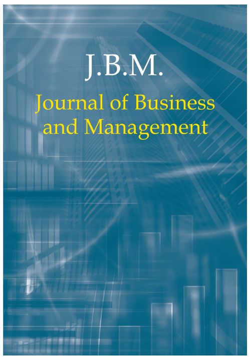

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Navigating the digital frontier: thriving in remote work through AI and human connection

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Navigating the digital frontier: thriving in remote work through AI and human connection

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Abstract: This study explores how integrating artificial intelligence (AI) fosters thriving in remote work by combining AI adoption with organisational understanding and social connections. Utilising a quantitative survey of remote workers from three large US universities, we tested a moderated mediation model examining AI adoption, AI-assisted learning, social ties, organisational understanding, and thriving at work. Findings indicate that while AI adoption promotes continuous learning, genuine thriving depends on fulfilling competence, autonomy, and relatedness needs. Organisational understanding and robust social ties are critical for AI to drive thriving among remote workers. This research contributes to the AI in remote work literature by highlighting organisational and social factors as key conditions for AI's positive impact on employee thriving, aligning with self-determination theory. Organisations should support AI with strong social connections and comprehensive role understanding to enhance employee well-being and growth.

Keywords: AI adoption; AI learning; thriving at work; remote worker; human connection.

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1 Introduction

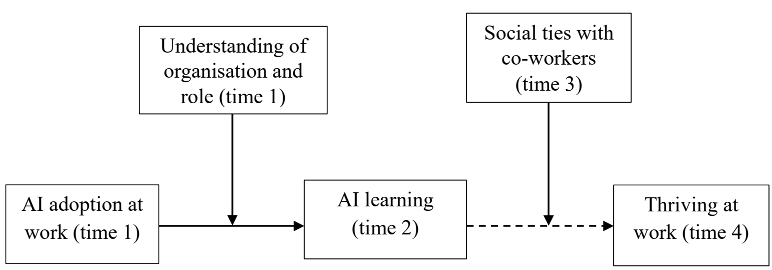
After the pandemic, remote work became the norm (Deloitte, 2023). It offers benefits like better work-life balance and cost savings but raises concerns, especially among Gen Z and millennials, about its long-term impact. One major challenge of remote work is forming meaningful professional relationships, which are crucial for career growth. Remote settings also limit access to mentorship and sponsorship, both key to career advancement. Additionally, the isolation inherent in remote work can detrimentally impact mental well-being, leading to feelings of disconnection (Deloitte Global, 2023). Although much research has been conducted on remote and gig workers post-pandemic (e.g., Schertler et al., 2024), studies on thriving in remote work settings are still limited (Ashford et al., 2018; Porath et al., 2022).

2023 marks a significant year for AI technology, particularly generative AI (McKinsey & Company, 2023). Its introduction is reshaping workforce dynamics and organisational structures profoundly (Taşkan et al., 2020). McKinsey & Company (2023) anticipates a major transformation in job roles, with a trend toward re-skilling rather than workforce reduction. The McKinsey Global Institute (2023) further notes an accelerated adoption of automation, fuelled by the accessibility and integration of generative AI. This evolution is expected to increase automation in tasks requiring expertise, human interaction, and creativity, potentially affecting 29.5% of work hours by 2030. The integration of AI into the workplace is poised to influence worker well-being and learning outcomes, enhancing job satisfaction for some, while potentially exacerbating job insecurity and stress for others (McKinsey Global Institute, 2023).

Despite these significant changes, there is little empirical academic research specifically focused on understanding AI's impact on individual workers' well-being and learning outcomes. Current literature primarily addresses the broader economic and organisational implications of AI, neglecting its personal and psychological effects on workers. This highlights an urgent need for comprehensive empirical studies to understand and navigate AI's multifaceted impact on the workforce, emphasising both the challenges and opportunities it presents (McKinsey Global Institute, 2023).

In this study, we examine the intersection of the burgeoning trend of AI adoption and the prevalence of remote working. Our focus is on how strategically implemented AI can foster a thriving work environment for remote workers. Specifically, AI offers unique opportunities for continuous learning, especially for those with a deep understanding of organisational functions. However, we argue that AI-assisted continuous learning alone is insufficient for remote workers to truly thrive. Our research suggests that a holistic approach is necessary. To achieve a state of thriving at work, remote workers must not only effectively utilise AI for learning purposes but also maintain robust relationships with their peers. This dual emphasis on technological proficiency and interpersonal connections forms the crux of our proposition, underscoring the complex nature of thriving in the AI-enhanced remote work era. Figure 1 delineates a conceptual model that encapsulates the primary rationale underscoring this paper.

Figure 1 Theoretical model



Notes: Solid lines indicate hypothesised relationships while the dotted line indicates a non-hypothesised relationship.

Our study significantly contributes to the literature on thriving, especially in the context of remote work. Firstly, we respond to Porath et al.'s (2022) call by focusing on the thriving of remote workers, identifying the unique challenges and opportunities they face. Specifically, we demonstrate that understanding one's organisation and role is a crucial boundary condition for successfully using AI in learning activities, and that social ties play an essential role in supporting thriving outcomes for remote workers. Second, we expand on self-determination theory (SDT) by addressing the challenges of fulfilling autonomy, competence, and relatedness needs in AI-enhanced remote work environments. We show that effective AI adoption, supported by organisational understanding and interpersonal relationships, can facilitate the fulfilment of these needs, ultimately leading to thriving. Third, we provide empirical insights into how AI interacts with the social and organisational environment to shape thriving outcomes for remote workers. Our research illustrates that AI adoption, when coupled with a deep understanding of one's role and strong peer relationships, can transform AI from a mere tool into a catalyst for personal growth and thriving. Ultimately, our study emphasises that AI alone is insufficient to foster thriving without comprehensive organisational understanding and robust social connections. We advocate for a balanced approach that integrates technology with human elements, providing a nuanced perspective on thriving in remote work environments.

