and AI-based decision making in national security contexts. *International Studies Quarterly, 68*(2). doi.org/10.1093/isq/sqae020

Hsieh, J. J., & Wang, W. (2007). Explaining employees' extended use of complex information systems. *European Journal of Information Systems, 16*(3), 216–227. doi.org/10.1057/palgrave.ejis.3000663

Huang, M.-H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research, 21*(2), 155–172. doi.org/10.1177/1094670517752459

Huang, M.-H., & Rust, R. T. (2021). Engaged to a robot? The role of AI in service. *Journal of Service Research, 24*(1), 30–41. doi.org/10.1177/1094670520902266

Hughes, R. T., Zhu, L., & Bednarz, T. (2021). Generative adversarial networks–enabled human–artificial intelligence collaborative applications for creative and design industries: A systematic review of current approaches and trends. *Frontiers in Artificial Intelligence, 4*, 604234. doi.org/10.3389/frai.2021.604234

Hussain, R., Sabir, A., Lee, D.-Y., Zaidi, S. F. A., Pedro, A., Abbas, M. S., & Park, C. (2024). Conversational AI-based VR system to improve construction safety training of migrant workers. *Automation in Construction, 160*, 105315. doi.org/10.1016/j.autcon.2024.105315

Hwang, C. Y., Kang, S. W., & Choi, S. B. (2023). Coaching leadership and creative performance: A serial mediation model of psychological empowerment and constructive voice behavior. *Frontiers in Psychology, 14*, 1077594. doi.org/10.3389/fpsyg.2023.1077594

Hwang, S., & Beauregard, T. A. (2022). Contextualising intersectionality: A qualitative study of East Asian female migrant workers in the UK. *Human Relations, 75*(4), 609–634. doi.org/10.1177/0018726721989790

Hyun, J. (2005). *Breaking the bamboo ceiling: Career strategies for Asians: The essential guide to getting in, moving up, and reaching the top*. Harper Business.

IBM. (2023). Best practices for augmenting human intelligence with AI. *IBM AI Ethics Board*. https://www.ibm.com/blog/best-practices-for-augmenting-human-intelligence-with-ai/

Ibrahim, T., & Rashad, H. (2024). The evolving role of healthcare professionals in the age of AI: Impacts on employment, skill requirements, and professional development. *Journal of Artificial Intelligence and Machine Learning in Management, 8*(2), 14–21. doi.org/10.1093/inthealth/ihaa007

Ikotun, A. M., Ezugwu, A. E., Abualigah, L., Abuhaija, B., & Heming, J. (2023). K-means clustering algorithms: A comprehensive review, variants analysis, and advances in the era of big data. *Information Sciences, 622*, 178–210. doi.org/10.1016/j.ins.2022.11.139

Jaiswal, A., Arun, C. J., & Varma, A. (2022). Rebooting employees: Upskilling for artificial intelligence in multinational corporations. *The International Journal of Human Resource Management, 33*(6), 1179–1208. doi.org/10.1080/09585192.2021.1891114

Jarrahi, M. H., Askay, D., Eshraghi, A., & Smith, P. (2023). Artificial intelligence and knowledge management: A partnership between human and AI. *Business Horizons, 66*(1), 87–99. doi.org/10.1016/j.bushor.2022.03.002

Jones, E., Sundaram, S., & Chin, W. (2002). Factors leading to sales force automation use: A longitudinal analysis. *Journal of Personal Selling & Sales Management, 22*(3), 145–156. doi.org/10.1080/08853134.2002.10754303

Jun, S., Phillips, L. T., & Foster-Gimbel, O. A. (2023). The missing middle: Asian employees' experience of workplace discrimination and pro-Black allyship. *Journal of Applied Psychology, 108*(2), 225–240. doi.org/10.1037/apl0001068

Kanbach, D. K., Heiduk, L., Blueher, G., Schreiter, M., & Lahmann, A. (2023). The GenAI is out of the bottle: Generative artificial intelligence from a business model innovation perspective. *Review of Managerial Science, 18*, 1–32. doi.org/10.1007/s11846-023-00696-z

Karimikia, H. (2017). *The impact of positive behaviours on the effectiveness of information systems departments* [Doctoral dissertation, Auckland University of Technology].

Karimikia, H., Safari, N., & Singh, H. (2020). Being useful: How information systems professionals influence the use of information systems in enterprises. *Information Systems Frontiers, 22*, 429–453. doi.org/10.1109/HICSS.2016.585

Kaymakcı, R., Görener, A., & Toker, K. (2022). The perceived overqualification's effect on innovative work behaviour: Do transformational leadership and turnover intention matter? *Current Research in Behavioral Sciences, 3*, 100068. doi.org/10.1016/j.crbeha.2022.100068

Keith, N., & Frese, M. (2005). Self-regulation in error management training: Emotion control and metacognition as mediators of performance effects. *Journal of Applied Psychology, 90*(4), 677–691. doi.org/10.1037/0021-9010.90.4.677

Kim, H.-W., & Gupta, S. (2014). A user empowerment approach to information systems infusion. *IEEE Transactions on Engineering Management, 61*(4), 656–668. doi.org/10.1109/TEM.2014.2354693

Krefft, A., Marcus, B., & Weigelt, O. (2024). Facets of constructive voice behavior: Construct clarification, theoretical refinement, and measurement. *Journal of Business Psychology*, 1–21. doi.org/10.1007/s10869-024-09932-z

Lee, J., & Zhou, M. (2015). *The Asian American achievement paradox*. Russell Sage Foundation.

Li, T. J.-J., Lu, Y., Clark, J., Chen, M., Cox, V., Jiang, M., Yang, Y., Kay, T., Wood, D., & Brockman, J. (2022). A bottom-up end-user intelligent assistant approach to empower gig workers against AI inequality. In *Symposium on Human-Computer Interaction for Work '22*, Durham, US.

