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Article

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AI Dependency and Work Engagement: The Dual Roles of Cognitive Vigilance and Offloading under AI Hallucinations, evidence from Vietnam's MNC Employee. Applying PLS-SEM, Artificial Neural Network, Fuzzy-set Qualitative Comparative Analysis, Necessary Condition Analysis method

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Purpose: This study aims to investigate the underlying mechanisms through which work stress influences employee work engagement in the era of conversational artificial intelligence (AI). Specifically, it unravels the cognitive “black box” by examining the dual mediating roles of cognitive vigilance and cognitive offloading, driven by a multidimensional conceptualization of AI dependence (instrumental and emotional). Furthermore, it assesses the moderating effect of perceived AI hallucinations on these cognitive responses.

Design/methodology/approach: Adopting a cross-sectional quantitative design, data were collected from 236 employees working in multinational corporations (MNCs) in Vietnam. To capture causal complexity, a pioneering multi-methodological approach was employed. This integration included Partial Least Squares Structural Equation Modeling (PLS-SEM) to estimate linear relationships, Artificial Neural Networks (ANN) for non-linear predictive modeling, fuzzy-set Qualitative Comparative Analysis (fsQCA) to uncover asymmetric configurations (equifinality), and Necessary Condition Analysis (NCA) to identify indispensable bottleneck factors.

Findings: The results indicate that work stress strongly fuels both instrumental and emotional AI dependence. Notably, both forms of dependence significantly increase cognitive offloading without undermining cognitive vigilance. In terms of moderation, a profound "automation bias" was uncovered: the awareness of AI hallucinations neither diminishes cognitive offloading nor heightens cognitive vigilance. Crucially, the triangulation of the four analytical methods demonstrates that cognitive offloading is not only the most dominant predictor but also the singular necessary condition for achieving high work engagement.

Originality/value: This paper makes three major theoretical contributions. First, it reconceptualizes conversational AI dependence as a multidimensional construct encompassing emotional attachment, moving beyond pure instrumental utility . Second, grounded in the Job Demands-Resources (JD-R) theory, it challenges traditional cognitive psychology paradigms by reframing cognitive offloading as a valuable "job resource" that optimizes employee capacity, rather than a manifestation of intellectual laziness . Third, it establishes a new methodological benchmark by combining symmetrical (PLS-SEM, ANN) and asymmetrical (fsQCA, NCA) approaches in human-AI interaction research.

Keywords: Conversational AI Dependence; Cognitive Offloading; Cognitive Vigilance; Work Engagement; Job Demands-Resources (JD-R) Theory; Multi-methodology (PLS-SEM, ANN, fsQCA, NCA).

1. INTRODUCTION

Employee engagement has emerged as a strategic priority for organizations seeking to maintain competitiveness in increasingly dynamic and knowledge-intensive business environments (Taneja et al. 2015; Tsoni et al. 2025). Engaged employees are more productive, innovative, resilient, and committed to organizational goals, whereas disengaged employees contribute to substantial productivity losses and organizational inefficiencies (Ghani et al. 2024; Saraiva & Teresa Nogueiro, 2025). Consequently, understanding the factors that foster work engagement remains a central concern within organizational behavior and management research.

Simultaneously, the nature of work is undergoing profound transformation due to the widespread adoption of generative artificial intelligence (Agarwal et al. 2026). Conversational AI systems such as ChatGPT, Gemini, Claude, and Copilot are increasingly integrated into daily work activities, assisting employees in information retrieval, content generation, decision-making, and problem-solving (Zhang & Yan, 2026). Unlike previous generations of workplace technologies, conversational AI actively participates in cognitive processes, fundamentally reshaping how employees allocate attention, process information, and accomplish work-related tasks (Li et al., 2026).

As AI becomes embedded within everyday work routines, employees are increasingly developing various forms of reliance on these systems (Lee et al. 2026). Recent research suggests that such reliance extends beyond simple technology usage and evolves into conversational AI dependence, a multidimensional construct comprising instrumental dependence and emotional dependence. Instrumental dependence reflects the tendency to rely on AI for task accomplishment and cognitive support, whereas emotional dependence captures the extent to which individuals seek psychological comfort, companionship, and emotional reassurance from AI systems. Given the growing prevalence of AI-assisted work, understanding the consequences of these forms of dependence has become an important research priority (Li et al. 2026).

Despite increasing scholarly attention toward AI dependence, existing studies have predominantly focused on its antecedents and psychological consequences, including trust, technology addiction, loneliness, anxiety, and technology acceptance (Østergaard, 2025). Comparatively little attention has been devoted to understanding how AI dependence influences important workplace outcomes, particularly work engagement. More importantly, prior studies have largely treated the relationship between AI dependence and employee outcomes as a direct process, providing limited insight into the cognitive mechanisms through which such effects occur (Khoa et al. 2022, Cui et al. 2026).

This limitation is particularly important because employees do not merely use AI; they cognitively respond to it. Emerging literature suggests that two distinct cognitive responses

may play a central role in shaping employee outcomes (Cui *et al.* 2026). The first is cognitive vigilance, referring to employees' tendency to critically evaluate, verify, and monitor AI-generated outputs (Gilbert *et al.* 2022). The second is cognitive offloading, whereby individuals strategically delegate cognitive tasks to AI in order to preserve mental resources for higher-value activities (Iqbal *et al.* 2025). While both mechanisms are increasingly discussed in the AI literature, existing studies rarely examine them simultaneously, and little is known about how different forms of AI dependence stimulate these contrasting cognitive responses. Consequently, the cognitive pathways linking AI dependence and work engagement remain insufficiently understood.

Furthermore, the rapid rise of generative AI has introduced a new challenge in the form of AI hallucinations, where AI systems generate plausible but inaccurate, fabricated, or misleading information (Kim *et al.* 2025). Although AI hallucinations have attracted considerable attention from practitioners and policymakers, research examining their role within organizational settings remains limited. In particular, little is known about whether employees' awareness of AI hallucinations influences the relationship between AI dependence and subsequent cognitive responses (Christensen *et al.* 2024). This represents an important boundary condition that has been largely overlooked in existing research.

To address these gaps, this study develops and tests a research model explaining how work stress contributes to conversational AI dependence and how instrumental and emotional dependence subsequently influence work engagement through cognitive vigilance and cognitive offloading. In addition, this study investigates the moderating role of perceived AI hallucinations in shaping these relationships. Drawing upon the Job Demands–Resources (JD-R) perspective and Conservation of Resources theory, this research seeks to provide a more comprehensive understanding of employee engagement in AI-enabled workplaces.

This study contributes to the literature in several important ways. First, it extends the emerging literature on conversational AI dependence by distinguishing between instrumental and emotional dependence and examining their differential effects on

employee cognition. Second, it advances understanding of the cognitive mechanisms linking AI dependence and work engagement by simultaneously incorporating cognitive vigilance and cognitive offloading. Third, it introduces perceived AI hallucination as a novel boundary condition influencing employee responses to AI. Finally, by integrating PLS-SEM, Artificial Neural Network (ANN), Fuzzy-set Qualitative Comparative Analysis (fsQCA), and Necessary Condition Analysis (NCA), this study provides complementary explanatory, predictive, configurational, and necessity-based perspectives on employee engagement in the age of generative AI.

2. LITERATURE REVIEW

The rapid development of conversational AI (CAI) systems, including chatbots and large-scale language models like Chatgpt, Gemini, Deepseek, has fueled the emergence of AI dependence in user behavior ([Avyay et al. 2024](#)). Recent studies show that frequent interaction with AI not only supports work performance but can also lead to cognitive and emotional dependence ([Chen et al. 2025](#)). Accordingly, AI dependence is understood as the degree to which individuals rely on AI in decision-making, information processing, and mood regulation, which can increase the risk of dependence or “addiction” to technology ([Hu et al. 2023](#)). However, previous studies have often approached this concept in a one-sided manner, failing to distinguish between functional dependence and emotional dependence clearly.

The concept of Conversational AI Dependence (CAID) is developed as a construct, comprising two main components: Instrumental Dependence and Emotional Dependence ([Li et al. 2026](#)). Instrumental dependence reflects the extent to which individuals use AI as a cognitive support tool, particularly in offloading the burden of information processing to optimize performance ([Skjuve et al. 2024](#)). Emotional dependence refers to an overdependence on CAI to regulate emotions and reduce psychological distress, potentially displacing authentic human relationships ([Li et al. 2026](#)). Research shows that AI can create a sense of belonging, even acting as a social object, thereby increasing emotional attachment and psychological dependence ([Yang & Osho, 2025](#)). This leads to an anxious

attachment state, in which users tend to maintain continuous interaction with the AI to alleviate feelings of insecurity or loneliness.

Furthermore, the phenomenon of AI dependence can be explained through various theoretical frameworks. Self-Determination Theory (SDT) suggests that individuals are motivated by the fulfillment of three fundamental psychological needs: autonomy, competence, and relatedness (Deci & Ryan, 1985, 2000). In the context of artificial intelligence (AI), employees are more likely to develop positive attitudes and stronger reliance on AI when they perceive AI as enhancing their control over work tasks (autonomy), improving their ability to perform effectively (competence), and facilitating social connection or emotional support (relatedness) (Savolainen et al. 2026; Parray & Iqbal, 2026). Conversely, concerns that AI may reduce human control, challenge personal capabilities, or weaken interpersonal interactions can generate negative reactions toward AI systems. Therefore, SDT provides a useful lens for understanding why employees may increasingly depend on conversational AI technologies and how such dependence shapes subsequent workplace behaviors. Meanwhile, the Conservation of Resources theory emphasizes that interacting with AI can both save cognitive resources and potentially cause stress by altering work structures (Liu & Li, 2025). Simultaneously, factors such as belief in AI and AI anxiety also play a significant role in shaping the level of user dependence, especially when they perceive AI as trustworthy or, conversely, feel a loss of control over the system (Yang & Osho, 2025).

The above arguments suggest that dependence on AI is not merely a technological phenomenon, but a complex process combining cognitive and emotional factors, stemming from both functional use and psychological engagement. Approaching CAI dependence as a higher-order construct encompassing both instrumental and emotional dependence provides a more comprehensive perspective. In particular, the duality of this dependence suggests that its effects may be transmitted through different cognitive mechanisms.

3. HYPOTHESIS DEVELOPMENT

3.1. Work stress on Instrumental Dependence and Emotional Dependence

Work stress has become an increasingly prevalent challenge in contemporary workplaces, particularly under conditions characterized by excessive workloads, role ambiguity, limited job control, and heightened performance pressures (Maulik, 2017; Chen et al. 2022). According to the job demands perspective, persistent exposure to such stressors depletes employees' cognitive, emotional, and psychological resources, thereby impairing their ability to cope effectively with work-related demands (Demerouti, 2025; Bakker & D. de Vries, 2020). As employees experience resource exhaustion, they often seek alternative mechanisms to reduce cognitive effort and maintain performance outcomes.

