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**To cite this article:** João M. Lopes, Sofia Gomes, Elisabete Nogueira, João J. Ferreira & Marina Dabić (12 Feb 2026): Exploring psychosocial predictors of AI use intention: the moderating role of organisational culture in diverse workplaces, Behaviour & Information Technology, DOI: [10.1080/0144929X.2026.2626743](https://doi.org/10.1080/0144929X.2026.2626743)

**To link to this article:** <https://doi.org/10.1080/0144929X.2026.2626743>



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Published online: 12 Feb 2026.



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# Exploring psychosocial predictors of AI use intention: the moderating role of organisational culture in diverse workplaces

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## ABSTRACT

Artificial intelligence (AI) is transforming workplaces and shaping how employees perceive and interact with technology. Drawing on the Technology Acceptance Model (TAM) and Organisational Culture Theory, this study examines how psychosocial predictors, promotion focus, positive reinterpretation and technostress influence workers' perceived usefulness of AI and their intention to use it. It also tests whether an adaptable organisational culture strengthens the relationship between perceived usefulness and intention to use AI. Data were collected from 422 Portuguese respondents and analysed using partial least squares. Results show that both promotion focus and positive reinterpretation positively affect perceived usefulness and the intention to use AI at work. Technostress negatively affects perceived usefulness but does not significantly impact intention to use AI. Perceived usefulness mediates the effects of psychosocial predictors on intention: the indirect effects are positive for promotion focus and positive reinterpretation and negative for technostress. Moreover, a highly adaptable organisational culture amplifies the positive link between perceived usefulness and employees' intention to adopt AI. The study extends TAM by incorporating psychosocial antecedents and provides empirical support for the moderating role of cultural adaptability, offering insights for fostering responsible and sustainable AI adoption across diverse organisational contexts.

## ARTICLE HISTORY

Received 10 June 2025  
Accepted 29 January 2026

## KEYWORDS

Artificial Intelligence;  
psychosocial predictors;  
organisational culture;  
Environmental, Social, and  
Governance

## 1. Introduction

The integration of artificial intelligence (AI) into the workplace has emerged as a pivotal strategy for organisations seeking to enhance productivity and foster innovation (Khan et al. 2023). Moreover, when aligned with Environmental, Social, and Governance (ESG) principles – specifically environmental sustainability, social equity, and responsible governance – AI technologies can contribute to a more equitable and sustainable technological landscape by reducing carbon footprints, promoting inclusive access, and ensuring ethical deployment (Cha et al. 2024; Li et al. 2025). Psychosocial factors, such as promotion focus, positive reinterpretation, and technostress, significantly influence how employees engage with AI systems (Chang et al. 2024). These factors influence the acceptance and effective use of AI, particularly in environments working

towards increased sustainability and fairness. The adaptability of organisational culture serves as a critical framework, not only facilitating AI implementation, but also supporting the alignment of technology with ESG goals to create inclusive and environmentally conscious workplaces (Dittmar, Sposato, and Portillo 2025; Li et al. 2025). In this context, resistance to change emerges as a key psychosocial barrier, often manifesting as status quo bias or fear of disruption, undermining AI readiness and exacerbating technostress by hindering employees' willingness to adapt to new technological paradigms (Li et al. 2023; Murire, 2024). This resistance is particularly relevant when integrating AI with ESG objectives, as it can perpetuate inequities in access and ethical deployment if not addressed through adaptive cultural mechanisms. By considering these psychological and cultural dynamics alongside ESG-driven AI

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adoption, this perspective underscores the potential for technology to drive both organisational success and broader societal benefits.

Yet, while AI promises substantial gains in efficiency and innovation, its adoption remains inconsistent across organisations, often undermined by individual-level resistance and contextual barriers (Venkatesh et al. 2003). Recent empirical evidence highlights how resistance to change directly impedes AI implementation, with studies showing that entrenched status quo biases undermine employees' willingness to adopt AI, thereby stalling productivity gains and ethical alignment in workplace transformations (Li et al. 2023; Murire, 2024). The current literature predominantly explains AI acceptance through cognitive constructs, such as perceived usefulness and ease of use within the Technology Acceptance Model (TAM) (Davis 1989). Still, it offers limited insight into how motivational dispositions (e.g. promotion focus), coping mechanisms (e.g. positive reinterpretation), and stress responses (e.g. technostress) jointly shape these perceptions and behavioural intentions. Moreover, although organisational culture is recognised as influential in technology diffusion (Schein 2010), there is little empirical evidence on whether its adaptability amplifies or attenuates the link between perceived AI usefulness and usage intention. This gap is critical because unaddressed psychosocial frictions can erode AI's ESG-aligned benefits – such as equitable access and ethical governance – while adaptive cultures could accelerate responsible adoption, yielding competitive advantages and societal value (Dabbous, Barakat, and Sayegh 2022). Overcoming resistance to change is thus essential in this dynamic, as it directly influences the efficacy of psychosocial predictors in fostering positive AI perceptions and intentions, particularly in adaptive cultures that prioritise change management in order to mitigate biases and promote ESG-driven innovation (Li et al. 2023; Murire, 2024). Understanding these mechanisms is theoretically vital in extending TAM and Organisational Culture Theory beyond static predictors, and they are practically essential when it comes to designing interventions that mitigate adoption failures, reduce employee burnout, and align AI deployment with sustainable organisational outcomes.

Despite AI's promising potential, several challenges arise when implementing it in the workplace. One of the primary issues is the psychosocial risks associated with AI integration, such as increased anxiety, motivation fluctuations, and dependency on technology (Baptista, 2024). These risks can hinder the seamless adoption of AI, creating barriers that organisations must overcome to leverage its capabilities fully.

Additionally, technostress emerges as a critical challenge, affecting individuals' mental and physical well-being and influencing their engagement with AI technologies (Caporusso 2023). Understanding these problems is essential for organisations seeking to mitigate negative impacts and foster a supportive environment for AI use. By addressing these psychosocial challenges, organisations can better prepare their workforce for the transition to AI-driven processes.

Several recent studies have examined the intersection between AI technology and organisational dynamics (Alghazzawi 2024; Dabbous, Barakat, and Sayegh 2022), with a particular focus on how AI-driven stressors can influence employees' adoption intentions (Chang et al. 2024; Baptista, 2024; Tuan 2022). Chang et al. (2024) indicate that stressors arising from AI-driven technologies can have a positive effect, thereby increasing the workforce's intention to adopt AI solutions. AI can be a source of technostress, but it can also influence organisational outcomes by promoting proactive employee engagement. However, a knowledge gap remains with regards to understanding how psychosocial predictors, such as focuses on promotion and positive reinterpretation, correlate with workers' perceptions of AI's usefulness and their intention to use AI technologies. Furthermore, Murire (2024) explored how AI integration can drive cultural transformation within organisations, emphasising the need for adaptability in organisational culture in order to harness AI's full potential.