Li, Y., Li, Y., Yang, P., & Zhang, M. (2022). Perceived overqualification at work: Implications for voice toward peers and creative performance. *Frontiers in Psychology, 13*, 835204. doi.org/10.3389/fpsyg.2022.835204

Liao, M., Zhang, M. J., Carnevale, J. B., Huang, C., & Wang, L. (2024). Capable fish or deficient ponds? A meta-analysis of consequences, mechanisms, and moderators of perceived overqualification. *Journal of Management*. doi.org/10.1177/01492063241239298

Lin, T.-A., & Chen, P.-H. C. (2022). Artificial intelligence in a structurally unjust society. *Feminist Philosophy Quarterly, 8*(3/4). doi.org/10.5206/fpq/2022.3/4.14191

Lindström, N., Koutsikouri, D., Stier, J., & Arvidsson, M. (2020). Migrant employment integration and artificial intelligence (AI). In *Proceedings of the 32nd Annual Workshop of the Swedish Artificial Intelligence Society* (SAIS), Stockholm, Sweden.

Liu, H., Yu, K.-H., & Wright, C. F. (2024). Precarious multiculturalism: The racialized experience of Asian in/exclusion in Australia. *American Behavioral Scientist*. doi.org/10.1177/00027642241231319

Liu, S., Luksyte, A., Zhou, L., Shi, J., & Wang, M. (2015). Overqualification and counterproductive work behaviors: Examining a moderated mediation model. *Journal of Organizational Behavior, 36*(2), 250–271. doi.org/10.1002/job.1979

Liu, Y., Du, X., & Ma, S. (2023). Innovative study on clustering center and distance measurement of K-means algorithm: MapReduce efficient parallel algorithm based on user data of JD mall. *Electronic Commerce Research, 23*(1), 43–73. doi.org/10.1007/s10660-024-09837-2

Liu, Y., Liu, D., Du, H., Liu, S., & Zhou, X. (2022). The multilevel study on the impact of high-performance human resource practices on employees' voice behavior: A moderated mediation model. *Frontiers in Psychology, 13*, 792329. doi.org/10.3389/fpsyg.2022.792329

Lu, J. G. (2022). A social network perspective on the bamboo ceiling: Ethnic homophily explains why East Asians but not South Asians are underrepresented in leadership in multiethnic environments. *Journal of Personality and Social Psychology, 122*(6), 959–977. doi.org/10.1037/pspa0000292

Lu, J. G. (2023). A creativity stereotype perspective on the bamboo ceiling: Low perceived creativity explains the underrepresentation of East Asian leaders in the United States. *Journal of Applied Psychology, 109*(2), 238–256. doi.org/10.1037/apl0001135

Ma, C., Ganegoda, D. B., Chen, Z. X., Jiang, X., & Dong, C. (2020). Effects of perceived overqualification on career distress and career planning: Mediating role of career identity and moderating role of leader humility. *Human Resource Management, 59*(6), 521–536. doi.org/10.1002/hrm.22009

Mackey, W., Coates, B., & Sherrell, H. (2022). *Migrants in the Australian workforce: A guidebook for policy makers*. Grattan Institute. https://grattan.edu.au/report/migrants-in-the-australian-workforce/

Mael, F. A., & Tetrick, L. E. (1992). Identifying organizational identification. *Educational and Psychological Measurement, 52*(4), 813–824. doi.org/10.1177/0013164492052004002

Mantello, P., Ho, M.-T., Nguyen, M.-H., & Vuong, Q.-H. (2023). Bosses without a heart: Socio-demographic and cross-cultural determinants of attitude toward emotional AI in the workplace. *AI & Society, 38*(1), 97–119. doi.org/10.1007/s00146-021-01290-1

Martinko, M. J., & Gardner, W. L. (1982). Learned helplessness: An alternative explanation for performance deficits. *The Academy of Management Review, 7*(2), 195–204. doi.org/10.2307/257297

Maynard, D. C., Joseph, T. A., & Maynard, A. M. (2006). Underemployment, job attitudes, and turnover intentions. *Journal of Organizational Behavior, 27*(4), 509–536. doi.org/10.1002/job.389

Maynard, M., Luciano, M., D'Innocenzo, L., Mathieu, J., & Dean, M. (2014). Modeling time-lagged reciprocal psychological empowerment-performance relationships. *Journal of Applied Psychology, 99*(4), 737–749. doi.org/10.1037/a0037623

McElheran, K., Li, J. F., Brynjolfsson, E., Kroff, Z., Dinlersoz, E., Foster, L., & Zolas, N. (2024). AI adoption in America: Who, what, and where. *Journal of Economics & Management Strategy, 33*(2), 375–415. doi.org/10.3386/w31788

Methot, J. R., Lepine, J. A., Podsakoff, N. P., & Christian, J. S. (2016). Are workplace friendships a mixed blessing? Exploring trade-offs of multiplex relationships and their associations with job performance. *Personnel Psychology, 69*(2), 311–355. doi.org/10.1111/peps.12109

Mittal, P., Jora, R. B., Sodhi, K. K., & Saxena, P. (2023). A review of the role of artificial intelligence in employee engagement. In *Proceedings of the 2023 9th International Conference on Advanced Computing and Communication Systems* (ICACCS), Tamil Nadu, India.

Mogaji, E., Viglia, G., Srivastava, P., & Dwivedi, Y. K. (2024). Is it the end of the technology acceptance model in the era of generative artificial intelligence? *International Journal of Contemporary Hospitality Management*. doi.org/10.1108/IJCHM-08-2023-1271

Molix, L., & Bettencourt, B. A. (2010). Predicting well-being among ethnic minorities: Psychological empowerment and group identity. *Journal of Applied Social Psychology, 40*(3), 513–533. doi.org/10.1111/j.1559-1816.2010.00585.x

Monod, E., Mayer, A.-S., Straub, D., Joyce, E., & Qi, J. (2024). From worker empowerment to managerial control: The devolution of AI tools' intended positive implementation to their negative consequences. *Information and Organization, 34*(1), 100498. doi.org/10.1016/j.infoandorg.2023.100498

Morris, R. (2008). Looking through the twin lens of race and gender: A new politics of surveillance in Asian Australian and Asian Canadian women's writing.