One potential consequence of this process is the development of instrumental dependence on artificial intelligence (AI). Instrumental dependence reflects a tendency to rely on AI primarily as a functional tool for task completion, problem-solving, and decision support (Li et al. 2026; Sarker, 2022). Research underlying the Conversational AI Dependence (CAID) framework suggests that instrumental dependence is associated with elevated stress, anxiety, lower conscientiousness, and reduced self-efficacy (Li et al. 2026; Skjuve et al. 2024; Zhang et al. 2024). When employees experience chronic work stress, the depletion of cognitive resources and declining confidence in their own capabilities may motivate them to avoid effortful thinking and conserve psychological energy (Chen et al. 2022). Consequently, AI systems become attractive cognitive shortcuts that help employees cope with increasing job demands while minimizing mental effort (Grinschgl & Neubauer, 2021; Risko & Gilbert, 2016). Over time, repeated reliance on AI for task completion may gradually evolve into instrumental dependence.

Beyond its cognitive consequences, work stress also generates substantial emotional and psychological burdens (Park et al. 2016; Lu et al. 2020). Excessive workplace pressure, toxic organizational environments, and persistent performance demands can contribute to psychological distress, anxiety, loneliness, and emotional exhaustion (Rasool et al. 2021; Hassanie et al. 2026). Moreover, workplace cultures often stigmatize mental health

concerns, discouraging employees from openly seeking emotional support from colleagues or supervisors (Scheid, 2005; Follmer & Jones, 2017) . As a result, many individuals experience unmet social and emotional needs while simultaneously avoiding interpersonal help-seeking behaviors.

In this context, AI-based conversational systems may serve as an alternative source of emotional comfort and psychological reassurance (Li et al. 2026). Unlike human interactions, AI provides immediate availability, predictable responses, and a nonjudgmental communication environment. Prior research indicates that emotional dependence on AI often emerges from psychological vulnerabilities such as loneliness, social anxiety, depression, and emotional distress. Employees experiencing high levels of work stress may increasingly turn to AI not only for functional assistance but also for emotional support, companionship, and temporary escape from workplace pressures. Through repeated interactions, individuals may develop pseudosocial bonds with AI and gradually become emotionally attached to these systems. Consequently, work stress is likely to strengthen employees' emotional reliance on AI. Therefore, the following hypothesis is proposed:

H1: Work Stress is positively associated with Instrumental Dependence (CAID).

H2: Work Stress is positively associated with Emotional Dependence (CAID).

3.2. Instrumental Dependence (CAID) on Cognitive Vigilance and Cognitive Offloading

Instrumental Dependence (ID) refers to an excessive reliance on artificial intelligence for accomplishing task-oriented objectives, whereby users perceive AI as an indispensable means of avoiding cognitively demanding activities (Li et al. 2026). While AI can function as a valuable cognitive partner that supports information processing and decision-making, excessive instrumental dependence fundamentally changes the nature of human–AI interaction (Farhat, 2026; Guthrie et al. 2025). Rather than using AI strategically to augment cognitive capabilities, individuals with high levels of ID increasingly rely on AI

as a substitute for independent thinking, critical evaluation, and problem-solving (Brynjolfsson et al. 2018, Tang et al. 2023).

From the perspective of Cognitive Offloading (CO), strategic offloading can be beneficial when individuals intentionally delegate routine or low-level cognitive tasks to external tools in order to preserve cognitive resources for higher-order reasoning, reflection, and creativity (Gilbert et al. 2022). However, instrumental dependence transforms this adaptive mechanism into a maladaptive form of intellectual outsourcing (Ye et al. 2024) . Users become motivated by convenience, efficiency, and task avoidance rather than cognitive optimization. Consequently, they increasingly delegate substantial portions of their cognitive workload to AI, not to enhance learning or understanding, but to bypass effortful thinking processes (Bucinca et al. 2021; Chen et al. 2023). This tendency is reinforced by lower levels of self-efficacy and conscientiousness, which make users more likely to rely on AI as a compensatory mechanism for perceived deficiencies in their own abilities (Zhu et al. 2026). Over time, excessive dependence encourages the habitual transfer of cognitive responsibilities to AI systems, resulting in greater levels of cognitive offloading (Hasan, 2025).

At the same time, instrumental dependence undermines Cognitive Vigilance (CV), which refers to the systematic and critical evaluation of AI-generated information through processes such as fact-checking, source verification, error detection, and reasoned skepticism (Celik, 2023). Maintaining cognitive vigilance requires considerable cognitive effort and a willingness to scrutinize AI outputs before accepting them (Wang & Zhang, 2026). However, individuals exhibiting high levels of instrumental dependence are often characterized by inert thinking, task-avoidance tendencies, and a preference for minimizing cognitive effort (Huiqing & Junjie, 2026; Yang et al. 2025). As a result, they become less motivated to engage in the demanding process of verifying AI-generated content and are more likely to accept outputs without sufficient scrutiny.

Furthermore, instrumental dependence weakens the collaborative partnership that should ideally exist between humans and AI (Hao et al. 2025). Instead of viewing AI as a cognitive

collaborator whose outputs require monitoring and evaluation, dependent users increasingly perceive AI as a convenient shortcut for accomplishing tasks (Jiang & Chen, 2026). This shift reduces their sense of intellectual responsibility and diminishes the motivation to oversee the quality and accuracy of AI-generated information. The desire for efficiency and rapid task completion further amplifies this effect, leading users to prioritize speed over accuracy and encouraging automation bias, whereby AI-generated recommendations are accepted even when they may be inaccurate or suboptimal (Ye et al. 2025; Zhai et al. 2024).

The negative influence of instrumental dependence on cognitive vigilance is further exacerbated by diminished self-efficacy (Lee et al. 2026). Individuals who lack confidence in their own cognitive abilities are less likely to challenge, question, or critically evaluate AI-generated content (Noorbehbahani & Oyibo, 2026). Instead, they place excessive trust in AI systems and become increasingly reluctant to rely on their own judgment (Romeo & Conti, 2025). Consequently, instrumental dependence erodes users' epistemic vigilance while simultaneously increasing their tendency to offload cognitive responsibilities to AI.

Taken together, the literature suggests that instrumental dependence transforms AI from a cognitive support tool into a mechanism that encourages intellectual outsourcing and cognitive passivity. While strategic AI use can enhance human cognition, excessive instrumental dependence promotes greater cognitive offloading and suppresses critical evaluation processes. Therefore, instrumental dependence is expected to increase users' reliance on cognitive offloading while reducing their level of cognitive vigilance.

***H3a:** Instrumental Dependence negatively influences Cognitive Vigilance.*

***H3b:** Instrumental Dependence positively influences Cognitive Offloading.*

3.3. Emotional Dependence (CAID) on Cognitive Vigilance and Cognitive Offloading

Emotional Dependence (ED) refers to an excessive reliance on AI for psychological comfort, companionship, and emotional regulation (Li et al. 2026). Individuals with high levels of emotional dependence tend to develop pseudo-social bonds with AI and

increasingly perceive AI as a trusted companion rather than a technological system (Mantello & Ho, 2024). As a result, their interactions with AI are primarily driven by socio-affective needs, such as reducing loneliness, seeking emotional reassurance, and escaping real-world stressors, rather than accomplishing task-related objectives (Merril et al. 2024; Leo-Liu, 2023).

Cognitive vigilance requires users to maintain a questioning attitude toward AI outputs and continuously monitor their quality and accuracy. However, when users form pseudo-social relationships with AI, they may gradually develop blind trust toward the system (Goddard et al. 2014). The perception of AI as a supportive and non-judgmental companion can weaken users' motivation to challenge, verify, or critically assess AI-generated content (Le & Kunz, 2026). Furthermore, individuals who rely on AI for emotional comfort often seek a safe and predictable interaction environment (Martončík & Lokša, 2016; Boyd & Markowitz, 2026). Because cognitive vigilance requires intellectual friction and critical questioning, emotionally dependent users may avoid such evaluative behaviors in order to preserve psychological comfort and emotional security.

At the same time, emotional dependence may also weaken Cognitive Offloading (CO). This process is inherently task-oriented, requiring users to intentionally assign lower-level cognitive activities to AI while reserving mental resources for higher-order thinking (Tian & Zhang, 2025). In contrast, emotionally dependent users engage with AI primarily for socio-affective regulation rather than task accomplishment. Consequently, their interactions are often spontaneous, unstructured, and detached from learning or work-related goals, reducing the likelihood of strategic cognitive task delegation (Li et al. 2026).

More importantly, emotional dependence may shift users from cognitive offloading toward social offloading. Rather than using AI to reduce cognitive effort, emotionally dependent individuals increasingly rely on AI to alleviate social pressures, emotional burdens, and interpersonal difficulties (Huang et al. 2024). Through the formation of pseudo-social bonds, AI becomes a substitute for certain forms of human interaction, allowing users to avoid social risks, emotional conflicts, and relational uncertainty (Zhai et al. 2025).

Therefore, the dependence fostered by ED is directed toward socio-emotional relief rather than cognitive task delegation, ultimately reducing engagement in strategic cognitive offloading behaviors.

Based on the above arguments, emotional dependence is expected to negatively influence both users' critical evaluation of AI-generated information and their engagement in strategic cognitive offloading behaviors.

Therefore, this study puts forth the following hypotheses for examination:

H4a: Emotional Dependence negatively affects Cognitive Vigilance.

H4b: Emotional Dependence negatively affects Cognitive Offloading.

3.4. AI Hallucination as a Moderator

AI hallucination refers to situations in which AI systems generate outputs that appear plausible but are factually incorrect, logically inconsistent, or entirely fabricated (Kushwah & Dave, 2025). As users become increasingly aware of the possibility that AI may produce inaccurate information, this perception can fundamentally alter how dependence on AI influences subsequent cognitive responses. Specifically, perceived AI hallucination may either activate greater monitoring behaviors among users who rely on AI for instrumental purposes (Lee et al. 2025) or reinforce maladaptive reliance among users who are emotionally attached to AI. Accordingly, the moderating role of perceived AI hallucination is expected to differ across the two dimensions of AI dependence.

3.4.1. Perceived AI Hallucination, Instrumental Dependence, and Cognitive Vigilance

Individuals with high instrumental dependence tend to exhibit lower levels of cognitive vigilance because they increasingly treat AI as a convenient shortcut for problem-solving and decision-making (Li et al. 2026). However, the task-oriented nature of instrumental dependence means that users remain strongly concerned about performance outcomes and the accuracy of information. In work and academic settings, inaccurate information can

directly threaten task effectiveness, decision quality, and professional credibility (Balalle & Pannilage, 2025).

When users possess a high level of perceived AI hallucination, they become more aware that AI systems may generate factual inaccuracies, reasoning errors, or fabricated information (Sun et al. 2024; Lee et al. 2025). Such awareness introduces a significant performance risk that directly threatens the primary goals motivating instrumental AI use. As a result, even users who are highly instrumentally dependent on AI may feel compelled to monitor, verify, and evaluate AI-generated outputs more carefully. The fear of negative consequences associated with AI hallucinations therefore constrains the tendency of instrumental dependence to suppress cognitive vigilance. In other words, perceived AI hallucination pushes the relationship between instrumental dependence and cognitive vigilance in a more positive direction by encouraging greater monitoring behaviors. Therefore, the following hypothesis is proposed:

H5a: Perceived AI Hallucination positively moderates the relationship between Instrumental Dependence and Cognitive Vigilance.

