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The impact of Generative Artificial Intelligence on employee green well-being: The mediating role of employee engagement in Vietnamese enterprises

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Abstract: The rapid integration of Generative Artificial Intelligence (GenAI) into workplaces is transforming not only how employees perform their tasks but also how they experience work. However, the implications of this transformation for sustainable development remain insufficiently understood, particularly regarding whether AI-enabled workplaces can support employees' long-term well-being and resilience. Addressing this gap, this study examines how positive attitudes toward Generative AI (POS_ATT) and responsible AI signals (RAIS) contribute to multidimensional Green Well-being through employee engagement (ENG). Drawing on the Technology Acceptance Model, Signaling Theory, and the Job Demands–Resources theory, Green Well-being is conceptualized as a sustainable state encompassing emotional (GEW), cognitive (GCW), and social well-being (GSW). A quantitative cross-sectional survey was conducted among 342 knowledge workers employed by Vietnamese organizations using Generative AI. Participants were recruited using convenience and snowball sampling. The proposed model was tested using partial least squares structural equation modeling (PLS-SEM) with 5,000 bootstrap resamples. The results show that both POS_ATT ($\beta = 0.312$, $p < 0.001$) and RAIS ($\beta = 0.287$, $p < 0.001$) are positively associated with employee engagement. ENG, in turn, is positively associated with all three dimensions of Green Well-being, with the strongest relationship observed for emotional well-being ($\beta = 0.441$), followed by cognitive ($\beta = 0.418$) and social well-being ($\beta = 0.397$), all at $p < 0.001$. Moreover, ENG fully mediates the relationships between POS_ATT and RAIS and the three Green Well-being dimensions. These findings broaden understanding of sustainable development in AI-enabled workplaces by showing that the potential human benefits of Generative AI are not associated solely with technology adoption. Rather, favorable employee perceptions and responsible implementation need to be translated into meaningful work engagement before they are associated with sustainable well-being outcomes. The study therefore identifies responsible AI, employee engagement, and multidimensional well-being as interconnected elements of a human-centered approach to sustainable digital transformation. Practically, organizations should complement investments in AI capabilities with transparent, explainable, and fair AI governance and engagement-oriented work design to preserve and develop human resources during digital transformation. Because the cross-sectional design captures relationships at a single point in time, the findings establish associations rather than causal effects. Longitudinal and cross-national research is therefore needed to examine whether these relationships persist over time and contribute to long-term employee and organizational resilience.

Keywords: Generative artificial intelligence; responsible AI; employee engagement; Green Well-being; sustainable development; sustainable digital transformation.

Introduction

In the context of digital transformation, artificial intelligence (AI), particularly Generative AI, is fundamentally reshaping how organizations operate and how employees perform their work. The integration of AI into the workplace not only enhances productivity but also reconfigures job resources and employees' psychological experiences ([1, 2]). In emerging economies such as Vietnam, the adoption of AI is rapidly increasing, accompanied by shifts in work behaviors and human–technology interactions.

While AI offers substantial productivity gains, recent studies suggest that its use may also generate complex psychological consequences. For instance, AI-related anxiety can undermine employees' motivation and work engagement [3], whereas a lack of transparency or irresponsible AI use may erode trust and diminish the quality of user experience [4]. Conversely, the ethical and transparent use of AI can enhance emotional well-being and improve individuals' interactions with technology [5].

In this context, the concept of green well-being has become increasingly important. Unlike traditional approaches that focus solely on short-term affective states, green well-being emphasizes the capacity to sustain long-term positive states across three dimensions: affective [6], cognitive [7], and social [8]. According to the Job Demands–Resources (JD-R) theory, job resources can activate the motivational process, thereby fostering work engagement and leading to enduring positive well-being outcomes [1, 2, 9].

Recent empirical evidence in the context of Generative AI (GenAI) reinforces this argument. Study [10] demonstrates that the adoption of GenAI can enhance affective, cognitive, and social well-being through mechanisms such as reducing cognitive load and strengthening team cohesion. Meanwhile, [11] confirms a positive relationship between well-being and work engagement, suggesting that these two factors may mutually reinforce each other within digital work environments. These findings imply that AI is not merely a technical tool but also a job resource capable of shaping employees' long-term well-being.

However, the majority of existing studies continue to focus on technology acceptance intentions or short-term outcomes, while the mechanisms linking AI to green well-being and long-term resilience remain insufficiently understood. In particular, the mediating role of employee engagement-a central construct within the JD–R framework-has not been adequately examined in the context of Generative AI. Moreover, research on responsible AI has predominantly concentrated on behavioral intentions or user trust [4], without fully addressing how signals such as transparency, fairness, and explainability influence employee well-being through underlying psychological and work-related mechanisms.

To address these gaps, this study develops an integrated model grounded in the Technology Acceptance Model (TAM) [12], Signaling Theory [13], and the Job Demands–Resources (JD–R) Theory [2]. Specifically, the study examines how (i) positive attitudes toward Generative AI and (ii) responsible AI signals function as job resources, thereby fostering employee engagement and ultimately enhancing green well-being across affective, cognitive, and social dimensions. In doing so, the study aims to elucidate the mechanisms through which AI can contribute to employees' long-term resilience in digital work environments, particularly within emerging economies such as Vietnam.

