The Double-Edged Sword of AI for Employee Recovery: Understanding Its Dual Impact Through Competence Satisfaction and Frustration

by

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Abstract

This thesis investigated the "double-edged sword" of artificial intelligence (AI) in the workplace, examining how employees' cognitive appraisals of AI affected work recovery. Drawing on the Challenge-Hindrance Stressor Framework and Self-Determination Theory, this study explored how appraising AI as an empowering challenge (techno-mastery) or an overwhelming hindrance (techno-complexity) influenced psychological detachment and mastery experiences via the basic psychological need for competence. Data were collected from 341 full-time U.S. employees using AI via a three-wave, time-lagged survey design. Path analysis results revealed an asymmetrical mediation pattern: the pursuit of growth-oriented mastery experiences was exclusively mediated by competence satisfaction, whereas psychological detachment was exclusively mediated by competence frustration. Thus, AI techno-mastery promoted recovery by satisfying competence and reducing frustration, while AI techno-complexity impaired recovery by thwarting competence. These findings suggest organizations must both mitigate AI-induced frustration and cultivate AI-driven mastery to protect employee well-being.

Artificial Intelligence (AI) Disclosure Statement

In the preparation of this thesis, no Artificial Intelligence (AI) tools were used.

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List of Abbreviations

AI	Artificial Intelligence
TM	Techno-Mastery
TC	Techno-Complexity
CS	Competence Satisfaction
CF	Competence Frustration
PD	Psychological Detachment
ME	Mastery Experiences
SDT	Self-Determination Theory
CHSF	Challenge-Hindrance Stressor Framework
REQ	Recovery Experiences Questionnaire
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
RMSEA	Root Mean Square Error of Approximation
SRMR	Standardized Root Mean Square Residual
df	Degrees of freedom
M	Mean
SD	Standard Deviation

Introduction

The growing integration of artificial intelligence (AI) into organizational work has sparked both excitement and concern. Researchers emphasize AI's potential to improve efficiency, streamline decision-making, and reduce workload, while noting risks such as job insecurity, complexity, and employee strain (Li et al., 2025; Ma et al., 2024). As AI becomes embedded in tools ranging from email assistants to decision support platforms, it is no longer the question of whether employees use AI at work, but how (Jarrahi, 2018). This thesis examined the "double-edged sword" of AI by investigating how employees' experiences of AI through techno-mastery (i.e., the extent to which technology use motivates employees to achieve competence, efficiency, and proficiency at work; Tarafdar et al., 2024) or techno-complexity (i.e., situations where technology use makes employees feel inadequate in their computer skills and forces them to spend extra time and effort learning and understanding the systems; Ragu-Nathan et al., 2008) are associated with workplace recovery experiences.

Specifically, I focused on two work recovery outcomes, psychological detachment and mastery experiences, that are crucial to restoring energy and preventing strain (Sonnentag & Fritz, 2007). These outcomes capture employees' ability to mentally disengage from work demands (psychological detachment) and to pursue growth-oriented activities (mastery experiences) (Sonnentag & Fritz, 2007). Recovery is a vital construct in occupational health psychology because it is consistently linked with long-term well-being, burnout prevention, and resilience (Headrick et al., 2023; Sonnentag & Geurts, 2009; Sonnentag & Fritz, 2015).

Much of the workplace AI literature has emphasized its bright side, portraying AI as a driver of efficiency, productivity, and decision-making quality (Ma et al., 2024). However, evidence shows a potential darker side when AI is in context with employee well-being.

Researchers have documented that technology demands can reduce connectedness, drain emotional energy, and interfere with recovery processes (Dakin et al., 2025; Wurtenberger et al., 2025). This contrast highlights an important tension: while AI can enhance performance, it can also hinder employee functioning. This study used psychological detachment and mastery experiences as indicators of whether AI sustains employees' ability to recover from work.

Despite the growing recognition of both positive and negative outcomes, it remains unclear why employees sometimes benefit from AI and at other times feel depleted by it. The challenge-hindrance stressor framework (Cavanaugh et al., 2000) provides a perspective for understanding this distinction. This thesis proposed that the difference lies in how AI is experienced: as a challenge (techno-mastery) or as a hindrance (techno-complexity). When employees perceive AI as a positive challenge, it can encourage skill development and reinforce competence; conversely, when they perceive it as overly complex or difficult, it can frustrate competence and hinder performance. Additionally, drawing from the self-determination theory (Deci & Ryan, 2000), I conceptualized competence need satisfaction/frustration as a crucial psychological mechanism underlying these relationships, explaining why certain AI experiences may be linked to more positive or negative outcomes. Together, these frameworks clarify why appraising AI as mastery-supporting versus complexity-inducing should be associated with different work recovery experiences. Thus, this study tested a parallel mediation model that explains how employees' AI-related experiences of techno-mastery and techno-complexity are associated with work recovery outcomes, specifically psychological detachment and mastery experiences, through the mediating roles of competence satisfaction and competence frustration. The proposed model is presented in Figure 1.

This thesis offers several contributions to the literature. First, this study extends AI at work research by shifting attention from traditional outcomes such as productivity (e.g., Brynjolfsson et al., 2025) and overload (e.g., Rikala et al., 2025) to recovery outcomes. In line with recent calls for future research to examine how new technologies relate to recovery (Sonnentag et al., 2022), this thesis positions psychological detachment and mastery experiences as critical indicators of whether AI supports or disrupts employee recovery. These outcomes, long recognized as being vital to occupational health psychology (Sonnentag et al., 2022; Headrick et al., 2023), remain largely overlooked in AI research.

Second, the study introduces a dual-pathway approach model that incorporates both challenge (techno-mastery) and hindrance (techno-complexity) experiences of AI. While some research has emphasized AI as a burden that generates strain and overload (e.g., Dakin et al., 2025; Wurtenberger et al., 2025), other studies highlight its role as an enabler or performance and growth (e.g., Ma et al., 2024; Brynjolfsson et al., 2025). By applying the challenge-hindrance stressor framework (Cavanaugh et al., 2000), my study offers a more balanced understanding of why AI can sometimes motivate growth but, on other occasions, be overwhelming.

Third, the study advances applications of the self-determination theory by testing both competence satisfaction and competence frustration as mediators. While competence is well established as a basic psychological need that promotes motivation and well-being (Van den Broeck et al., 2010), to my knowledge, few studies have examined how workplace AI experiences simultaneously satisfy or frustrate this need, which is expected to shape work recovery outcomes. Even beyond the workplace AI literature, past research has often emphasized need satisfaction while overlooking need frustration, despite meta-analytic evidence showing that frustration is important for predicting negative outcomes (Van den Broeck et al., 2016). Similarly, Deci et al. (2017) specifically called for research that assesses both workplace need satisfaction and need frustration, noting that this dual focus is necessary for understanding how work experiences predict both positive and negative outcomes. By incorporating both pathways, this study responds to these calls and offers a more comprehensive account of how AI influences work recovery.

Finally, this research provides practical implications for organizations. Findings can inform strategies to minimize unnecessary AI complexity while fostering mastery opportunities and skill-building, helping organizations introduce AI tools in ways that protect and enhance employee well-being. More broadly, these insights can guide organizations in striking a balance between the efficiency gains of AI and practices that ensure long-term employee sustainability and resilience.

Theoretical Framework

This thesis integrates the challenge-hindrance stressor framework (CHSFM) (Cavanaugh et al., 2000) and the self-determination theory (SDT; Deci & Ryan, 2000) to justify the proposed model. The CHSFM (Cavanaugh et al., 2000) distinguishes between stressors that employees appraise as opportunities for growth and achievement (i.e., challenge stressors) versus those that are seen as obstacles that limit personal development or performance (i.e., hindrance stressors). Empirical evidence supports this distinction, showing that challenge and hindrance demand relate differently to health and behaviors through motivational processes (Kim & Beehr, 2018; Podsakoff et al., 2023). Challenge stressors, such as workload or responsibility, are often linked with motivation and positive outcomes, while hindrance stressors, such as role ambiguity or bureaucratic red tape, are typically associated with strain and withdrawal (LePine et al., 2005).

This study applies CHSFM by conceptualizing techno-mastery as a challenge appraisal of AI and techno-complexity as a hindrance appraisal. By doing so, CHSFM provides the foundation for why AI experiences may produce both positive and negative outcomes for employees.

SDT is a broad theory of human motivation that emphasizes the importance of satisfying psychological needs for optimal functioning and well-being (Deci & Ryan, 2000). The three central needs are autonomy (i.e., sense of volition), relatedness (i.e., sense of connection with others), and competence (i.e., sense of effectiveness). Although SDT notes all three psychological needs, this thesis focuses specifically on competence because of its relevance to recovery from AI techno-mastery and AI techno-complexity experiences at work. These AI experiences directly implicate competence because they require employees to learn, adapt, and apply new skills. When AI is experienced as techno-mastery (e.g., providing clear feedback, visible skill gains, and opportunities to refine workflows), it reinforces competence satisfaction by helping employees feel effective and capable (Tarafdar et al., 2024). By contrast, when AI is experienced as techno-complexity (e.g., systems that are opaque, rapidly evolving, or difficult to control), it frustrates competence by hindering employees' sense of capability and leaving them feeling ineffective (Tarafdar et al., 2019; Diebel et al., 2024). Recent research suggests that competence needs may be more important for recovery outcomes than autonomy and relatedness (Olafsen et al., 2025). Competence plays a key role in employees' ability to restore energy and disengage from work, making it a key mechanism for understanding recovery. These findings suggest that competence provides the clearest psychological need mechanism for the proposed model.