3.4.2. Perceived AI Hallucination, Instrumental Dependence, and Cognitive Offloading

Individuals with high instrumental dependence frequently engage in cognitive offloading by delegating substantial cognitive responsibilities to AI systems (Gerlich, 2025; Jiang & Chen, 2026). Such offloading is attractive because it reduces mental effort and allows users to complete tasks more efficiently (Chirayath et al. 2025). However, the benefits of cognitive offloading depend heavily on the reliability of the delegated system.

When users recognize that AI systems may hallucinate by producing fabricated content, unsupported claims, or nonexistent references, the perceived reliability of AI decreases (Diomidis Spinellis, 2025; Qin et al. 2024). Under such circumstances, users may realize that correcting AI-generated mistakes can require substantial additional effort, sometimes exceeding the cognitive costs of completing the task independently. Consequently,

perceived AI hallucination undermines the expected convenience associated with AI use and weakens users' willingness to fully delegate complex cognitive tasks to AI systems (Gkinko & Elbanna, 2023). Therefore, perceived AI hallucination is expected to weaken the positive effect of instrumental dependence on cognitive offloading. Thus, the following hypothesis is proposed:

H5b: Perceived AI Hallucination negatively moderates the relationship between Instrumental Dependence and Cognitive Offloading.

3.5. Cognitive Vigilance and Cognitive Offloading on Work Engagement

From the perspective of the AI-as-partner approach, cognitive vigilance reflects a collaborative relationship between humans and AI rather than a replacement of human cognition (Dóra Göndöcs, 2025; Zhao & Han, 2026). When users perceive AI as a cognitive collaborator, a sense of relational accountability emerges, whereby individuals feel jointly responsible for the quality and outcomes of the work produced (Celik, 2023). This responsibility motivates users to engage in continuous monitoring, cross-checking, and evaluation of AI outputs. Such active participation requires sustained concentration and intellectual involvement, which closely corresponds to the dedication and absorption dimensions of work engagement (Yupin Aungsuroch *et al.* 2024; Gede & Huluka, 2024) .

Furthermore, the Job Demands–Resources (JD-R) model suggests that not all job demands are detrimental. A distinction exists between hindrance demands, which obstruct performance and contribute to strain, and challenge demands, which stimulate learning, growth, and achievement (French *et al.* 2019; Bao *et al.* 2024). The process of maintaining cognitive vigilance toward AI-generated outputs, particularly identifying subtle inaccuracies and potential AI hallucinations, represents a cognitively demanding yet intellectually stimulating challenge (Rick *et al.* 2024). By encouraging active problem-solving and deeper cognitive involvement, these challenge demands generate positive psychological experiences and motivate employees to invest greater energy in their work. Consequently, cognitive vigilance may strengthen employees' vigor, dedication, and absorption, thereby enhancing overall work engagement.

According to the Job Demands–Resources (JD-R) model, job resources are factors that help employees reduce job demands, maintain well-being, and achieve work goals more effectively (Li et al. 2025). When used strategically, AI functions as a valuable job resource by simplifying routine cognitive activities such as information summarization, drafting, basic analysis, and data organization (Kong et al. 2023; López Jziménez & Ouariachi, 2020). By reducing the burden of repetitive and low-value tasks, AI enables employees to preserve psychological energy and maintain higher levels of vigor and engagement at work (Marvi et al. 2025).

Importantly, cognitive offloading should not be viewed as the abandonment of thinking but rather as a process of resource reallocation. By delegating routine tasks to AI, employees can free cognitive bandwidth for higher-order thinking, reflection, creativity, and complex problem-solving activities. Prior research suggests that meaningful work is among the strongest predictors of work engagement (Pal & Bodhi, 2026; Khusanova et al. 2021). Consequently, when AI assumes responsibility for time-consuming yet relatively low-value activities, employees are able to devote greater attention and commitment to tasks they perceive as meaningful and impactful (Wu et al. 2026).

Empirical evidence further indicates that employees who utilize AI technologies report higher levels of work engagement than those who do not (Liu & Li, 2025; Rick et al. 2024). The ability to offload micro-tasks to AI enhances efficiency, increases perceived autonomy, and allows employees greater flexibility in organizing their work activities. As a result, strategic cognitive offloading provides employees with valuable cognitive resources that support sustained vigor, deeper absorption, and stronger dedication to their core responsibilities.

Therefore, this study puts forth the following hypotheses for examination:

H6: Cognitive vigilance is positively associated with work engagement.

H7: Cognitive offloading is positively associated with work engagement.

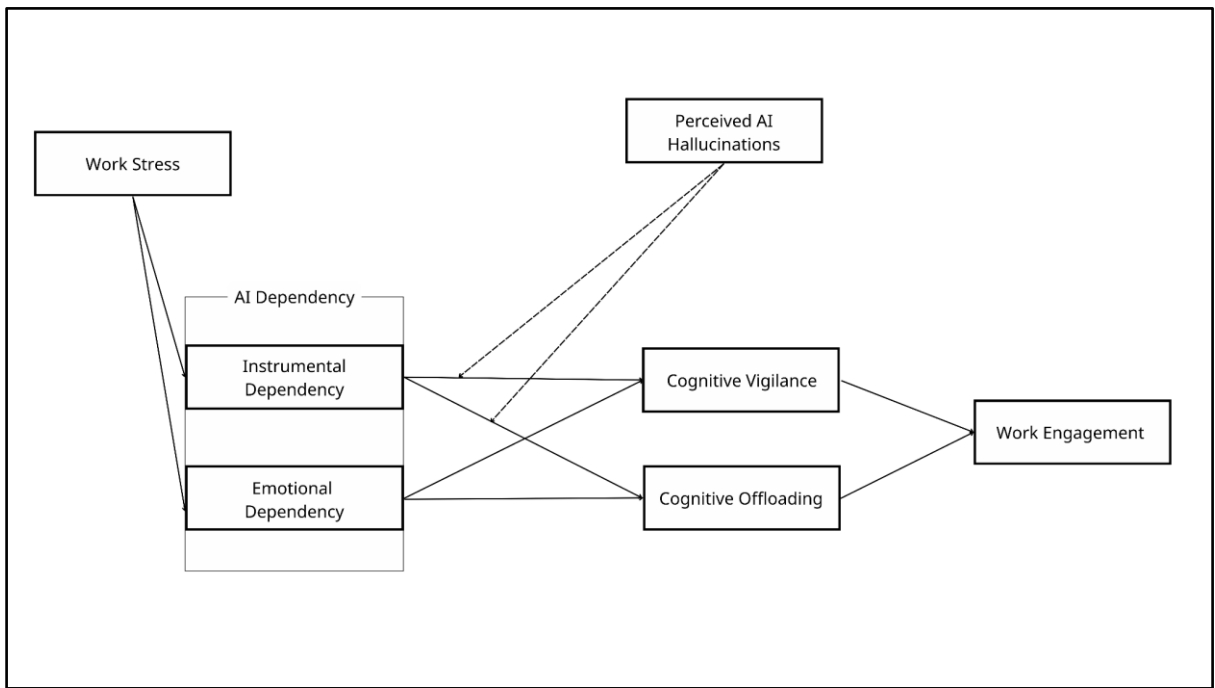


Figure 1: Research model

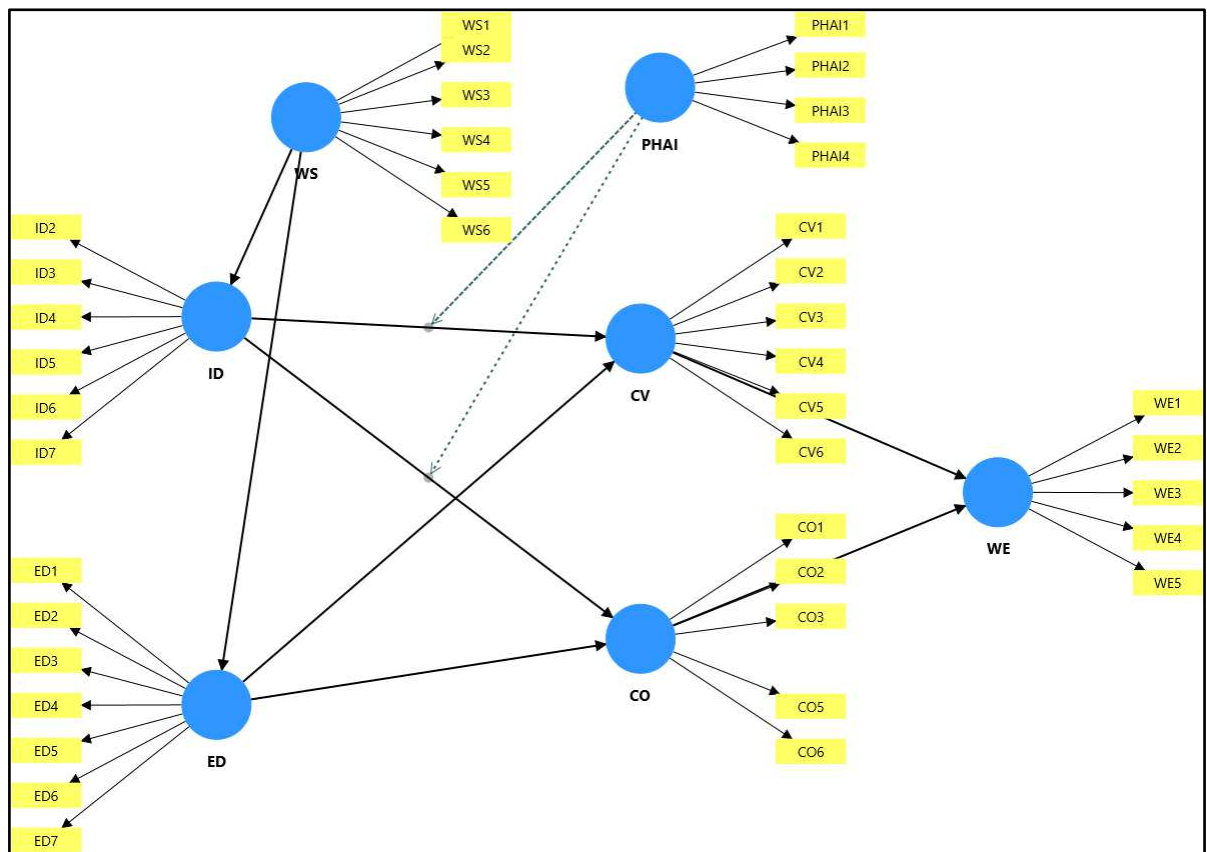


Figure 2: Graphical output

4.METHODOLOGY

4.1. Research Design and Data Collection

A pilot questionnaire involving 30 respondents was conducted to assess the clarity, linguistic readability, together with comprehensibility of the questionnaire items. Since all measurement instruments were based on prior studies followed by Vietnamese translation, several wordings were modified to facilitate linguistic clarity and ensure that respondents could accurately interpret the intended meanings of the items.

The study relied on a non-probability sampling strategy, specifically purposive sampling, to recruit participants who possessed relevant experience with conversational artificial intelligence (AI) tools in work-related contexts. Following the recommendations of Hair *et al.* (2019), a minimum sample size of 200 observations is generally considered adequate for Structural Equation Modeling (SEM) analysis to ensure sufficient statistical power and model stability. The resulting dataset consisted of 236 usable responses, surpassing the recommended minimum and was therefore deemed appropriate for subsequent SEM analysis.