Muraven, M., & Baumeister, R. F. (2000). Self-regulation and depletion of limited resources: Does self-control resemble a muscle? *Psychological Bulletin, 126*(2), 247–259. doi.org/10.1037/0033-2909.126.2.247

Ng, E. H., & Kim, H. W. (2009). Investigating information systems infusion and the moderating role of habit: A user empowerment perspective. In *Proceedings of the 30th International Conference for Information Systems* (ICIS), Phoenix, Arizona, US.

Norton, T. A., Parker, S. L., Zacher, H., & Ashkanasy, N. M. (2015). Employee green behavior: A theoretical framework, multilevel review, and future research agenda. *Organization & Environment*, *28*(1), 103–125. doi.org/10.1177/1086026615575773

Nunnally, J. (1978). An overview of psychological measurement. In *Clinical Diagnosis of Mental Disorders: A Handbook* (pp. 97–146). doi.org/10.1007/978-1-4684-2490-4

Oetting, M. (2009). Empowered involvement. In *Ripple Effect: How Empowered Involvement Drives Word of Mouth* (pp. 73–81). Gabler. doi.org/10.1007/978-3-8349-8372-5_5

Ozturkcan, S., & Gashi Nulleshi, S. (2024). Generative artificial intelligence (Gen AI) as a co-creator: Exploring the collaboration between human and machine entrepreneurs. In *Proceedings of the Nordic Academy of Management*, Reykjavik, Iceland.

Perifanis, N.-A., & Kitsios, F. (2023). Investigating the influence of artificial intelligence on business value in the digital era of strategy: A literature review. *Information, 14*(2), 85. doi.org/10.3390/info14020085

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879–903. doi.org/10.1037/0021-9010.88.5.879

Preminger, J. (2020). Meritocracy in the service of ethnocracy. *Citizenship Studies, 24*(2), 247–263. doi.org/10.1080/13621025.2020.1720604

Pritiprada, P., Satpathy, I., Patnaik, B., & Thaichon, P. (2024). Fostering women's empowerment in Europe: Case studies of innovation in AI, blockchain, and the metaverse. In *Technology and Luxury Hospitality* (pp. 80–92). Routledge.

Reis, T., Bruchhaus, S., Vu, B., Bornschlegl, M. X., & Hemmje, M. L. (2021). Towards modeling AI-based user empowerment for visual big data analysis. *CEUR Workshop Proceedings, 2863*, 50–58. https://ceur-ws.org/Vol-2863/paper-07.pdf

Precedence Research. (2024). *Artificial intelligence (AI) market – 2024-2034 (global industry analysis, size, share, growth, trends, regional outlook, and forecast)*. https://www.precedenceresearch.com/artificial-intelligence-market

Rude, B., & Giesing, Y. (2022). Technological change and immigration – A race for talent or of displaced workers. In *Beiträge zur Jahrestagung des Vereins für Socialpolitik 2022: Big Data in Economics*, Kiel, Germany.

Ruiz, N. G., Noe-Bustamante, L., & Shah, S. (2023). Demographic profile of Asian American adults. In *Diverse cultures & shared experiences shape Asian American identities*. Pew Research Center. https://www.pewresearch.org/2023/05/08/asian-american-identity-appendix-demographic-profile-of-asian-american-adults/

Ruttiman, J. (2009). Breaking through the "bamboo ceiling" for Asian American scientists. *Science, 29*(09).

Sarker, S., Susarla, A., Gopal, R., & Thatcher, J. B. (2024). Democratizing knowledge creation through human-AI collaboration in academic peer review. *Journal of the Association for Information Systems, 25*(1), 158–171. doi.org/10.17705/1jais.00872

Schultheiss, D. E., & Davis, B. L. (2015). Immigrant workers: Career concerns and barriers. In *APA handbook of career intervention, Volume 1: Foundations* (pp. 259–277). American Psychological Association. doi.org/10.1037/14438-015

Schwartz, J., Denny, B., Mallon, D., Durme, Y. V., Hauptmann, M., Yan, R., & Poynton, S. (2020). Superteams: Putting AI in the group. In *Paradox as a path forward*. Deloitte. https://www.deloitte.com/global/en/our-thinking/insights/topics/talent/human-capital-trends/2020/human-ai-collaboration.html

Schwarz, A. H. (2003). *Defining information technology acceptance: A human-centered, management-oriented perspective* [Doctoral dissertation, University of Houston].

Segars, A. H., & Grover, V. (1998). Strategic information systems planning success: An investigation of the construct and its measurement. *MIS Quarterly, 22*(2), 139–163. doi.org/10.2307/249393

Sehgal, R. (2007). *User empowerment: An enabler of enterprise systems success* [Doctoral dissertation, Queensland University of Technology].

Seibert, S. E., Silver, S. R., & Randolph, W. A. (2004). Taking empowerment to the next level: A multiple-level model of empowerment, performance, and satisfaction. *Academy of Management Journal, 47*(3), 332–349. doi.org/10.5465/20159585

Shahapure, K. R., & Nicholas, C. (2020). Cluster quality analysis using silhouette score. In *Proceedings of the 2020 IEEE 7th International Conference on Data Science and Advanced Analytics* (DSAA), Piscataway, US.

Shi, Y., & Deng, B. (2024). Finding the sweet spot: Exploring the optimal communication delay for AI feedback tools. *Information Processing & Management, 61*(2), 103572. doi.org/10.1016/j.ipm.2023.103572

Shrestha, N. J. (2021). Factor analysis as a tool for survey analysis. *American Journal of Applied Mathematics and Statistics, 9*(1), 4–11. dx.doi.org/10.12691/ajams-9-1-2

Shukla, S. (2023). Creative computing and harnessing the power of generative artificial intelligence. *Journal of Environmental Sciences and Technology, 2*(1), 556–579. doi.org/10.5281/zenodo.10847103

Sison, A. J. G., Daza, M. T., Gozalo-Brizuela, R., & Garrido-Merchán, E. C. (2023). ChatGPT: More than a "weapon of mass deception" – Ethical challenges and responses from the human-centered artificial intelligence (HCAI) perspective. *International Journal of Human–Computer Interaction*, 1–20. doi.org/10.1080/10447318.2023.2225931

Sowa, K., Przegalinska, A., & Ciechanowski, L. (2021). Cobots in knowledge work: Human–AI collaboration in managerial professions. *Journal of Business Research, 125*, 135–142. doi.org/10.1016/j.jbusres.2020.11.038