SDT is applied to this thesis by focusing on competence satisfaction and frustration as the psychological mechanisms that explain why challenge-like AI experiences (techno-mastery) may support recovery, while hindrance experiences (techno-complexity) may hinder it. Research on the SDT shows that need satisfaction and frustration operate through distinct pathways rather than as opposite ends of a continuum (Van den Broeck et al., 2016). According to SDT, when needs are satisfied, individuals tend to experience greater motivation and engagement (Van den Broeck et al., 2016; Deci et al., 2017). Need satisfaction provides the psychological resources necessary for growth, supporting outcomes such as persistence and effective coping (Deci & Ryan, 2000). In organizational settings, competence satisfaction specifically has been linked to stronger intrinsic motivation, improved performance, and health adjustment to work demands (Gagne & Deci, 2005). Conversely, need frustration reflects more than the absence of satisfaction; it involves the active experience of feeling thwarted in one's needs (Vansteenkiste & Ryan, 2013). When competence is frustrated, employees may feel insecure, ineffective, or unable to meet demands, which is associated with strain, disengagement, and ill-being (Deci et al., 2017; Van den Broeck, 2010).

Although previous SDT research has rarely positioned recovery as an outcome, this thesis argues that competence-related experiences should be linked to recovery outcomes. Specifically, I focus on psychological detachment and mastery experiences. Psychological detachment refers to an employee's ability to mentally disengage from work demands during nonwork time, which is important for preventing prolonged strain and maintaining long-term well-being (Sonnentag & Fritz, 2007). Mastery experiences capture the pursuit of challenging and growth-oriented activities outside of work, which can restore energy and build personal resources (Headrick et al., 2023). These two types of work recovery experiences are relevant when considered through the lens of SDT: competence satisfaction provides energy and motivation that can facilitate detachment and engagement in growth-oriented off-job activities, where competence frustration depletes these resources and hinders recovery (Van den Broeck et al., 2010; Van den Broeck et al., 2016; Bartholomew et al., 2011). They represent key outcomes that demonstrate how AI-related experiences of techno-complexity and techno-mastery may carry over into employees' recovery.

In summary, SDT and CHSFM provide complementary perspectives for understanding how employees respond to AI experiences at work. CHSFM explains how AI-related demands may be appraised as either challenges (e.g., techno-mastery) or hindrances (e.g., techno-complexity). SDT explains why these appraisals matter by highlighting competence as a core psychological mechanism. When employees experience AI as a challenge, they are more likely to feel competent and capable; when they experience AI as a hindrance, they are more likely to feel frustrated and ineffective. Building on these frameworks, this study proposes the following hypotheses for how employees' experiences with AI are associated with recovery outcomes through the mediating roles of competence satisfaction and frustration.

AI Techno-Mastery and Competence Satisfaction

Technology is not simply a tool but can be a source of stimulation that encourages users to explore new features, develop new skills, and innovate in how they approach tasks (Tarafdar et al., 2024). Employees who experience techno-mastery often describe technology as something that expands their capabilities and prompts them to refine their work processes in productive ways. This framing as a challenge stressor aligns with the notion of "techno-eustress" from the technostress literature, which emphasizes the energizing and motivating qualities of technology when appraised positively (Tarafdar et al., 2019). Recognizing techno-mastery is particularly important in the AI context, as AI systems are often designed to enhance decision-making, automate routine tasks, and create space for higher-level, innovative work.

When AI is experienced as a positive challenge, it can encourage employees to view their work as an opportunity for growth (Tarafdar et al., 2019; 2024). From an SDT perspective, these opportunities reinforce employees' sense of capability and effectiveness, which aligns with the psychological need for competence (Van den Broeck et al., 2010). When AI tools are seen as enhancing one's abilities, employees are more likely to feel satisfied with their competence.

In turn, this competence satisfaction from AI techno-mastery experiences is expected to have implications for work recovery outcomes. One key pathway is psychological detachment. Employees who feel competent in handling AI demands are less likely to experience lingering doubts or reflect on their work tasks. A strong sense of efficacy can facilitate mental disengagement from work demands, thereby supporting recovery during nonwork hours (Sonnentag & Fritz, 2007; 2015). By reducing uncertainty and increasing confidence, competence satisfaction helps employees "switch off" without being preoccupied by unfinished tasks or fears of inadequacy. Prior research has shown that psychological detachment is a significant predictor of health and well-being (Headrick et al., 2023; Sonnentag et al., 2022). Thus, AI mastery experiences that build competence are expected to promote greater psychological detachment.

Competence satisfaction is also expected to contribute to mastery experiences outside of work. Employees who feel effective in managing AI tools may be more likely to pursue growth-oriented activities in their personal lives, such as learning new skills or engaging in challenging hobbies. These activities foster energy, providing an additional route to recovery (Headrick et al., 2023). Mastery experiences depend on confidence in one's abilities because individuals are less inclined to take on new challenges when they feel insecure or depleted (Deci & Ryan, 2000; Sonnentag & Fritz, 2007). By reinforcing competence, positive AI experiences of techno-mastery are expected to enhance employees' engagement in mastery activities beyond the workplace.

H1: AI techno-mastery at Time 1 has an indirect positive effect on psychological detachment at Time 3 via competence satisfaction at Time 2.

H2: AI techno-mastery at Time 1 has an indirect positive effect on mastery experiences at Time 3 via competence satisfaction at Time 2.

AI Techno-Complexity and Competence Frustration

When employees encounter AI systems that are non-transparent, rapidly evolving, or require skills they do not possess, these technologies are more likely to be seen as hindrance stressors consistent with the CHSFM (Cavanaugh et al., 2000). Considering techno-complexity as a hindrance stressor allows researchers to capture how AI can create barriers rather than opportunities, which is crucial for assessing its impact on employees' well-being. In the context of AI, techno-complexity is especially significant because many AI applications can be hard for employees to fully understand or trust (Atrian & Ghobbeh, 2023). Such experiences hinder employees' sense of capability and lead to feelings of inefficacy, which represent the frustration of the competence need (Vansteenkiste & Ryan, 2013). Prior research on technostress shows that techno-complexity can reduce job satisfaction, hinder self-efficacy, and increase techno-strain (Tarafdar et al, 2019; Atrian & Ghobbeh, 2023). Thus, AI techno-complexity should have a positive relationship with competence frustration. Consistent with SDT, competence frustration captures the active experience of feeling thwarted in one's ability to meet demands, rather than simply the absence of competence satisfaction (Bartholomew et al. 2011).

Competence frustration induced by techno-complexity is expected to hinder psychological detachment. When employees struggle with complex or confusing AI systems, they may continue to reflect on these frustrations outside of work hours, worrying about unfinished tasks or doubting their abilities. This “carry-over” of unresolved demands is associated with difficulty for employees to mentally disengage, trapping them in a cycle of persistent work-related thoughts (Sonnentag & Fritz, 2007). Instead of recovery, employees may remain cognitively and emotionally tethered to the competence-thwarting difficulties they faced at work when using AI. Research on computer interaction suggests that poorly designed or overly complex systems can frustrate users' competence needs, making disengagement more difficult and hindering overall well-being (Peters, 2023). Thus, AI complexity that frustrates competence is expected to hinder psychological detachment, as unresolved struggles with technology are likely to carry over into nonwork time.

Similarly, competence frustration from AI techno-complexity is likely to interfere with mastery experiences during nonwork time. Individuals who feel insecure or ineffective in managing AI systems may be less inclined to engage in challenging or growth-oriented activities outside of work, as job stressors and fatigue make it harder to pursue mastery experiences during off-job time (Sonnentag & Fritz, 2007; Marvi et al., 2025). Struggling with AI at work can leave employees depleted of confidence and energy, reducing the motivation to pursue personal mastery activities that require effort and persistence (Headrick et al., 2023). Recent evidence shows that adopting mastery goals in AI use promotes engagement and growth-oriented behavior (Marvi et al., 2025). By undermining competence, AI complexity is expected to reduce employees’ motivation and energy to engage in mastery activities beyond the workplace.

H3: AI techno-complexity at Time 1 has an indirect negative effect on psychological detachment at Time 3 via competence frustration at Time 2.

H4: AI techno-complexity at Time 1 has an indirect negative effect on mastery experiences at Time 3 via competence frustration at Time 2.

AI Techno-Mastery and Competence Frustration

Research in SDT commonly models both need satisfaction and need frustration as parallel mediators, with evidence that they operate not only through distinct pathways but also via cross-linked effects (Haerens et al., 2015; Trepanier et al., 2015; Reeve et al., 2023). When employees approach AI as a chance to build mastery, they experience small but meaningful wins, such as clear feedback, visible skill gains, and a growing sense of control, which help alleviate feelings of ineffectiveness (Chen et al., 2015). These experiences not only increase competence satisfaction but also reduce the likelihood of feeling ineffective or thwarted (Chen et al., 2015). In practice, learning to prompt more effectively, interpret outputs, and adapt workflows helps employees feel capable, lowering competence frustration and its negative consequences (Gustaw, 2021).

This likely matters for distinct recovery experiences. For psychological detachment, competence frustration is closely tied to perseverative thoughts like rumination, which makes it difficult to mentally disconnect from work (Vansteenkiste & Ryan, 2013). By lowering competence frustration, techno-mastery should reduce this cycle and make detachment easier. Meng et al. (2024) demonstrated that competence frustration often pushes individuals to restore a sense of capability through renewed effort. Techno-mastery offers a direct path for this restoration; each successful interaction with AI provides an opportunity to rebuild competence, reducing frustration before it spills over into impaired recovery. Evidence from broader technology use points in the same direction. Nascimento et al. (2025) found that when remote workers viewed technology as useful and manageable, they experienced positive psychological responses instead of strain. Although Nascimento et al. (2025) examines ICT more broadly, the principles may also apply to AI. When employees frame AI as a manageable challenge, it prevents competence need frustration, supporting work recovery pathways.