Although these explorations provide valuable insights into the broader impacts of AI on organisational practices, there is a lack of literature that specifically addresses whether the adaptability of organisational culture influences the relationship between workers' perceptions of AI's usefulness and their intention to use it. To systematically address what is unknown and needed, the field requires integrative models that: (i) quantify the direct and mediated effects of psychosocial predictors on TAM outcomes; (ii) test organisational culture adaptability as a boundary condition; and (iii) link these dynamics to ESG-aligned AI deployment. This knowledge is indispensable in contributing towards the creation of theories for developing predictive frameworks for human-AI interaction, and practices to inform targeted training, culture-shaping policies, and ethical AI governance, thus preventing adoption failures and promoting inclusive digital transformation. That said, two important questions need to be answered: (1) How do psychosocial predictors of AI engagement influence workers' perceptions of AI usefulness and their intention to use AI? and (2) To what extent does the adaptability of organisational culture moderate the relationship

between perceived AI usefulness and workers' intention to use AI?

Addressing these research questions, this study examines how psychosocial predictors (promotion focus, positive reinterpretation, and technostress) shape workers' perceptions of AI usefulness and their intention to use it, while analyzing the moderating role of organisational culture adaptability in the relationship between perceived AI usefulness and intention to use AI. To this end, 422 responses were collected, using the partial least squares statistical method.

This study makes contributions to both theory and practice in the field of AI adoption within organisational settings. Firstly, it reinforces and extends the TAM by demonstrating that psychosocial predictors, such as promotion focus and positive reinterpretation, significantly enhance employees' perceived usefulness of AI, thereby influencing their intention to use it and broadening TAM's explanatory scope through the integration of motivational and emotional factors into the model as antecedents of perceived usefulness. This underscores the importance of cognitive coping styles and goal-orientated dispositions in shaping positive technology evaluations and use intentions, offering a more nuanced understanding of user behaviour in technologically evolving environments.

Secondly, it provides empirical validation for the mediating role of perceived usefulness in the relationship between psychosocial factors – including technostress – and AI use intention. This reveals that, while technostress negatively impacts perceived usefulness indirectly, promotion focus and positive reinterpretation align with psychological theories of motivation and coping, thus fostering positive AI engagement, while simultaneously integrating relevant psychological theories and highlighting the critical importance of managing adverse emotional responses in technology adoption processes.

Thirdly, the study expands and enriches Organisational Culture Theory by revealing that an adaptive organisational culture, characterised by openness and agility, strengthens the link between perceived AI usefulness and intention to use AI, highlighting the critical moderating role of contextual factors in technology adoption and providing empirical support for the proposition that organisational culture plays a decisive role in shaping employee attitudes and behaviours towards technological innovation. This establishes organisational environment as either a critical enabler or a potential barrier. These theoretical contributions are necessary for research, as they evolve predictive frameworks of human-AI interaction beyond static predictors, facilitating the development of more comprehensive models that account for dynamic psychosocial and cultural influences.

Fourthly, from a practical standpoint, the findings encourage employees to cultivate promotion focus and positive reinterpretation skills in order to enhance AI acceptance, while managing technostress through proactive coping strategies and active participation in AI implementation processes. This includes fostering a robust promotion focus (characterised by goal achievement and a growth mindset), reframing AI-related challenges as opportunities, and developing mechanisms to manage digital overload, ultimately mitigating resistance and amplifying AI's perceived benefits as a supportive tool.

Fifthly, organisations are advised to foster an adaptive culture through training programs that promote positive AI perceptions, address technostress via technical support and user-centered design, and align AI implementation with employee needs in order to maximise perceived usefulness. They should prioritise openness, agility, continuous learning, and tolerance for errors, implementing communication strategies that emphasise AI's contributions to professional goals and conducting proactive assessments of technostress factors to ensure successful adoption that extends beyond technical aspects to social dimensions.

Finally, Policymakers should support AI adoption by promoting AI literacy programs to foster pro-innovation attitudes, reward adaptive organisations, and establish ethical AI regulations to ensure transparency, worker well-being, and algorithmic fairness, thereby facilitating sustainable digital transformation through targeted interventions like public programs for digital and emotional AI literacy, formal recognition of innovative organisations via certifications or incentives, and comprehensive ethical frameworks that safeguard well-being and promote inclusive ecosystems. These practical implications are essential for practice, as they inform targeted interventions that mitigate adoption failures, reduce employee burnout, and align AI deployment with sustainable, ESG-driven organisational outcomes.

## 2. Literature review

### 2.1. Theoretical framework

The Technology Acceptance Model (TAM) serves as a foundational framework for understanding how users engage with technology (Davis 1989), particularly in the context of artificial intelligence (AI) applications (Dabić et al. 2025; Gomes, Lopes, and Sousa 2025). This model posits that perceived usefulness and perceived ease of use are crucial predictors of users' behavioural intention to adopt new technologies (Troise et al. 2021). However, in the context of AI adoption, TAM has notable limitations: it primarily captures cognitive

evaluations at a single point in time, often overlooking dynamic psychosocial processes such as motivational states (promotion focus), emotional coping mechanisms (positive reinterpretation), and stress responses (technostress) that evolve during prolonged technology interaction. Moreover, TAM underemphasises contextual boundary conditions, particularly the role of organisational culture adaptability in moderating the translation of perceived usefulness into actual behavioural intention. The TAM directly addresses perceived usefulness and intention to use – the primary outcomes of this study – facilitating the modelling of how psychosocial predictors (such as promotion focus, positive reinterpretation, and technostress) influence perceptions of AI's utility and, consequently, the intention to use it. By integrating these psychosocial factors as antecedents, this study addresses TAM's limitations by accounting for non-cognitive drivers of acceptance. This framework is particularly suited to this study, as it provides a structured approach to modelling how individual psychological factors influence technology adoption in organisational settings. Aldraiweesh and Alturki (2025) and Shao et al. (2025) have confirmed the relevance of TAM in various technological contexts, providing insights into how these perceptions influence individuals' attitudes towards AI tools. Moreover, TAM's flexibility enables the inclusion of contextual variables (such as organisational culture) as moderators that enhance its applicability to workplace AI adoption. This extension mitigates TAM's original constraint of treating external variables as mere additives rather than interactive moderators. By incorporating these moderators, TAM facilitates a nuanced understanding of how external influences interact with individual perceptions. Consequently, when users perceive AI systems as beneficial and easy to use, their likelihood of engaging with these technologies increases significantly (Cui 2025). Consequently, understanding the dynamics of TAM is essential for organisations aiming to enhance AI adoption among workers.

Organisational Culture Theory complements the TAM by emphasising the role of organisational values, norms, and practices in shaping employees' attitudes towards technology (Alshammari, Alshallaqi, and Al-Mamary 2024; Yip et al. 2020). This theory views organisational culture as a set of shared values, beliefs, and practices that influence members' behaviours, and it is particularly relevant when it comes to understanding the adaptive capacity of organisational culture in fostering AI acceptance. By testing adaptability as a moderator, this study directly addresses TAM's limitation in contextualising adoption within varying organisational environments. By fostering a culture that embraces

change and innovation, organisations can align technology adoption with employees' values, thereby reducing resistance to AI implementation. A supportive organisational culture creates an environment conducive to AI adoption by mitigating barriers, such as technostress, while amplifying the positive effects of psychosocial factors, such as promotion focus and positive reinterpretation. For instance, organisations that prioritise innovation and continuous learning foster higher levels of engagement with AI tools, as employees are more likely to align technology use with organisational goals (Chuang, Chiang, and Lin 2025). By embedding AI initiatives within the organisation's core cultural values, leaders can cultivate a receptive atmosphere that enhances both productivity and employee satisfaction. This synergy between cultural alignment and technology adoption underscores the theory's relevance to the study's focus on adaptive organisational contexts. Thus, Organisational Culture Theory enriches TAM by contextualising cultural adaptability as a key moderator that shapes the relationships between psychosocial predictors and outcomes such as perceived usefulness and intention to use, thereby providing a more comprehensive framework for understanding AI engagement.