Sparreboom, T., & Tarvid, A. (2016). Imbalanced job polarization and skills mismatch in Europe. *Journal for Labour Market Research, 49*, 15–42. doi.org/10.1007/s12651-016-0196-y

Spreitzer, G. M. (1995). Psychological empowerment in the workplace: Dimensions, measurement, and validation. *Academy of Management Journal, 38*(5), 1442–1465. doi.org/10.5465/256865

Stewart, K. J., Darcy, D. P., & Daniel, S. L. (2006). Opportunities and challenges applying functional data analysis to the study of open source software evolution. *Statistical Science, 21*(2), 167–178. doi.org/10.1214/088342306000000141

Sum, N., Lahiri-Roy, R., & Belford, N. (2023). Hope theory as resistance: Narratives of South Asian scholars in Australian academia. *Equality, Diversity and Inclusion: An International Journal*. doi.org/10.1108/EDI-03-2023-0085

Sumi, E. J., Kabir, M. S., & Alam, M. N. (2024). Artificial intelligence in migrant labour management: A comprehensive review. *International Journal for Multidisciplinary Research, 6*(1). doi.org/10.36948/ijfmr.2024.v06i01.13041

Sundaram, S., Schwarz, A., Jones, E., & Chin, W. W. (2007). Technology use on the front line: How information technology enhances individual performance. *Journal of the Academy of Marketing Science, 35*, 101–112. doi.org/10.1007/s11747-006-0010-4

Syed, J. (2008). Employment prospects for skilled migrants: A relational perspective. *Human Resource Management Review, 18*(1), 28–45. doi.org/10.1016/j.hrmr.2007.12.001

Tadampali, A. C. T., & Hadi, A. (2017). The effect of job satisfaction and organizational commitment on work engagement and performance. In *Proceedings of the 2nd International Conference on Education, Science, and Technology (ICEST 2017)* (pp. 19). doi.org/10.2991/icest-17.2017.19

Taherizadeh, A., & Beaudry, C. (2023). An emergent grounded theory of AI-driven digital transformation: Canadian SMEs' perspectives. *Industry and Innovation, 30*(9), 1244–1273. doi.org/10.1080/13662716.2023.2242285

Thomas, K. W., & Velthouse, B. A. (1990). Cognitive elements of empowerment: An "interpretive" model of intrinsic task motivation. *Academy of Management Review, 15*(4), 666–681. doi.org/10.2307/258687

Underwood, T. (2024). Will AI make us overconfident? https://tedunderwood.com/2024/08/31/will-ai-make-us-overconfident/

Usmani, U. A., Happonen, A., & Watada, J. (2023). Human-centered artificial intelligence: Designing for user empowerment and ethical considerations. In *Proceedings of the 2023*

5th International Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA), Istanbul, Turkey.

Vardaman, J. M., Amis, J. M., Dyson, B. P., Wright, P. M., & Van de Graaff Randolph, R. (2012). Interpreting change as controllable: The role of network centrality and self-efficacy. *Human Relations, 65*(7), 835–859. doi.org/10.1177/0018726712441642

Venkatesh, V. (2022). Adoption and use of AI tools: A research agenda grounded in UTAUT. *Annals of Operations Research, 308*(1), 641–652. doi.org/10.1007/s10479-020-03918-9

Vichi, M., & Saporta, G. (2009). Clustering and disjoint principal component analysis. *Computational Statistics & Data Analysis, 53*(8), 3194–3208. doi.org/10.1016/j.csda.2008.05.028

Vomberg, A., & Klarmann, M. (2022). Crafting survey research: A systematic process for conducting survey research. In C. Homburg, M. Klarmann, & A. Vomberg (Eds.), *Handbook of Market Research* (pp. 67–119). Springer International Publishing. doi.org/10.1007/978-3-319-57413-4_4

Von Krogh, G. (2018). Artificial intelligence in organizations: New opportunities for phenomenon-based theorizing. *Academy of Management Discoveries, 4*(4), 404–409. doi.org/10.5465/amd.2018.0084

Wang, M., Beal, D. J., Chan, D., Newman, D. A., Vancouver, J. B., & Vandenberg, R. J. (2017). Longitudinal research: A panel discussion on conceptual issues, research design, and statistical techniques. *Work, Aging and Retirement, 3*(1), 1–24. doi.org/10.1093/workar/waw033

Wang, S. M., Scott, K. M., Artemenko, M., Miceli, M., & Berendt, B. (2023). "We try to empower them" – Exploring future technologies to support migrant jobseekers. In *Proceedings of the 2024 ACM Conference on Fairness, Accountability, and Transparency* (FAccT), Rio de Janeiro, Brazil.

Wilson, H. J., & Daugherty, P. R. (2018). Collaborative intelligence: Humans and AI are joining forces. *Harvard Business Review, 96*(4), 114–123.

Wong, L.-W., Tan, G. W.-H., Ooi, K.-B., & Dwivedi, Y. (2024). The role of institutional and self in the formation of trust in artificial intelligence technologies. *Internet Research, 34*(2), 343–370. doi.org/10.1108/INTR-07-2021-0446

Wu-Gehbauer, M., & Rosenkranz, C. (2024). Towards a framework for developing artificial intelligence systems for human-artificial intelligence augmentation. In *Proceedings of the 32nd European Conference on Information Systems* (ECIS), Paphos, Cyprus.

Yan, L., & Grossman, G. M. (2023). *Robots and AI: A new economic era*. Taylor & Francis.

Yildiz, K., Akoğlu, H. E., Emir, E., Angosto, S., & García-Fernández, J. (2024). The perceived effect of digital transformation and resultant empowerment on job performance of employees in the fitness family business. *Journal of Family Business Management*. doi.org/10.1108/JFBM-02-2024-0038

Yip, T., Cheah, C. S., Kiang, L., & Hall, G. C. N. (2021). Rendered invisible: Are Asian Americans a model or a marginalized minority? *American Psychologist, 76*(4), 575–586. doi.org/10.1037/amp0000857

Zaza, I., & Junglas, I. (2016). IT self-service engagement: A theory of trying perspective. In *Proceedings of the Thirty-Seventh International Conference on Information Systems* (ICIS), Dublin, Ireland.

