Technophobia and the manager’s intention to adopt generative AI: The impact of self-regulated learning and open organisational culture

Abstract

Purpose — Using the Cognitive-Affective-Normative (CAN) model, this study highlights the role of self-regulated learning (SRL) and organisational culture and delves into the link between technophobia and a manager’s intention to adopt generative artificial intelligence (AI) in management practices.

Design/methodology/approach — An empirical study was conducted through a survey of 528 business managers from China.

Findings — The study reveals that technophobia is negatively related to a manager’s intention to adopt generative AI, while SRL is positively related to the intention to adopt generative AI. Moreover, SRL reduces the negative impact of technophobia on AI adoption. Open organisational cultures reduce the need for SRL.

Originality — This study goes beyond a purely technical perspective towards a "human-side" view on understanding managers’ adoption of generative AI. This study is an early attempt to apply the CAN model to analysing the connection between technophobia, SRL, organisational culture, and the intention to adopt generative AI.

Keywords: Technophobia; self-regulated learning (SRL); innovation adoption; generative AI; Cognitive-Affective-Normative (CAN) model

Introduction

Business managers, despite their vast experience and knowledge, may not instinctively embrace new technologies (Albrechtsen & Hovden, 2009; Carlsson, 2023). Technophobia is not exclusive to certain individuals or groups; it can impact anyone’s emotions and psychological state (Di Giacomo et al., 2019; Khasawneh, 2018a; Subero-Navarro et al., 2022; Yang & Wang, 2023). Overcoming management technophobia is pivotal in driving digital transformation and innovation adoption within organisations (Carlsson, 2023).

Generative AI is a disruptive technology based on deep learning models that can generate human-like content, such as images, voices, and texts, in response to complex prompts like language, instructions, and questions (Lim et al., 2023). It offers significant advantages for management, including improving the efficiency of speech processing, stimulating advertising creativity, and accelerating data handling. However, due to concerns over customer acceptance (Ma & Huo, 2023), unexplainable decisions (Benbya et al., 2020), potential misuse (Kostygina et al., 2023), and ethical/privacy concerns (Dwivedi et al., 2023; Oniani et al., 2023), managers remain cautious about adopting generative AI.

Previous studies have extensively explored technophobia of various user groups, including IT users (Baker et al., 2014), young individuals (Khasawneh, 2018b), students (Hsu et al., 2009; Korobili et al., 2010), and older adults (Di Giacomo et al., 2019), but little attention has been paid to business managers. Moreover, despite existing research exploring factors influencing managers' intention to adopt generative AI, Existing research predominantly adopts a technology-centric perspective, assuming that technology is inherently positive and emphasizing that its efficiency and effectiveness should drive adoption (Straub, 2009; Turel et al., 2021). However, this stance should be challenged in the context of generative AI, because it overlooks the complex psychological processes managers experience during adoption, as well as the interactions between their cognition, emotional responses, and social norms.

Therefore, the field needs to beyond the purely technical perspective towards a "human-side" view, with more focuses on the psychological processes managers experience during adoption and considers how their cognition, emotional responses, and external social norms interact to collectively shape their attitudes towards generative AI.

In this paper, supported by the cognitive-affective-normative model (CAN) (Pelegrin-Borondo et al., 2016), we emphasize the interplay between technophobia (Yang & Wang, 2023), SRL (Iodice et al., 2022), organisational culture (Fousiani et al., 2024), and a manager's adoption of generative AI. This research contributes to the existing literature in three ways: (1) it goes beyond a purely technical perspective towards a "human-side" view, revealing business managers' technophobia towards generative AI, as prior studies mainly focused on other user groups, such as IT users (Baker et al., 2014), students (Hsu et al., 2009; Korobili et al., 2010), and older adults (Di Giacomo et al., 2019); (2) it extends the application of the CAN model to explore business managers' adoption of generative AI. It also comprehends CAN model by combining technophobia, SRL, and organisational culture into a more integrated framework; (3) it explicates the role of SRL and organisational culture in overcoming psychological barriers and enhancing generative AI adoption, an aspect presently missing from the literature.

The next section reviews the theoretical underpinnings and factors affecting generative AI adoption, which leads to the development of hypotheses. This is followed by research methods and data analysis. This paper then offers discussion about findings, implications, and future research.