The analysis of psychosocial predictors (promotion focus, positive reinterpretation, and technostress) further illuminates their significant influence on workers' perceptions of AI's usefulness and their intention to use it. These factors extend TAM by introducing motivational, coping, and stress-related mechanisms absent in its core constructs. Promotion focus, defined as an individual's motivation to achieve positive outcomes (Memmert, Hüttermann, and Orliczek 2013), enhances the view of AI as a valuable tool that supports personal and professional goals. This motivational orientation aligns with TAM's emphasis on perceived usefulness, as goal-driven employees are more likely to see AI as instrumental to their success. Similarly, positive reinterpretation – the ability to constructively reframe technological challenges – reduces technostress and the anxiety associated with technology use (Garg, Verma, and Palframan 2023). By transforming potential stressors into opportunities for growth, positive reinterpretation fosters a more favourable perception of AI, directly supporting its adoption. When employees perceive AI as a supportive resource rather than a source of stress, they are more likely to find it useful and express a stronger intention to adopt it actively (Callari and Puppione 2025). Together, these psychosocial factors interact with organisational culture to create a dynamic interplay that shapes AI engagement, highlighting the importance of addressing both individual and contextual influences. Thus, addressing these

psychosocial factors is crucial for organisations seeking to promote effective AI integration in the workplace.

## 2.2. Hypotheses

### 2.2.1. Psychosocial predictors of AI engagement, intention of AI use, and AI's perceived usefulness

The ways in which employees interact with AI systems are significantly shaped by psychosocial factors, such as promotion focus, positive reinterpretation, and technostress (Chang et al. 2024). Promotion focus serves as a proactive indicator of an individual's aspirations for growth and upward mobility, as suggested by Wallace et al. (2016). According to Lazarus and Folkman (1984), positive reinterpretation involves assigning positive significance to events that are otherwise stressful. Technostress can be understood as the stress employees face when they believe they lack the skills or capacity to manage the demands of technology in their work (Ayyagari, Grover, and Purvis 2011).

Promotion focus can serve as a mechanism through which employees' perceptions are translated into behaviours (Horng et al. 2016). Driven by growth aspirations, individuals with a strong promotion focus proactively address information technology demands by seeking solutions to enhance performance and maintain control through active evaluation and coping strategies, ultimately leveraging technology to their benefit (Tuan 2022), thereby positively influencing their intention to use AI. Employees exhibit positive reinterpretation mechanisms in challenging situations through positive reappraisal and active modification of their work practices in response to novel digital technologies (Pirkkalainen et al. 2019). This proactive orientation is posited to influence their intention to use AI positively.

The integration of AI in workplaces can increase technostress, as the faster pace creates pressure to work outside of hours (Chen et al. 2022) and causes learning difficulties (Dijmărescu et al. 2022). AI can also generate workplace threats (Korzynski et al. 2021), making it hard for users to adapt to evolving technologies (Ramos, Ferrittu, and Goulart 2022). Consequently, technostress is expected to negatively influence employees' inclination to adopt and use AI technologies.

H1: Psychosocial Predictors of AI Engagement – (a) promotion focus, and (b) positive reinterpretation – positively influence employees' intention to use AI, and (c) technostress negatively influences this intention.

Perceived usefulness is understood as the degree to which someone anticipates that using a particular system will lead to improvements in their job performance (Davis 1989) and can be influenced by

psychosocial predictors of AI engagement. Promotion-focused individuals who possess strong abstract reasoning abilities demonstrate an enhanced capacity to comprehend AI's potential for enhancing job performance, recognising its utility and completing a cognitive evaluation of their work environment in order to determine whether AI characteristics function as beneficial resources or potential impediments (Stamate, Sauvé, and Denis 2021). Moskowitz (2010) posited that positive reinterpretation is a coping mechanism consistently linked to favourable outcomes in the face of stress. By proactively adopting a positive outlook towards persistent technology-related stressors, individuals can engage in an evaluative process to identify beneficial aspects within their IT interactions, even when technology generates demands (Pirkkalainen et al. 2019).

Technostress, arising from prolonged exposure to technology, manifests as negative affective states and, ultimately, cognitive overload when individuals perceive an inability to manage technological stimuli (Kamel 2025). This can impede further technology adoption, with factors such as information overload and system complexity contributing to its emergence (Kamel 2025) and negatively influencing the perceived usefulness of AI.

H2: Psychosocial Predictors of AI Engagement – (a) promotion focus, and (b) positive reinterpretation – positively influence employees' AI perceived usefulness, and (c) technostress negatively influences this perception.

Perceived usefulness is a significant predictor of technology adoption across various domains (Fam et al. 2025). It exerts a substantial influence on the intention to adopt artificial intelligence (Rahman et al. 2023). Studies show that, when employees perceive AI as practically beneficial for their work (by making them more efficient and improving their decision-making) they are much more likely to want to use it (Rahman et al. 2025). This is also seen in fields like hiring, where useful AI systems are readily adopted to improve processes (Albert 2019). Further research supports this view, indicating that, when employees perceive AI as beneficial to their job functions, they are significantly more inclined to integrate it into their routine work activities.

H3: The perceived usefulness of AI by employees positively influences employees' intention to use AI.

### 2.2.2. The mediating role of AI's perceived usefulness

AI's perceived usefulness has been investigated for the mediating role it plays in explaining the mechanisms

underpinning technological adoption across various contexts (Kim et al. 2025; Kim, Merrill, and Collins 2021). This is based on evidence suggesting its comparatively stronger association with factors influencing adoption when juxtaposed with other technology-related perceptions (Davis 1989; Venkatesh and Davis 2000). Promotion focus and positive reinterpretations enhance employees' intention to use AI by increasing their perception of its usefulness. Promotion-focused individuals tend to see AI as a tool for improving performance (Stamate, Sauv e, and Denis 2021), whereas those who use positive reinterpretations cope with technological stress by identifying its benefits (Moskowitz, 2010; Pirkkalainen et al. 2019). These perceptions of usefulness significantly boost employees' willingness to adopt AI across various domains (Kim, Merrill, and Collins 2021). This is particularly evident in the context of AI-powered coding assistants, where a strong perception of utility significantly enhances the likelihood of adoption (Fam et al. 2025). Thus, AI's perceived usefulness serves as a critical mechanism through which psychosocial predictors of AI engagement influence a person's intention to use AI.