Prior to the online questionnaire, participants first received a short explanation about the research purpose and the concept of conversational AI, accompanied by examples of widely used AI tools such as ChatGPT, Gemini, Copilot, and Claude. Participants were assured that their identities would remain confidential and that the collected information would be used exclusively for academic purposes. .

Participant eligibility was verified through a screening question placed at the start of the questionnaire: “Have you ever used conversational AI tools (e.g., ChatGPT, Gemini, Copilot, or Claude) for work-related purposes?” Respondents who selected “No” were excluded from the study. The questionnaire required approximately 10–12 minutes to complete.

The data collection process yielded 277 responses in total. Following eligibility screening and data cleaning, forty-one questionnaires were excluded because they failed to meet the inclusion criteria. Consequently, 236 valid responses were retained for further analysis.

Regarding demographic characteristics, female respondents accounted for 62.0% of the final sample, while males represented 38%. In terms of age, the majority of respondents were between 18 and 24 years old (60%), followed by those aged 25–34 (33%) and 35–44 (7%).

With respect to occupational background, respondents came from a variety of professional fields. Marketing and Sales represented the largest group (25.8%), followed by Business and Management (16.5%), Other occupations (14.8%), Education (14.0%), Information Technology (11.4%), Finance and Banking (11.4%), and Manufacturing (5.9%).

Finally, respondents generally reported substantial prior experience using generative AI technologies. More than half of the participants (50.4%) indicated that they had used GenAI on a daily basis for over one year, while 30.9% reported regular usage for six to twelve months. In addition, 14.4% had used GenAI occasionally for three to six months, whereas only a small proportion reported limited experience or no prior experience. These figures suggest that the sample was largely composed of active and experienced users of conversational AI tools, thereby providing an appropriate context for examining AI dependence, cognitive responses, and work-related outcomes.

4.2 Measurement

The measurement items employed in this study were adapted from validated scales established in prior research. The proposed model comprises six constructs, including Work Stress, Instrumental Dependence, Emotional Dependence, Cognitive Vigilance, Cognitive Offloading, Perceived AI Hallucination, and Work Engagement. All measurement items were translated from English into Vietnamese and underwent minor wording modifications to ensure contextual appropriateness and comprehensibility for Vietnamese respondents (Harkness *et al.* 2004). A seven-point Likert scale was utilized to capture participants' responses, ranging from (1) Strongly Disagree to (7) Strongly Agree.

AI Dependency, encompassing both Instrumental Dependence and Emotional Dependence dimensions, was measured using fourteen items adapted from Li *et al.* (2026). Cognitive

Vigilance and Cognitive Offloading were assessed using twelve items adopted from Wang & Zhang (2026). Work Stress was measured using six items adapted from Paoline *et al.* (2015). Perceived AI Hallucination was assessed using four items derived from Lim *et al.* (2025). Finally, Work Engagement was measured using five items adapted from Schaufeli *et al.* (2002).

All scales were adapted to reflect the context of conversational AI technologies, including platforms such as ChatGPT, Gemini, Copilot, and Claude. The questionnaire was reviewed and refined during the pilot study phase to ensure content clarity, linguistic accuracy, and contextual relevance before being administered in the main survey.

Table 1. Demographic characteristics.

Variable	Responses	Total number	Percentage %
Gender	Total	236	
	Male	89	37.7
	Female	147	62.3
Age	Total	236	
	From 18 to 24 years old	142	60
	From 25 to 34 years old	77	33

	From 34 to 44 years old	17	7
Work Field	Total	236	
	Marketing & Sales	61	25.8
	Business & Management	39	16.5
	Education	33	14
	Information Technology	27	11.4
	Finance & Banking	27	11.4
	Manufacturing	14	5.9
	Others	35	14.8

4.3 Data Analysis

To test the conceptual model, this research utilized Partial Least Squares Structural Equation Modeling (PLS-SEM) through SmartPLS 4 software ([Becker *et al.* 2022](#)). PLS-SEM was selected because of its suitability for estimating several relationships concurrently between latent constructs and its ability to handle complex structural models containing mediation and moderation mechanisms ([Hair *et al.* 2019](#); [Hair *et al.* 2022](#)). In addition, this analytical technique is particularly suitable for exploratory and predictive research, particularly when the objective is to assess measurement performance together with structural paths in a unified modeling framework.

Data analysis was performed using a two-stage procedure suggested by previous PLS-SEM studies. Initially, the measurement model was assessed by examining reliability of the measurement indicators, internal consistency reliability, convergent construct validity, and discriminant construct validity. Thereafter, the structural relationships were evaluated through the examination of path coefficients, explanatory power (R^2). The statistical significance of the hypothesized paths was assessed using a bootstrapping technique based on resampling techniques, in accordance with of Dijkstra & Henseler ([2015](#)) and Hair *et al.* ([2022](#)).

Additionally, collinearity among predictor variables was assessed prior to hypothesis testing to ensure the robustness of the model estimates. Given its flexibility, predictive orientation, and ability to evaluate moderation effects, SmartPLS 4.1.1.2 was considered an appropriate analytical tool for testing the proposed research model and hypotheses.

5. RESULTS

5.1. Common method bias (CMB)

As data used in this research were collected via a self-administered questionnaire obtained from a single respondent source, the possibility of common method bias (CMB) cannot be entirely excluded. Based on the recommendations provided by Campbell & Fiske ([1959](#)), both procedural and statistical approaches were employed to reduce and evaluate the impact of CMB.

Once data collection had been completed, statistical analyses were performed to evaluate the possible influence of common method variance. First, the full collinearity approach introduced by Kock (2015) was carried out based on the Variance Inflation Factor (VIF). The findings showed that every VIF value remained below the recommended cutoff value of 5.0, indicating that neither collinearity nor common method bias posed substantial concerns. Second, Harman's single-factor analysis was performed to assess whether one latent factor explained most of the variance in the data (Fuller *et al.* 2016). The findings indicated that the first unrotated factor accounted for 27.417% of the overall variance, considerably lower than the commonly adopted cutoff of 50%.

Collectively, the results of the procedural and statistical evaluations suggest that common method bias is unlikely to materially affect the validity of the study findings.

5.2 Measurement model

The measurement model was assessed based on four key criteria, including indicator reliability together with internal consistency, convergent validity, and discriminant validity. As shown in Table 2, every indicator loading surpassed the recommended benchmark of 0.70, ranging from 0.705 to 0.901. The results demonstrate that the observed indicators adequately represent their corresponding latent constructs and confirm adequate indicator reliability (Hair *et al.* 2022).

Convergent validity was assessed using the Average Variance Extracted (AVE). The AVE scores ranged between 0.581 to 0.776, with every value exceeding the recommended minimum of 0.50 (Hair *et al.* 2022). The results suggest that each construct explains more than half of the variance in its indicators, providing evidence of satisfactory convergent validity.

Measurement scale reliability was evaluated through Cronbach's alpha together with Composite Reliability (CR). The results revealed that Cronbach's Alpha values ranged from 0.820 to 0.952, while Composite Reliability values ranged from 0.874 to 0.960.

Because all values were above the recommended cutoff of 0.70, the constructs exhibited high internal consistency and acceptable reliability (Hair *et al.* 2022).

To evaluate discriminant validity, the heterotrait-monotrait ratio (HTMT) was applied. According to Table 3, every HTMT value remained below the suggested threshold of 0.90, confirming that each construct is empirically different from the remaining constructs and that satisfactory discriminant validity was achieved (Henseler *et al.* 2015). Further evidence supporting discriminant validity was obtained through correlation analysis of the latent constructs.

Taken together, the results offer substantial evidence that the measurement model meets acceptable standards of reliability and validity . As a result, all constructs were kept for the subsequent assessment of the structural model and hypothesis testing.

5.3. Structural model

The structural model's explanatory power was assessed using the R^2 statistic. The R^2 values for WE (0.384), indicating a moderate level of explanatory power (Hair *et al.* 2022). To strengthen methodological rigor, model fit was evaluated using PLS-SEM-specific fit indices (Table 5). The SRMR value for the saturated model was 0.071, which falls below the recommended threshold of 0.08, indicating an acceptable model fit. However, the SRMR value for the estimated model was reached 0.100, slightly above the suggested cutoff value and implying potential room for model improvement. But, the Normed Fit Index (NFI) values for the saturated (0.768) and estimated (0.757) models surpassed the commonly accepted cutoff value of 0.70, thereby providing evidence for the adequacy of the proposed model (Hair *et al.* 2019). Although these results indicate that the model does not achieve an ideal global fit from a covariance-based SEM perspective, such outcomes are commonly observed. In prediction-oriented PLS-SEM studies, where the primary objective is explanation and prediction rather than exact model fit (Henseler *et al.* 2015; Hair *et al.* 2019). Taken together, despite the limitations reflected in the SRMR, the model demonstrates an acceptable level of fit and provides an adequate basis for subsequent structural model evaluation and hypothesis testing.

Table 2: The reliability and convergent validity.

Constructs	FL	CA	CR	AVE
Cognitive Offloading		0.820	0.874	0.581
CO1	0.736			
CO2	0.757			
CO3	0.786			
CO5	0.787			
CO6	0.746			
Cognitive vigilance		0.872	0.904	0.611
CV1	0.750			
CV2	0.781			
CV3	0.757			

CV4	0.760
-----	-------

CV5	0.820
-----	-------

CV6	0.818
-----	-------

Emotional Dependence

0.952	0.960	0.776
-------	-------	-------

ED1	0.842
-----	-------

ED2	0.879
-----	-------

ED3	0.876
-----	-------

ED4	0.900
-----	-------

ED5	0.901
-----	-------

ED6	0.878
-----	-------

ED7	0.889
-----	-------

Instrumental Dependence

0.858	0.894	0.586
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ID2		0.711			
ID3		0.705			
ID4		0.777			
ID5		0.802			
ID6		0.825			
ID7		0.765			
Perceived AI Hallucination			0.890	0.924	0.753
PHAI1		0.886			
PHAI2		0.898			
PHAI3		0.864			
PHAI4		0.822			
Work Engagement			0.847	0.891	0.621

WE1	0.778			
WE2	0.795			
WE3	0.818			
WE4	0.830			
WE5	0.716			
Work Stress		0.891	0.917	0.647
WS1	0.771			
WS2	0.800			
WS3	0.817			
WS4	0.821			
WS5	0.807			
WS6	0.808			

Abbreviations: FL: Factor loading; CA: Cronbach's alpha; CR: Composite reliability; AVE: Average variance extracted. ED2, CO4 was removed (<0.70)

Table 3: Heterotrait-monotrait ratio (HTMT).

	CO	CV	ED	ID	PHAI	WE	WS
CO							
CV	0.535						
ED	0.204	0.107					
ID	0.645	0.405	0.465				
PHAI	0.409	0.680	0.040	0.432			
WE	0.547	0.427	0.226	0.255	0.325		

WS	0.368	0.478	0.283	0.480	0.659	0.134
----	-------	-------	-------	-------	-------	-------

Notes: CO = Cognitive Offloading; CV = Cognitive Vigilance; ED = Emotional Dependence; ID = Instrumental Dependence; PHAI = Perceived AI Hallucination; WE = Work Engagement; WS = Work Stress.