Literature review

Technophobia

Technophobia is an irrational fear or anxiety towards new technology that disrupts routine job tasks, and it manifests in active avoidance and passive distress (Khasawneh, 2018b). This fear arises from various factors, including personality, cognitive orientation (Korukonda, 2005), technology experience (Hou et al., 2017; Korukonda, 2005), skills (Korukonda, 2005), and so on.

Past studies on technophobia mainly focused on computer contexts, discussing users' computer fear/anxiety (Baker et al., 2014; Di Giacomo et al., 2019). One study explored how computer anxiety affects IT users' attitudes towards technology usage through computer self-efficacy. Results showed a negative correlation between computer anxiety and self-efficacy, and a positive correlation between self-efficacy and technology usage (Baker et al., 2014). A survey with Michigan small business employees found a negative correlation between technophobia and technology acceptance, with organisational climate positively regulating this relationship (Khasawneh, 2018a).

In recent years, with the rapid development of AI, its widespread application has introduced new uncertainties and risks, including the challenge of technophobia (Zhan et al., 2023). Hence, scholars have started to explore technophobia's impact on AI adoption (e.g., Subero-Navarro et al., 2022).

Self-regulated learning (SRL)

Technophobia potentially can be mitigated by SRL which involves learners' self-motivated approach to planning, implementing, and adjusting their learning strategies (Zimmerman, 1986). Previous studies indicate that self-regulated learning reduces academic anxiety (Kesici et al., 2011), enhances technological self-efficacy in online learning (Wang et al., 2013), promotes positive learning attitudes (Li, 2019), and predicts online course continuation (Zhu et al., 2020).

For example, a survey study found that learning strategies like rehearsal, organisation, and metacognitive regulation reduced statistical anxiety, emphasizing its role in coping with challenges (Kesici et al., 2011). Another study showed a positive correlation between self-regulated learning and technological self-efficacy, with experienced online learners being more motivated (Wang et al., 2013). A study on 94 college students revealed that self-regulatory factors predicted their intention to continue online learning (Zhu et al., 2020). Moreover, self-regulated learning strategies can impact learners' perceived affective learning (Li, 2019). The general consensus amongst researchers is that SRL has the potential to divert managers' anxiety levels and affect their intentions to adopt disruptive innovations.

Theoretical underpinning of generative AI adoption

Past researchers have extensively explored diverse factors that affect users' acceptance and adoption of new technologies through various theoretical frameworks, including the Theory of Planned Behaviour (TPB) (Ajzen, 2011), the Technology Acceptance Model (TAM) (Davis, 1989; Venkatesh & Davis, 2000), the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), and the CAN model (Pelegrin-Borondo et al., 2016). These theories have broadened the comprehension of new technology adoption and provided valuable theoretical underpinnings for studying generative AI adoption.

TPB postulates that behaviour intentions lead to actual behaviour, and these intentions are influenced by attitude, subjective norms, and perceived control (Ajzen, 2011). On the other hand, TAM emphasizes that individuals' acceptance of IT is mainly influenced by perceived usefulness and ease of use (Davis, 1989). The Extended TAM research (Venkatesh & Davis, 2000) incorporates social influence, individual differences, and intention to use, potentially broadening its scope in AI adoption. Other researchers combined TAM with the perceived contingency model to predict AI-driven personalized feature adoption on digital news platforms (Lim & Zhang, 2022). UTAUT combines key variables from various technology acceptance models, emphasizing behavioural intention as a crucial determinant of usage. This intention is influenced by performance, effort, social influence, and facilitating conditions (Venkatesh et al., 2003).

In recent years, the CAN model, which combines cognition, affect, and norms to explain decision-making and behaviour (Pelegrin-Borondo et al., 2016), has been highlighted and it offers a more comprehensive understanding of technology adoption. The CAN model can offer a better explanation, because it not only considers the cognitive evaluation of users towards the technology, but also considers their emotional responses (such as technophobia) and social norms (such as organisational context). This multidimensional approach enables a more comprehensive understanding of the decision-making process of business managers, and hence is adopted by this study.