2 Theory and hypothesis development

2.1 AI work adoption and AI continuous learning

Building on the concept that technology use is influenced by both conscious intentions and unconscious habits, as well as emotional responses (De Guinea and Markus, 2009), we posit that the adoption of AI at work will naturally lead to its continuous use for an expanding range of tasks, potentially fulfilling the need for competence as conceptualised by SDT (Deci and Ryan, 2000). AI fosters an environment conducive to continuous learning and skill development when employees are adequately supported. As employees become more accustomed to AI tools, these technologies become integral to their work routines, enhancing their proficiency and leading to the acquisition of new skills and knowledge. This process creates a virtuous cycle, where the habitual use of AI encourages ongoing learning and adaptation.

Hypothesis 1 AI adoption at work facilitates AI's use for continuous learning.

We also propose that this positive impact of AI on competence is amplified when employees have a comprehensive understanding of their organisational roles and functions. SDT suggests that fulfilling the need for competence is crucial for motivation at work (Deci and Ryan, 2000). In the context of AI adoption, employees who understand their role and how it fits into the broader organisational framework are better equipped to use AI tools effectively, thereby fulfilling their competence need. This sense of mastery encourages deeper engagement with AI tools, fostering sustained learning and growth. While AI adoption at work is on the rise, it is still in a formative stage, requiring substantial adjustments from employees (McElheran et al., 2023). This adaptation is often marked by a period of uncertainty, especially among those with limited AI knowledge or expertise (Chowdhury et al., 2022; Lee et al., 2022). This uncertainty is more pronounced in remote work settings, where limited feedback and information availability can hinder employees' confidence and their ability to develop competence (e.g., Reizer et al., 2022). However, cultivating a comprehensive understanding of their organisation and roles helps remote workers overcome these challenges, fulfilling their need for competence as outlined by SDT.

This comprehensive understanding not only fulfils the competence need but also positively influences employees' perception of AI technology in line with the technology acceptance model (TAM) (Davis and Venkatesh, 1996). Employees who understand their organisational roles are more likely to experience an increased perceived ease of use of AI, defined as the belief that using the technology will be effortless (Hwang, 2005; Liaw and Huang, 2013). This understanding also helps them recognise the usefulness of AI in enhancing job performance, contributing to their perceived usefulness of the technology (Ashill and Jobber, 1999). Together, these perceptions foster a positive attitude toward AI adoption, ultimately encouraging its continuous use. Supporting this, Lin et al. (2021) found that reduced uncertainty about robotic services increases revisit intentions, while Lee and Allaway (2002) observed that perceived control enhances the perceived value of self-service technology, fostering adoption intention. By reducing uncertainty and enhancing perceived control, a comprehensive understanding of one's organisational role not only reinforces competence but also strengthens the perceived ease of use and usefulness of AI tools. This dual perspective – grounded in both SDT and TAM – explains how greater organisational understanding amplifies the positive relationship between AI adoption and continuous learning. We therefore hypothesise that an employee's comprehensive understanding of their organisation and individual role positively reinforces the relationship between AI implementation and its use for ongoing learning and development. As this understanding becomes more profound, it will magnify the facilitating effect of adopting AI in the workplace, leading to more effective and sustained learning through AI tools.

Hypothesis 2 Employees' understanding of their organisation and role moderates the positive relationship between AI adoption at work and its use for continuous learning, with the positive effect becoming stronger when the level of understanding is high.

2.2 Thriving through self-determination

SDT serves as the primary theoretical framework for understanding thriving at work, positing that the fulfilment of autonomy, competence, and relatedness needs is crucial for psychological health, motivation, and well-being (Deci and Ryan, 2000). These needs serve as essential 'nutrients' for personal growth, and their satisfaction enhances self-motivation, well-being, and thriving. Building on SDT, the socially embedded model of thriving (SEMT) further illustrates how the work environment and social context can facilitate or hinder the satisfaction of these needs, thereby influencing an individual's ability to thrive – defined as the joint experience of vitality and learning (Spreitzer and Doneson, 2005; Porath et al., 2022). SEMT emphasises the importance of social interactions and organisational culture, providing a deeper contextual understanding of how SDT's core needs are fulfilled in specific work environments. Thriving is conceptualised as a dynamic process in which individuals actively seek, utilise, and replenish resources related to vitality and learning. This process contributes to a self-sustaining cycle of growth, learning, and well-being (Spreitzer and Doneson, 2005).

In remote and gig work settings, the nature of work arrangements uniquely affects how these needs are met. Autonomy is typically fulfilled through the flexibility that this mode of work provides, as employees have increased control over their work schedules and work environments. Competence is addressed through AI adoption – when AI tools are available and used effectively, they support continuous learning and skill development, thereby fulfilling this need (Ryan and Deci, 2000). However, relatedness poses a significant challenge in remote work environments, as physical separation often impedes the formation of meaningful connections (Ashford et al., 2018). Remote and gig workers might need to employ more deliberate strategies to sustain their vitality and learning, such as creating structured routines for self-care, seeking professional development opportunities independently, and fostering virtual communities to satisfy their relatedness needs (Porath et al., 2022). In conclusion, SDT provides a comprehensive framework for understanding how the fulfilment of autonomy, competence, and relatedness needs facilitates thriving. SEMT serves as a contextual extension, illustrating how the work environment and social context can support or hinder the satisfaction of these needs. This process is particularly challenging for remote and gig workers, who face unique difficulties in maintaining these essential resources due to the nature of their work (Goh et al., 2022).

2.3 AI continuous learning, co-worker relationships, and thriving at work

The adoption of AI in the realm of remote work offers a dual-edged sword. On the one hand, it presents a dynamic tool for continuous learning and skill development, catering to the individual needs of remote workers and enhancing their professional competencies (e.g., Darvishi et al., 2024). This personalised approach to learning is aligned with the SDT, which underscores the importance of autonomy and competence for intrinsic motivation and effective performance (Ryan and Deci, 2000). AI-driven platforms can adapt to the learning pace and style of each individual, providing a sense of control over their professional development and enabling a self-directed learning experience (e.g., Budhwar et al., 2023).