Table 4. Fornell - Larcker Criterion

	CO	CV	ED	ID	PHAI	WE	WS
CO	0.763						
CV	0.452	0.782					
ED	0.152	0.073	0.881				
ID	0.544	0.358	0.411	0.765			
PHAI	0.351	0.605	0.014	0.389	0.868		
WE	0.460	0.370	0.193	0.220	0.283	0.788	
WS	0.314	0.420	0.269	0.432	0.589	0.112	0.804

Notes: CO = Cognitive Offloading; CV = Cognitive Vigilance; ED = Emotional Dependence; ID = Instrumental Dependence; PHAI = Perceived AI Hallucination; WE = Work Engagement; WS = Work Stress.

Table 5. Model Fit summary.

	Saturated model	Estimated model
SRMR	0.071	0.100
d_ULS	3.942	7.767
d_G	1.190	1.298
Chi-square	1526.117	1594.221
NFI	0.768	0.757

Table 6: Latent variable correlations.

	CO	CV	ED	ID	PHAI	WE	WS
CO	1.000						
CV	0.452	1.000					

ED	0.152	0.073	1.000				
ID	0.544	0.358	0.411	1.000			
PHAI	0.351	0.605	0.014	0.389	1.000		
WE	0.460	0.370	0.193	0.220	0.283	1.000	
WS	0.314	0.420	0.269	0.432	0.589	0.112	1.000

Notes: CO = Cognitive Offloading; CV = Cognitive Vigilance; ED = Emotional Dependence; ID = Instrumental Dependence; PHAI = Perceived AI Hallucination; WE = Work Engagement; WS = Work Stress

Table 7: Path coefficients-mean, p values

Hypothesis	Original Sample	P values	Decision
WS → ID	0.432	0.000	Supported
WS → ED	0.269	0.000	Supported
ID → CV	0.141	0.064	Not Supported

ID→ CO	0.511	0.000	Supported
ED → CV	0.007	0.902	Not Supported
ED→ CO	-0.059	0.411	Not Supported
PHAI x ID→ CV	-0.003	0.962	Not Supported
PHAI x ID→ CO	0.013	0.866	Not Supported
CV→ WE	0.203	0.027	Supported
CO → WE	0.368	0.000	Supported

Notes: CO = Cognitive Offloading; CV = Cognitive Vigilance; ED = Emotional Dependence; ID = Instrumental Dependence; PHAI = Perceived AI Hallucination; WE = Work Engagement; WS = Work Stress

6. ARTIFICIAL NEURAL NETWORK

To complement the linear prediction capabilities of PLS-SEM and capture potential non-linear relationships among the constructs, this study employed Artificial Neural Network (ANN) analysis as a robustness and predictive validation technique (Maier *et al.* 2023). Based on the significant paths obtained from the PLS-SEM analysis, an ANN model was subsequently developed using a multilayer perceptron (MLP) architecture composed of one input layer, one hidden layer, and one output layer. The ANN model was trained through a feedforward backpropagation learning algorithm employing the hyperbolic tangent

activation function, which enables the model to learn complex and non-linear patterns among the variables.

ANN analysis was performed using a feedforward backpropagation learning algorithm together with the hyperbolic tangent as the activation function ([Alnoor *et al.* 2024](#)). To minimize overfitting and enhance the model's generalizability as recommended by Aguirre-Urreta & Hu, ([2024](#)), a 10-fold cross-validation procedure was applied. In each run, approximately 90% of the observations were allocated to the training dataset, while the other 10% were reserved for testing. The procedure was performed over ten repeated runs, generating ten independent neural network models. To evaluate the importance of the study variables, a neural network model was trained using the research dataset. The neural network architecture implemented in this study, presented in Figure 3, includes one input layer, one hidden layer, and one output layer. Hyperbolic tangent activation functions were applied to both the hidden and output layers to facilitate the learning process and improve predictive performance. Model performance was assessed using the Root Mean Square Error (RMSE), which measures the discrepancy between predicted and observed values.

As presented in Table 8, the average RMSE scores for the training and testing datasets were 0.602 and 0.518, respectively. The relatively small difference between training and testing RMSE values (Mean Difference = 0.084) indicates stable predictive performance and suggests that the model does not suffer from substantial overfitting. Furthermore, the standard deviations of RMSE across the ten network runs were 0.042 for the training phase and 0.080 for the testing phase, demonstrating consistency and robustness of the neural network predictions.

Taken together, the ANN analysis provides additional evidence for the predictive effectiveness of the proposed model and complements the conclusions drawn from the PLS-

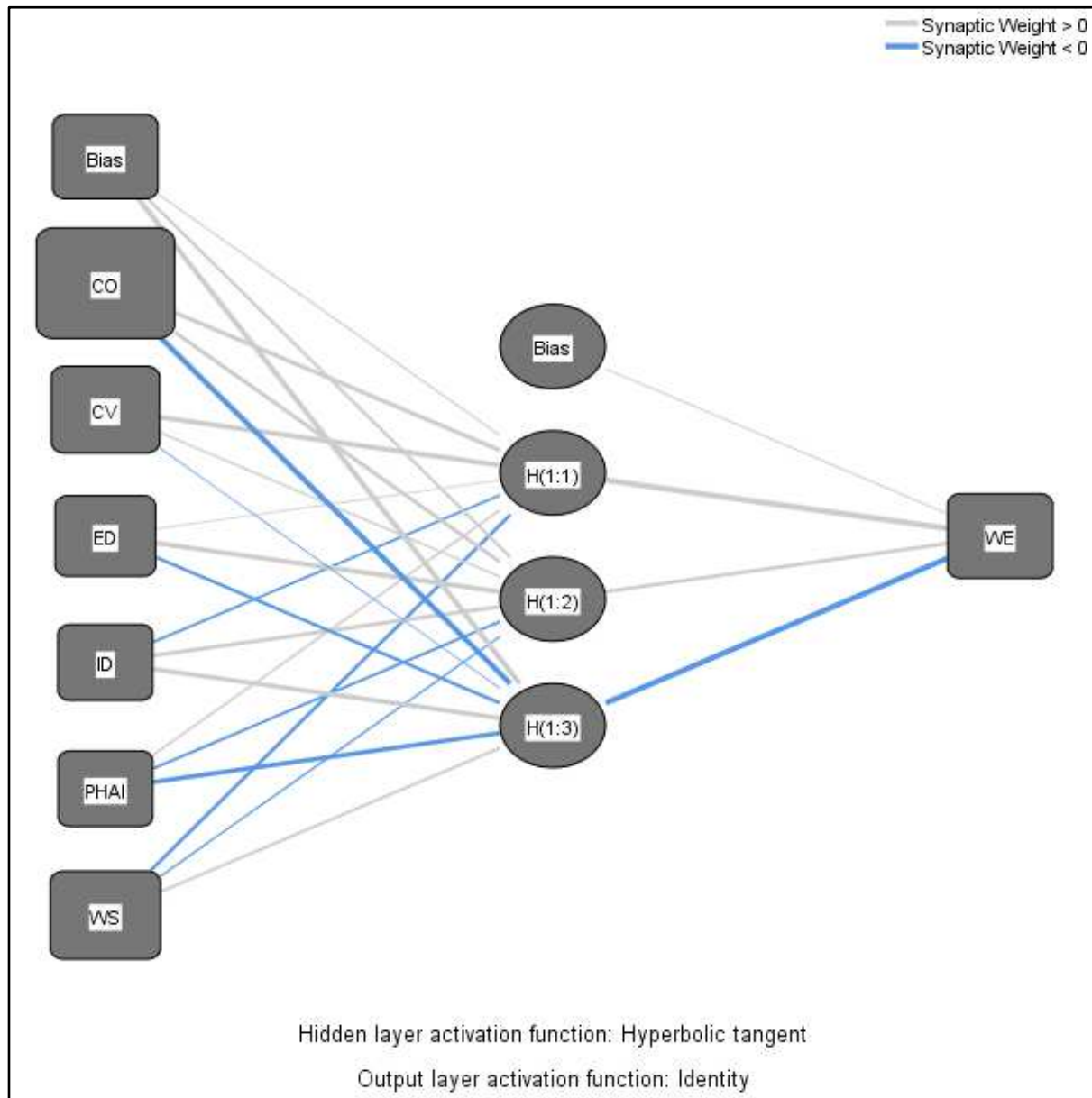


Figure 3: Artificial Neural Network (Author's work)

Table 8: RMSE value of 10-fold ANN models.

Net work	Sum of square error (Training)	Sum of square error (Testing)	RMSE (Training)	RMSE (Testing)
1	69.863	7.862	0.590	0.474
2	73.710	7.241	0.590	0.549
3	75.859	5.979	0.607	0.446
4	81.604	6.255	0.628	0.464
5	67.915	9.691	0.562	0.679
6	106.478	3.588	0.700	0.435
7	58.005	6.957	0.529	0.490
8	77.070	11.451	0.607	0.651
9	74.266	5.811	0.595	0.473
10	80.272	5.26	0.610	0.513
Mean	76.504	7.010	0.602	0.517
SD	11.884	2.134	0.042	0.080

Table 9: Sensitivity analysis for the ANN models.

	NI	NI	NI	NI	NI	NI	NI	NI	NI	AI	NI (%)
CO	1.00	1.00	1.00	1.00	0.42	1.00	1.00	1.00	1.00	0.94	100%
CV	0.55	0.43	0.36	0.54	0.32	0.54	0.69	0.48	0.16	0.45	48%
ED	0.43	0.29	0.39	0.46	0.59	0.40	0.44	0.42	0.28	0.41	44%
ID	0.34	0.41	0.53	0.54	0.44	0.48	0.23	0.28	0.22	0.39	41%
PHAI	0.34	0.36	0.17	0.24	0.68	0.60	0.28	0.49	0.76	0.44	47%
WS	0.58	0.57	0.17	0.50	1.00	0.51	0.08	0.56	0.26	0.47	50%

Notes: NI = Normalized Importance; AI = Average Importance; NI (%) = Normalized Importance expressed as a percentage relative to the most important predictor (100%).

Notes: CO = Cognitive Offloading; CV = Cognitive Vigilance; ED = Emotional Dependence; ID = Instrumental Dependence; PHAI = Perceived AI Hallucination; WE = Work Engagement; WS = Work Stress

To provide a more comprehensive assessment of the proposed model, this study employed both PLS-SEM and Artificial Neural Network (ANN) techniques. While PLS-SEM evaluates the significance and magnitude of causal relationships through path coefficients, ANN focuses on predictive capability and determines the relative importance of input variables through sensitivity analysis. The integration of these two approaches allows both explanatory and predictive perspectives to be examined simultaneously.

Table 10 compares the findings obtained from PLS-SEM and ANN analyses. Overall, the results reveal a high degree of consistency between the two methods. Specifically, the relationship between Cognitive Offloading (CO) and Work Engagement (WE) emerged as the most influential predictor in both analyses, exhibiting the largest path coefficient in the

PLS-SEM model ($\beta = 0.368$) and the highest normalized importance in the ANN model (100%). This consistency suggests that Cognitive Offloading plays a central role in enhancing employees' work engagement.