Zhang, P. (2023). Taking advice from ChatGPT. *arXiv Preprint arXiv:2305.11888*. dx.doi.org/10.48550/arXiv.2305.11888

Appendix 1 AIEMP Supplementary Analysis Results

Table 7 and Figure 4, Figure 5 show that the four dimensions of AIEMP factor did not follow a normal distribution.

Variable	Shapiro-Wilk *W*	p-value
Meaningfulness		
AIEMP_Meaningfulness_1	0.909***	<0.001
AIEMP_Meaningfulness_2	0.908***	<0.001
AIEMP_Meaningfulness_3	0.912***	<0.001
Competence		
AIEMP_Competence_1	0.911***	<0.001
AIEMP_Competence_2	0.909***	<0.001
AIEMP_Competence_3	0.906***	<0.001
Self-determination		
AIEMP_SD_1	0.912***	<0.001
AIEMP_SD_2	0.923***	<0.001
AIEMP_SD_3	0.904***	<0.001
Impact		
AIEMP_Impact_1	0.913***	<0.001
AIEMP_Impact_2	0.901***	<0.001
AIEMP_Impact_3	0.910***	<0.001

Table 7 Shapiro-Wilk Normality test results

Note*: * $p < .05$, ** $p < .01$, *** $p < .001$.*

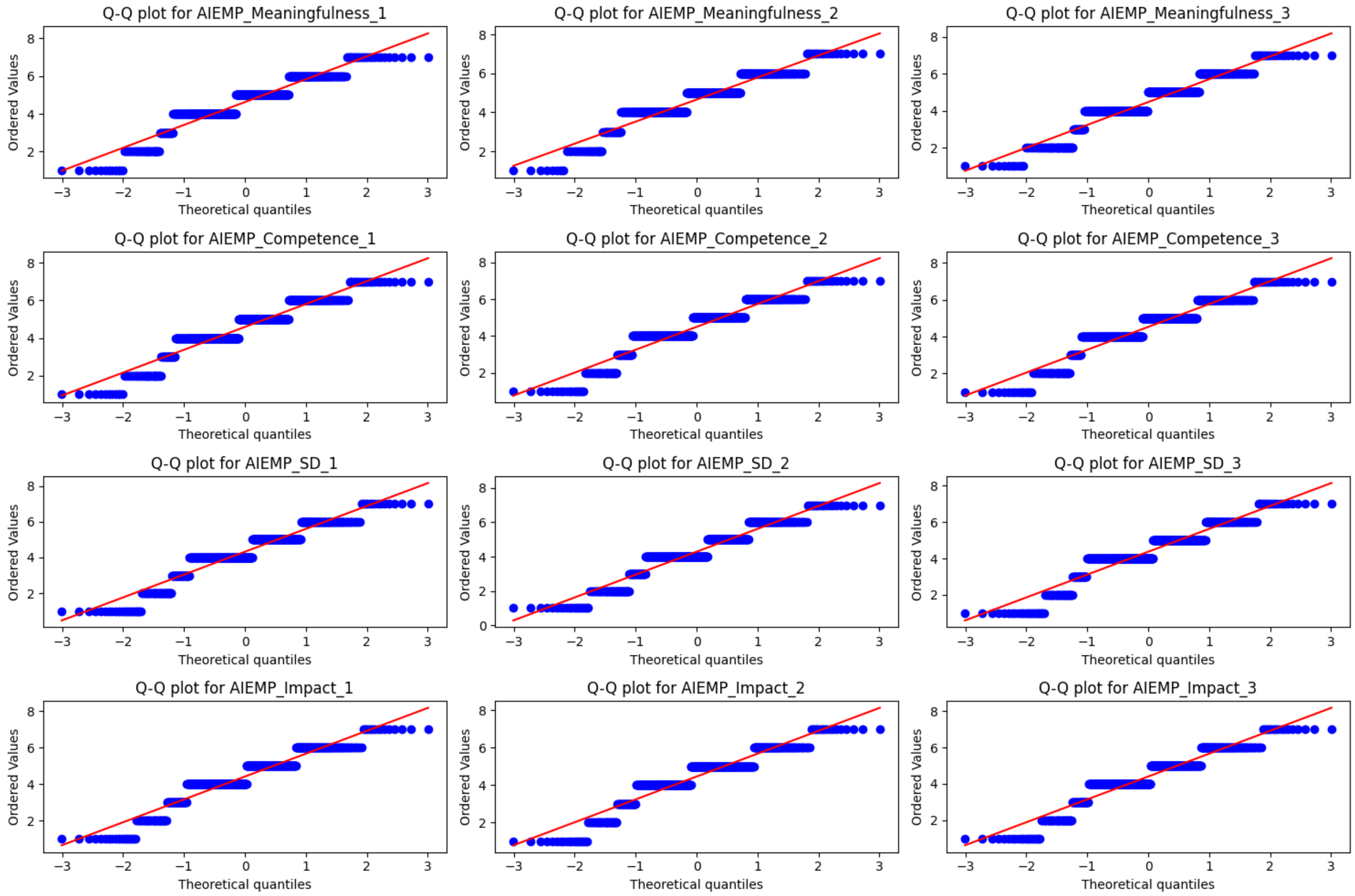


Figure 4 Q-Q plots for the four dimensions in AIEMP

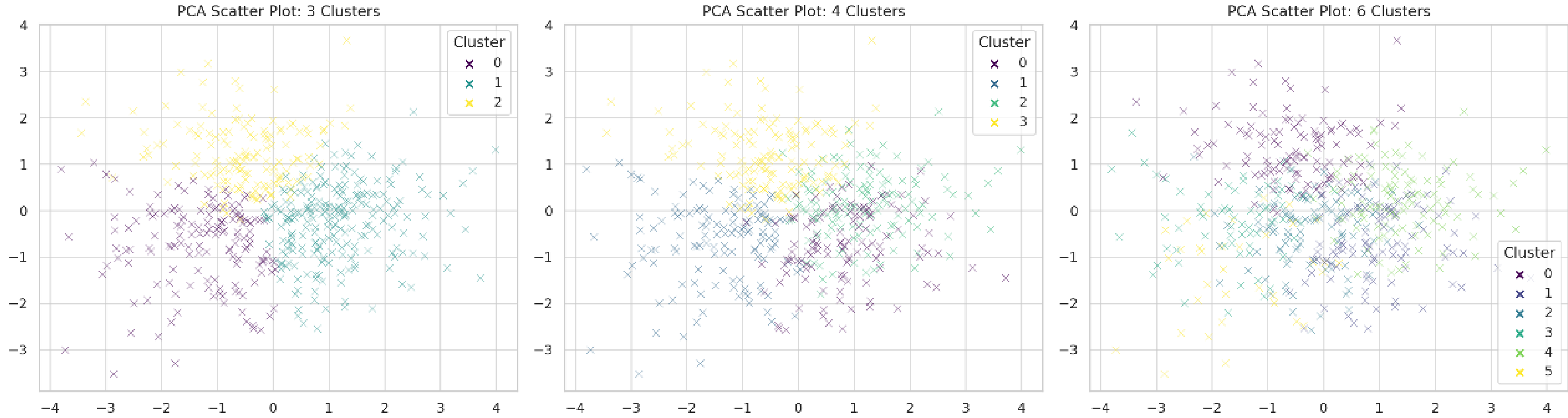
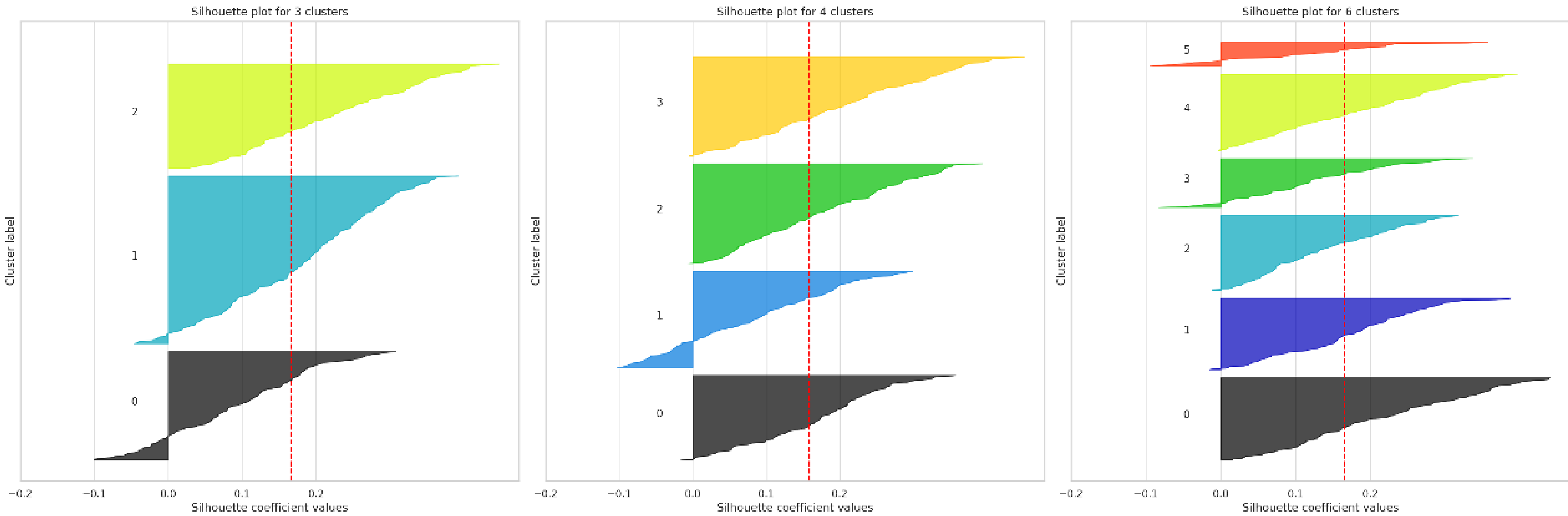