Technostress, characterised by feelings of anxiety, fear, and cognitive overload in response to digital technologies, can undermine employees' perceptions of AI as a helpful and effective tool (Salanova, Llorens, and Cifre 2013; Zhang and Tong 2024). This psychological strain often leads to cognitive distancing and skepticism, reducing individuals' openness to engaging with technological systems (Kamel 2025). Research has shown that anxiety associated with AI negatively affects how users perceive its value and functionality (Kaya et al. 2024), and similar patterns have been observed with broader digital technologies, such as the internet (Cazan, Cocorad a, and Maican 2016). Thus, technostress reduces employees' perceived usefulness of AI which, in turn, reduces their intention to adopt it, as perceived usefulness is a key driver of technology acceptance (Fam et al. 2025; Rahman et al. 2023).

H4: Psychosocial Predictors of AI Engagement – (a) promotion focus, and (b) positive reinterpretation – positively influence employees' intention to use AI, and (c) technostress negatively influences this intention, when mediated by their perceived usefulness of AI.

### 2.2.3. Adaptability capacity of Organisational culture

Organisational culture has a critical role to play in shaping employees' attitudes and behaviours toward technology adoption (Ke and Wei 2008; Peansupap and Walker 2005). A culture that embraces innovation not

only fosters favourable perceptions of new technologies, but also helps embed them into the organisation's core values (AlBar and Hoque 2019). This cultural alignment encourages employees to view AI not just as a functional tool, but as an integral part of their work environment, reinforcing their willingness to adopt it (Dabbous, Barakat, and Sayegh 2022). Moreover, adaptive cultures enhance managers' and employees' abilities to process technological information effectively and make informed decisions (Liu et al. 2010), further validating the perceived usefulness of AI and supporting its practical implementation. This cultural support amplifies the impact of perceived usefulness on adoption behaviour, thereby strengthening the link between the two.

H5: The association between employees' perceived usefulness of AI and their intention to use it is stronger when the adaptability capacity of the organizational culture is high.

Figure 1 illustrates the research model and the proposed hypotheses.

## 3. Methods

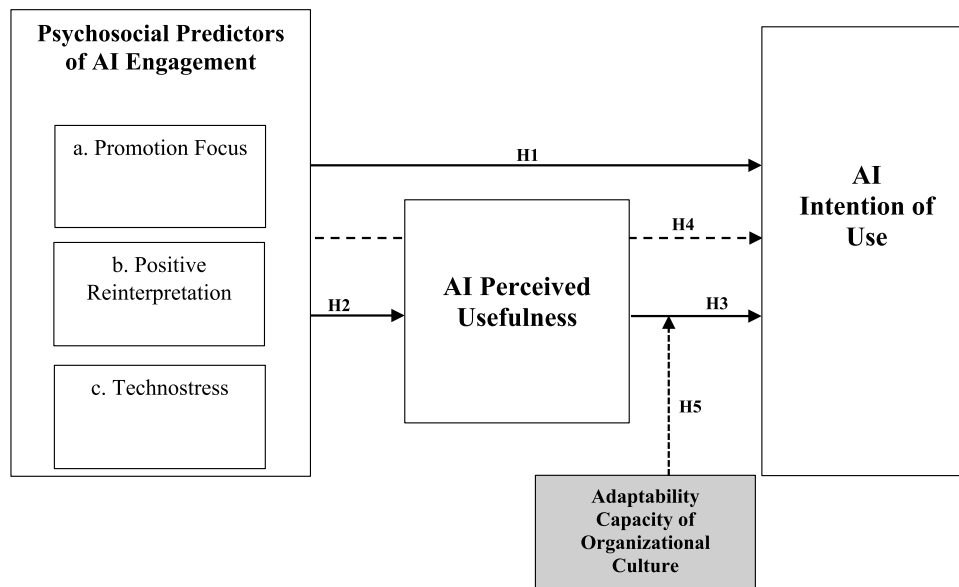
### 3.1. Sample

The data for this study was collected via an online questionnaire distributed through the authors' personal and professional networks between September and December 2024. Participation was voluntary and anonymous, with informed consent obtained from all respondents. Eligibility criteria included being at least 18 years old and residing in Portugal for at least 6 months. A total of 422 valid responses were collected. Before the main data collection, a pre-test was conducted with 12 individuals from diverse sociodemographic backgrounds to evaluate question clarity and estimate the average completion time, which was approximately seven minutes.

With regards to sociodemographic characteristics, 54.5% of participants identified as male and 45.5% identified as female. Participants' ages ranged from 18 to 65 years, with an average of 35.45 years. In terms of educational attainment, 25.6% had completed secondary education, 55% held a bachelor's degree, and 14.2% had a master's degree. Most respondents (80.6%) were employed. Regarding net monthly income, 21.3% earned between €825 and €1,000, 44.1% between €1,001 and €1,500, and 17.5% between €1,501 and €2,000.

### 3.2. Description of variables

The questionnaire is divided into five parts. The first section gathers sociodemographic characteristics about



**Figure 1.** Research model. Note: Direct Effects (→) and Indirect Effects (→).

the participants. The second section includes items assessing psychosocial predictors of AI engagement: promotion focus (9 items), positive reinterpretation (3 items), and technostress (5 items). All items were adapted from Tuan (2022) and were measured on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The third section contains three items on organisational culture, three on the perceived usefulness of AI, and four on intention to use AI. All items were adapted from Dabbous, Barakat, and Sayegh (2022) and also employ a 5-point Likert scale. Detailed descriptions of the items can be found in Appendix A Table A1.

### 3.3. Data analysis

The data analysis for this study was carried out in four distinct phases. Initially, descriptive statistics were generated for all items within each construct using SPSS software (Version 25) to summarise the central tendencies and dispersion of the data. The second phase consisted of a two-step factor analysis. Firstly, an Exploratory Factor Analysis (EFA) was conducted to examine the underlying factor structure, identify item groupings, and assess each item's communalities. Secondly, a Confirmatory Factor Analysis (CFA) was performed to verify the factor structure, consider whether the indicators accurately reflect the intended latent constructs, and evaluate the reliability and validity of the measurement model. In the third phase, the research model was analyzed using Partial Least Squares Structural Equation Modelling (PLS-SEM) with SmartPLS software (Version 4). PLS-SEM is a robust and flexible

statistical approach particularly suited for complex models involving multiple constructs, small to medium sample sizes, and non-normally distributed data, as was the case in this study, where skewness and kurtosis values confirmed non-normality. Unlike Covariance-Based SEM (CB-SEM), PLS-SEM prioritises maximising the explained variance of the dependent (endogenous) constructs, making it particularly useful for exploratory research and predictive modelling. It estimates both the measurement model (relationships between latent constructs and their observed indicators) and the structural model (relationships among latent constructs) simultaneously. This method has been applied in other studies on similar topics, such as those by Kim et al. (2024), Alghazzawi (2024), and Malodia et al. (2022).