H5: AI techno-mastery at Time 1 has an indirect positive effect on psychological detachment at Time 3 via competence frustration at Time 2.

H6: AI techno-mastery at Time 1 has an indirect positive effect on mastery experiences at Time 3 via competence frustration at Time 2.

AI Techno-Complexity and Competence Satisfaction

By contrast, complex AI often removes the cues people need to feel effective, such as clear instructions, usable feedback, and a sense of control. Even without leading to full frustration, these issues are associated with lower competence satisfaction, the feeling of being capable and effective at work (Van den Broeck et al., 2010). Previous research has shown that techno-complexity is linked to lower self-efficacy and greater strain, supporting the idea that it hinders competence satisfaction (Tarafdar et al., 2019). As a result, complex AI is expected to reduce satisfaction and weaken the motivational energy needed for recovery.

Recent evidence reinforces this expectation. Li and Xie (2025) found that techno-complexity lowered users' self-efficacy and increased anxiety, both of which reduced satisfaction with digital services. Although their sample consisted of older adults engaging with e-government, the implications may be relevant to workplace AI. When systems are confusing and demand more effort than users feel capable of providing, the results may wear on competence satisfaction. In this way, their findings illustrate how AI's complexity can drain the basic psychological resources employees rely on at work, even if the technology is different.

This pattern also appears in AI-specific contexts. Wong et al. (2025) examined software developers using AI-assisted coding tools and found mixed outcomes for competence satisfaction. While some workers felt more proactive and capable, others reported reduced competence satisfaction when the complexity or unpredictability of AI left them doubting their own skills or fearing deskilling. When AI takes over tasks in ways that feel opaque or difficult to manage, employees may lose that sense that they are effective in their roles. These findings align with hypotheses, suggesting that AI can reduce competence satisfaction when employees perceive the technology as overly complex.

Reduced competence satisfaction has important implications for recovery outcomes. Employees who feel ineffective at work struggle more to mentally disengage, since lingering doubts and unfinished concerns carry into nonwork time, making psychological detachment less likely (Sonnentag and Fritz, 2007). Lower competence satisfaction also hinders the energy and motivation needed for growth, as employees who doubt their capabilities are less inclined to invest in challenging off-job activities that foster mastery (Van den Broeck et al., 2010). In this way, declines in competence satisfaction weaken both recovery processes, making employees less able to detach and less likely to pursue mastery experiences.

H7: AI techno-complexity at Time 1 has an indirect negative effect on psychological detachment at Time 3 via competence satisfaction at Time 2.

H8: AI techno-complexity at Time 1 has an indirect negative effect on mastery experiences at Time 3 via competence satisfaction at Time 2.

Methods

Procedure and Participants

Data collection consisted of an eligibility survey and a three-wave, time-lagged study design, with each wave spaced one week apart. This specific interval was selected because it was appropriate for capturing short-term fluctuations in cognitive appraisals of AI, competence states, and weekly recovery experiences. This approach is consistent with Wolff et al. (2024), who successfully applied a one-week time lag to examine similar short-term affective responses to workplace technology. Following recommendations from Podsakoff et al. (2012), temporal separation also served as a procedural remedy for common method bias. All timepoints were administered through the crowdsourced platform Prolific. Participants first completed an eligibility survey to confirm they met the inclusion criteria (see Appendix A for the complete Prolific pre-screening criteria). Participants were required to be full-time employees currently working in the United States who utilized AI as part of their work at least once per week.

I initially recruited 450 participants for the eligibility survey. I compensated participants $1.00 for this 5-minute survey and $2.00 for each of the three 10-minute main surveys, allowing participants to earn a total possible compensation of $7.00, consistent with Prolific's recommended wage calculator. To ensure a high-quality sample, I systematically filtered responses. To verify that participants integrated AI into their work tasks in a substantial way, I included an open-ended item in the eligibility survey: "Please describe how you use AI tools or systems as part of your work tasks in your primary job. Please do not use AI tools or external resources; we are specifically interested in your genuine, personal experience and thoughts." A review of those responses confirmed that participants utilized AI across diverse industries (e.g., finance, IT, management, academia, and customer service) for task-embedded activities, such as drafting emails, summarizing data, and coding. I excluded participants who provided irrelevant responses or demonstrated non-substantial AI use (e.g., “I don’t use AI tools at work), ensuring only eligible participants advanced to the main study.

I also embedded multiple data quality checks in the eligibility survey and at each subsequent wave to ensure rigorous data validity and defend against careless or fraudulent responses. First, I utilized automated security features, including Qualtrics’ reCAPTCHA bot-detection, duplicate respondent tracking, and Prolific’s platform-level Authenticity Checks. Second, I embedded both instructed-response attention checks and demographic consistency checks throughout the surveys to identify careless responding. Finally, I administered a three-item self-reported data quality assessment at the conclusion of each survey to verify participant attention, accuracy, and truthfulness. I evaluated the data across all three waves and ensured that participants who failed these embedded checks, provided careless qualitative data, or reported low response quality were not invited to participate in the remaining surveys.

During the eligibility survey, I removed 14 participants for failing to meet the inclusion criteria and 2 participants due to data quality concerns. During the main study, I removed 9 participants at Wave 1, 4 at Wave 2, and 8 at Wave 3 due to specific data quality concerns (e.g. failed attention checks, bot-like responses). An additional 60 participants withdrew or timed out across the study phases. While 353 participants successfully passed all quality checks and completed all three survey waves, I excluded 12 participants from the main analyses due to missing data. This screening process resulted in a final analytic sample of 341 participants.

The final sample consisted of 58.94% male, 39.59% female, and 1.47% non-binary participants. The average age of participants was 42.12 years (*SD* = 10.76), and the average organizational tenure was 8.75 years (*SD* = 7.06). The sample identified predominantly as White (76.25%), followed by Hispanic/Latino (11.14%), and Black/African American (9.09%).

Regarding education, 75.66% of participants held a bachelor's degree or higher. Participants represented a diverse range of occupational backgrounds, with the top job sectors being business and financial operations (16.13%), computer and mathematical occupations (14.37%), and a tie between education, training, and library (10.56%) and sales and related occupations (10.56%). When asked how often participants use AI or tools that use AI as part of their work, the top three responses were: 35.19% reported using it 2-6 times a week, 34.60% reported using it multiple times every day, and 23.17% reported using it every day. Additionally, 32.84% of participants somewhat or strongly agreed that they use AI to carry out most of their job functions, and 52.20% somewhat or strongly agreed that they work with AI to make major work decisions.

Measures

Demographic information, including age, gender, and organizational tenure, was collected in the eligibility survey. At Time 1 (T1), participants completed measures of AI techno-mastery and techno-complexity. At Time 2 (T2), participants reported their experiences of competence satisfaction and competence frustration. Finally, at Time 3 (T3), they completed recovery outcome measures, including psychological detachment and mastery experiences. Appendix B presents all measures and their respective items used in this study. Unless otherwise noted, all items were rated on a 5-point Likert agreement scale (1 = Strongly Disagree, 5 = Strongly Agree). The Recovery Experience Questionnaire (Sonnentag & Fritz, 2007) employed a 5-point frequency scale, ranging from 1 (Not at all) to 5 (Very Much).

Techno-Complexity

Techno-complexity was measured using the 5-item subscale from Ragu-Nathan et al. (2008), which captures the extent to which employees perceive AI technology as difficult, confusing, or overwhelming to use. The items reflect participants' experiences with AI technology specifically. Example items include: “I do not know enough about this AI technology to handle my job satisfactorily” and “I often find it too complex for me to understand and use new AI technologies.” In the present study, these items yielded a strong reliability coefficient ($\alpha = .85$).

Techno-Mastery

Techno-mastery was measured using a 5-item scale by Tarafdar et al. (2024). The scale captured the extent to which AI technology used for work is experienced as positively challenging and motivating. Again, the items reflect participants’ experiences with AI technology. The items are introduced with the prompt: “The AI technology I use for work challenges me in a positive way and motivate me to…” followed by statements such as “make my work methods more efficient” and “make my work methods more innovative.” This scale demonstrated excellent internal consistency ($\alpha =.93$).

Competence Satisfaction

Competence satisfaction was measured using the 3-item competence satisfaction subscale from the need satisfaction and frustration scale (NSFS; Longo et al., 2016). This scale captured the extent to which employees feel effective and capable in their work. Items include “I feel highly effective at what I do”, “I feel I am very good at the things I do”, and “I feel I can accomplish even the most difficult tasks”. Higher scores indicate greater competence satisfaction. The scale demonstrated excellent internal consistency ($\alpha = .93$).

Competence Frustration

Competence frustration was measured using the 3-item competence frustration subscale from the need satisfaction and frustration scale (NSFS; Longo et al., 2016). This scale captured the active experience of feeling ineffective or incapable of meeting demands. Items include “I doubt whether I am able to carry out my tasks properly", "Occasionally, I feel incapable of succeeding in my tasks", and "I sometimes feel unable to master hard challenges". Higher scores reflected greater competence frustration. The scale demonstrated excellent internal consistency ($\alpha = .91$).

Recovery

Recovery was assessed using two subscales from the Recovery Experience Questionnaire (REQ: Sonnentag & Fritz, 2007): psychological detachment and mastery experiences. Psychological detachment refers to the individual's ability to mentally disengage from work-related thoughts and demands during off-job time. Example items include "I forget about work" and "I don't think about work at all." Reliability for this subscale was excellent ($\alpha = .95$). Mastery experiences capture the extent to which individuals engage in off-job experiences that promote growth, learning, or personal challenge. Example items include "I seek out intellectual challenges" and "I do something to broaden my horizons." This measure demonstrated excellent internal consistency ($\alpha = .94$) for psychological detachment.