On the other hand, the nature of remote and gig work often leads to a fragmentation of traditional work relationships. The lack of physical co-presence can make it more difficult for workers to establish and maintain the meaningful connections that are vital for satisfying the need for relatedness, another core component of the SDT (Ashford et al., 2018). AI, while facilitating certain aspects of work, can inadvertently contribute to this challenge (e.g., Chen et al., 2023). Granulo et al. (2024) suggest that algorithmic management decreases prosocial motivation because it leads to the objectification of others. This means co-workers are perceived less as individuals with emotions and more as tools or means to an end, reducing the inclination to engage in prosocial behaviours. Responsiveness and reactivity in AI can simulate support and empathy, improving human-agent relationships to some extent without compromising task accuracy (e.g., Zhou et al., 2023). However, over-reliance on these interactions can ‘deskill’ humans in their natural reciprocity skills, fostering a competitive and individualistic work environment that may deteriorate the richness of human interaction (e.g., Bankins and Formosa, 2020; Dennis and Ziliotti, 2023). Moreover, the human-AI interaction is reshaping traditional human-human psychological contracts, moving towards more transactional relationships that may lack the depth and warmth of human interactions (e.g., Raeder, 2021). Social presence theory [Short et al., (1976), pp.61–76] suggests that co-presence surpasses telepresence or virtual interactions in fulfilling the perceived need for human connection (Chen et al., 2023). Consequently, while digital communication increases transparency and mutual understanding, it may not satisfy the intrinsic need for face-to-face interaction.

Therefore, in the context of remote work, the challenge of fostering a sense of relatedness is significantly heightened by the pervasive adoption of AI in a multitude of work-related functions. While AI’s capacity to personalise and enhance learning experiences addresses the needs for autonomy and competency admirably, aligning with the precepts of the SDT, this does not wholly equate to a thriving remote workforce. For remote workers to experience a comprehensive sense of thriving, a condition that transcends mere job satisfaction and performance efficiency, the fulfilment of their need for relatedness is imperative. AI, despite its sophisticated algorithms and data-driven insights, often lacks the intricate emotional intelligence inherent to human interactions, which are foundational to building robust interpersonal ties. The continual engagement with AI-driven interfaces risks relegating these critical social interactions to the background, potentially leading to a depersonalised work experience. Consequently, remote workers might find themselves proficient and autonomous, yet disconnected and professionally isolated, which SDT suggests could impede their overall well-being and motivation (Ryan and Deci, 2000). Hence, we propose that true thriving is attainable only when the need for relatedness is also satisfied – specifically through the cultivation of robust ties with peers. It is these connections that foster a sense of belonging, shared purpose, and communal support. Such interconnectivity counteracts the potential for alienation that arises not only from the widespread adoption of AI but also from the inherent isolation of remote work settings.

Hypothesis 3 Social ties with co-workers moderate the relationship between AI usage for continuous learning and thriving at work, such that AI usage for continuous learning results in remote workers' thriving at work only when they maintain robust ties with peers.

2.4 The moderated mediation model

We now propose a moderated mediation relationship that outlines a complex pathway: AI adoption at work leads to its continuous use for learning and skill development, which contributes to remote workers' thriving only when robust ties with peers are present. We suggest that while the adoption of AI leads to its continuous use for learning and skill development, this in itself is not sufficient to ensure remote workers' thriving. Instead, the positive trajectory from AI adoption to thriving is conditional upon the presence of robust ties with peers. These ties provide a necessary social framework that can either amplify or mute the benefits derived from AI-enhanced learning. The presence of robust, supportive social ties provides the emotional and collegial support that can make the difference between mere skill acquisition and true thriving, where employees feel connected, engaged, and continuously growing (Spreitzer and Doneson, 2005). In essence, strong interpersonal relationships act as a crucial moderating factor, determining the extent to which continuous AI use translates into genuine thriving.

Hypothesis 4 The indirect effect of AI adoption on remote workers' thriving, mediated by its use for learning and skill development, is moderated by social ties with co-workers; AI adoption leads to thriving only when remote workers have strong peer connections.

2.5 The moderated moderated mediation model

We also propose that the strength of the moderated mediation relationship is significantly amplified when remote workers fulfil their need for competence through a comprehensive understanding of their organisation and role. This deeper understanding enables them to more effectively utilise AI technologies by engaging in customised and personalised learning tailored to their specific situation, role expectations, skill levels, career motivations, job requirements, and organisational context, ultimately enhancing their competence and facilitating higher levels of learning crucial for thriving at work. When remote workers are well-informed about their organisational landscape and their role within it, they are better equipped to align AI tools with their professional aspirations and job requirements (e.g., Zhang and Chen, 2024). This alignment fulfils their need for competence, leading to a more meaningful engagement with AI technologies. By contextualising AI-driven feedback and learning within the broader spectrum of their career development and the organisation's objectives (Perez et al., 2022), workers feel more capable and confident, thereby fulfilling their competence needs per SDT. Consequently, this leads to more effective and satisfying interactions with AI tools, enhancing their learning experiences and contributing to a greater sense of professional growth and fulfilment. Additionally, a deep organisational understanding also indirectly supports the need for relatedness, as it includes an awareness of the social networks within the organisation. This facilitates relationship-building and the networking process, allowing remote workers to use AI in a manner that complements and enhances social connections rather than replacing them, thereby reinforcing the pathway to thriving at work (e.g., Budhwar et al., 2023). This understanding helps workers integrate AI in a way that supports their connections with peers, fulfilling their need for relatedness, which is crucial for thriving. Furthermore, a better understanding of the organisation reduces uncertainty, thereby supporting autonomy and competence – two of the critical needs outlined by SDT. This allows them to allocate their energies more efficiently without the depletion that comes from constant adjustment and ambiguity. In essence, comprehensive knowledge of one's role and organisation transforms AI from a mere tool for efficiency to a catalyst for fulfilling the needs for autonomy, competence, and relatedness, thereby supporting personal growth and thriving in the remote work environment.