Research hypotheses

Technophobia and the manager's intention to adopt generative AI

According to the CAN model, individuals' decision-making and behavioural choices are not only influenced by cognition, but also driven by emotions (Pelegrin-Borondo et al., 2016). For a business manager, technophobia has a potential impact on their intention to adopt generative AI for three reasons. First, emotions play a crucial role in the decision-making process of enterprise managers (Lerner et al., 2015). Technophobia, as an emotional response, manifests as negative emotions such as anxiety, unease, and concern among managers towards new technologies and potential consequences of adopting them (Dwivedi et al., 2023; Khasawneh, 2018b). This fear can lead to resistance towards new technologies, thereby negating a manager's intention to adopt generative AI.

Secondly, technophobia has a negative impact on managers' cognitive judgments, leading to doubt about the functionality and benefits of generative AI (Bedue & Fritzsche, 2022). Due to the presence of fear, managers may magnify potential risks and problems of the technology while ignoring its competitive advantage gains for the organisation (Alshahrani et al., 2022). This negative bias not only weakens managers' trust in generative AI (Bedue & Fritzsche, 2022) but also reduces their willingness to adopt.

Thirdly, technophobia can lower managers' self-efficacy. Self-efficacy is described as one of the most critical determinants of digital system usage capability (Shao et al., 2024; Ulfert-Blank & Schmidt, 2022). Studies have shown that when users feel capable of understanding and using AI, they are more likely to have a positive attitude towards these technologies (Shao et al., 2024). However, when individuals feel they cannot effectively control new technologies or worry that their technical abilities are insufficient to cope with the changes brought by the technology, their self-efficacy decreases (Xi et al., 2022). This reduced self-efficacy can lead to resistance towards new technologies and decreased willingness towards adoption. Therefore,

H1: *The level of technophobia is negatively related to a manager's intention to adopt generative AI.*

SRL and a manager's intention to adopt generative AI

In this study, we also recognise the role of SRL. This is because SRL provides an important perspective on understanding users' evaluation of technology, emphasizing the dynamic development of their cognition. As managers engage in SRL, their evaluation of new technologies will gradually change (Yang & Wang, 2023).

SRL emphasizes individuals' active management and the adjustment of their own learning process, with goal-orientation being a notable feature (Panadero, 2017; Zimmerman, 1986). For managers, their learning objectives are often closely connected to the business development and strategic needs of the organisation. Managers with SRL may actively seek knowledge related to generative AI by reading, participating in training, engaging in industry exchanges, and continuously enhancing their understanding and capabilities. As they gain a deeper understanding of generative AI, managers increasingly recognise its immense potential in improving work efficiency and business decision-making (Dwivedi et al., 2023). Therefore, the stronger the managers' ability to self-regulate their learning, the more likely they are to actively adopt generative AI and effectively apply it into practice.

Moreover, previous studies highlight the crucial role of SRL in enhancing technological self-efficacy (Wang et al., 2013). By utilising SRL, managers can set clear learning goals, select effective strategies, and monitor their progress in real-time. This approach will not only boost their confidence in applying generative AI but also reduce fear of the unknown, thereby enhancing their decision-making capabilities. Therefore, not only can SRL effectively enhance managers' professional knowledge about generative AI, but also strengthen their technological self-efficacy, thereby stimulating their willingness to adopt generative AI. Hence,

H2: *SRL is positively related to a manager's intention to adopt generative AI.*

Moderating effect of SRL on the relationship between technophobia and intention to adopt generative AI

When managers have technophobia, especially related to generative AI, having the ability to SRL enables managers to actively learn, understand, and adapt to this disruptive new technology. By adjusting their cognitive structures, managers with SRL can gradually overcome their fear of generative AI, thereby enhancing their willingness to adopt. In this process, SRL plays a crucial role as an active coping and adaptation mechanism for managers at the cognitive level. This mechanism can largely "buffer" the negative impact of technophobia, allowing managers to maintain an open and receptive attitude towards generative AI. Through active SRL, managers can not only overcome technophobia, but also cultivate their emotional regulation abilities, better coping with the challenges of generative AI. Therefore,

H3: *SRL has moderating effect on the negative relationship between technophobia and a manager's intention to adopt generative AI.*

Organisational context: The three-way moderating effect of open organisational culture

The role that organisational context plays in decision-making is increasingly highlighted. As Levinthal & Newark (2023) pointed out, decision-makers are not individuals unrelated to institutional and social factors. Contextual factors, including organisational size (Aboelmaged, 2014), readiness (Issa et al., 2022), culture/climate (Behl et al., 2022; Fousiani et al., 2024), and task context (Wan et al., 2012) significantly influence decision-makers.