Control Variables

Control variables included participant age, gender, organizational tenure, and organizational AI support. Age was controlled for because previous research indicates that age can significantly influence an individual's job attitude and overall susceptibility to technostress (Marchiori et al., 2019). Gender was included because past studies have found significant gender differences in technology adoption and the experience of technology-induced stress (La Torre et al., 2020). Organizational tenure was controlled for because employees with longer tenure possess more organization-specific experience, which can help them assimilate and cope with the stress-creating effects of new technologies in their specific work context (Ragu-Nathan et al., 2008). Finally, organizational AI support was measured at T1 using items adapted from Ragu-Nathan et al. (2008) (α = .90). This variable was controlled for because organizational support mechanisms may act as vital resources that can influence the impacts of technology-induced demands on employee well-being (Day et al., 2012).

Analytic Approach

Prior to hypothesis testing, descriptive statistics, zero-order correlations, and scale reliabilities were calculated to evaluate the suitability of the data. To test the hypothesized parallel mediation model, path analysis was conducted in RStudio using the *lavaan* package (Rosseel, 2012). The model examined whether Time 1 (T1) techno-mastery and techno-complexity predict Time 3 (T3) employee recovery outcomes (psychological detachment and mastery experiences) through Time 2 (T2) mediators: competence satisfaction and competence frustration. To test the significance of the indirect effects (Hypotheses 1-8), 95% bias corrected confidence intervals (CIs) were estimated using bootstrapping with 10,000 resamples (Hayes & Scharkow, 2013). Control variables (i.e., participant age, gender, organizational tenure, and T1 organizational AI support) were included as covariates in the model to rule out alternative explanations.

Results

Preliminary Analysis

Means, standard deviations, and correlations for all main study variables and covariates are presented in Table 1. The main study variables were significantly correlated with each other in the expected directions. Specifically, techno-mastery was positively associated with competence satisfaction (r = .71, p < .01) and mastery experiences (r = .21, p < .01) and negatively associated with competence frustration (r = -.33, p < .01) but was not significantly related to psychological detachment (r = -.01, $p > .05$). Conversely, techno-complexity was positively associated with competence frustration ($r = .56$, $p < .01$) and negatively associated with competence satisfaction ($r = -.41$, $p < .01$), psychological detachment ($r = -.14$, $p < .01$), and mastery experiences ($r = -.17$, $p < .01$). Furthermore, regarding the recovery outcomes, competence satisfaction was positively associated with mastery experiences ($r = .28$, $p < .01$) but was not significantly related to psychological detachment (r = .09, $p > .05$). In contrast, competence frustration was negatively associated with psychological detachment (r = -.17, $p < .01$) and mastery experiences (r = -.13, $p < .05$).

Measurement Model

I conducted a confirmatory factor analysis (CFA) using the *lavaan* package in RStudio to assess the measurement model for the study constructs. The hypothesized six-factor model included the following latent constructs: techno-mastery, techno-complexity, competence satisfaction, competence frustration, psychological detachment, and mastery experiences, and demonstrated good fit to the data, X^2 (237) = 493.16, $p < .001$, CFI = 0.97, RMSEA = 0.06, SRMR = 0.04.

The six-factor model was compared to several alternative models. The one-factor model, X^2 (252) = 4851.38, $p < .001$, CFI = 0.37, RMSEA = 0.23, SRMR = 0.20, fit significantly worse than the six-factor model, ΔX^2 (15) = 4358.22, $p < .001$. The three-factor model, where items were grouped by time points, X^2 (249) = 3176.50, $p < .001$, CFI = 0.60, RMSEA = 0.18, SRMR = 0.19, also fit significantly worse than the six-factor model ΔX^2 (12) = 2683.30, $p < .001$). Similarly, three five-factor models in which theoretically related constructs were combined all demonstrated significantly poorer fit than the six-factor model: combining techno-mastery and techno-complexity, X^2 (242) = 1301.85, $p < .001$, CFI = 0.85, RMSEA = 0.11, SRMR = 0.13,

ΔX^2 (5) = 808.69, $p < .001$; combining competence satisfaction and competence frustration, X^2 (242) = 1158.12, $p < .001$, CFI = 0.87, RMSEA = 0.10, SRMR = 0.08, ΔX^2 (5) = 664.97, $p < .001$; and combining psychological detachment and mastery experiences, X^2 (242) = 1763.04, $p < .001$, CFI = 0.79, RMSEA = 0.13, SRMR = 0.14, ΔX^2 (5) = 1269.90, $p < .001$. Together, these results provide strong support for the distinctiveness of the six-factor measurement model.

Hypothesis Testing

Prior to evaluating the hypotheses, the path analysis model was assessed for overall fit using recommended indices (Hu & Bentler, 1999). The proposed model demonstrated excellent fit to the data ($\chi^2(9) = 6.958$, $p = .642$, CFI = 1.000, RMSEA = .000, SRMR =.033). To maintain focus on the primary study hypotheses of evaluating indirect effects of AI experiences on recovery via psychological needs, all specific individual direct path coefficients (e.g., T1 predictors to T2 mediators to T3 outcomes) and covariate effects are detailed in Table 2.

For Hypothesis 1, I predicted that AI techno-mastery (T1) has an indirect positive effect on psychological detachment (T3) via competence satisfaction (T2). This hypothesis was not supported, as the 95% confidence interval crossed zero (Estimate = 0.08, 95% CI [-0.073, 0.237]). Hypothesis 2 was that AI techno-mastery (T1) has an indirect positive effect on mastery experiences (T3) via competence satisfaction (T2). This hypothesis was supported. Results indicated a significant indirect positive effect (Estimate = 0.16, 95% CI [0.040, 0.300]).

For Hypothesis 3, I predicted that AI techno-complexity (T1) has an indirect negative effect on psychological detachment (T3) via competence frustration (T2). This hypothesis was supported, demonstrating a significant indirect negative effect (Estimate = -0.11, 95% CI [-0.216, -0.007]). Hypothesis 4 was that AI techno-complexity (T1) has an indirect negative effect on mastery experiences (T3) via competence frustration (T2). This hypothesis was not supported, as the confidence interval crossed zero (Estimate = 0.04, 95% CI [-0.048, 0.131]).

For Hypothesis 5, I predicted that AI techno-mastery (T1) has an indirect positive effect on psychological detachment (T3) via competence frustration (T2). This hypothesis was supported, showing a significant indirect positive effect (Estimate = 0.04, 95% CI [0.003, 0.095]). Hypothesis 6 was that AI techno-mastery (T1) has an indirect positive effect on mastery experiences (T3) via competence frustration (T2). This hypothesis was not supported, as the confidence interval crossed zero (Estimate = -0.01, 95% CI [-0.049, 0.014]).

For Hypothesis 7, I predicted that AI techno-complexity (T1) has an indirect negative effect on psychological detachment (T3) via competence satisfaction (T2). This hypothesis was not supported, as the confidence interval crossed zero (Estimate = -0.03, 95% CI [-0.103, 0.027]). Finally, Hypothesis 8 was that AI techno-complexity (T1) has an indirect negative effect on mastery experiences (T3) via competence satisfaction (T2). This hypothesis was supported, as indicated by a significant indirect negative effect (Estimate = -0.06, 95% CI [-0.125, -0.017]).

Discussion

Drawing on the Challenge-Hindrance Stressor Framework (CHSFM) and Self-Determination Theory (SDT), the present study explored the “double-edged sword” of artificial intelligence (AI) in the workplace. Specifically, I examined how cognitive appraisals of AI as either an empowering challenge (techno-mastery) or an overwhelming hindrance (techno-complexity) relate to work recovery outcomes, and the mediating role of the basic psychological need for competence. As AI becomes widespread, employees increasingly interact with AI systems in their daily tasks, making it important to understand how these experiences relate to employee well-being and recovery (Jarrahi, 2018; Sonnentag et al., 2022).

My study provided important insights into the application of both CHSFM and SDT regarding the relationship between AI use at work and employee recovery. AI techno-mastery and techno-complexity were related to both mastery experiences and psychological detachment. Specifically, the findings revealed that techno-mastery was positively associated with growth-oriented recovery (mastery experiences) through increased competence satisfaction, and with restorative recovery (psychological detachment) through decreased competence frustration. Conversely, techno-complexity was negatively associated with restorative recovery via increased competence frustration, and with growth-oriented recovery via decreased competence satisfaction. These findings suggest that employees' appraisals of AI as either a challenge or hindrance relate to recovery outcomes through distinct competence-related psychological pathways. Importantly, these indirect relationships remained significant even when controlling for organizational AI support, age, gender, and organizational tenure.

Taken together, these findings suggest that the implications of AI for employee recovery depend on how employees appraise their interactions with AI and how those experiences relate to their competence-related psychological states. Although I hypothesized that both psychological need states would mediate the relationships between AI appraisals and both recovery outcomes, the results revealed an asymmetrical pattern: competence satisfaction exclusively predicted mastery experiences, while competence frustration exclusively predicted psychological detachment. This pattern of findings reveals a more nuanced understanding: the fulfillment of competence needs is associated with engagement in growth-oriented recovery experiences, while the thwarting of competence needs is associated with difficulty disengaging from work and reduced restorative recovery (Ryan & Deci, 2000; Sonnentag & Fritz, 2007). The theoretical implications of these supported and unsupported pathways are discussed below.