Therefore, we propose a moderated moderated mediation model, in which the moderated mediation relationship between AI adoption at work and remote workers' thriving at work, mediated by continuous usage of AI for learning and skill development and moderated by remote workers' ties with peers, is further moderated by their understanding of the organisation and roles within it. So, the better the understanding, the stronger the moderated mediation relationship. In other words, employees' deeper understanding of the organisation and the role increases the ability of AI adoption at work to fulfil their competence, autonomy, and relatedness needs, thereby strengthening the moderated mediation relationship. This comprehensive knowledge not only strengthens the direct relationships involved but also enhances the effect of social ties and continuous AI usage on thriving, thereby illustrating a more intricate and dynamic interplay among these factors.

Hypothesis 5 The indirect effect of AI adoption on remote workers' thriving, mediated by AI's use in learning and skill development and moderated by social ties with co-workers, is further moderated by remote workers' understanding of their organisation and role, such that deeper understanding strengthens this moderated mediation relationship.

3 Method

3.1 Sample, procedure, and participants

Participants engaged in remote work on behalf of an employer were recruited from three large universities in the USA in exchange for extra credits. This procedure was approved by the University Institutional Review Board (IRB-FY2024-40; Title: Remote Worker Thriving) of the first author. To be more specific, the authors contacted instructors at different universities in the USA through personal connections. Instructors who agreed to help shared the survey invitation with their students via email and provided a few extra credit points for students in their classes who completed the screening survey and four main surveys. All surveys were conducted through Qualtrics. Students were able to participate in the screening survey (i.e., Time 0 Survey) through the link included in the survey invitation. Those who were currently employed and worked partially or fully at home were invited to participate in the four main surveys (i.e., Time 1, Time 2, Time 3, and Time 4 Surveys). Each survey was open for completion within a week, with a two-week interval between each survey. Out of the 457 individuals who took part in the screening survey, 345 met the recruitment criteria and were invited to complete the following four surveys. We emailed the survey links to all eligible individuals and received 198 responses from Time 1 Survey (response rate: 57.39%), 175 responses from Time 2 Survey (response rate: 88.38%), 145 responses from Time 3 Survey (response rate: 82.86%), and 126 responses from Time 4 Survey (response rate: 86.90%). Therefore, the final sample size is 126. AI adoption at work, understanding of organisation and role, and background information were measured at Time 1. AI learning was measured at Time 2, social ties with co-workers was measured at Time 3, and thriving at work was measured at Time 4.

Among the respondents, 46.8% identified as male, 51.6% identified as female, one participant identified themselves as trans-female and one participant did not respond to the gender question. Of the participants, 76.2% were White, 3.2% were Black, 6.3% were Asian or Pacific Islander, 8.7% were Hispanic or Latino/a/x, 2.4% were Biracial, 1.6% were Middle Eastern or North African, and 1.6% identified as other. The mean age of participants was 24.25 years (SD = 6.69). 16.7% have been working for their current employer for less than two months, 11.9% for two to four months, 9.5% for four to six months, and 61.9% for more than six months.

3.2 Measures

- *Focal variables:* The survey instruments of the key variables are summarised in Table 1. Specifically, we assessed *AI adoption at work* with three items revised from Brown et al.'s (2010) system use scale – "how frequently do you use <the actual system name>." Participants were asked about their frequency of using AI in their work using a seven-point Likert scale (1 = 'strongly disagree' to 7 = 'strongly agree'). The three items of AI adoption at work were "I frequently use AI in my current role; I always utilise AI in my workplace, whether I'm working in the office or remotely; I regularly employ AI tools for various tasks." The Cronbach's alpha of the scale was 0.96. *Understanding of organisation and role* was measured with the five-item understanding subscale of organisational socialisation inventory developed by Taormina (2004) based on a seven-point Likert scale (1 = 'strongly disagree' to 7

= ‘strongly agree’). A sample item was “I know very well how to get things done in this organisation.” The Cronbach’s alpha of the scale was 0.78. *AI learning* was measured with eight items adapted from Bezuijen et al.’s (2010) employee engagement in learning activities scale, with the inclusion of AI in each item. A sample item was “I use AI to perform learning tasks that improve my abilities beyond my regular job duties.” The response options ranged from 1 to 7 using a seven-point Likert scale (1 = ‘never’ to 7 = ‘always’). Cronbach’s alpha of AI learning was 0.97. We used seven items to assess *social ties with co-workers*, with six items adopted from Law et al.’s (2000) personal ties with co-workers scale, and one item adopted from Chen et al. (2009). Participants were asked to indicate their agreement on a seven-point scale (1 = ‘strongly disagree’ to 7 = ‘strongly agree’) regarding the strength of social ties with their co-workers. A sample item was “During holidays or after office hours, I contact my co-worker(s), or visit him/her/them.” The Cronbach’s alpha of the scale was 0.91. *Thriving at work* was measured using Porath et al.’s (2012) ten-item thriving scale. Participants indicated their agreement on a seven-point scale (1 = ‘strongly disagree’ to 7 = ‘strongly agree’). A sample item of the learning dimension was “I continue to learn more as time goes by.” And a sample item of the vitality dimension was “I feel alive and vital.” Cronbach’s alpha of the scale was 0.92.

Table 1 Measurements of key variables

Variable	*Variable type*	*Source*	*Sample item*	*Time measured*
AI adoption at work	Predictor	Brown et al. (2010)	I frequently use AI in my current role.	Time 1
Understanding of organisation and role	First-stage moderator	Taormina (2004)	I know very well how to get things done in this organisation.	Time 1
AI learning	Mediator	Bezuijen et al. (2010)	I use AI to perform learning tasks that improve my abilities beyond my regular job duties.	Time 2
Social ties with co-workers	Second-stage moderator	Law et al. (2000) and Chen et al. (2009)	During holidays or after office hours, I contact my co-worker(s), or visit him/her/them.	Time 3
Thriving at work	Outcome	Porath et al. (2012)	I feel alive and vital.	Time 4
Demographic variables	Control variables	/	How would you identify your gender; How long have you been working for your current employer? Please write down your age here:	Time 1
Virtuality (three dimensions: psychological distance, physical distance, and technology)	Control variable	Chudoba et al. (2005)	Collaborate with people in different time zones; work at different sites; work on projects that have changing team members.	Time 1

- *Control variables:* We controlled participants' age, gender, and tenure in the organisation. Additionally, given the nature of the sample that most participants were working remotely to some extent, we also controlled the level of virtuality using the 12-item virtuality scale developed by Chudoba et al. (2005). Participants were asked to indicate their virtuality in three dimensions – psychological distance, physical distance, and technology using a seven-point scale (1 = 'strongly disagree' to 7 = 'strongly agree'). Sample items for these three dimensions were "collaborate with people in different time zones", "work at different sites", and "work on projects that have changing team members", respectively. The Cronbach's alphas were 0.74 for psychological distance, 0.58 for physical distance, and 0.74 for technology.