Researchers have started using the perspective of organisational context to observe the adoption of AI (Behl et al., 2022; Issa et al., 2022). For example, a competitive organisational climate is found to positively correlate with employees' AI acceptance over time (Fousiani et al., 2024). Others have explored the impact of organisational context on SRL. For instance, the intellectual demands and cooperative norms in the workplace are found to affect how employees adjust their learning strategies (Wan et al., 2012).

The integrated CAN model suggests that an individual's behaviour is not only influenced by their cognitions and emotions, but is also constrained and guided by values and ethical norms formed within their social and cultural backgrounds (Pelegrin-Borondo et al., 2016). In organisations, culture profoundly impacts managers' decisions and actions, shaping their values, beliefs, and behavioural norms (Al-Yahya, 2009). Based on this, we argue that in assessing managers' generative AI adoption, the organisational culture, as the learning environment, is paramount.

In an open culture, managers trust the organisation will support their gaining of insights on disruptive innovations like generative AI (Hurley & Hult, 1998; Ke & Wei, 2008). This culture encourages innovation and experimentation, making managers more inclined to live with AI (Robinson, 2020). Because of the positive role of an open organisational culture, the moderating effect of SRL on the relationship between technophobia and intention to adopt generative AI may be enhanced.

In a highly open environment, managers can easily access information about generative AI, boosting their confidence and reducing technophobia. Open communication further supports AI adoption by encouraging feedback and strategy adjustments. Conversely, in less open environments, the benefits of SRL are limited. A conservative atmosphere restricts information flow, hindering managers from obtaining current AI knowledge. Even with strong SRL skills, managers may struggle to overcome technophobia and fail to adopt generative AI due to insufficient resources and support. Therefore,

H4: *An open organisational culture positively moderates the positive moderating effect of SRL on the relationship between technophobia and intention to adopt generative AI.*

The hypothesized relationships are presented in the theoretical model shown in Fig. 1.

====== Fig. 1 about here ======

Methodology

Data collection

This study focuses on the direct effect of technophobia, and the moderating role of SRL and organisational culture in managers' generative AI adoption. Quantitative data are needed to capture managers' perceptions of their attitudes and their intention to adopt generative AI. Survey was predominantly used in similar previous research to generate large scale perception data of users (e.g., Lim & Zhang, 2022; Ma & Huo, 2023). Likewise, we chose the survey method to test the research hypotheses, 5,000 questionnaires were randomly distributed via a Chinese internet marketing education platform (Feicheng Education[1]) targeting traditional enterprises' digital transformation. This platform includes business managers interested in technological innovation, AI applications and learning in different regions of China. The platform has a major presence in mainland China, serving over 20,000 enterprise clients and boasting more than 56,880 registered learners. It also enjoys over 4.6 billion views online. These make it an ideal sample frame for our research. Additionally, the platform's extensive user base and high level of activity ensure a higher response rate, supporting more sophisticated statistical analysis. The questionnaire, designed for relevance and response efficiency (Dillman et al., 2014), covered four key areas: technophobia towards AI, SRL, intention to adopt generative AI, and open organisational culture.

The questionnaire was distributed through "Wenjuanxing" (a renowned online survey platform in China) from February to April 2024. After several rounds of reminders, 528 valid responses were

[1] https://feichengedu.com/

collected, resulting in a response rate of 10.56%. Respondents cover various managerial levels, with 31.63% being business founders or senior managers, 23.86% being middle-level managers, and 24.05% being junior level managers (see Table I).

====== Table I about here ======

Measurement

All survey items (see Appendix) were sourced from previous studies and adjusted to fit this study. Khasawneh's scale (2018b) was revised to measure technophobia towards AI. SRL was measured based on Gravill and Compeau's (2008) scale. Managers' intention to adopt generative AI was measured using the Davis scale (Davis, 1985). All these constructs were measured on a five-point Likert-type scale. To assess open organisational culture, a question was designed based on multiple researchers' scales (Behl et al., 2022; Hurley & Hult, 1998; Ke & Wei, 2008; Robinson, 2020), to understand managers' perception of their organisation's openness towards adopting new technologies. The scale ranged over 5 points, from very conservative to very open.