The ANN sensitivity analysis therefore complements the PLS-SEM findings by providing additional insights into the relative contribution of each predictor. The convergence of results across the two analytical methods enhances the robustness of the study and strengthens confidence in the proposed theoretical framework.

Table 8 reports the ANN predictive accuracy based on ten-fold cross-validation, whereas Table 9 presents the sensitivity analysis and normalized importance values. Finally, Table 10 summarizes the comparison between PLS-SEM and ANN results, demonstrating substantial agreement in predictor rankings across the two methods.

Table 10: Comparison of PLS-SEM and ANN results.

PLS-SEM path	Original sample (O)/Path Coefficient	ANN results: Normalize d relative importance	Ranking (PLS-SEM) [based on Path Coefficient]	Ranking (ANN) [based on Normalized relative importance]	Remar k
CO → WE	0.368	100%	1	1	Match
CV → WE	0.203	48%	2	3	Not match

7. FUZZY-SET QUALITATIVE COMPARATIVE ANALYSIS (fsQCA)

This study employed fsQCA analysis by using fsQCA 4.1 software. The analysis was designed to reveal the combinations of causal conditions that are associated with high work engagement in organizational contexts. In accordance with the fsQCA procedure fsQCA,

the raw values of both the outcome variable and causal conditions were converted into fuzzy-set scores ranging with values bounded between 0 and 1, reflecting varying degrees of set membership. This calibration method enables identification of causal complexity beyond conventional variable-centered analyses (Fiss, 2011). Consistent with prior fsQCA studies, calibration was performed using three qualitative breakpoints recommended by Veríssimo (2018): the 5th percentile as the threshold for full non-membership (0.05), the 50th percentile as the crossover point (0.50), and the 95th percentile as the threshold for full membership (0.95). Table 11 presents the descriptive statistics together with the calibration anchors for all variables included in the analysis.

Table 11: Calibration

Condition		Calibration		
		Fully in	Crossover point	Fully out
Antecedent				
	ID	6.500	5.000	2.475
	ED	6.020	3.290	1.000
	CV	6.833	5.500	3.142
	CO	7.000	5.400	3.600
	WS	6.000	4.920	3.330
	PHAI	7.000	5.500	2.750
Outcome	WE	6.800	5.000	2.800

Notes: CO = Cognitive Offloading; CV = Cognitive Vigilance; ED = Emotional Dependence; ID = Instrumental Dependence; PHAI = Perceived AI Hallucination; WE = Work Engagement; WS = Work Stress

Table 12: Configurations for achieving high level of WE

Factors	S1	S2	S3	S4	S5	S6	S7	S8
ID	●	⊗	⊗	●	⊗	●	⊗	●
ED		⊗	●	●	⊗	⊗	⊗	●
CV	●		●	⊗	⊗	⊗	●	
CO	●	●	●	⊗	●	●		●
WS		⊗	⊗	⊗	⊗	⊗	●	●
PHAI	●	⊗	●	⊗	●	●	●	●
Raw coverage	0.493	0.269	0.267	0.266	0.293	0.289	0.291	0.376
Unique coverage	0.075	0.040	0.016	0.026	0.024	0.011	0.009	0.016
Consistency	0.876	0.907	0.892	0.887	0.826	0.846	0.888	0.913
Solution Coverage = 0.760								
Solution Consistency = 0.791								

Notes: ● indicates the presence of a condition; ⊗ indicates the absence of a condition; blank cells indicate that the condition is irrelevant to the corresponding configuration.

Notes: CO = Cognitive Offloading; CV = Cognitive Vigilance; ED = Emotional Dependence; ID = Instrumental Dependence; PHAI = Perceived AI Hallucination; WE = Work Engagement; WS = Work Stress

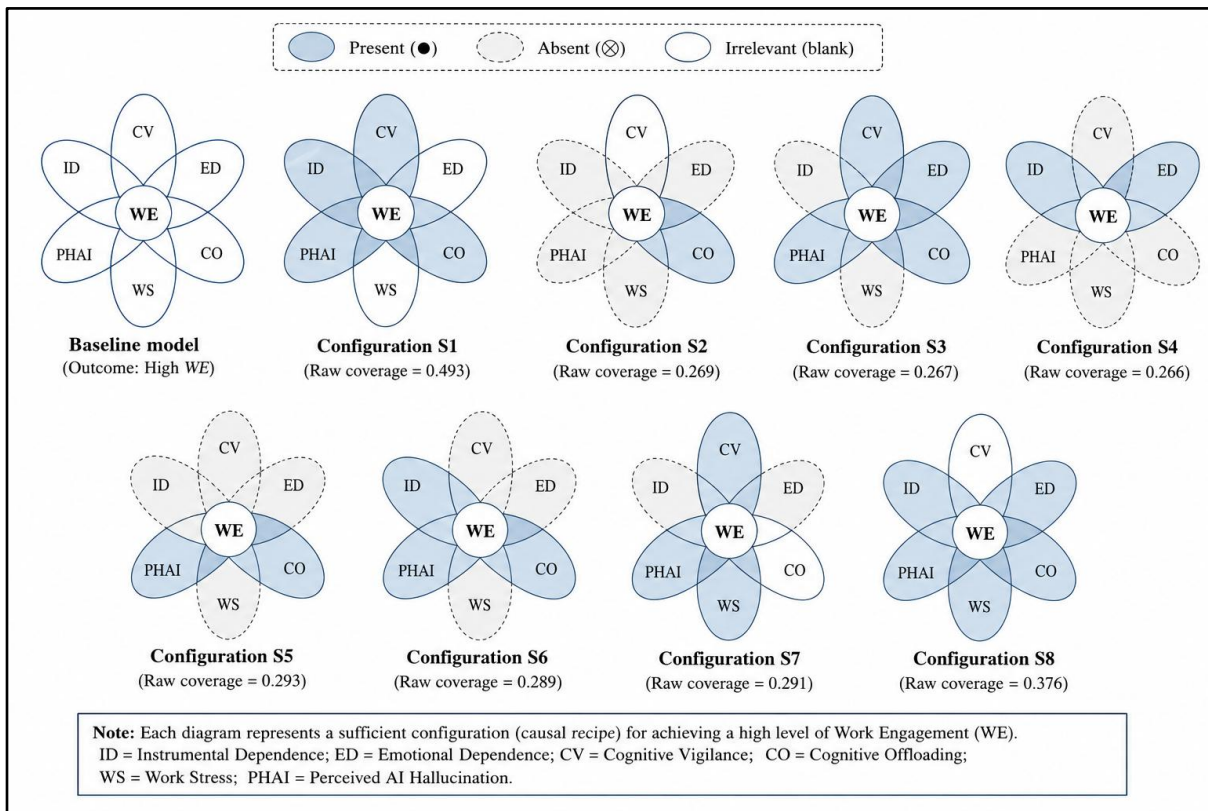


Figure 4: Graphical representation of fsQCA solutions*

Table 12 presents the fsQCA results identifying eight sufficient configurations associated with high levels of Work Engagement (WE). Consistent with the principle of equifinality, the findings suggest that multiple combinations of AI dependence, cognitive responses, perceived AI hallucinations, and work stress can jointly lead to the same outcome. All identified configurations exhibit consistency values above the recommended threshold of 0.75 (Ragin, 2008), ranging from 0.826 to 0.913, indicating that the causal recipes are sufficiently reliable (Pappas & Woodside, 2021).

The overall solution coverage is 0.760, suggesting that the eight configurations collectively explain approximately 76.0% of the cases exhibiting high Work Engagement. In addition, the overall solution consistency reaches 0.791.

Among the identified pathways, Configuration S1 (Figure 4) emerges as the dominant configuration, with the highest raw coverage (0.493) and a consistency value of 0.876. This configuration combines Instrumental Dependence (ID), Cognitive Vigilance (CV),

Cognitive Offloading (CO), and Perceived AI Hallucination (PHAI), suggesting that employees are more likely to exhibit high Work Engagement when they simultaneously rely on AI for task accomplishment, actively monitor AI-generated outputs, strategically offload cognitive tasks, and remain aware of the potential limitations of AI systems.

The results further reveal that Cognitive Offloading (CO) appears in six of the eight configurations (S1, S2, S3, S5, S6, and S8), highlighting its prominent role in achieving high Work Engagement. Likewise, Perceived AI Hallucination (PHAI) is present in six configurations, indicating that awareness of AI-generated inaccuracies frequently coexists with high engagement outcomes. In contrast, Work Stress (WS) appears in only two configurations (S7 and S8) and is absent in several others, suggesting that high Work Engagement can be achieved under different stress conditions depending on the broader combination of factors.

Overall, the fsQCA findings support the existence of multiple alternative pathways leading to high Work Engagement, emphasizing that employee engagement emerges from the interaction of AI dependence, cognitive processing mechanisms, and perceptions of AI reliability rather than from any single factor alone.

8. NECESSARY CONDITION ANALYSIS

In addition to the fsQCA findings, a Necessary Condition Analysis (NCA) was performed to determine whether any antecedent serves as a necessary condition for attaining high levels of Work Engagement (WE). NCA extends configurational analysis by quantifying the minimum level of a condition required for a desired outcome and provides additional insights through ceiling line estimation and bottleneck analysis (Dul, 2016). Considering that all variables were measured using seven-point Likert scales, both the Ceiling Regression–Free Disposal Hull (CR-FDH) and Ceiling Envelopment–Free Disposal Hull (CE-FDH) techniques were employed.

As suggested by Dul (2015), a condition can be considered necessary when it exhibits both a meaningful effect size ($d \geq 0.10$) and a statistically significant permutation test. The

findings reported in Table 13 indicate that Cognitive Offloading (CO) is the only construct fulfilling these requirements across both CE-FDH ($d = 0.306$, $p < 0.001$) and CR-FDH ($d = 0.296$, $p < 0.001$) techniques. Following the recommended guidelines: Effect sizes are categorized into four thresholds: very large effect ($0.5 \leq d < 1$), large effect ($0.3 \leq d < 0.5$), medium effect ($0.1 \leq d < 0.3$), and small effect ($0 < d < 0.1$), recommended by Chen & Chen, (2024), this effect size represents a medium-level necessary condition for achieving high Work Engagement. By contrast, Cognitive Vigilance (CV), Instrumental Dependence (ID), Emotional Dependence (ED), and Work Stress (WS) exhibited either negligible effect sizes or statistically non-significant permutation test results and therefore cannot be considered necessary conditions .

To further explore the minimum level of necessity, a bottleneck analysis was performed. The bottleneck table & NCA chart (Table 14 & Figure 5) indicates that the required level of Cognitive Offloading increases substantially as the desired level of Work Engagement rises. For example, achieving 80% of the maximum Work Engagement requires at least 10.169 units of Cognitive Offloading, whereas achieving the maximum Work Engagement level requires a minimum Cognitive Offloading level of 37.712. Instrumental Dependence emerges as a bottleneck condition only from the 40% outcome level onward, requiring a minimum threshold of 0.847. Cognitive Vigilance appears only at the highest outcome level, where a minimum value of 6.356 is required to achieve maximum Work Engagement. Emotional Dependence and Work Stress do not appear as bottleneck conditions at any outcome level.