Figure 5 Principal Component Analysis (PCA) processed clusters scatter plot



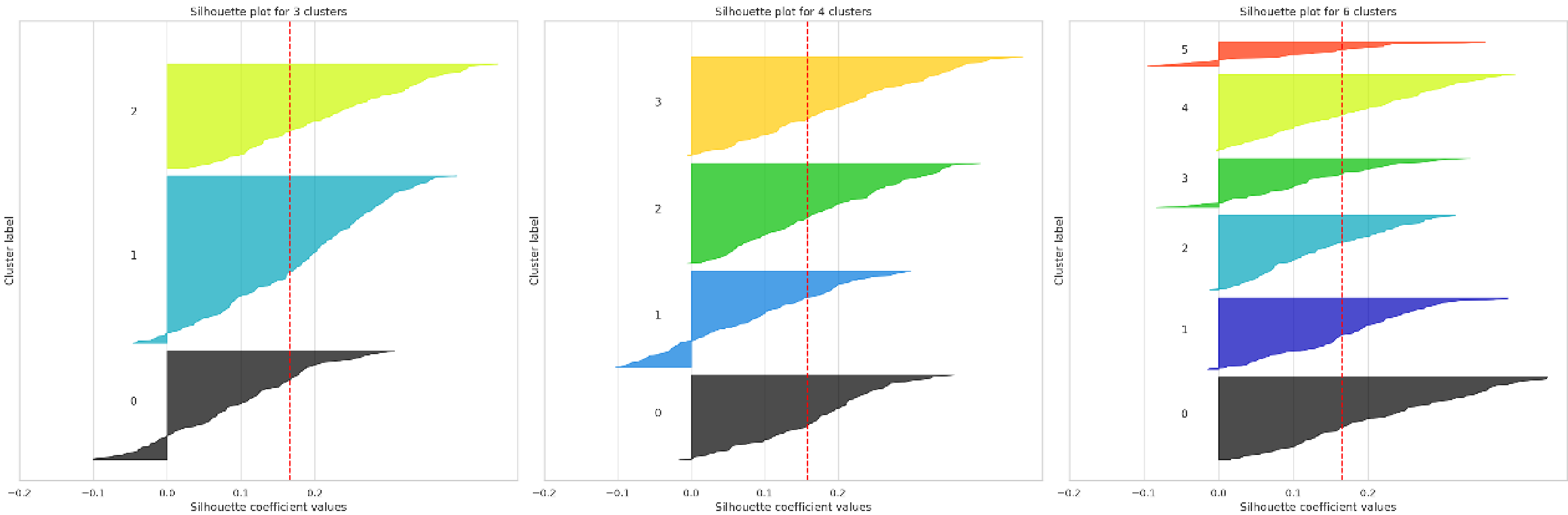


Figure 6 Silhouette plots for the solutions

In accordance with the evaluation criteria suggested by Hair et al. (2006) and Chen et al. (2005), our confirmatory factor analysis (CFA) results (see Table 8) indicate that the second-order model performs comparably to three alternative first-order factor models: a Unidimensional model, an Uncorrelated model, and a Correlated model. Specifically, Model 1 posits that a single first-order factor explains the variance among the 12 items. Model 2 assumes that these items form four uncorrelated first-order factors—meaningfulness, competence, self-determination, and impact. Model 3 allows these four factors to correlate freely. Model 4 is our second-order factor model which accounts for the relationships among the four first-order factors.

As Chen et al. (2005) say, a second-order model is preferable for several reasons: it estimates fewer parameters and thus offers more degrees of freedom, enhancing parsimony. Furthermore, it simplifies the interpretation of complex models by distilling the core variances of first-order factors and effectively isolating the measurement errors and unique variances associated with these factors. This ability to clarify the underlying structure without compromising the model's integrity makes the second-order factor model particularly valuable in our analysis. Thus the second order model is able to better quantify and understand how specific dimensions (first-order constructs) contribute to a broader, more comprehensive construct (second-order construct) particularly beneficial in fields like psychology or business, where complex constructs are common and comprise various underlying factors (Segars & Grover, 1998), and thus by using a second-order model, researchers and practitioners can more accurately assess these composite constructs, leading to better decision-making and more targeted interventions.

Model		DoF	Chi-square	CFI	GFI	NFI	RMSEA
First order	Unidimensional	54	628.879	0.882	0.872	0.872	0.143
	Uncorrelated	54	1626.049	0.677	0.670	0.670	0.236
	Correlated	48	130.945	0.983	0.973	0.973	0.057
Second-Order		50	190.491	0.971	0.961	0.961	0.073

Table 8 CFAs for the Alternative Measurement Models for AIEMP

Note: CFI, comparative fit index; GFI, goodness-of-fit index; NFI, normed fit index; RMSEA, root mean square error of approximation

Appendix 2 Cluster Supplementary Materials

We used Principal Component Analysis (PCA), a dimensionality-reduction method, to prepare the visualization of the clusters (Vichi & Saporta, 2009). We standardized the range of the continuous initial variables so that each one of them has a mean of 0 and a standard deviation of 1. Then we computed the covariance matrix of the data, and, from the covariance matrix, the eigenvalues and eigenvectors are computed. The eigenvectors were then sorted by decreasing eigenvalues to rank the corresponding principal components in order of significance.

Then, the data can be projected onto the new feature space, so we could develop the clustering visualization as in Figure 5. Note in the figure, the x-axis is the first principal axis and captures the maximum variance in the data. It effectively represents a weighted combination of the original variables that accounts for the largest amount of variability in the dataset. The specific weights (or loadings) for each original variable can give insight into which variables contribute most to this component. The y-axis is the second principal axis and captures the maximum remaining variance that is orthogonal (i.e., uncorrelated) to the first principal component. It provides the second most significant way of seeing the variability in the data.

We conducted another analysis to compare the silhouette scores following prior research (Shahapure & Nicholas, 2020). The silhouette widths for the 3, 4 and 6-Cluster solutions were shown in

, indicating no major differences and all have a silhouette value higher than 1. The 3 and 6-Cluster solutions were slightly better than the 4-cluster solution.

Appendix 3 Concepts Correlations

The correlation table is presented in Table 9.

	AGE	GENDER	EDUCATION	TENURE	AIEMP	IU	JP	CV	EI
AGE	1.00								
GENDER	0.04	1.00							
EDUCATION	0.12	-0.05	1.00						
TENURE	0.35	-0.01	-0.07	1.00					
AIEMP	-0.14	0.07	0.09	-0.12	1.00				
IU	-0.08	-0.02	0.09	-0.09	0.49	1.00			
JP	0.13	-0.09	0.01	0.09	-0.03	0.07	1.00		
CV	0.07	0.00	0.08	-0.04	0.21	0.26	0.28	1.00	
EI	0.00	-0.05	-0.03	-0.07	0.26	0.22	0.02	0.15	1.00

Table 9 Correlations Matrix

Note: AGE, quantified as a categorical variable with ranges from 1 (less than 21 years) to 5 (more than 50 years); GENDER, coded as -1 for female, 0 for others (including "prefer not to say"), and 1 for male; EDUCATION, ranging from 0 (high school and lower) to 4 (doctoral degree); TENURE, indicating the length of current employment in months; AI Empowerment (AIEMP) [Time 1], which measures how individuals utilize AI to enhance job performance, with aspects like Meaningfulness, Competence, Self-Determination, and Impact; Infusion Use (IU) [Time 2], assessing the comprehensive utilization and integration of system capabilities; Job Performance (JP) [Time 3], *evaluated through self-report ratings of task-focused contributions; Constructive Voicing (CV) [Time 3], involving expressions of constructive and change-oriented messages; and Ethnic Identity (EI) [Time 1], exploring personal identification with Asian ethnicity through reactions to societal feedback and shared achievements.*

Appendix 4 Methods for Attention Checks and Filtering of Unqualified Participants

To ensure the reliability of our data, we employed two primary methods for attention checks and filtering out unqualified participants: one utilizing the Octopus Group's methods[4], and the other one is based on our own tailored approach. This appendix provides a detailed account of our own procedures.