We also included control variables of personal background (age, education, position) and corporate information (sector, region, number of employees), because they potentially affect the readiness of managers to adopt generative AI.

Data quality, validity, and reliability

To assess non-response bias, a multivariate t-test comparing early and late questionnaire responses (Lehman et al., 2013) was conducted. The results showed no significant difference, hence minimising the impact of non-response bias. To prevent common method biases, we followed Podsakoff et al., (2003) to 1) randomising the order of main construct items in the questionnaire; 2) ensured the questionnaire was anonymous throughout; 3) employed the Harman's single-factor test to examine the primary constructs. The results showed five distinct factors explaining 64.7% of the variance, with the first factor accounting for 32.3% of the variance. This suggests that common method bias is not a major concern in this study; 4) adopted a single-method-factor approach to evaluating the data by controlling the impact of an unmeasured latent common method factor. The results showed no significant improvement in the model fit indices, further confirming that the data is not significantly influenced by common method bias.

Confirmatory factor analysis based on SPSSAU (see Table II) revealed that Technophobia1 and Technophobia4 had standardized factor loadings below 0.6, so they were excluded from the formal analysis. Deleting Technophobia2 also improved convergent validity, indicating this item's limited contribution to the construct and potential for error. Table II shows high Cronbach's α (0.803-0.962) and composite reliability (CR > 0.8) for main constructs, indicating strong internal consistency (Nunnally, 1978). Average variance extracted (AVE) values (0.502-0.584) exceed the 0.5 threshold, demonstrating good convergent validity (Fornell & Larcker, 1981).

====== Table II about here ======

For discriminant validity testing, the key is that each variable's AVE square root exceeds its correlation with other variables (Fornell & Larcker, 1981). Table III shows that diagonal values (AVE square roots) are greater than off-diagonal values (correlation coefficients), hence meeting the threshold condition and confirming good discriminant validity.

====== Table III about here ======

Result

Table IV shows the mean, standard deviation, and correlation of independent variables, dependent variables, and control variables. Multicollinearity was tested using the variance inflation factor (VIF), with the maximum VIF value being 1.336, far less than the recommended threshold of 10, indicating that multicollinearity is not a concern.

====== Table IV and Table V about here ======

To validate hypotheses, hierarchical regression analysis was conducted using SPSS (see Table V). Model 1 and Model 2 explored the relationship between technophobia and dependent variable. Model 1 included only control variables, revealing a weak negative correlation between 2 control variables (education and sector) and intention to adopt generative AI. Model 2 has technophobia added as an independent variable. The R^2 is significantly increased (from 0.074 to 0.1) and shows a negative relationship between technophobia and a manager's intention to adopt generative AI ($b = -0.198$, $p < 0.001$). Therefore, Hypothesis 1 is supported.

Model 3 analysed the relationship between SRL and a manager's intention to adopt generative AI. The results showed a significant positive relationship between SRL and adoption intention ($b = 0.612$, $p < 0.001$). The R^2 significantly increased, emphasizing the crucial role of SRL. Therefore, Hypothesis 2 is also supported.

Model 4 analyzed the combined effects of technophobia and SRL on the dependent variable. To delve deeper into the moderating role of SRL in the relationship between technophobia and a manager's intention to adopt generative AI, Model 5 included both variables as independent variables, and as the product of the two variables. Regression results indicated significant coefficients for technophobia×SRL and intention to adopt generative AI ($b = 0.152$, $p < 0.001$). Therefore, Hypothesis 3 is supported. The slope plots of moderating effects are shown in Fig. 2.

====== Fig. 2 about here ======

Model 6 to Model 8 examines the joint effect of technophobia, SRL, and open organisational culture on a manager's intention to adopt generative AI. In model 8, the results show that the three-way interaction between technophobia, SRL, and open organisational culture is significant and positively related to intention to adopt generative AI ($b = 0.081$, $p < 0.01$). The findings confirmed their significance in influencing a manager's intention to adopt generative AI. Notably, open organisational culture showed an interfering effect, leading to changes in the regression coefficients of technophobia and SRL. Therefore, H4 is supported. The slope plots of moderating effects are shown in Fig. 3.