The application of PLS enables researchers to assess the strength and significance of direct and indirect paths in a model while accommodating both reflective and formative measurement models. In this study, the evaluation of the measurement model followed the guidelines proposed by Hair and Alamer (2022), using the following criteria: (i) internal consistency reliability via Cronbach's alpha ( $\alpha > 0.70$ ); (ii) composite reliability ( $CR > 0.70$ ); (iii) convergent validity through Average Variance Extracted ( $AVE > 0.50$ ); and (iv) discriminant validity using the Heterotrait-Monotrait ratio (HTMT), where values below 0.85 are considered acceptable. In the final phase, bootstrapping with 5,000 resamples was conducted to assess the statistical significance and stability of the model's path coefficients. Bootstrapping in PLS-SEM enables robust inference regarding the relationships between latent variables and their indicators, providing confidence intervals and  $p$ -values

that support hypothesis testing. This procedure enhances the reliability of the conclusions drawn about the impact of psychosocial and organisational variables on AI-related behaviours in an organisational context.

## 4. Results

### 4.1. Descriptive statistics of the items

Table A1 (in the Appendix) presents the descriptive statistics (mean and standard deviation) for the items measuring the constructs. On average, all items generated high agreement among participants. The items that generated the most agreement were AI Intention of Use ( $M = 3.95$ ) and AI Perceived Usefulness ( $M = 3.94$ ). On average, the items related to job insecurity received less agreement ( $M = 3.53$ ).

### 4.2. Factor analysis

The outcomes of the factor analyses (EFA and CFA) are presented in Table A2 (in the Appendix). The Exploratory Factor Analysis (EFA) identified six distinct factors, each aligning with the constructs defined in the research model. Together, these factors accounted for 59.14% of the total variance, with none of the individual factors exceeding 50% of the explained variance. The Confirmatory Factor Analysis (CFA) confirmed that the model follows a reflective measurement structure. All items exhibited strong standardised factor loadings (above 0.70), indicating adequate individual reliability and confirming their suitability for the model without the need for item removal.

### 4.3. Evaluation of the measurement models

The model derived using the Partial Least Squares (PLS) method was evaluated for convergent validity, internal reliability, and discriminant validity. Following the guidelines proposed by Hair and Alamer (2022), the model demonstrated adequate convergent validity, as all constructs presented Average Variance Extracted (AVE) values exceeding the recommended threshold

of 0.50. Reliability was also confirmed, with both Cronbach's Alpha and Composite Reliability (CR) values surpassing the minimum acceptable level of 0.70, as shown in Table 1. Furthermore, discriminant validity was assessed using the Heterotrait-Monotrait ratio (HTMT). All HTMT values were below the 0.85 threshold, indicating that the constructs were empirically distinct (Table 1). These results collectively support the robustness and adequacy of the measurement model for the subsequent structural analysis.

Additionally, the model presents a good fit according to the following measures calculated: (i) the Goodness-of-Fit Index (GFI) (0.966; reference value  $> 0.90$ ); (ii) Comparative Fit Index (CFI) (0.965; reference value  $> 0.90$ ); (iii) Incremental Fit Index (IFI) (0.988; reference value  $> 0.90$ ), and (iv) Root Mean Square Approximation Error (RMSEA) (0.069; reference value  $< 0.08$ ).

Variance Inflation Factor (VIF) values were used to identify multicollinearity. All VIF values are less than 3, indicating no multicollinearity. The model's predictive capacity was assessed using the coefficient of determination ( $R^2$ ), while its predictive relevance was examined using Stone-Geisser's  $Q^2$  coefficient, obtained via a blindfolding procedure. According to Cohen's (2013) guidelines, the dependent variables – AI Intention of Use ( $R^2 = 0.658$ ) and AI Perceived Usefulness ( $R^2 = 0.385$ ) – exhibit substantial explanatory power, indicating that the model explains a considerable proportion of the variance in these outcomes. In addition, the model demonstrates satisfactory predictive relevance, as indicated by  $Q^2$  values greater than zero for both dependent constructs: AI Intention of Use ( $Q^2 = 0.375$ ) and AI Perceived Usefulness ( $Q^2 = 0.274$ ). These results confirm that the model not only fits the data well, but also demonstrates strong out-of-sample predictive performance, reinforcing its robustness in explaining and predicting employee responses to AI adoption.

### 4.4. Research model estimation

Table 2 shows the results of the bootstrapping analysis performed to test the statistical significance of the

**Table 1.** Convergence, reliability, and discriminant validity.

	C $\alpha$	CR	AVE	HTMT Criterion					
				PF	PR	TEC	OC	PU	IU
Promotion Focus (PF)	0.775	0.833	0.558						
Positive Reinterpretation (PR)	0.786	0.827	0.614	0.645					
Technostress (TEC)	0.929	0.946	0.779	0.691	0.691				
Organisational Culture (OC)	0.755	0.860	0.671	0.789	0.739	0.740			
AI Perceived Usefulness (PU)	0.812	0.888	0.726	0.637	0.793	0.468	0.566		
AI Intention of Use (IU)	0.759	0.847	0.581	0.707	0.744	0.526	0.800	0.706	

**Table 2.** Direct and mediating effects.

	Confidence Intervals					Hypothesis Support
	$\beta$	T-value	P-Values	2.5%	97.5%	
H1a: Promotion Focus $\rightarrow$ AI Intention Use	0.190	3.451	0.001	0.087	0.293	Yes
H1b: Positive Reinterpretation $\rightarrow$ AI Intention Use	0.226	4.425	0.000	0.123	0.323	Yes
H1c: Technostress $\rightarrow$ Intention Use	-0.058	1.154	0.249	-0.158	0.036	No
H2a: Promotion Focus $\rightarrow$ AI Perceived usefulness	0.148	2.011	0.045	0.004	0.297	Yes
H2b: Positive Reinterpretation $\rightarrow$ AI Perceived usefulness	0.435	7.571	0.000	0.327	0.566	Yes
H2c: Technostress $\rightarrow$ AI Perceived usefulness	-0.126	2.221	0.027	-0.176	0.042	Yes
H3: AI Perceived usefulness $\rightarrow$ AI Intention Use	0.369	7.944	0.000	0.271	0.459	Yes
H4a: Promotion Focus $\rightarrow$ AI Perceived usefulness $\rightarrow$ Intention Use	0.255	2.003	0.046	0.101	0.308	Yes
H4b: Positive Reinterpretation $\rightarrow$ AI Perceived usefulness $\rightarrow$ AI Intention Use	0.360	5.119	0.000	0.202	0.425	Yes
H4c: Technostress $\rightarrow$ AI Perceived usefulness $\rightarrow$ Intention Use	-0.046	2.170	0.030	-0.090	0.007	Yes
H5: AI Perceived Usefulness $\rightarrow$ AI Intention Us (moderate by adaptability capacity of organisational culture)	0.192	3.026	0.003	0.123	0.198	Yes

paths in the research model. Based on 5,000 subsamples, this resampling technique was applied to estimate the stability and confidence intervals of the structural relationships between constructs. The standardised path coefficients ( $\beta$ ), t-values, and *p*-values are reported, allowing us to assess the strength and significance of each hypothesised relationship. The findings support the robustness of the model and provide empirical evidence for the proposed theoretical framework.