1. Mechanistic Filtering Methods

Our first approach involved mechanistic filtering to exclude unqualified participants. We implemented the following criteria:

> **Completion of All Study Waves:** Each participant was assigned a unique ID that they were required to use consistently across all three waves of data collection. By merging data from the three waves based on these IDs as key, we were able to identify and exclude participants who failed to complete at least one of the waves.
> **Survey Completion Time:** We monitored the total duration each participant spent on the survey. Participants who completed the survey in less than two minutes were excluded, as this indicated insufficient time for thoughtful responses.

2. Interaction with an AI Question to Check Attention

In addition to mechanistic filtering, we assessed participants' familiarity with AI, as well as their attention, by incorporating a question derived from the study by Sowa et al. (2021). This question was designed to categorize human-AI interaction into four tiers (Separation (No Collaboration), Complementary Collaboration, Dependent Collaboration, and Hybrid Collaboration). Specifically, the question is:

Please choose the level of collaboration that best describes the current state of human-AI interaction in your work environment, considering the descriptions below:

> Option A: Level 1: Separation (No Collaboration) - Human workers compete with or work completely separately from AI machines.
> Option B: Level 2: Complementary Collaboration - Humans and AI complement each other by focusing on tasks they are individually good at.
> Option C: Level 3: Dependent Collaboration - AI and humans become dependent on each other, with AI sometimes needing human guidance for decision-making.
> Option D: Level 4: Hybrid Collaboration - AI becomes an extension of the human brain, and the two work together collaboratively as a 'centaur.'

This is also an attention checking mechanism because we introduced an additional E. Level 0: No engagement with AI. Participants who selected Level 0 were presumed to have overlooked the survey requirements, as all participants were required and informed to have prior experience with AI in their work. This oversight was considered indicative of a lack of attention, leading to the exclusion of these individuals from our analysis.

By employing these multi-faceted filtering techniques, we validated our data and ensured its reliability for our study.

---

[4] *We briefly introduced the methods in the main body. For details, please see: https://support.octopusgroup.com.au/*

Appendix 5 AIEMP supplementary analysis results

In recent years, there has been a growing body of research exploring various AI-related concepts such as AI use/adoption, AI integration, AI transformation, and AI collaboration. While these topics are closely related to our core concept of AI Empowerment, they are distinguishable in several key aspects. The details of these distinctions are outlined below.

Concept	Summary	Comments on difference
AI Use/Adoption	AI adoption normally refers to the decision-making process that individuals or organizations undergo when deciding to adopt AI technologies. It focuses on the initial acceptance and willingness to integrate AI into the work environment, influenced by factors such as perceived usefulness, ease of use, and external pressures. Commonly, AI use and AI adoption are discussed together, as seen in Venkatesh (2022). Nonetheless, as in McElheran et al. (2024) and (Wong et al., 2024), AI use in some research can be more broadly understood as the practical application of AI technologies within firms, varying in intensity and scope from basic, exploratory use to advanced, widespread integration across different aspects of the business.	Our AI Empowerment concept centres on the idea that employees feel empowered when they perceive that an external intelligence system supports them in achieving their work goals and overcoming work-related challenges. This concept primarily operates at the individual level, focusing on how AI influences personal outcomes such as job satisfaction, performance, and proactive behaviours in the workplace. Unlike AI use/adoption, which often involves simpler metrics like a dummy variable indicating AI usage or a single-level scale (see Venkatesh (2022), Czarnitzki et al. (2023) and Almaiah et al. (2022)), our AI Empowerment employs a two-level scale to measure how individuals utilize AI in their jobs, integrating psychological empowerment theories with AI-specific behaviours.
AI Integration/ self–AI integration	According to Alabed et al. (2022), AI Integration, or self–AI integration, can be viewed as a more advanced stage than mere adoption. It involves reconfiguring work processes and enhancing capabilities through AI by incorporating an anthropomorphized AI agent into one's self-schema. This integration occurs through a cognitive match between AI and the self, known as self-congruence, where AI becomes a part of the user's identity, thereby enhancing their sense of identity and social belonging (Huang & Rust, 2021).	Although both AI Integration and AI Empowerment involve the utilization of AI technologies to improve work outcomes, AI Empowerment focuses on how employees feel empowered by the presence and use of AI technologies but does not emphasize the psychological process where individuals perceive AI as an extension of themselves. Empowerment literature typically addresses how technologies empower employees by making them feel more competent, meaningful, determined, and impactful in their roles, as Seibert et al. (2004) guided, rather than integrating AI into their self-schema.

AI Transformation	AI transformation, or AI-driven digital transformation (AIDT), according to Taherizadeh and Beaudry (2023), , refers to the profound and comprehensive changes that AI technologies bring to an organization's activities, boundaries, and goals. This concept extends beyond the mere adoption or use of AI, involving a holistic reconfiguration of organizational processes, structures, and strategies to fully leverage AI's potential. It evolves from the broader concept of digital transformation. AI transformation drives significant shifts in how organizations operate, compete, and deliver value, often leading to the creation of new business models and restructuring organizational boundaries (Holmström, 2022).	AI Empowerment, on the other hand, focuses on the individual's experience and perception of how AI technologies enhance their ability to achieve work-related goals and overcome challenges. It is concerned with how AI influences personal job satisfaction, performance, and proactive behaviors by making employees feel more competent, autonomous, and impactful in their roles.
AI Collaboration	This concept discusses the interdependence between AI systems and employees in performing tasks together to achieve shared goals. AI collaboration can range from AI assisting with routine tasks to AI and humans co-creating solutions, making decisions, and enhancing productivity in complex work environments(Davenport & Miller, 2022). Sowa et al. (2021) provide a framework for measuring AI collaboration across different levels, from minimal interaction to fully integrated collaboration where AI and humans work together as a 'centaur.'	Both AI-Human Collaboration and AI Empowerment involve leveraging AI technologies to enhance human capabilities in the workplace. However, AI-Human Collaboration focuses on the dynamic levels of interaction between AI systems and humans. In contrast, AI Empowerment is more specifically focused on the psychological and motivational aspects of AI usage, concentrating on how AI makes individuals feel more empowered in their specific roles.

Copyright

doi: https://doi.org/10.3127/ajis.v29.5189