Theoretical Implications

This study offers several contributions to the literature spanning occupational health psychology, technostress, and work recovery. By integrating the motivational mechanisms of SDT within the CHSFM, this research moves beyond simply identifying AI as a uniform workplace demand to mapping the distinct psychological pathways through which it relates to employee well-being. Specifically, this study advances the current literature through three major theoretical implications: the dual challenge-and-hindrance nature of AI, the asymmetrical “bright and dark” pathways of psychological needs, and the nuanced nature of modern work recovery.

First, the study extends the technostress literature by providing empirical evidence for the “double-edged” nature of modern workplace technology (Reinke & Ohly, 2021). Historically, research has often framed new technology as a uniform stressor that inevitably leads to strain and exhaustion (Reinke & Ohly, 2021; Tarafdar et al., 2007). However, by positioning techno-mastery as a challenge stressor and techno-complexity as a hindrance stressor within the CHSFM, this study showed that AI is associated with employee well-being in diverging ways (Cavanaugh et al., 2000; Ragu-Nathan et al., 2008). The results revealed that these AI experiences demonstrate cross-relationships with both competence satisfaction and competence frustration (Ryan & Deci, 2000; Vansteenkiste et al., 2020). Specifically, techno-mastery was positively related to competence satisfaction and negatively related to competence frustration, while techno-complexity showed the opposite pattern.

This pattern of findings provides an important theoretical bridge between the CHSFM and SDT. When AI is experienced as an empowering tool that allows employees to bypass mundane tasks and elevate their output (i.e., techno-mastery), it functions as a “techno-eustress” creator that relates to positive psychological states (Tarafdar et al., 2024). When employees feel capable of leveraging AI to solve complex problems, technology is associated with intrinsic motivation, higher competence satisfaction, and lower competence frustration (Ryan & Deci, 2000; Vansteenkiste et al., 2020). Alternatively, when AI is experienced as an opaque, rapidly changing, or difficult to control system (techno-complexity), it functions as a hindrance stressor that is perceived to exceed the individual's coping resources (Cavanaugh et al., 2000). The cognitive burden of constantly adapting to complex algorithms threatens professional efficacy, which relates to higher competence frustration and lower competence satisfaction (Reinke & Ohly, 2021; Tarafdar et al., 2019). By demonstrating how challenge and hindrance demands relate to distinct psychological needs, this study addresses calls to investigate not just the dark side of technology, but also the bright side, where AI is associated with professional growth and motivation (Tarafdar et al., 2024).

Second, this research provides significant empirical support for the theoretical claim that need satisfaction and need frustration are not merely opposite ends of the same continuum, but rather distinct constructs that relate to entirely different recovery processes (Van den Broeck et al., 2016). Historically, organizational research has often treated basic psychological needs as a single bipolar continuum, inadvertently assuming that low satisfaction equates to high frustration (Bartholomew et al., 2011; Van den Broeck et al., 2016). However, by separating competence satisfaction from competence frustration in the measurement model, this study illustrates the asymmetrical "bright" and "dark" pathways of human functioning in the context of AI (Vansteenkiste & Ryan, 2013). Building upon this theoretical discussion, the findings demonstrate that these two need states operate independently and do not compensate for one another. As demonstrated by the mediation results, simply avoiding the frustration of complex

AI is insufficient to facilitate active recovery, just as experiencing the satisfaction of empowering AI does not guarantee mental disengagement.

By analyzing these needs separately, this study establishes a clear theoretical boundary in the literature, linking specific SDT mechanisms to distinct types of recovery work (Headrick et al., 2023). This study revealed that competence satisfaction uniquely predicts the pursuit of mastery experiences. When AI use allows employees to improve their work methods, it acts as a psychological nutrient that is directly associated with the pursuit of new intellectual challenges during free time (Ryan & Deci, 2000; Sonnentag & Fritz, 2007). Conversely, competence frustration uniquely and negatively predicts psychological detachment. Functioning as a psychological burden (Bartholomew et al., 2011), the frustration of feeling inadequate in the face of AI complexity is negatively associated with an employee's ability to mentally unplug at home. If competence had been measured as a single continuum, these divergent recovery pathways may have been obscured. Ultimately, this demonstrates that the distinct psychological experiences of AI use have a long reach, extending beyond the boundary between work and home to predict how an employee recovers.

While the supported findings clarify how competence-related pathways operate, the unsupported hypotheses also offer important theoretical insight into the boundaries of these mechanisms.

Regarding the unsupported hypotheses linking competence satisfaction to psychological detachment (H1 and H7), the nature of the recovery processes offers a plausible explanation. Psychological detachment is a restorative, protective process that requires individuals to mentally disengage from work (Headrick et al., 2023; Sonnentag & Fritz, 2015). When employees experience high competence satisfaction through their AI use, they may remain cognitively engaged with work-related accomplishments and problem-solving experiences (Vansteenkiste & Ryan, 2013). Rather than helping them “switch off”, this positive cognitive engagement may actually keep them mentally connected to their work accomplishments, acting similarly to positive work reflection (Headrick et al., 2023). Thus, while competence satisfaction relates to active pursuits, it does not necessarily facilitate the mental disengagement required for psychological detachment.

Similarly, regarding the unsupported hypotheses linking competence frustration to mastery experiences (H4 and H6), the distinction between removing a cognitive burden and providing psychological fuel is critical. Although competence frustration acts as a depleting psychological burden, simply avoiding or removing this frustration does not automatically generate the motivational resources necessary to engage in active, growth-oriented recovery outside of work (Sonnentag & Fritz, 2007). Because mastery experiences demand active effort and learning, they specifically require the psychological “nutrient” of need satisfaction (Ryan & Deci, 2000). The mere absence of frustration is insufficient to predict engagement in mastery experiences.

Practical Implications

For organizations and managers, the findings of this study offer actionable takeaways for navigating the integration of AI in the modern workplace. Because the findings suggest that AI relates to employees through dual psychological pathways, interventions should simultaneously aim to mitigate technology-induced frustration and actively cultivate technology-driven mastery.

First, organizations should rethink how they select and assign AI technologies by prioritizing person-job fit and wellbeing-supportive design (Peters, 2023). The findings indicate that when AI is perceived as overly complex, it is associated with the frustration of employees’ psychological needs and impairs their ability to recover. To prevent this, IT departments and leadership are encouraged to evaluate AI tools not solely on their promised efficiency, but also on their usability (Peters, 2023), and transparency (Zayid et al., 2024), ensuring optimal alignment with the employee's existing capabilities. As mentioned by Zayid et al. (2024), ensuring a high degree of person-job fit when implementing algorithmic and AI-driven management practices serves as a critical buffer, significantly reducing the likelihood of job burnout and perceived threat. Furthermore, organizations can apply general human-computer interaction principles to AI integration by adopting well-being-supportive design. For example, selecting digital systems that provide clear, non-evaluative feedback and support an "optimal challenge" level can prevent the technology from overwhelming the user and functioning as a hindrance stressor (Peters, 2023).

Second, to harness the positive edge of the AI sword, techno-mastery, managers are encouraged to move beyond mandatory, rigid training modules and cultivate competence through safe exploration and organizational support (Ma et al., 2024). When workers feel supported in their technology adoption, they are more likely to appraise AI as an empowering mastery experience (Day et al., 2012). To facilitate this, organizations should create risk-free "sandbox" environments or host innovation "hackathons" in which employees are challenged and motivated to autonomously discover new AI features at their own pace (Tarafdar et al., 2024). Importantly, during this learning curve, managers must be incredibly mindful of how they evaluate employees' progress. Recent research demonstrates that negative feedback and excessive workload are primary sources of daily competence frustration (Olafsen et al., 2025). Therefore, organizations should train supervisors to provide feedback regarding AI implementation that is informational and constructive, rather than critical or punitive, ensuring that the learning process satisfies, rather than thwarts, the need for competence (Olafsen et al., 2025; Peters, 2023).

Finally, employers should take active steps to protect the boundary between work and off-work to mitigate AI-induced cognitive burdens. Because AI-related competence frustration acts as a psychological tether that is negatively associated with an employee's ability to detach at home, managers should be aware of the toll it may take on their teams. To counter this, organizations should implement explicit boundary-management policies to protect non-work time (Sonnentag & Fritz, 2015). For example, leadership should set clear expectations that learning to navigate new AI technologies or troubleshooting algorithmic errors should be strictly done during paid working hours. Additionally, supervisors play a significant role in this process by modeling healthy detachment behaviors (Sonnentag & Fritz, 2015), such as avoiding assigning nonessential AI-related tasks or sending communications outside standard hours. Finally, increasing transparency in how AI systems operate and evaluate work can alleviate the perceived threats and emotional exhaustion that often accompany complex technology, thereby potentially reducing the stress that employees carry home (Zayid et al., 2024). By facilitating detachment, organizations can help ensure their workforce remains rested, resilient, and capable of sustained high performance.

Limitations & Future Research

Although this study offers several theoretical and practical contributions, certain limitations must be acknowledged to contextualize the findings and guide future studies. First, the reliance on self-report data introduces potential concerns regarding common method bias, as participants' subjective interpretations may inflate the observed relationships between AI appraisals and recovery outcomes. While basic psychological needs and recovery experiences are subjective psychological states typically assessed via self-report (Deci & Ryan, 2000; Sonnentag & Fritz, 2007), future research could incorporate objective or other-report data specifically for the AI appraisals. For example, researchers could utilize unobtrusive system logs such as error rates, task completion speed, or help-feature usage to objectively assess techno-complexity (Tarafdar et al., 2019) or employ supervisor and peer evaluations to measure an employee's demonstrated techno-mastery. However, procedural remedies were proactively implemented to mitigate this risk. Specifically, a three-wave time-separated design with a one-week time lag between surveys was utilized. As noted by Podsakoff et al. (2012), temporal separation reduces inflated correlations due to method biases and diminishes retrospective recall bias. Additionally, common method bias was mitigated by minimizing shared scale properties across the study variables (Podsakoff et al., 2012). For example, while AI appraisals and basic psychological needs were measured using a 5-point agreement scale, the recovery outcomes were assessed using a 5-point frequency scale. Varying these responses anchors reduces the likelihood that participants rely on stylistic response tendencies across different constructs, protecting the validity of the observed relationships.