The results reveal that psychosocial predictors of employee AI engagement – promotion focus and positive reinterpretation of AI use – positively influence the intention to use AI at work. However, this influence does not have the same intensity. Thus, positive reinterpretation of AI use by employees is the antecedent that most strongly influences the intention to use AI at work ( $\beta = 0.226$ ), compared to promotion focus ( $\beta = 0.190$ ). Technostress related to AI use in the workplace was not statistically significant in influencing the intention to use AI. Therefore, hypotheses H1a and H1b are accepted, and hypothesis H1c is rejected.

Regarding the relationship between psychosocial predictors of AI engagement by employees and their perceived usefulness of AI, promotion focus and the positive reinterpretation of AI use positively influence perceived usefulness ( $\beta = 0.148$  and  $\beta = 0.435$ , respectively). In contrast, technostress negatively influences perceived usefulness ( $\beta = -0.126$ ). Thus, hypotheses H2a, H2b, and H2c are confirmed.

The results also reveal that employees' perceptions of AI's usefulness positively influence their intention to use AI ( $\beta = 0.369$ ); therefore, hypothesis H3 is accepted. When the relationships established between psychosocial predictors of AI engagement and the intention to use AI are mediated by the AI's perceived usefulness, they become stronger and more significant. Thus, promotion focus and positive reinterpretations of AI use positively influence the intention to use AI when mediated by perceived usefulness ( $\beta = 0.255$  and  $\beta =$

0.360, respectively) and technostress negatively ( $\beta = -0.046$ ). Thus, hypotheses H4a, H4b, and H4c are confirmed. Furthermore, technostress can negatively influence the intention to use AI, with employees' perceived usefulness mediating this relationship. These results do not occur when the relationship between technostress and the intention to use AI is measured directly.

The results reveal that the association between AI's perceived usefulness to employees and their intention to use AI at work is stronger when the adaptability capacity of organisational culture is high. Thus, hypothesis H5 is confirmed.

## 5. Discussion

This study investigates how psychosocial factors (specifically promotion focus, positive reinterpretation, and technostress) influence employees' perceived usefulness of AI and their intention to use it, while also considering the moderating effect of organisational culture adaptability.

The results indicate that both promotion focus and positive reinterpretation positively influence employees' perceived usefulness of AI and their intention to use it, with positive reinterpretation emerging as the stronger predictor. This aligns with existing research suggesting that employees with a strong promotion focus are generally more resilient to the emotional strain associated with AI implementation (Zhou et al. 2024). Driven by a desire for growth and success, they tend to reinterpret AI-related challenges as developmental opportunities rather than threats (Liang et al. 2022), thereby strengthening their recognition of AI's practical value and enhancing their willingness to adopt it (Zhou et al. 2024). Similarly, positive reinterpretation has been found to correlate positively with AI-enabled productivity (Yin, Wang, and Liu 2024). This cognitive coping mechanism allows individuals

to reframe difficulties as manageable challenges, fostering greater persistence and engagement (Pirkkalainen et al. 2019). Together, these psychosocial traits enhance perceptions of AI's usefulness and increase employees' intention to use such technologies in their work routines. The greater predictive power of positive reinterpretation compared to promotion focus can be attributed to its nature as a more direct and adaptive coping strategy. Positive reinterpretation directly involves cognitive reframing, enabling individuals to reconstruct AI-related challenges as manageable and beneficial. This active mental adjustment directly addresses perceived threats posed by stressors, transforming them into opportunities for growth and positive outcomes.

With regards to technostress, the findings show that its relationship with the intent to use AI is not statistically significant. However, its negative influence on AI's perceived usefulness suggests that technostress may still impede employees' perceptions of AI's value by generating emotional strain and cognitive overload. This shifts attention away from potential benefits and towards perceived challenges. As Khlaif, Sanmugam, and Ayyoub (2023) have noted, technostress is a key determinant in continued technology use, largely because it erodes the user's belief in the system's value. Verkijika (2018) similarly found that technostress directly reduces perceived usefulness by impairing individuals' confidence in the technology's ability to enhance their performance. In this context, AI may be perceived less as a helpful tool and more as a source of pressure or disruption, lessening employees' intentions to adopt it. The absence of a significant direct effect of technostress on employees' intention to use AI, despite its negative association with perceived usefulness, suggests a more intricate process. Technostress may operate indirectly through cognitive overload, where excessive technological demands impair rational evaluations of technology benefits (Srivastava, Chandra, and Shirish 2015; Tarafdar, Cooper, and Stich 2019). This aligns with the concept of suppression effects, in which stress-induced anxiety coexists with compliance to digital demands, thereby diminishing the direct predictive power of technostress on behavioural intention (Ayyagari, Grover, and Purvis 2011). Furthermore, prior research indicates that technostress may influence technology use indirectly by reducing trust and self-efficacy (Califf, Sarker, and Sarker 2020; Ragu-Nathan et al. 2008). Such mechanisms imply that technostress may not prevent technology use outright but instead erode users' confidence and perceived control over AI systems, leading to more cautious or reluctant adoption behaviours.

The findings indicate that perceived usefulness significantly contributes to employees' intention to use AI. Previous studies have highlighted that technologies that enhance perceptions of usefulness tend to promote greater adoption (Yang, Zhang, and Feng 2024). When individuals recognise the practical value of AI, their motivation to engage with it is likely to increase (Dhiman and Jamwal 2023). This positive evaluation of AI's utility can shape behavioural intentions by reinforcing beliefs in its effectiveness (Song et al. 2024). Users generally demonstrate a propensity to accept and use technologies they consider advantageous (Portz et al. 2019), and this direct link between perceived usefulness and intention to use has also been confirmed in AI-specific contexts (Topsakal 2024).

With respect to the mediating role of AI's perceived usefulness, the results reveal that this significantly mediates the relationship between psychosocial predictors of AI engagement and employees' intention to use AI. Specifically, this mediation is positive and significant for promotion focus and positive reinterpretation, and negative for technostress. These findings align with and reinforce prior research, suggesting that perceived usefulness plays a critical role in shaping technology adoption behaviours (Ismatullaev and Kim 2024; Norzellan, Mohamed, and Mohamad 2024). In this context, employees' recognition of AI's practical value appears to be a key mechanism through which psychosocial traits influence their willingness to engage with the technology. As highlighted by Zhang et al. (2023), the perception of tangible benefits is central to motivating individuals to incorporate AI into their professional routines.

The findings suggest that the link between employees' perceived usefulness of AI and their intention to use it in the workplace becomes stronger in organisational cultures characterised by high adaptability. Organisational culture plays a crucial role in shaping employees' intention to adopt AI technologies. As noted by Dabbous, Barakat, and Sayegh (2022), a supportive organisational culture positively influences individuals' willingness to engage with AI. Furthermore, Twati and Gammack (2006) highlight that organisational culture is a key determinant of how firms respond to and embrace technological innovation, significantly affecting their acceptance of new technologies. An adaptive organisational culture, characterised by flexibility and openness to change, reduces employee apprehension towards new technologies (Sarwar et al. 2020). This fosters a mindset wherein employees are more inclined to see the advantages of AI, such as efficiency gains and improved decision-making capabilities (Rožman, Tominc, and Milfelner 2023). Such a

culture then reinforces existing positive perceptions of AI, aligning its adoption with company goals and work processes (Dabbous, Barakat, and Sayegh 2022). Ultimately, this cultural support acts as a catalyst, strengthening employees' intentions to integrate AI into their work.