4 Results

4.1 Confirmatory factor analysis and descriptive analysis

A confirmatory factor analysis was conducted to ensure that AI adoption at work, understanding of organisation and role, AI learning, social ties with co-workers, and thriving at work were distinct from each other. Given thriving at work has two dimensions, we ran a two-stage confirmatory factor analysis in R to examine discriminate validity. The results showed that the five-factor model had an acceptable model fit, $\chi^2(485, N = 125) = 808.45$, $p < 0.001$, CFI = 0.91, TLI = 0.90, RMSEA = 0.07 with 90% confidence interval [0.06, 0.08], and SRMR = 0.09. Additionally, the five-factor model was significantly better than all other alternative models (see Table 2 for the comparison with six alternative models).

Table 2 Results of CFAs and chi-square difference tests

Models	*χ^2 (df)*	*$\Delta\chi^2$ (df)*	*CFI*	*TLI*	*RMSEA*		*SRMR*
					Estimates	*90% CI*	
Basic model	808.45*** (485)		0.91	0.90	0.07	[0.06, 0.08]	0.09
Model 1	974.56*** (489)	166.11*** (4)	0.87	0.86	0.09	[0.08, 0.10]	0.11
Model 2	863.70*** (489)	55.25*** (4)	0.90	0.89	0.08	[0.07, 0.09]	0.16
Model 3	1,437.33*** (489)	628.88*** (4)	0.74	0.72	0.13	[0.12, 0.13]	0.15
Model 4	929.76*** (492)	121.31*** (7)	0.88	0.87	0.08	[0.08, 0.09]	0.34
Model 5	1,092.34*** (494)	283.89*** (9)	0.84	0.83	0.10	[0.09, 0.11]	0.34
Model 6	1,106.83*** (495)	298.39*** (10)	0.83	0.82	0.10	[0.09, 0.11]	0.39

Notes: N = 125. There was one case with missing data and listwise deletion was applied. Basic model: AI adoption at work (AID), understanding of organisation and role (UN), AI learning (AIL), social ties with co-workers (TIE), thriving at work (THR); model 1: AID + UN, AIL, TIE, THR; model 2: AID, UN, AIL + THR, TIE; model 3: AID, UN, AIL + TIE, THR; model 4: AID, UN, AIL + TIE + THR; model 5: AID + UN, AIL + TIE + THR; model 6: AID + UN + AIL + TIE + THR. CI = confidence interval. *** $p < 0.001$.

Table 3 Means, standard deviations, correlations, and reliabilities

	Variable	*Mean*	*SD*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*
1	Age	24.25	6.69	/										
2	Gender	0.48	0.50	0.10	/									
3	Tenure	3.17	1.18	0.20*	–0.07	/								
4	Psychological distance	3.30	1.84	0.21*	–0.04	0.05	(0.74)							
5	Physical distance	3.42	1.37	0.17	–0.01	0.10	0.49**	(0.58)						
6	Technological distance	3.19	1.81	0.12	0.00	0.06	0.54**	0.47**	(0.74)					
7	AI adoption at work	2.15	1.50	–0.01	–0.02	–0.06	0.03	0.18*	0.17	(0.96)				
8	Understanding of organisation and role	5.57	0.82	0.05	–0.11	0.18*	0.19*	0.19*	0.23**	0.00	(0.78)			
9	AI learning	2.99	1.56	–0.08	0.10	–0.04	0.11	–0.03	0.11	0.41**	–0.07	(0.97)		
10	Social ties with co-workers	4.03	1.50	–0.01	0.05	0.12	–0.21*	–0.06	–0.10	0.09	–0.04	–0.01	(0.93)	
11	Thriving at work	4.87	1.05	0.00	–0.01	–0.07	0.01	0.20*	0.09	–0.08	0.19*	0.02	0.09	(0.92)

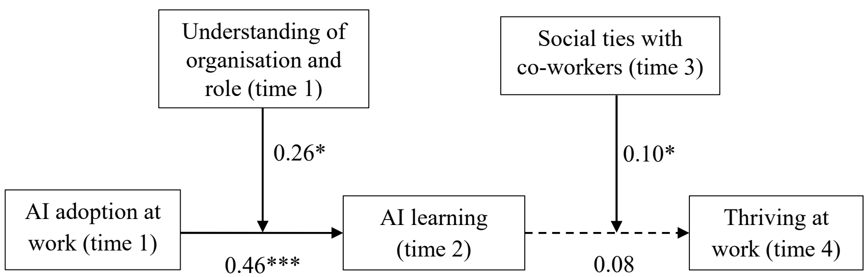
Notes: N = 124. There were two cases with missing data and listwise deletion was applied. Gender was coded as 1 = male and 0 = female. Reliabilities are in parentheses. $^{*}p < 0.05$; $^{**}p < 0.01$.

Table 3 presents the means, standard deviations, bivariate correlations, and Cronbach's alphas for all the variables. All focal variables have acceptable alpha values above 0.70, indicating that all the scales measuring the variables in the theoretical model have good reliability.

4.2 Test of hypotheses

Following Lim and Tai (2014), we used SPSS macro (Hayes, 2022) to test both mediation and moderated mediation models. First, we tested Hypotheses 1 through 3 and 5 using SPSS PROCESS Model 21, which is suitable for a model with one first-stage moderator, one meditator, and one second-stage moderator. Then we tested hypothesis 4 using SPSS PROCESS Model 14, which is feasible for a model with one mediator and one second-stage moderator.