Future research should expand the scope of this model by employing daily diary experience sampling methods. Cognitive appraisals of AI (i.e., techno-mastery, and techno-complexity) and their resulting psychological need states (i.e., competence satisfaction and frustration) are not static; they can be elicited by specific, momentary events instead of general attitudes (Reinke & Ohly, 2021). As noted by Olafsen et al. (2025), basic psychological need frustration significantly fluctuates at the daily within-person level, predicting immediate consequences for evening recovery. Therefore, tracking daily interaction with AI could provide a more granular understanding of how episodic AI use relates to employee well-being over time.

For example, researchers could investigate whether an employee's ability to psychologically detach on a given evening varies depending on the specific AI tasks, and the associated techno-mastery or techno-complexity they experience during that specific workday.

A second limitation pertains to the use of Prolific, a crowdsourcing platform, for data collection. While this approach successfully yielded a diverse, cross-occupational sample of full-time employees who utilize AI, a general crowdsourced sample may not capture the nuanced, shared organizational culture or specific IT climates of a single company. Nonetheless, recent methodological literature supports the claim that high-quality crowdsourcing platforms exhibit reliability and data quality comparable to, or even exceeding, those of traditional organizational samples (Hauser & Schwarz, 2016).

Future research should explore how the "double-edged sword" of AI relates to employee recovery in highly specific, high-stakes organizational contexts, such as the sports industry. Modern sports organizations are undergoing a massive data revolution, rapidly integrating AI to enhance athletic performance, injury prediction, and talent identification (Atasoy et al., 2021; Munoz-Macho et al., 2024). While much of the sports literature focuses on athletes themselves, the front-office staff, sports analysts, and coaches are the employees tasked with operating these complex AI systems and predictive models (Naraine & Wanless, 2020). Operating in a hyper-competitive environment, these professionals must constantly interact with AI-driven analytics to make rapid decisions. Future research should investigate how these unique pressures influence the appraisal of AI. For example, when AI is used as a conversational decision-support system for scouting (Sartor et al., 2026), does it foster techno-mastery and support an analyst's competence satisfaction? Alternatively, if the AI systems used for predicting match outcomes are overly complex ("black box" algorithms), do they relate to competence frustration for coaches?

Because the sports industry inherently blurs the lines between work and personal life, understanding how AI-induced frustration acts as a psychological tether that hinders recovery represents a fascinating frontier for future research.

Finally, a limitation of this study is that it focused specifically on the basic psychological need for competence as the sole mediating mechanism between AI appraisals and recovery outcomes. While the findings provide strong support for the diverging pathways of competence satisfaction and competence frustration, there are likely additional psychological mechanisms involved that were not measured in the current model.

To remedy this theoretical limitation and further disentangle these pathways, future research should build upon this dual-mediator model by testing additional variables. For the “bright” path, researchers could investigate whether techno-mastery enhances mastery experiences specifically by building psychological capital and generating competence-related resources. Because active recovery strategies require mobilizing energy, identifying these specific resources would add strong theoretical value. Conversely, to better understand the “dark” path, future studies should measure whether competence frustration is associated with techno-complexity manifesting as a specific behavioral/cognitive response, such as work-related rumination or defensiveness. Testing whether these specific variables are negatively associated with psychological detachment would provide a more comprehensive understanding of exactly how the psychological experiences of AI use carry over into the home domain.

Conclusion

As artificial intelligence continues to fundamentally alter the landscape of the modern workplace, it is no longer a question of whether employees will interact with these systems, but how these interactions relate to their overall well-being. By integrating the challenge-hindrance stressor framework with self-determination theory, this study demonstrated that AI is not a uniform technological demand. Instead, the findings reveal that the way employees appraise AI, as either empowering techno-mastery or overwhelming techno-complexity, functions as a key mechanism for their basic psychological need for competence. In turn, these divergent psychological states extend beyond the office to predict distinct recovery pathways. While competence satisfaction acts as a psychological nutrient that is associated with growth-oriented mastery experiences, competence frustration operates as a psychological tether that disrupts restorative psychological detachment. Ultimately, this research shifts the conversation from viewing AI solely as an engine for organizational productivity to understanding it as an experience that relates to employee well-being. To sustainably integrate AI into the future of work, organizations must look beyond efficiency and recognize that the cognitive experiences of navigating modern technology have profound and lasting implications for an employee’s ability to unplug, recover, and thrive.

References

Atasoy, B., Efe, M., & Tutal, V. (2021). Towards the artificial intelligence management in sports. *International Journal of Sport Exercise and Training Sciences-IJSETS*, *7*(3), 100-113. https://doi.org/10.18826/useeabd.845994

Atrian, A., & Ghobbeh, S. (2023). Technostress and job performance: Understanding the negative impacts and strategic responses in the workplace [Preprint]. *arXiv* https://doi.org/10.48550/arXiv.2311.07072

Bartholomew, K. J., Ntoumanis, N., Ryan, R. M., & Thøgersen-Ntoumani, C. (2011). Psychological need thwarting in the sport context: Assessing the darker side of athletic experience. *Journal of Sport and Exercise Psychology*, *33*(1), 75-102. https://doi.org/10.1123/jsep.33.1.75

Brynjolfsson, E., Li, D., & Raymond, L. (2025). Generative AI at work. *The Quarterly Journal of Economics*, *140*(2), 889-942. https://doi.org/10.1093/qje/qjae044

Cavanaugh, M. A., Boswell, W. R., Roehling, M. V., & Boudreau, J. W. (2000). An empirical examination of self-reported work stress among US managers. *Journal of Applied Psychology*, *85*(1), 65. https://doi.org/10.1037//0021-9010.85.1.65

Chen, B., Vansteenkiste, M., Beyers, W., Boone, L., Deci, E. L., Van der Kaap-Deeder, J., Duriez, B., Lens, W., Matos, L., Mouratidis, A., Ryan, R. M., Sheldon, K. M., Soenens, B., Van Petegem, S., & Verstuyf, J. (2015). Basic psychological need satisfaction, need frustration, and need strength across four cultures. *Motivation and Emotion, 39*(2), 216–236. https://doi.org/10.1007/s11031-014-9450-1

Dakin, F., Hemmings, N., Kalin, A., Moore, L., Ladds, E., Payne, R. E., ... & Greenhalgh, T. (2025). Technostress, technosuffering, and relational strain: A multi-method qualitative study of how remote and digital work affects staff in UK general practice. *British Journal of General Practice*. 10.3399/BJGP.2024.0322

Day, A., Paquet, S., Scott, N., & Hambley, L. (2012). Perceived information and communication technology (ICT) demands on employee outcomes: The moderating effect of organizational ICT support. *Journal of Occupational Health Psychology*, *17*(4), 473. https://doi.org/10.1037/a0029837

Deci, E. L., Olafsen, A. H., & Ryan, R. M. (2017). Self-determination theory in work organizations: The state of a science. *Annual Review of Organizational Psychology and Organizational Behavior*, *4*, 19-43. https://doi.org/10.1146/annurev-orgpsych-032516-113108

Diebel, C., Goutier, M., Adam, M., & Benlian, A. (2025). When AI-based agents are proactive: Implications for competence and system satisfaction in human–AI collaboration. *Business & Information Systems Engineering*, 1-20. https://doi.org/10.1007/s12599-024-00918-y

Fang, H., He, B., Fu, H., Zhang, H., Mo, Z., & Meng, L. (2018). A surprising source of self-motivation: Prior competence frustration strengthens one's motivation to win in another competence-supportive activity. *Frontiers in Human Neuroscience*, *12*, 314. https://doi.org/10.3389/fnhum.2018.00314

Gagne, M., & Deci, E. L. (2005). Self-determination theory and work motivation. *Journal of Organizational Behavior*, *26*(4), 331-362. https://doi.org/10.1002/job.322

Gustaw, G. (2021). Measuring the satisfaction and frustration of basic psychological needs in the workplace. *Zarządzanie Publiczne*, *56*(4), 183-193. https://orcid.org/0000-0001-9153-3387

Haerens, L., Aelterman, N., Vansteenkiste, M., Soenens, B., & Van Petegem, S. (2015). Do perceived autonomy-supportive and controlling teaching relate to physical education students' motivational experiences through unique pathways? distinguishing between the bright and dark side of motivation. *Psychology of Sport and Exercise*, *16*, 26-36. https://doi.org/10.1016/j.psychsport.2014.08.013

Hauser, D. J., & Schwarz, N. (2016). Attentive Turkers: MTurk participants perform better on online attention checks than do subject pool participants. *Behavior Research Methods*, *48*(1), 400-407. https://doi.org/10.3758/s13428-015-0578-z

Headrick, L., Newman, D. A., Park, Y. A., & Liang, Y. (2023). Recovery experiences for work and health outcomes: A meta-analysis and recovery-engagement-exhaustion model. *Journal of Business and Psychology*, *38*(4), 821-864. https://doi.org/10.1007/s10869-022-09821-3

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1-55. https://doi.org/10.1080/10705519909540118

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. Business Horizons, 61(4), 577-586. https://doi.org/10.1016/j.bushor.2018.03.007

Kim, M., & Beehr, T. A. (2018). Challenge and hindrance demands lead to employees' health and behaviours through intrinsic motivation. *Stress and Health*, *34*(3), 367-378. https://doi.org/10.1002/smi.2796

La Torre, G., De Leonardis, V., & Chiappetta, M. (2020). Technostress: How does it affect the productivity and life of an individual? results of an observational study. *Public Health*, *189*, 60-65.