Finally, in addressing the study's research questions, the findings provide clear insights into the roles of psychosocial predictors and organisational cultures in shaping AI adoption behaviours. In response to the first research question (how do psychosocial predictors of AI engagement influence workers' perceptions of AI usefulness and their intention to use AI?), the findings confirm that promotion focus and positive reinterpretation are key facilitators, with positive reinterpretation exerting the strongest impact. Although technostress does not directly influence adoption intention, its negative impact on perceived usefulness highlights its indirect inhibitory effect on AI engagement behaviours (Khlaif, Sanmugam, and Ayyoub 2023; Tarafdar, Cooper, and Stich 2019). With regards to the second research question (to what extent does the adaptability of organisational culture moderate the relationship between perceived AI usefulness and workers' intention to use AI?), the results indicate that adaptive organisational cultures significantly strengthen this relationship. Environments characterised by openness, flexibility, and support for innovation reinforce positive perceptions of AI's benefits, mitigating apprehension and aligning AI use with organisational goals (Dabbous, Barakat, and Sayegh 2022; Rozman, Tominc, and Milfeller 2023; Sarwar et al. 2020). Conversely, rigid or less adaptive cultures may impede the realisation of AI's perceived value, underscoring the critical moderating role of organisational culture in facilitating technology integration.

### 5.1. Theoretical implications

This study offers several theoretical implications for the field of technology adoption, particularly in the context of AI within organisational settings. Firstly, the findings reinforce and extend the TAM. By demonstrating that psychosocial predictors – specifically, promotion focus and positive reinterpretation – significantly influence employees' perceptions of AI's usefulness, which subsequently predicts their intention to use it, this research broadens TAM's explanatory scope. The introduction of these individual-level motivational and emotional factors as antecedents to perceived usefulness underscores the importance of cognitive coping styles and goal-orientated dispositions in shaping positive technology evaluations and usage intentions. Furthermore, the

inclusion of technostress as a negative but indirect predictor enriches TAM by incorporating stress-related constraints, thereby offering a more nuanced understanding of user behaviour within technologically evolving environments (Weinert et al. 2020).

Secondly, this study provides empirical validation for the mediating role of perceived usefulness in the relationship between psychosocial factors and a person's intention to use AI. The observed significant mediation effect for both promotion focus and positive reinterpretation aligns with the core beliefs of the TAM framework, while simultaneously integrating relevant psychological theories of motivation and coping. Although technostress did not directly predict the intention to use AI, its significant negative association with perceived usefulness underscores the critical importance of managing adverse emotional responses within technology adoption processes (Norzellan, Mohamed, and Mohamad 2024).

Thirdly, the findings expand organisational culture theory by showing that an organisation's adaptability capacity significantly strengthens the relationship between AI's perceived usefulness and the intention to use AI. This illustrates the crucial moderating effect of contextual variables, providing empirical support for the theoretical proposition that organisational culture decisively shapes employee attitudes and behaviours towards technological innovation. An adaptive culture facilitates a critical alignment between individual perceptions of technology and the organisation's overarching support for innovation, thereby amplifying the impact of perceived usefulness on behavioural intentions and establishing the organisational environment as a critical enabler or potential barrier (Abdelrahman et al. 2025).

### 5.2. Practical implications

Based on empirical findings, several practical implications emerge for key stakeholders involved in integrating AI technologies within the workplace. These implications are delineated across employee, organisational, and policy levels. Employees are encouraged to cultivate specific emotional and cognitive competencies in order to facilitate effective AI adoption. This includes fostering a robust promotion focus, characterised by a strong orientation toward goal achievement, and a growth mindset. Simultaneously, developing skills in positive reinterpretation is crucial for reframing AI-related challenges as opportunities. These cognitive strategies are hypothesised to enhance AI acceptance, mitigate resistance, and amplify the perceived benefits of AI as a supportive tool. In line with this, research

in the entrepreneurship context has demonstrated that creativity, when mediated by perceived usefulness and perceived ease of use, significantly bolstered intention to adopt new technologies (Putro and Takahashi 2024). By this logic, employees who actively engage in motivational and coping capacities could similarly elevate their perceptions of AI's usefulness and thereby increase their degree of intention to use it. Furthermore, given the observed negative impact of technostress on the perceived usefulness of AI, employees should proactively develop coping mechanisms and strategies to manage digital overload. Recognising that perceived usefulness is a strong predictor of intention to use, active employee involvement in AI adoption processes – from the initial stages through to feedback contributions and the articulation of practical needs – is highly recommended.

Organisations are advised to prioritise cultivating an adaptive organisational culture. This type of culture, characterised by high levels of openness, agility, continuous learning, and tolerance for errors, is expected to significantly strengthen the positive relationship between the perceived usefulness of AI and the intention to use it. Research on organisational adaptation highlights that leaders can fine-tune cultural dimensions, beliefs, and prosocial values to improve both innovation and adherence to beneficial practices, thereby enhancing overall adaptation and performance (Brahm and Poblete 2024). Companies should implement training programs specifically designed to stimulate a promotion focus and guide employees in positively reinterpreting the integration of AI. Communication strategies should consistently emphasise AI's contribution to achieving professional goals, rather than framing it as a threat to job security. The proactive assessment and management of factors contributing to technostress, such as informational overload, technological ambiguity, and perceived insecurity, are essential. This can be achieved through regular evaluations, the provision of robust technical support, and the application of user-centered design principles in AI system development. Organisations must recognise that the perceived usefulness of AI goes beyond just technical factors and includes social considerations. Therefore, successful AI adoption necessitates active listening to end-users (employees), tailoring technologies to their operational realities, and ensuring that implementation paces align with team capacities.

Policymakers play a pivotal role in shaping a supportive ecosystem for AI adoption through targeted interventions. This primarily involves formulating and implementing policies focused on training and AI literacy. Establishing public programs to develop digital

and emotional AI literacy is crucial for fostering pro-innovation attitudes and mitigating technostress across diverse population segments. Furthermore, policies that formally recognise and reward adaptive and innovative organisations (for instance, through certifications or tax incentives) can serve as powerful accelerators for sustainable digital transformation. Recent research on AI-based innovation ecosystems reveals that AI adoption can transform traditional operating models into more agile, innovative, and value-driven systems, promoting collaboration between multiple actors and generating value beyond purely economic gains (Secundo et al. 2025). Lastly, empirical evidence underscores the profound influence of subjective perceptions on AI adoption, highlighting the urgent need for comprehensive regulation and ethical guidance on AI use in the workplace. These frameworks must ensure that AI applications adhere to clear ethical principles, uphold transparency, safeguard worker well-being, and guarantee algorithmic fairness.

## 6. Conclusion

This study explores the influence of psychosocial predictors of AI engagement (promotion focus, positive reinterpretation, and technostress) on employees' perceived usefulness of AI and their intention to use AI at work. Additionally, the moderating role of cultural differences (measured by the adaptability capacity of an organisation's culture) in the relationship between AI's perceived usefulness and the intent to use it is examined.