Figure 2 Outcomes of Hayes' process macro for the research model



Notes: Solid lines indicate significant relationships while the dotted line indicates a non-significant relationship. $*p < 0.05$; $**p < 0.01$; $***p < 0.001$.

Figure 3 Moderation effect of understanding of organisation and role

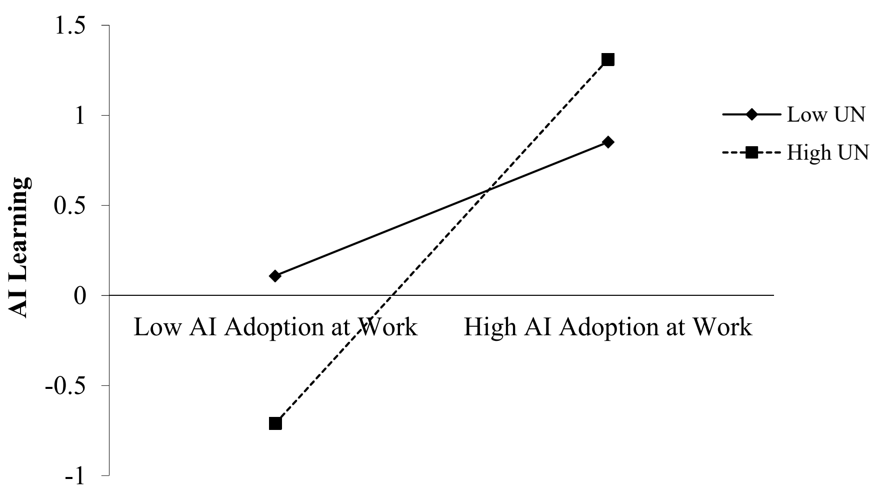


Figure 2, Table 4, and Table 5 summarise the results of the entire model. As shown in Table 4, AI adoption at work was positively related to AI learning (B = 0.49, SE = 0.09, $p < 0.001$), the interaction of AI adoption at work and understanding of organisation and role was positively related to AI learning (B = 0.26, SE = 0.11, $p < 0.05$), and the interaction of AI learning and social ties with co-workers was positively related to thriving at work (B = 0.10, SE = 0.04, $p < 0.05$), supporting Hypotheses 1 to 3. We further conducted simple slope tests to better clarify the patterns of the interaction effects that were statistically significant. As shown in Figure 3 and Table 5, the relationship between AI adoption at work and AI learning was stronger when understanding of organisation and role was high (simple slope = 0.67, $p < 0.001$) versus low (simple slope = 0.25, $p < 0.05$). Figure 4 and Table 5 showed that when AI learning was positively related to thriving at work only when employees had a high level of social ties with co-workers (simple slope = 0.23, $p < 0.05$). Therefore, simple slope tests further supported Hypotheses 2 and 3.

Table 4 Moderated regression analyses predicting AI learning and thriving at work

Variable	*First stage dependent variable = AI learning*			*Second stage dependent variable = thriving at work*		
	B	*SE*	*t*	*B*	*SE*	*t*
Constant	0.39	0.60	0.66	4.54	0.43	10.47***
Age	–0.03	0.02	–1.52	0.00	0.01	–0.00
Gender	0.40	0.25	1.58	–0.10	0.19	–0.52
Tenure in the organisation	0.09	0.11	0.79	–0.09	0.08	–1.12
Psychological distance	0.21	0.09	2.41*	–0.06	0.07	–0.91
Physical distance	–0.24	0.11	–2.13*	0.22	0.08	2.61*
Technology	–0.00	0.09	–0.02	0.04	0.06	0.67
AID	*0.46*	*0.09*	*5.36****	–0.14	0.07	–1.93
UN	–0.11	0.16	–0.69			
AID × UN	*0.26*	*0.11*	*2.28**			
AI learning				0.08	0.07	1.13
TIE				0.12	0.06	1.79
AI learning × TIE				*0.10*	*0.04*	*2.42**
F		4.63***			1.99*	
R^2		0.27			0.15	

Notes: N = 124. There were two cases with missing data and listwise deletion was applied when running SPSS PROCESS model 21. Unstandardised beta coefficients are reported. AID = AI adoption at work; UN = Understanding of organisation and role; TIE = social ties with co-workers. Values in italic are relevant to tests of hypothesis. *$p < 0.05$; ***$p < 0.001$.

The results of the moderated mediation hypothesis (i.e., Hypothesis 4) and the moderated moderated mediation hypothesis (i.e., Hypothesis 5) were summarised in Table 6 and Table 7. As shown in Table 6, AI adoption affected thriving at work via AI learning when social ties with co-workers was high (B = 0.10, 95% CI [0.02, 0.22], which did not include 0), but not when social ties with co-workers was low (B = –0.04, 95% CI [–0.15, 0.06]). Additionally, the index of the moderated mediation model was 0.05, with 95% CI [0.01, 0.10], which did not contain 0. Collectively, the results supported Hypothesis 4. Similarly, the results summarised in Table 7 supported Hypothesis 6. Additionally, the index of the moderated moderated mediation model was 0.03, with 95% CI [0.00, 0.07], which did not contain 0. To be more specific, employees' AI adoption at work promoted their thriving at work via AI learning only when social ties with co-workers were high; such relationship was strengthened when employees had a better understanding of their organisations and job roles (see Table 7 for indirect effects with high/medium/low levels of two moderators).

Table 5 Conditional effects

Paths	*Moderator*	*Estimate*	*SE*
AI adoption at work -> AI learning	UN_{Low}	0.25*	0.12
	UN_{Mean}	0.45***	0.09
	UN_{High}	0.67***	0.13
AI learning -> thriving at work	TIE_{Low}	–0.08	0.10
	TIE_{Mean}	0.08	0.07
	TIE_{High}	0.23*	0.09

Notes: N = 124. There were two cases with missing data and listwise deletion was applied. UN was –0.82 (i.e., 1 SD below the mean) and 0.82 (i.e., 1 SD above the mean) for low and high levels of UN, respectively. TIE was –1.51 (i.e., 1 SD below the mean) and 1.51 (i.e., 1 SD above the mean) for low and high levels of TIE, respectively. UN = Understanding of organisation and role; TIE = social ties with co-workers. *p < 0.05; ***p < 0.001.