LePine, J. A., Podsakoff, N. P., & LePine, M. A. (2005). A meta-analytic test of the challenge stressor–hindrance stressor framework: An explanation for inconsistent relationships among stressors and performance. *Academy of Management Journal*, *48*(5), 764-775. https://doi.org/10.5465/amj.2005.18803921

Li, Y., & Xie, W. (2025). It makes me feel incompetent and anxious: An exploratory study of how techno-stressors affect older adult satisfaction toward e-government service. *Journal of Technology in Human Services*, 1-27. https://doi.org/10.1080/15228835.2025.2511304

Li, C., Zhang, Y., Niu, X., Chen, F., & Zhou, H. (2023). Does artificial intelligence promote or inhibit on-the-job learning? Human reactions to AI at work. *Systems*, *11*(3), 114. https://doi.org/10.3390/systems11030114

Longo, Y., Gunz, A., Curtis, G. J., & Farsides, T. (2016). Measuring need satisfaction and frustration in educational and work contexts: The need satisfaction and frustration scale (NSFS). *Journal of Happiness Studies*, *17*(1), 295-317. https://doi.org/10.1007/s10902-014-9595-3

Ma, L., Yu, P., Zhang, X., Wang, G., & Hao, F. (2024). How AI use in organizations contributes to employee competitive advantage: The moderating role of perceived organization support. *Technological Forecasting and Social Change*, *209*, 123801. https://doi.org/10.1016/j.techfore.2024.123801

Marchiori, D. M., Mainardes, E. W., & Rodrigues, R. G. (2019). Do individual characteristics influence the types of technostress reported by workers?. *International Journal of Human–Computer Interaction*, *35*(3), 218-230.

Marvi, R., Foroudi, P., & AmirDadbar, N. (2025). Dynamics of user engagement: AI mastery goal and the paradox mindset in AI–employee collaboration. *International Journal of Information Management*, *83*, 102908. https://doi.org/10.1016/j.ijinfomgt.2025.102908

Meng, L., He, L., Chen, M., & Huang, Y. (2024). The compensation effect of competence frustration and its behavioral manifestations. *PsyCh Journal*, *13*(4), 654-662. https://doi.org/10.1002/pchj.746

Munoz-Macho, A. A., Domínguez-Morales, M. J., & Sevillano-Ramos, J. L. (2024). Performance and healthcare analysis in elite sports teams using artificial intelligence: A scoping review. *Frontiers in Sports and Active Living*, *6*, 1383723. https://doi.org/10.3389/fspor.2024.1383723

Naraine, M. L., & Wanless, L. (2020). Going all in on AI: Examining the value proposition of and integration challenges with one branch of artificial intelligence in sport management. *Sports Innovation Journal*, 1, 49-61. https://doi.org/10.18060/23898

Nascimento, L., Correia, M. F., & Califf, C. B. (2025). Techno-eustress under remote work: A longitudinal study in higher education teachers. *Education and Information Technologies*, 1-38. https://doi.org/10.1007/s10639-025-13459-y

Olafsen, A. H., Kujanpää, M., & Bentzen, M. (2025). Daily within-fluctuations in need frustration and implications for employee recovery and well-being: A mixed-methods study. *Scandinavian Journal of Psychology*, *66*(1), 98-110. https://doi.org/10.1111/sjop.13067

Peters, D. (2023). Wellbeing supportive design–research-based guidelines for supporting psychological wellbeing in user experience. *International Journal of Human–Computer Interaction*, *39*(14), 2965-2977. https://doi.org/10.1080/10447318.2022.2089812

Podsakoff, N. P., Freiburger, K. J., Podsakoff, P. M., & Rosen, C. C. (2023). Laying the foundation for the challenge–hindrance stressor framework 2.0. *Annual Review of Organizational Psychology and Organizational Behavior*, *10*(1), 165-199. https://doi.org/10.1146/annurev-orgpsych-080422052147

Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of method bias in social science research and recommendations on how to control it. *Annual Review of Psychology*, *63*(1), 539-569. https://doi.org/10.1146/annurev-psych-120710-100452

Ragu-Nathan, T. S., Tarafdar, M., Ragu-Nathan, B. S., & Tu, Q. (2008). The consequences of technostress for end users in organizations: Conceptual development and empirical validation. *Information Systems Research*, *19*(4), 417-433. https://doi.org/10.1287/isre.1070.0165

Reeve, J., Jang, H. R., Cheon, S. H., Moss, J. D., Ko, H., & Jang, H. (2023). Extending self-determination theory's dual-process model to a new tripartite model to explain diminished functioning. *Motivation and Emotion*, *47*(5), 691-710. https://doi.org/10.1007/s11031-023-10019-0

Reinke, K., & Ohly, S. (2021). Double-edged effects of work-related technology use after hours on employee well-being and recovery: The role of appraisal and its determinants. *German Journal of Human Resource Management: Zeitschrift Für Personalforschung*, *35*(2), 224-248. https://doi.org/10.1177/2397002221995797

Rikala, P., Heilala, V., Karhapää, A., & Hämäläinen, R. (2025). Exploring technostress and meta-work: Identifying subgroups among finnish employees. *International Journal of Human–Computer Interaction*, 1-25. https://doi.org/10.1080/10447318.2025.2531276

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist, 55*(1), 68–78. https://doi.org/10.1037/0003-066X.55.1.68

Sartor, F., Rosito, S. A., Raimo, M., Beato, M., & Bertollo, M. (2025). Artificial intelligence in sport psychology: Implications for the identification and development of talent. *Psychology of Sport and Exercise*, 102977. https://doi.org/10.1016/j.psychsport.2025.102977

Sonnentag, S., Cheng, B. H., & Parker, S. L. (2022). Recovery from work: Advancing the field toward the future. *Annual Review of Organizational Psychology and Organizational Behavior*, *9*(1), 33-60. https://doi.org/10.1146/annurev-orgpsych-012420091355

Sonnentag, S., & Fritz, C. (2015). Recovery from job stress: The stressor-detachment model as an integrative framework. *Journal of Organizational Behavior*, *36*(S1), S72-S103. https://doi.org/10.1002/job.1924

Sonnentag, S., & Fritz, C. (2007). The recovery experience questionnaire: Development and validation of a measure for assessing recuperation and unwinding from work. *Journal of Occupational Health Psychology, 12*(3), 204–221. https://doi.org/10.1037/1076-8998.12.3.204

Sonnentag, S., & Geurts, S. A. (2009). Methodological issues in recovery research. In S. Sonnentag, P. L. Perrewé, & D. C. Ganster (Eds.), *Current Perspectives on Job Stress*

Recovery (pp. 1–36). Emerald Group Publishing Limited. https://doi.org/10.1108/S1479-3555(2009)0000007004

Tarafdar, M., Cooper, C. L., & Stich, J. F. (2019). The technostress trifecta-techno eustress, techno distress and design: Theoretical directions and an agenda for research. *Information Systems Journal*, *29*(1), 6-42. https://doi.org/10.1111/isj.12169

Tarafdar, M., Stich, J.-F., Maier, C., & Laumer, S. (2024). Techno-eustress creators: Conceptualization and empirical validation. *Information Systems Journal, 34*(6), 2097–2131. https://doi.org/10.1111/isj.12515

Tarafdar, M., Tu, Q., Ragu-Nathan, B. S., & Ragu-Nathan, T. S. (2007). The impact of technostress on role stress and productivity. *Journal of Management Information Systems*, *24*(1), 301-328. https://doi.org/10.2753/MIS0742-1222240109

Trépanier, S. G., Forest, J., Fernet, C., & Austin, S. (2015). On the psychological and motivational processes linking job characteristics to employee functioning: Insights from self-determination theory. *Work & Stress*, *29*(3), 286-305. https://doi.org/10.1080/02678373.2015.1074957

Van den Broeck, A., Ferris, D. L., Chang, C. H., & Rosen, C. C. (2016). A review of self-determination theory's basic psychological needs at work. *Journal of Management*, *42*(5), 1195-1229. https://doi.org/10.1177/0149206316632058

Van den Broeck, A., Vansteenkiste, M., De Witte, H., Soenens, B., & Lens, W. (2010). Capturing autonomy, competence, and relatedness at work: Construction and initial validation of the work-related basic need satisfaction scale. *Journal of Occupational and Organizational Psychology*, *83*(4), 981-1002. https://doi.org/10.1348/096317909X481382

Vansteenkiste, M., Ryan, R. M., & Soenens, B. (2020). Basic psychological need theory: Advancements, critical themes, and future directions. *Motivation and Emotion*, *44*(1), 1-31. https://doi.org/10.1007/s11031-019-09818-1

Vansteenkiste, M., & Ryan, R. M. (2013). On psychological growth and vulnerability: Basic psychological need satisfaction and need frustration as a unifying principle. *Journal of Psychotherapy Integration*, *23*(3), 263. https://doi.org/10.1037/a0032359

Wolff, M. S., White, J. C., Abraham, M., Schnabel, C., Wieser, L., & Niessen, C. (2024). The threat of electronic performance monitoring: Exploring the role of leader-member exchange on employee privacy invasion. *Journal of Vocational Behavior*, *154*, 104031. https://doi.org/10.1016/j.jvb.2024.104031