====== Fig. 3 about here ======

Discussion and conclusion

Based on the CAN model, this study conducted a questionnaire survey of 528 business managers in China to investigate the relationship between technophobia and a manager's intention to adopt generative AI, as well as the role of SRL and open organisational culture in this process. The hypothesis test generated important findings that revealed the mechanisms of a major hindrance to generative AI adoption by business managers - technophobia.

Firstly, the study found a negative relationship between technophobia and a manager's intention to adopt generative AI. This is not surprising since the higher the level of technophobia, the more anxiety to disruptive innovations and the lower the manager's intention to adopt generative AI (e.g., (Khasawneh, 2018a).

Secondly, SRL is positively related to a manager's intention to adopt generative AI. This finding echoes (Yang & Wang, 2023) qualitative study on SRL (e.g., participation in professional training), effectively alleviating technophobia.

Thirdly, this study also discovered that SRL moderates the negative relationship between technophobia and AI adoption intention, indicating its ability to mitigate technophobia's negative impact. While prior studies noted SRL's potential in facilitating education (Kesici et al., 2011; Wang et al., 2013), this study validates its moderating effect leading to a manager's decision to adopt disruptive new technologies.

Lastly, we found that open organisational culture influences how SRL alleviates the negative effect of technophobia on generative AI adoption intention. In an open culture, SRL can help managers to overcome technophobia, while in a closed culture, the positive moderating effect of SRL is likely to be constrained. This underscores the role of organisational culture in shaping managers' attitudes towards disruptive innovations. These findings align with previous studies highlighting the importance of organisational context in technology adoption (Behl et al., 2022; Fousiani et al., 2024).

Theoretical contribution

This research makes several distinctive contributions to the extant literature. First, this study expanded the discussion around the "human-side" of technology adoption by providing finer-grained understanding about how technophobia can be a primary barrier to generative AI adoption. Unlike the previous technology-centric perspective (e.g., Venkatesh & Davis, 2000), this study examines the psychological and emotional responses of business managers when facing generative AI.

Second, this study extended technophobia research domain into the field of generative AI. Previously, technophobia was primarily examined in the IT context, focusing on how computer anxiety affects IT users' attitudes towards technology usage through computer self-efficacy (Baker et al., 2014). Although there have been arguments suggesting that whenever there is new technology, there will always be a specific type of technophobia associated with it (Khasawneh, 2018b), few studies have investigated the technophobia of generative AI and its impact within the business management domain.

Third, by focusing on managers' technophobia regarding generative AI and by introducing SRL and organisational culture into the theoretical framework, this study not only provides additional evidence for the generalizability of the CAN model, but also comprehend the CAN model with additional relevant factors.

Fourth, this study confirms the positive relationship between SRL and a business manager's intention to adopt generative AI, clarifying SRL's role in alleviating technophobia's negative impact. SRL provides a novel perspective by emphasizing the dynamic development of users' cognitive processes towards new technology.

Last but not the least, this study further explicates the impact of open organisational culture, as a normative factor, on the role of SRL in alleviating the negative effects of technophobia. This extends the previous research, which primarily focused on the influence of social norms formed by social relationships on technology users' intention to adopt (Kwak et al., 2022), while paying less attention to organisational contextual factors, failing to observe the interaction between normative and cognitive factors.

Practical implications

The practical implications of this study are threefold. Firstly, managers should acknowledge the existence of technophobia, which is an important inhibitor in adopting disruptive new technologies like generative AI. Organisations can conduct targeted training and education programs for business managers to enhance their understanding of generative AI and reduce their fear of the technology.

Secondly, managers should prioritise SRL to address technophobia and enhance the adoption of new technologies. Managers should be encouraged to actively seek information and deepen their understanding of generative AI. Moreover, organisations can provide training on how to engage in SRL, helping managers better manage their cognitive processes and emotional responses when exposed to this disruptive new technology.

Thirdly, fostering an open organisational culture is crucial for promoting technology adoption and innovation (Robinson, 2020). Organisations should encourage managers and employees to proactively learn and adopt new technologies through incentive measures. For example, by rewarding innovative behaviours and establishing learning incentive mechanisms, organisations can promote a positive attitude among managers and employees throughout the adoption process of generative AI.