Figure 4 Moderation effect of social ties with co-workers

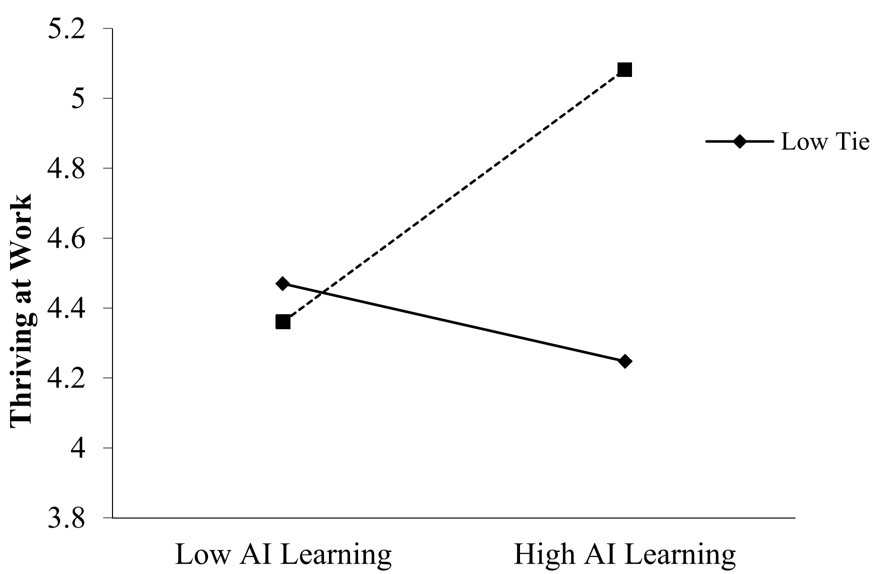


Table 6 Indirect effects with the second-stage moderator

Path	*Second-stage moderator*	*Estimate*	*BootSE*	*95% CI*
AI adoption at work -> AI learning -> thriving at work	TIE_{Low}	–0.04	0.05	[–0.15, 0.06]
	TIE_{Mean}	0.03	0.03	[–0.03, 0.11]
	TIE_{High}	0.10	0.05	[0.02, 0.22]

Notes: N = 124. There were two cases with missing data and listwise deletion was applied. TIE was –1.51 (i.e., 1 SD below the mean) and 1.51 (i.e., 1 SD above the mean) for low and high levels of TIE, respectively. Significance tests for the indirect effects were based on bias-corrected confidence intervals obtained from 5,000 bootstrapped samples. TIE = social ties with co-workers.

Table 7 Indirect effects with both moderators

First-stage moderator	*Second-stage moderator*	*Estimate*	*BootSE*	*95% CI*
UN_{Low}	TIE_{Low}	–0.02	0.03	[–0.09, 0.04]
	TIE_{Mean}	0.02	0.02	[–0.02, 0.08]
	TIE_{High}	0.06	0.04	[–0.00, 0.16]
UN_{Mean}	TIE_{Low}	–0.04	0.05	[–0.15, 0.06]
	TIE_{Mean}	0.04	0.03	[–0.03, 0.11]
	TIE_{High}	0.11	0.05	[0.02, 0.22]
UN_{High}	TIE_{Low}	–0.05	0.08	[–0.22, 0.08]
	TIE_{Mean}	0.05	0.05	[–0.05, 0.15]
	TIE_{High}	0.16	0.07	[0.03, 0.31]

Notes: N = 124. There were two cases with missing data and listwise deletion was applied. UN was –0.82 (i.e., 1 SD below the mean) and 0.82 (i.e., 1 SD above the mean) for low and high levels of UN, respectively. TIE was –1.51 (i.e., 1 SD below the mean) and 1.51 (i.e., 1 SD above the mean) for low and high levels of TIE, respectively. Significance tests for the indirect effects were based on bias-corrected confidence intervals obtained from 5,000 bootstrapped samples. UN = understanding of organisation and role; TIE = social ties with co-workers.

5 Discussion

All hypotheses proposed in our discussion have garnered support, painting a comprehensive picture of the dynamics between AI adoption, continuous learning, understanding of organisational roles, social ties, and thriving at work for remote workers. Hypothesis 1's confirmation indicates that AI adoption at work indeed acts as a catalyst for its continued use in facilitating continuous learning, setting the foundation for a technologically advanced learning environment. The support for Hypothesis 2 reinforces this by revealing that when employees have a deeper understanding of their organisation and role, they can leverage AI more effectively for continuous learning, which aligns with and extends prior work emphasising the role of contextual factors in technology acceptance (e.g., Davis and Venkatesh, 1996). This suggests that knowledge of the organisational context significantly amplifies AI's positive effects on learning and skill development, hence facilitating continuous use of AI for a more diverse range of activities. Further, the validation of Hypothesis 3 highlights the crucial role of social ties, indicating that the benefits of AI in learning and skill development translate into actual thriving at work only when underpinned by strong connections with peers. This finding echoes prior research on the SDT, which emphasises the importance of fulfilling relatedness needs (Spreitzer and Doneson, 2005; Porath et al., 2022). It highlights that while AI tools facilitate individual growth, thriving ultimately requires strong social support systems. Moreover, the support for Hypothesis 4 indicates that AI adoption at work will eventually enhance remote workers' thriving at work when they have robust ties with peers, corroborating findings from Bankins and Formosa (2020), who argued that human interaction remains a fundamental aspect of workplace well-being despite technological advancements. This further emphasises the pivotal role of social connections in the integration of AI into the workplace. Lastly, the support for Hypothesis 5 adds another layer of complexity, showing that the interplay between AI adoption, learning, and thriving is most potent when employees not only have robust social ties but also a profound understanding of their organisational context and roles. It is noteworthy that while the direct relationship between AI adoption at work and thriving at work is negative, though not significant, it might imply that AI adoption itself could be stressful for remote workers. This aligns with recent concerns regarding the potential negative implications of rapid AI adoption, such as technostress (Chowdhury et al., 2022), which underscores the importance of mitigating these risks through strong interpersonal support and organisational clarity. These insights collectively emphasise the multifaceted nature of thriving in a remote work setting, where technology, personal connections, and organisational understanding interweave to shape the professional growth and well-being of remote workers. Our findings extend the literature on AI's role in organisations by empirically demonstrating how AI adoption influences thriving not only through enhanced learning opportunities but also by emphasising the indispensable role of human connections and organisational clarity.