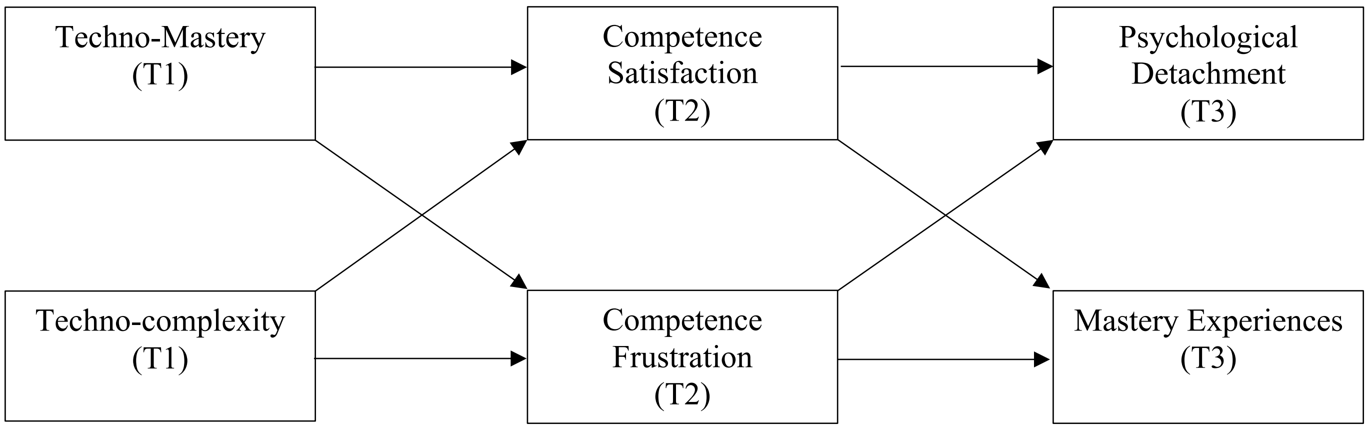
Wong, N., Cheng, N. Y., Oewel, B., Genuario, K. E., Stoeckl, S., Schueller, S. M., ... & Reddy, M. (2025, April). 'It's a spectrum': Exploring autonomy, competence, and relatedness in software development processes and tools. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems* (pp. 1-19). https://doi.org/10.1145/3706598.3713250

Würtenberger, A., Groneberg, D. A., & Mache, S. (2025). Digital stress perception and associations with work-and health-related outcomes among general practitioners in Germany: A quantitative study. *BMC Health Services Research*, *25*(1), 535. https://doi.org/10.1186/s12913-025-12653-5

Zayid, H., Alzubi, A., Berberoğlu, A., & Khadem, A. (2024). How do algorithmic management practices affect workforce well-being? A parallel moderated mediation model. *Behavioral Sciences*, *14*(12), 1123. https://doi.org/10.3390/bs14121123

Zhong, W., Luo, J., & Lyu, Y. (2024). How do personal attributes shape AI dependency in Chinese higher education context? insights from needs frustration perspective. *Plos One*, *19*(11), e0313314. https://doi.org/10.1371/journal.pone.0313314

Figure 1. Proposed Dual Mediation Model



Note. The model proposes dual mediation effects of competence satisfaction and competence frustration, linking AI techno-mastery and techno-complexity to recovery outcomes (psychological detachment and mastery experiences).

Table 1.

Means, standard deviations, and correlations among study and control variables

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9
1. Age	41.94	10.82									
2. Organizational Tenure Years	8.75	7.06	.45**								
3. Gender	0.41	0.49	.07	-.04							
4. Organizational AI support	2.86	1.14	.03	.08	-.02						
5. Techno-Complexity Time 1	1.84	0.76	-.04	-.09	.04	-.20**					
6. Techno-Mastery Time 1	4.02	0.89	.03	.10	-.04	.39**	-.28**				
7. Competence Satisfaction Time 2	3.96	0.93	.08	.09	-.02	.37**	-.41**	.71**			
8. Competence Frustration Time 2	1.68	0.84	-.09	-.04	-.02	-.22**	.56**	-.33**	-.52**		
9. Psychological Detachment Time 3	3.11	1.15	-.00	.03	-.07	.04	-.14**	-.01	.09	-.17**	
10. Mastery Experiences Time 3	3.22	1.05	-.00	.02	-.01	.35**	-.17**	.21**	.28**	-.13*	-.06

Note. $N = 341$. *M* and *SD* represent mean and standard deviation, respectively. Gender was dummy coded (0 = not female; 1 = female). $p < .05$. ** $p < .01$.

Table 2. Path Analysis Results for Direct Effects

	Mediators (T2)		**Outcomes (T3)**	
	Competence Satisfaction *b (SE)*	Competence Frustration *b (SE)*	Psychological Detachment *b (SE)*	Mastery Experiences *b (SE)*
Control Variables				
Age	.01 (.00)	-.01 (.00)	.00 (.01)	.00 (.01)
Org. Tenure (Years)	.00 (.01)	.01 (.01)	.01 (.01)	.00 (.01)
Gender (Female)	-.01 (.07)	-.07 (.07)	-.18 (.13)	.00 (.11)
Organizational AI Support (T1)	.07 (.03)**	-.04 (.04)	.00 (.07)	.26 (.05)***
Predictor Variables (T1)				
Techno-Complexity	-.25 (.05)***	.55 (.07)***	-.08 (.11)	-.11 (.08)
Techno-Mastery	.65 (.06)***	-.18 (.06)**	-.21 (.11)	-.08 (.09)
Mediator Variables (T2)				
Competence Satisfaction	-	-	.12 (.12)	.25 (.10)*
Competence Frustration	-	-	-.20 (.10)*	.07 (.08)

Note. N = 341. Unstandardized coefficients (b) are presented with standard errors in parentheses (SE). T1 = Time 1; T2 = Time 2; T3 = Time 3. TM = Techno-Mastery; TC = Techno-Complexity; CS = Competence Satisfaction; CF = Competence Frustration; PD = Psychological Detachment; ME = Mastery Experiences. $p < .05$*, $p < .01$**, $p < .001$***.

Table 3. Bootstrapped Indirect Effects

Indirect Effects (Hypotheses)	Estimate	Boot SE	95% CI	Hypothesis Support
H1: TM→ CS → PD	.08	.08	[-0.073, 0.237]	Not supported
H2: TM → CS→ ME	.16	.07	[0.040, 0.300]	Supported
H3: TC → CF → PD	-.11	.05	[-0.216, -0.007]	Supported
H4: TC → CF → ME	.04	.05	[-0.048, 0.131]	Not supported
H5: TM → CF → PD	.04	.02	[0.003, 0.095]	Supported
H6: TM → CF → ME	-.01	.02	[-0.049, 0.014]	Not supported
H7: TC → CS → PD	-.03	.03	[-0.103, 0.027]	Not supported
H8: TC → CS → ME	-.06	.03	[-0.125, -0.017]	Supported

Note. N = 341. Unstandardized coefficients (b) are presented. Bootstrapped standard errors. (Boot SE) are reported. The 95% confidence intervals (CI) are bias-corrected based on 10,000 bootstrap resamples. Indirect effects were considered significant if the 95% CI did not include zero; significant effects are presented in bold. TM = Techno-Mastery; TC = Techno-Complexity; CS = Competence Satisfaction; CF = Competence Frustration; PD = Psychological Detachment; ME = Mastery Experiences.

Appendix A

Prolific Pre-Screeners Used for Participant Recruitment

Prolific Screener Category	Filter	Criteria
Work	Employment status	Currently employed full-time
Work	Artificial Intelligence (AI) use at work	Must report using AI or AI enabled tools at work at least once per week
Geographic	Current country of residence	United States
Languages	Primary language	Fluent in English (to ensure comprehension)
Participation	Approval rate on Prolific	≥95%

Note. Pre-screener categories and wording are taken from Prolific's participant filters. These criteria were applied to ensure participants are full-time U.S. employees who use AI in their work.

Appendix B

Measure Items

Variable	Items	Citation
Techno-Complexity	1. I do not know enough about AI technologies to handle my job satisfactorily. 2. I need a long time to understand and use new AI technologies. 3. I do not find enough time to study and upgrade my AI-related skills. 4. I find new recruits to this organization know more about AI than I do. 5. I often find it too complex for me to understand and use AI technologies.	Ragu-Nathan et al. (2008)
Techno-Mastery	1. The AI technologies I use for work make my work methods more efficient. 2. The AI technologies I use for work make my work methods more innovative. 3. The AI technologies I use for work make my work methods more effective. 4. The AI technologies I use for work improve my work methods. 5. The AI technologies I use for work improve my work-related information processing.	Tarafdar et al. (2024)
Competence Satisfaction	1. I feel highly effective at what I do when using AI at work. 2. I feel I am very good at the things I do when using AI at work. 3. I feel I can accomplish even the most difficult tasks when using AI at work.	Longo et al. (2016)
Competence Frustration	1. I doubt whether I am able to carry out my tasks properly when using AI at work. 2. Occasionally, I feel incapable of succeeding in my tasks when using AI at work. 3. I sometimes feel unable to master hard challenges when using AI at work.	Longo et al. (2016)
Psychological Detachment	1. I forget about work. 2. I don't think about work at all.	Sonnentag & Fritz (2007)

	3. I distance myself from my work.	
	4. I get a break from the demands of work.	
Mastery Experiences	1. I learn new things	Sonnentag & Fritz (2007)
	2. I seek out intellectual challenges.	
	3. I do things that challenge me.	
	4. I do something to broaden my horizons.	

Note. Items were adapted from established scales: techno-complexity (Ragu-Nathan et al., 2008), techno-mastery (Tarafdar et al., 2024), competence satisfaction and competence frustration (Longo et al., 2016), and recovery (psychological detachment and mastery experiences; Sonnentag & Fritz, 2007). Responses were rated on a 5-point Likert scale unless otherwise noted. Reverse-coded items were recoded so that higher scores reflect greater levels of the construct.