Limitations and future research

This study has limitations which should be addressed by future researchers. Firstly, while this study surveyed 528 business managers in China with a wide coverage of region and sectors, the results can be contextualised in the Chinese business environment. Given that technophobia can be affected by differences in national culture and organisational culture, future research could expand the sample to wider international context with various organisational backgrounds. Secondly, although the questionnaire offered good quantitative evidence, future research could incorporate multiple methods such as in-depth interviews and field observations to enrich the understanding of the relationship between technophobia and generative AI adoption. Finally, although the CAN model provides a comprehensive view of a manager's generative AI adoption, there may be other psychological factors that were not included in this study, such as managers' personal traits, self-efficacy, and identity, which could be examined more extensively in future studies.

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Appendix：List of survey items (Source: Authors own creation)

Technophobia (Khasawneh, 2018b)**:**

1．I am afraid that someone might use AI technology to monitor and eavesdrop on my every move.

2．I am concerned that the development of AI will change our way of life, communication methods, and even affect our views and evaluation criteria of others.

3．I am afraid that as AI technology continues to advance, humans will become redundant or lose job opportunities in some areas.

4．I fear that AI will eventually replace my job.

5．I am worried that AI might make wrong decisions in some areas, leading to serious consequences.

6．I am afraid that if AI systems encounter problems, they will have a significant impact on society and individuals.

7．I am concerned that AI might interfere with my daily life, such as my emotions, physical and mental states.

8．I am afraid of using phone apps or features with AI functionality (such as smart assistants, voice recognition, etc.).

9．I am concerned that using search engines that rely on AI technology might leak my personal information.

10．I am afraid that when I am online, AI systems will track my behaviour and habits.

11．I feel uneasy when I have to use new devices with AI functionality.

12．I worry that learning how to interact with new AI-integrated systems or applications (such as smart homes, autonomous vehicles, etc.) will be difficult.

13．I am afraid that AI robots will develop to the point where they pose a threat to human safety.

14．I am concerned that search engines and other websites, due to their integration of AI technology, will be able to collect and analyze my personal information more easily.

15．I try to avoid using new technologies or devices with AI functionality because they make me feel uneasy.

16．When I see more and more fields starting to apply AI technology, I feel concerned and uneasy.

Self-regulated learning (Gravill & Compeau, 2008)**:**

1．I deeply reflect on how to apply the AI knowledge I have learned to specific management tasks.

2．I take detailed notes to assist me in deeply studying and memorizing AI-related knowledge.

3．I have pondered over which AI skills are most needed to be practiced and applied in my management work.

4．I strive to identify blind spots in AI applications and accordingly adjust my learning and application strategies.

5．I continuously monitor areas in AI applications that require further optimization and improvement.

6．When encountering doubts related to AI, I promptly seek answers before continuing with my in-depth study.

7．When trying to apply a new AI skill, I monitor my progress in mastering its requirements.

8．I seriously consider how the AI knowledge I have previously learned can be applied in practical work.

9．I reflect on what measures need to be taken to better learn AI.

10．I am aware of the mistakes I make when applying AI and focus on improving these areas.

11．I carefully select the AI content to focus on, aiming to improve weaknesses discovered during the application process.

12．I monitor the time spent learning AI skills to determine if these investments have brought expected returns.

13．I reflect on the effectiveness of my AI learning strategies and make corresponding adjustments.

14．Through self-questioning, I ensure a deep understanding of AI knowledge.

15．When learning AI, I try to carefully consider each topic and decide what I should learn from it, rather than blindly following trends.

16．I set clear AI learning goals to guide my learning activities and decisions. 17．I try to change my learning methods to adapt to the requirements of different AI topics or application scenarios. 18．I reflect on the setbacks and difficulties I encounter during the process of learning AI, and how to overcome them. 19．I establish a reward mechanism to motivate myself to achieve better results in AI learning. 20．I formulate some important issues related to AI to help me focus more on learning and applying AI technology.
Intention to adopt generative AI (Davis, 1985)**:** 1．Please evaluate the possibility of adopting generative AI in your future work based on your current understanding and expectations of generative AI. 2．Please predict the expected frequency of using generative AI in your future work. 3．Please provide a percentage of your acceptance of adopting generative AI in your work based on your feelings and judgment.
Open organisational culture (Fousiani et al., 2024) (Robinson, 2020) (Ke & Wei, 2008)**:** 1．How do you perceive your organisation's attitude towards adopting new technologies?