Overall, the NCA findings provide convergent evidence that Cognitive Offloading is not only a significant predictor in the PLS-SEM model but also the only meaningful necessary condition for achieving high levels of Work Engagement.

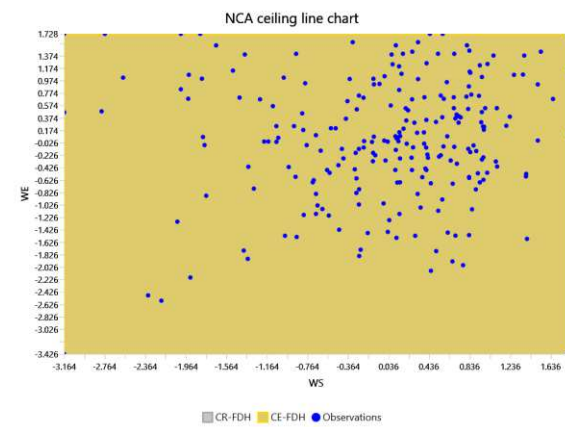
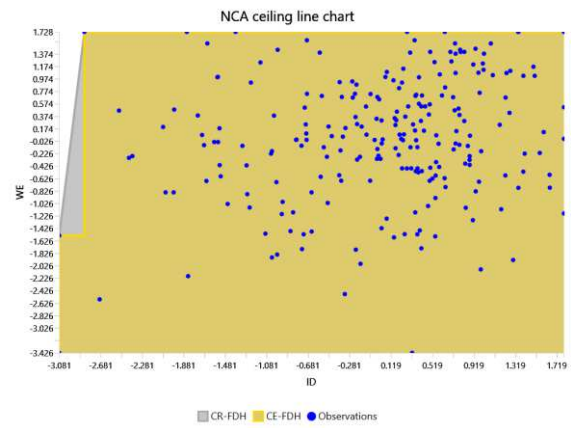
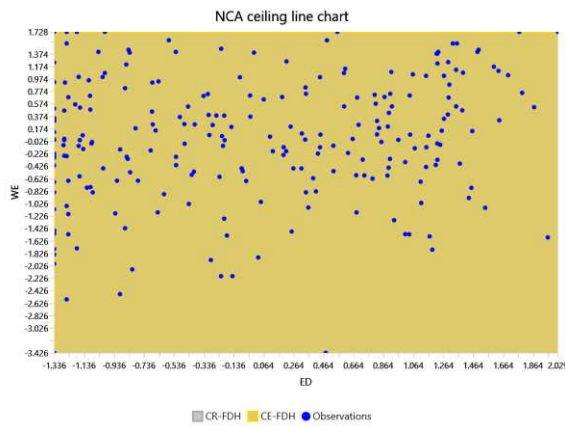
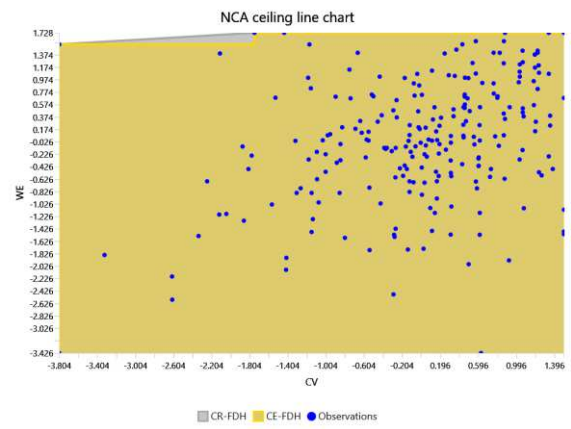
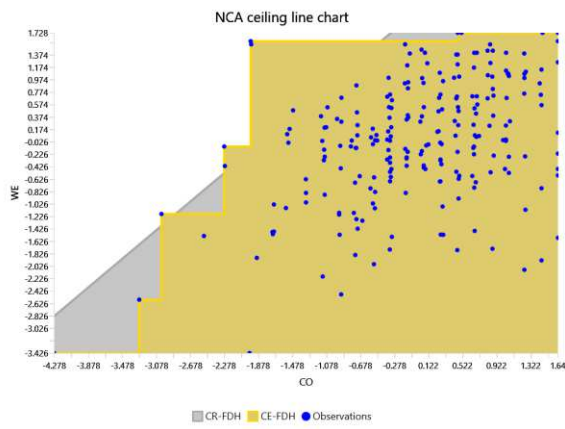


Figure 5: NCA results visualization (Author's work)**Table 13:** Analysis results of the necessary conditions of NCA

Conditions	Methods	C-accuracy	Effect size (d)	P-value (p)
CO	CR-FDH	97.46%	0.296	0.000
	CE-FDH	100.00%	0.306	0.000
CV	CR-FDH	100.00%	0.007	0.897
	CE-FDH	100.00%	0.014	0.896
ED	CR-FDH	100.00%	0.000	0.000
	CE-FDH	100.00%	0.000	0.000
ID	CR-FDH	99.58%	0.016	0.712
	CE-FDH	100.00%	0.032	0.584
WS	CR-FDH	100.00%	0.000	0.000
	CE-FDH	100.00%	0.000	0.000

Table 14: Bottleneck result

WE (%)	CO	CV	ED	ID	WS
0	NN	NN	NN	NN	NN
10	NN	NN	NN	NN	NN
20	0.424	NN	NN	NN	NN
30	0.424	NN	NN	NN	NN
40	1.271	NN	NN	0.847	NN
50	1.271	NN	NN	0.847	NN
60	2.542	NN	NN	0.847	NN
70	5.932	NN	NN	0.847	NN
80	10.169	NN	NN	0.847	NN
90	19.492	NN	NN	0.847	NN
100	37.712	6.356	NN	0.847	NN

Note: The bottleneck table is based on the CE-FDH ceiling line. *NN* indicates that the condition is not necessary for achieving the corresponding outcome level.

Table 15: Consolidated PLS-SEM, fsQCA, ANN, NCA results

Relationship	PLS-SEM	ANN	fsQCA	NCA	Interpretation
CV → WE	Supported ($\beta = 0.203$, $p = 0.027$)	NI = 48%	Present in 3 configurations (S1, S3, S7)	Not a necessary condition ($d = 0.014$)	Cognitive Vigilance positively contributes to Work Engagement and appears in several successful configurations. However, NCA indicates that it is not a prerequisite for achieving high levels of Work Engagement.
CO → WE	Supported ($\beta = 0.368$, $p < 0.001$)	NI = 100%	Present in 6 configurations (S1, S2, S3, S5, S6, S8)	Necessary condition ($d = 0.306$)	Cognitive Offloading is the most influential factor associated with Work Engagement across all analytical approaches. It demonstrates the

strongest net
effect, the highest
ANN importance,
appears in most
fsQCA
configurations,
and is the only
meaningful
necessary
condition
identified by
NCA.

The PLS-SEM analysis showed that the direct relationship between Cognitive Vigilance (CV) and Work Engagement (WE) was statistically significant ($\beta = 0.203$, $p = 0.027$), while the relationship between Cognitive Offloading (CO) and WE was considerably stronger ($\beta = 0.368$, $p < 0.001$). The artificial neural network (ANN) results further confirmed the strong influence of CO, with a normalized importance of 100%, whereas CV achieved a normalized importance of only 48%. The fsQCA configurational analysis also revealed that CO appeared in six out of eight sufficient configurations leading to high WE, whereas CV appeared in only three configurations. Finally, the NCA results indicated that CO was a medium-level necessary condition (effect size $d = 0.306$, $p < 0.001$) for achieving high WE, whereas CV exhibited a very small effect size and did not meet the criteria for a necessary condition ($d = 0.014$, $p = 0.896$).

Taken together, all analytical approaches consistently demonstrate that CO exerts a substantially stronger influence on work engagement than CV. Although CV has a positive effect on WE, its impact is relatively small and it is not required for achieving high levels of work engagement. In contrast, CO contributes significantly to enhancing WE and,

according to the NCA results, a minimum level of approximately 30.6% CO (based on the calibrated data) is necessary to achieve the highest level of work engagement.

9. DISCUSSION

AI Dependence and Work Stress

Our findings confirm the hypothesis that Work Stress promotes both forms of AI dependence, namely Instrumental Dependence (ID) and Emotional Dependence (ED). This finding is consistent with the Job Demands–Resources (JD-R) model (Bakker & Demerouti, 2007), which posits that individuals facing high job demands and stress are more likely to seek additional resources to cope with these pressures. The results are also aligned with Conservation of Resources (COR) theory, which suggests that stressed individuals attempt to preserve their cognitive resources by relying on external tools such as AI to reduce mental burden. Previous studies, including reviews of AI-assisted, have similarly suggested that AI can help regulate stress by alleviating cognitive load (Chirayath et al. 2025). The novelty of the present study lies in distinguishing between instrumental and emotional forms of AI dependence and demonstrating that both increase as work stress intensifies. Notably, emotional dependence, in which employees perceive AI as a psychological refuge or source of emotional support, also increases significantly under work-related pressure, a phenomenon that has received limited attention in prior research.

AI Dependence and Cognitive Responses

H3b was supported, indicating that Instrumental Dependence significantly increases Cognitive Offloading. This finding is consistent with theories of AI-assisted cognitive offloading, which suggest that individuals who depend on AI—whether for functional assistance—tend to transfer cognitive tasks to AI systems in order to conserve mental effort and free cognitive resources. Research in cognitive psychology similarly supports the notion that AI can facilitate cognitive offloading by reducing information-processing demands (Gerlich, 2025; Grinschgl & Neubauer, 2022; Chen et al. 2025). Recent studies, such as Yao *et al.* (2026), have likewise argued that AI use is associated with cognitive offloading as a means of avoiding unnecessary cognitive effort. However, Risko & Gilbert.

(2016); Zhai *et al.* (2024) warned that excessive offloading may come at the expense of critical thinking capabilities.

The findings of the present study offer a different perspective. Within workplace environments, cognitive offloading appears to enhance work engagement rather than merely impair cognitive skills. In contrast, Instrumental Dependence and Emotional Dependence did not reduce Cognitive Vigilance as originally expected, leading to the rejection of H3a and H4a. This finding is particularly noteworthy because, from a theoretical standpoint, excessive dependence on AI could be expected to encourage complacency and reduce monitoring behavior (Spatola, 2024). However, in real-world organizational settings, employees remain accountable for their work outcomes and are continuously evaluated based on their performance (Hosciuc Rendi *et al.* 2025). As a result, they maintain a baseline level of vigilance despite their reliance on AI. This finding contradicts the automation bias argument, which suggests that trust in automated systems diminishes human vigilance. Instead, professional responsibility appears to compel employees to continue monitoring, validating, and approving AI-generated outputs even when they become highly dependent on AI.

The Influence of Perceived AI Hallucinations (PHAI)

The hypothesis that concerns regarding AI hallucinations would reduce Cognitive Offloading or increase Cognitive Vigilance was not supported. This finding is aligned by Romeo & Conti. (2025) suggesting the presence of an automation bias effect, whereby familiarity with the convenience of AI makes individuals less responsive to concerns about potential inaccuracies. In other words, the desire to reduce effort and increase efficiency outweighs concerns regarding AI-generated errors.