The results reveal that promotion focus and the positive reinterpretation of AI use positively influence employees' perceived usefulness of AI and their intention to use it at work. Technostress negatively influences employees' perceived usefulness of AI. However, it does not significantly explain the intention to use AI at work. When AI's perceived usefulness mediates the relationship between psychosocial predictors of AI engagement and employees' intention to use AI, this relationship is significant and positive for promotion focus and positive reinterpretation, and negative for technostress. The results indicate that the relationship between employees' perceived usefulness of AI and their intention to use it at work is strengthened when the organisational culture demonstrates a high capacity for adaptability.

This study has some limitations. The sample used in this study was obtained through non-probabilistic sampling, which limits the generalizability of the findings to the broader population. To mitigate potential biases commonly associated with this type of

sampling, the robustness of the results was reinforced by increasing the number of subsamples in the bootstrapping analysis. Nevertheless, this methodological precaution does not fully overcome the inherent limitations of non-probabilistic designs. Therefore, future research is encouraged to replicate and extend the proposed model using larger, probabilistic, and cross-cultural samples in order to validate the findings and assess their generalizability across different organisational and national contexts.

While the TAM model offers a robust theoretical foundation, it also has limitations related to its fundamental assumptions, such as its emphasis on rational, linear intention-formation processes and its relative neglect of emotional and ethical aspects. These limitations could be particularly relevant in sensitive contexts. Future research may benefit from integrating theoretical models that consider these complementary dimensions. Although this study addresses Environmental, Social, and Governance (ESG) issues within the theoretical framework and organisational context, these dimensions were not operationalised in the empirical model. This absence represents a limitation, as ESG-related practices and perceptions could significantly influence attitudes and behaviours related to technology adoption.

Future researchers could explore the integration of ESG-related variables, such as organisational policies, sustainability values, or ethical perceptions, as potential moderators or mediators, thereby expanding our understanding of the role these dimensions play in contemporary organisational dynamics. Furthermore, this study examined promotion focus, positive reinterpretations of AI use, and technostress as psychosocial predictors of AI engagement. While these constructs capture key motivational and stress-related dimensions, future research could broaden this perspective by incorporating additional individual-level factors, such as self-efficacy in AI use, perceived behavioural control, the need for cognition, fear of automation, and attitudes toward AI. Moreover, social and relational variables may also play a crucial role in shaping engagement with AI systems. Constructs such as subjective norms, perceived organisational support, trust in AI technologies, and the communication climate (including openness and communication quality in the workplace) could provide a more comprehensive and context-sensitive understanding of the antecedents of AI engagement. Measuring the same constructs alongside other items may yield different results. The adaptability capacity of organisational culture was used as a moderator of the association between perceived AI usefulness and the intention to use AI. In this study, organisational

culture is measured solely by ‘adaptability,’ based on just three items. Future research could use more items to measure organisational culture across different dimensions, such as innovation orientation, psychological safety, leadership style, digital maturity, organisational learning climate, transformational or technological leadership, and internal policies on AI ethics and governance. Lastly, the factors impacting the intention to use AI in the workplace at a given time were evaluated using cross-sectional data. Longitudinal data could be used in future studies to address this limitation and determine whether or not these factors are subject to change over time.

## Acknowledgments

NECE-UBI, Research Centre for Business Sciences, Research Centre and this work are funded by FCT – *Fundação para a Ciência e a Tecnologia*, IP, project UIDB/04630/2020 and DOI identifier 10.54499/UIDB/04630/2020. rant

## Author contributions

CRedit: **João M. Lopes:** Conceptualization, Formal analysis, Resources, Writing – original draft; **Sofia Gomes:** Conceptualization, Methodology, Software, Validation; **Elisabete Nogueira:** Conceptualization, Investigation, Writing – original draft; **Marina Dabić:** Conceptualization, Writing – review & editing.

## Disclosure statement

No potential conflict of interest was reported by the author(s).

## Funding

This work was supported by NECE-UBI, Research Centre for Business Sciences, Research Centre and this work was supported by FCT - *Fundação para a Ciência e Tecnologia*, I.P. by project reference UID/04630/2023 and DOI identifier 10.54499/UID/04630/2023. This work was supported by the Slovenian Research Agency ([www.arrs.gov.si](http://www.arrs.gov.si)) under the Research Program P5-0441; Agencija za raziskovalno dejavnost Republike Slovenije [grant number: P5-0441].

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## Appendix

A. Questionnaire available at: <https://drive.google.com/file/d/1nRrs887sr61YWZGENrT3OJLlc7k2RX-p/view?usp=sharing>

**Table A1.** Descriptive statistics of the items.

Constructs	Mean	Standard Deviation
Promotion Focus	3.90	0.872
PF1	3.63	1.002
PF2	3.76	1.087
PF3	3.86	0.818
PF4	3.91	0.879
PF5	4.01	0.827
PF6	4.00	0.841
PF7	3.91	0.817
PF8	3.99	0.807
PF9	4.06	0.768
Positive Reinterpretation	3.93	0.802
PR1	3.81	0.733
PR2	3.96	0.876
PR3	4.02	0.798
Technostress	3.60	1.105
TEC1	3.59	1.020
TEC2	3.62	1.137
TEC3	3.53	1.113
TEC4	3.69	1.135
TEC5	3.58	1.118
Organisational Culture	3.85	0.857
OC1	3.80	0.837
OC2	3.93	0.847
OC3	3.83	0.886
AI Perceived Usefulness	3.94	0.882
PU1	3.98	0.824
PU2	3.97	0.972
PU3	3.86	0.849
AI Intention of Use	3.95	0.873
IU1	3.95	0.828
IU2	4.06	0.825
IU3	4.00	0.830
IU4	3.79	1.010

**Table A2.** Factor Analysis (EFA and CFA).

Constructs and Items	Factor						Communality	Confirmatory factor loads
	1	2	3	4	5	6		
Promotion Focus								
PF1	0.773						0.788	0.749
PF2	0.797						0.789	0.780
PF3	0.773						0.786	0.709
PF4	0.754						0.797	0.752
PF5	0.742						0.733	0.705
PF6	0.762						0.714	0.759
PF7	0.701						0.762	0.710
PF8	0.764						0.744	0.761
PF9	0.715						0.727	0.740
Positive Reinterpretation								
PR1		0.715					0.761	0.770
PR2		0.756					0.720	0.829
PR3		0.810					0.708	0.751
Technostress								
TEC1			0.771				0.777	0.866
TEC2			0.845				0.743	0.869
TEC3			0.870				0.786	0.889
TEC4			0.828				0.747	0.887
TEC5			0.854				0.793	0.901
Organisational Culture								
OC1				0.768			0.731	0.824
OC2				0.754			0.787	0.821
OC3				0.774			0.794	0.813
AI Perceived Usefulness								
PU1					0.712		0.795	0.809
PU2					0.713		0.766	0.891
PU3					0.772		0.774	0.855
AI Intention of Use								
IU1						0.700	0.778	0.759
IU2						0.729	0.730	0.775
IU3						0.777	0.795	0.819
IU4						0.714	0.744	0.692