6 Theoretical contributions

This study makes several theoretical contributions. First, we contribute to the literature on organisational AI adoption by demonstrating that understanding the organisation and one's role is a crucial boundary condition for the successful use of AI in learning activities. Previous studies have suggested that the integration of AI in workplaces can either enhance or hinder employee outcomes, particularly concerning relatedness and social connections (e.g., Bankins and Formosa, 2020; Chowdhury et al., 2022). Our findings reveal that remote workers, despite their adaptive capabilities in leveraging AI for learning, still require robust social ties with co-workers to thrive. This adds to existing literature by identifying that organisational understanding and interpersonal relationships serve as essential moderators for AI's positive impact in remote settings. Second, we respond directly to the call for further research into how SDT can be applied to the context of remote work and AI integration (Spreitzer and Doneson, 2005; Porath et al., 2022). We expand on the SDT by showing that the satisfaction of autonomy, competency, and relatedness needs is particularly challenging in remote work environments enhanced by AI. Our study demonstrates that organisational understanding and social ties are key moderators that enhance the ability of AI adoption to fulfil these needs. Our study highlights how effective AI adoption can synergistically facilitate these needs, ultimately contributing to thriving in remote work environments. Third, our study provides empirical insights into the practical application of SDT in the digital and remote work context. We contribute to understanding how AI technology interacts with the social and organisational environment to shape thriving outcomes for remote workers. Specifically, our research offers a concrete demonstration of how organisational knowledge and peer relationships can enhance the successful adoption of AI, transforming it into a tool that fulfils psychological needs and drives thriving. Overall, by identifying gaps in prior literature – such as the lack of understanding regarding the boundary conditions for successful AI integration and the potential of AI to impact social ties – our study provides a more nuanced view of thriving in a remote work setting. It emphasises that AI alone is insufficient for promoting thriving without the support of robust social connections and comprehensive organisational understanding. Thus, this research contributes to filling a critical gap in our understanding of how technology and human elements converge to foster thriving in remote work environments.

7 Practical implications

To effectively navigate the challenges of remote work and AI integration, organisations should adopt strategies that prioritise human connections alongside technological advancements. AI should augment, not replace, social communities within the workplace. It is crucial to ensure that AI tools are contextualised to fit employees' roles and the organisational framework, enhancing their relevance and effectiveness. Additionally, offering comprehensive onboarding, consistent feedback, and mentorship opportunities can facilitate a better understanding of AI tools and organisational roles. This not only enhances employees' capabilities but also strengthens their ties with peers and mentors.

In practice, AI can be leveraged to complement human interactions, for instance, by facilitating regular check-ins between team members or suggesting collaborative tasks that require human creativity and insight. Such careful integration respects the bonds integral to relational psychological contracts and preserves the authenticity of human relationships, as emphasised by Raeder (2021). This approach ensures that while remote workers benefit from AI's capabilities in learning and skill acquisition, they also remain engaged in a work culture that values and fosters meaningful interpersonal relationships, promoting a more holistic form of professional thriving in line with the SDT (Deci and Ryan, 2000).

Therefore, cultivating an environment conducive to genuine thriving requires organisations to prioritise and facilitate avenues for rich, meaningful social engagement among peers. This might involve creating collaborative virtual spaces, encouraging peer-to-peer mentorship programs, or fostering team-building activities focused on deepening relational bonds. By doing so, remote workers are empowered to excel through AI-enhanced competency and autonomy and are enriched by a sense of belonging and connectedness. Achieving this holistic state of thriving encompasses the personal, professional, and social dimensions of work life, ensuring that the true potential of remote work is realised where AI serves as an enabler rather than a substitute for the human elements of work.

8 Limitations and future directions

This study provides valuable insights into the intersection of AI adoption and remote working, yet it is not without limitations that open avenues for future research. Firstly, the reliance on student data may limit the generalisability of the findings to broader professional populations. While students represent a significant segment of remote workers, their experiences may not fully capture the diversity of the larger workforce across different industries and demographic backgrounds. Future research should incorporate a more diverse sample, including individuals from various professional fields, industries, and demographic categories, to enhance the external validity of the findings and better reflect the broader workforce. Secondly, the short time interval of the study may not capture the long-term effects of AI adoption on learning and thriving. Longer-term studies are needed to understand these dynamics fully. Thirdly, while this research provides a theoretical foundation, field experiments are crucial to test the hypotheses in real-world settings and provide empirical evidence for the proposed relationships. Additionally, the study does not distinguish between types of AI, which might have varying impacts on employee learning and thriving. Future research should differentiate between AI technologies to provide a more nuanced understanding of their effects. Another important direction is to extend the research beyond the work domain to explore how AI adoption influences thriving in non-work contexts, providing a more holistic view of its impact on individuals' lives. Furthermore, while the direct relation between AI adoption at work and thriving at work is not significantly negative, it suggests that AI adoption might lead to more negative than positive outcomes if not channelled through the continuous learning and skill development path. This observation hints at potential areas for future inquiry, encouraging subsequent research to explore the mechanisms under which AI adoption at work can cause stress or anxiety, and what possible coping strategies might mitigate these effects. Lastly, the potential link between thriving and overall well-being remains unexplored in this study. Subsequent research could investigate this relationship, examining how thriving at work facilitated by AI and personal connections contributes to broader aspects of employee well-being. These areas offer promising paths for further exploration, deepening our understanding of AI's role in shaping modern work and life.

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