Automation bias theory proposes that individuals tend to prioritize machine-generated recommendations and frequently overlook contradictory information (Ruscheimer & Hondrich, 2024). Our findings support this perspective. Even when employees are aware that AI systems may generate fabricated or inaccurate information, they continue to rely on AI as part of their routine work processes rather than increasing their monitoring efforts to

mitigate potential risks. Similar patterns have been observed in other industries like education (Cui et al. 2026; Abubakar et al. 2025), where operators frequently place excessive trust in automated recommendations and reduce cross-checking behaviors.

Cognitive Offloading and Work Engagement

This represents the most important contribution of the present study: Cognitive Offloading emerges as a key determinant of Work Engagement. Across all analytical approaches, delegating cognitive tasks to AI consistently emerged as a primary resource driving employees' energy, dedication, and enthusiasm toward their work.

This finding offers a new perspective relative to previous research. Within the JD-R framework, Cognitive Offloading can be conceptualized as a unique job resource that alleviates the mental burden associated with routine tasks, thereby enabling employees to focus on more meaningful and valuable work activities. Research on cognitive offloading has demonstrated that the use of external tools, such as calculators, can free working-memory resources and allow individuals to devote their newly available cognitive capacity to solving more complex problems. Similarly, in workplace settings, delegating routine cognitive activities to AI creates opportunities for employees to engage in creativity, problem-solving, and social interaction, all of which are known to enhance engagement.

While Tian *et al.* (2025) emphasized the potential negative consequences of cognitive offloading for critical thinking, the present study provides evidence of its positive role in enhancing employee motivation. Specifically, cognitive offloading enriches employees' internal resource pools and constitutes a necessary condition for achieving the highest levels of Work Engagement.

Consistent with the statistical results, H4b was not supported, as Emotional Dependence was found to have no significant impact on Cognitive Offloading. This non-significant finding suggests that relying on AI for psychological comfort and emotional regulation does not inherently translate into delegating cognitive or task-related responsibilities. Employees who form pseudo-social bonds with AI likely engage with the system primarily for affective relief rather than work efficiency. Therefore, emotional reliance operates independently of

cognitive task delegation, highlighting a clear boundary between using AI as an emotional refuge and using it as a cognitive tool.

10. CONCLUSION

10.1. Theoretical implications

First, this study substantially expands the scope of the Job Demands-Resources (JD-R) model and the Conservation of Resources (COR) theory within the context of human-AI interaction. Traditionally, technology in the workplace has been viewed merely as a functional tool. By empirically demonstrating that intense Work Stress drives employees to seek AI not only as a cognitive shortcut but also as a psychological refuge, this study extends the JD-R and COR frameworks. It establishes that in highly demanding environments, conversational AI systems act as complex resources that simultaneously address both cognitive depletion and socio-emotional vulnerabilities. Second, this study fills a critical gap in the existing literature regarding the "black box" between AI usage and workplace outcomes. While prior studies have predominantly focused on the direct psychological consequences of AI dependence (e.g., anxiety, loneliness) (Xie & Pentina, 2022; Laestadius et al. 2022), this research introduces and tests a mediational pathway. By simultaneously examining two contrasting cognitive responses—Cognitive Vigilance and Cognitive Offloading—this study unravels the specific cognitive mechanisms through which AI dependence translates into Work Engagement. It shifts the academic conversation from how much employees use AI to how they cognitively process their reliance on AI to maintain productivity and engagement. Third, this research resolves two significant tensions in the current literature. The first tension revolves around the nature of Cognitive Offloading. While cognitive psychology literature often warns that excessive offloading impairs critical thinking and promotes intellectual laziness (Pearson et al. 2026; Tian & Zhang, 2025), this study reframes it within the organizational context. The findings prove that delegating routine tasks to AI is actually a vital job resource that frees mental bandwidth, thereby becoming a key driver of Work Engagement. The second tension involves the relationship between Emotional Dependence and task-oriented behavior. This study found that Emotional Dependence does not significantly facilitate Cognitive

Offloading. This clarifies a theoretical ambiguity by confirming that using AI for emotional regulation operates entirely independently of cognitive task delegation in the workplace. Third, this study answers recent calls to investigate the boundary conditions of AI integration, particularly the phenomenon of AI hallucinations ([Gkinko & Elbanna, 2023](#); [Klingbeil *et al.* 2024](#)). By introducing Perceived AI Hallucination as a moderator, this research provides counterintuitive insights into Automation Bias theory. The rejection of the moderation hypotheses reveals a stark reality: employees' awareness of AI inaccuracies does not increase their vigilance nor decrease their offloading behaviors. This contributes profoundly to the literature by demonstrating that the human drive for convenience, cognitive conservation, and efficiency fundamentally overrides the perceived risks of machine errors in high-pressure environments. Finally, this study pioneers a novel methodological paradigm in Information Systems research by moving beyond traditional symmetrical, linear modeling. By integrating PLS-SEM with Artificial Neural Networks (ANN), Fuzzy-set Qualitative Comparative Analysis (fsQCA), and Necessary Condition Analysis (NCA) , it introduces a configurational and necessity-based perspective to the concept of Work Engagement. It empirically establishes the principle of equifinality—proving that multiple configurations of stress, dependence, and cognition can lead to high engagement . Most importantly, the NCA introduces a groundbreaking conceptual benchmark: Cognitive Offloading is not merely a contributing factor, but the only statistically significant necessary condition (a required bottleneck) for achieving high Work Engagement in the AI era.

10.2. Practical implications

The findings of this study provide several important implications for organizational leaders, human resource managers, and policymakers seeking to effectively integrate generative AI into contemporary workplaces. Most importantly, the results suggest that organizations should reconsider their approach to AI governance by addressing the underlying drivers of excessive AI dependence rather than merely regulating technology usage itself. The findings demonstrate that employees experiencing high levels of work stress increasingly rely on AI not only as a functional tool but also as a source of psychological comfort and

emotional support. Consequently, excessive emotional dependence on AI may signal deeper organizational problems, including workload pressure, resource depletion, and insufficient social support. Rather than imposing restrictive AI policies, organizations should focus on reducing excessive job demands, strengthening interpersonal support systems, and creating psychologically safe environments where employees can seek assistance from colleagues and supervisors without fear of judgment.

The study also highlights the strategic value of cognitive offloading in AI-enabled workplaces. Contrary to concerns that delegating tasks to AI may encourage intellectual laziness, the results consistently indicate that cognitive offloading represents the most influential factor driving work engagement. Evidence from PLS-SEM, ANN, fsQCA, and NCA collectively suggests that transferring routine and repetitive cognitive tasks to AI enables employees to preserve mental resources and redirect their attention toward higher-value activities such as creativity, innovation, and complex problem-solving. Organizations should therefore move beyond a culture of AI restriction and instead develop training programs that help employees engage in strategic cognitive offloading, allowing AI to handle routine work while human employees concentrate on activities requiring judgment, creativity, and strategic thinking.

Finally, the findings raise important concerns regarding organizational risk management in the age of generative AI. The non-significant moderating effects of perceived AI hallucination suggest that employees' awareness of AI inaccuracies does not necessarily increase their vigilance nor reduce their reliance on AI. This finding reveals the persistence of automation bias, whereby the desire for efficiency and cognitive resource conservation outweighs concerns about potential AI errors. As a result, organizations should not rely solely on employees to manually verify AI-generated outputs. Instead, companies must establish robust AI governance mechanisms, including human-in-the-loop verification procedures, peer-review systems for critical decisions, automated validation tools, and clear accountability structures for AI-assisted work. Such safeguards are essential for balancing the productivity benefits of AI with the need to maintain accuracy, reliability, and organizational accountability.

10.3. Limitations and future research

Despite the theoretical, methodological, and practical contributions of this study, several limitations should be acknowledged, which simultaneously provide promising directions for future research.

First, this study adopted a cross-sectional research design, which limits the ability to establish definitive causal relationships among the investigated constructs. Although the combined application of PLS-SEM, ANN, fsQCA, and NCA offers complementary explanatory, predictive, configurational, and necessity-based insights, the observed relationships capture only a single point in time. Given that AI dependence and work engagement are dynamic psychological states that may evolve as employees accumulate experience with AI technologies, future research should employ longitudinal designs, diary studies, or experimental approaches to examine how work stress gradually develops into instrumental and emotional dependence and how cognitive offloading influences engagement over extended periods.

Second, the generalizability of the findings may be constrained by the demographic and contextual characteristics of the sample. The study was conducted among 236 employees working in multinational corporations (MNCs) in Vietnam, with the majority of respondents belonging to the younger workforce segment. While this population represents one of the most active groups of generative AI users, the findings may not fully reflect the experiences of older employees or individuals working in different organizational contexts, such as small and medium-sized enterprises or public-sector organizations. Future studies are therefore encouraged to validate the proposed framework across different industries, age groups, and cultural settings to determine whether the mechanisms underlying AI dependence vary across organizational and societal contexts.

Third, this study relied on self-reported data, which may be susceptible to subjective biases. Although multiple statistical procedures were conducted to assess common method bias and the results indicated no serious validity concerns, self-reported assessments of cognitive vigilance and cognitive offloading may still be influenced by social desirability

bias or inaccuracies in self-perception. Future research should complement survey-based approaches with objective behavioral indicators, such as system usage logs, digital trace data, eye-tracking techniques, or supervisor-rated performance evaluations. Such approaches would provide a more comprehensive understanding of how employees interact with AI systems and respond cognitively in real workplace settings.

Finally, the boundary conditions surrounding AI dependence warrant further investigation. Contrary to expectations, perceived AI hallucinations did not significantly moderate the relationships between AI dependence and cognitive responses. This finding highlights the potential influence of automation bias and suggests that the mechanisms governing employees' reliance on AI remain only partially understood. Future studies should therefore explore additional moderators at both the individual and organizational levels. Individual characteristics such as AI literacy, technological self-efficacy, and personality traits may influence how employees respond to AI dependence, while organizational factors including AI governance policies, leadership support, and psychological safety may shape whether AI is used as a strategic cognitive resource or develops into maladaptive overreliance. Furthermore, although cognitive offloading emerged as a powerful driver of work engagement in the present study, future research should examine its potential long-term consequences, particularly whether excessive reliance on AI may eventually contribute to cognitive deskilling, diminished critical thinking, or erosion of professional expertise.

Ethical declaration

Ethics Committee approval was obtained from the Institutional Ethics Committee prior to the commencement of the study. Confirmation that informed consent was obtained from the study participants; confirmation that the guidelines outlined in the Declaration of Helsinki were followed.

CRedit authorship contribution statement

Ching-Tsung Jen: Conceptualization, Methodology, Supervision, Validation, Writing – review & editing. **Wen-Min Lu:** Methodology, Validation, Supervision, Resources, Writing – review & editing. **Tran Quoc Sang:** Formal analysis, Investigation, Data curation, Visualization, Writing – original draft, Writing – review & editing.

Consent to participate

For all research involving human subjects, freely-given, we have informed consent to participate in the study obtained from participants.

Declaration of competing interest

The authors certify that they have no known financial or personal interests that could be interpreted as influencing or compromising the integrity of the work presented in this paper.

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