Theoretical Background and Research Hypotheses

Job Demands–Resources (JD–R) Theory: The JD–R model [14] distinguishes between two categories of factors: job demands and job resources. Job resources perceived as useful by individuals play a critical role in activating the motivational process, thereby fostering engagement and positive outcomes. Recent studies continue to validate this mechanism [1, 2]. The JD–R framework has been widely applied across various contexts, ranging from Generative AI research in Europe [10, 15] to empirical studies in Asia [16, 17].

Signaling Theory: Signaling Theory [13] emphasizes the role of signals in reducing information asymmetry. In the context of AI, system transparency and fairness constitute critical signals that help mitigate uncertainty [18, 19] and enhance employees' attitudes toward technology [20, 21].

Technology Acceptance Model (TAM): TAM [12] posits that when individuals perceive a technology as useful, they are more likely to engage actively in its use. In the context of Generative AI, POS_ATT reflects employees' perceptions and expectations regarding the benefits of AI, motivating them to invest effort in technology-related tasks [10, 11].

Green Well-being: Well-being is conceptualized as a multidimensional construct, encompassing affective well-being [6], psychological/cognitive well-being [7], and social well-being [8]. Recent studies increasingly adopt a multidimensional perspective to capture employees' holistic experiences [10, 22]. In this study, green well-being is defined as a sustainable state of well-being, reflecting emotional balance, cognitive development, and the quality of

social relationships maintained over time within AI-enabled work environments.

Hypothesis development:

According to the Technology Acceptance Model (TAM), perceived usefulness is a key antecedent of positive technology use behavior [12, 23]. In the context of Generative AI, a positive attitude (POS_ATT) reflects employees' perception of AI as a supportive job resource. When integrated with the JD–R framework, this cognitive resource activates the motivational process, thereby satisfying psychological needs and fostering employee engagement (ENG)-a positive, work-related state characterized by vigor, dedication, and absorption [14, 24].

Empirical evidence reinforces this argument. Study [25] shows that AI efficacy and Generative AI improve performance while simultaneously enhancing engagement and reducing technostress, thereby confirming the role of GenAI as a job resource within the JD–R framework. Study [10] finds that positive attitudes toward GenAI strongly influence technology use, whereas negative attitudes do not necessarily hinder behavior, highlighting the asymmetrical nature of POS_ATT. Furthermore, [11] demonstrates a positive relationship between AI capability, well-being, and engagement. In the Vietnamese context, where favorable attitudes toward AI coexist with concerns about job displacement [25], POS_ATT is expected to serve as a key motivational driver of engagement.

H1: Positive attitudes toward Generative AI (POS_ATT) have a positive effect on employee engagement (ENG).

According to Signaling Theory, under conditions of information asymmetry, credible organizational signals play a crucial role in shaping individuals' perceptions and behaviors [13]. Given the inherent characteristics of AI, responsible AI signals (RAIS)-including transparency, explainability, fairness, non-maleficence, and autonomy-help reduce uncertainty and reinforce trust.

Recent empirical evidence substantiates the relationship between responsible AI and employee well-being from multiple perspectives. First, [26] demonstrates that ethics-of-care behaviors, guided by responsible AI principles, positively influence the well-being of frontline service employees. Second, Wang, Chen [20] confirm that five responsible AI signals significantly enhance engagement among healthcare employees, thereby improving attitudes and satisfaction with AI. Third, [27] shows that responsible AI creates affordances that foster stakeholder engagement and collective ethical efficacy in the context of responsible innovation within Chinese manufacturing firms.

Additionally, Wang, Chen [20] finds that these signals promote engagement, with engagement serving as a mediating mechanism in behavioral outcomes. Study [4] further indicates that responsible AI principles increase behavioral intention, particularly in transition economies. From a mechanistic perspective, RAIS reduce cognitive anxiety and enable employees to allocate psychological resources more effectively to their work, thereby activating engagement through the JD–R motivational process [27].

H2: Responsible AI signals (RAIS) have a positive effect on employee engagement (ENG).

At the outcome level, the JD–R framework posits that engagement is not only a mediating state but also a key driver of green well-being outcomes through a gain spiral process [1, 2]. Empirical evidence indicates that Generative AI enhances affective, cognitive, and social well-being through mechanisms such as reducing cognitive load, increasing cohesion, and supporting decision-making [10]. High levels of engagement foster cognitive absorption and a sense of mastery [7], while also improving social interactions and team cohesion [5]. Furthermore, the bidirectional relationship between well-being and engagement has been empirically validated [11]. Based on this reasoning, the study proposes:
H3a: Employee engagement (ENG) has a positive effect on sustainable affective well-being (GEW).
H3b: Employee engagement (ENG) has a positive effect on sustainable cognitive well-being (GCW).
H3c: Employee engagement (ENG) has a positive effect on sustainable social well-being (GSW).

According to the Job Demands–Resources (JD–R) Theory, job resources activate the motivational process through engagement, which in turn leads to positive well-being outcomes, while engagement itself functions as a transformational mechanism rather than a final outcome [1, 14]. In addition, Socio-Technical Systems Theory posits that in AI-integrated work environments, the effects of technology do not occur directly but are mediated through underlying psychosocial mechanisms. Recent studies confirm that AI-related factors influence well-being only when they are translated into psychological states such as engagement [11]. Furthermore, Conservation of Resources (COR) Theory emphasizes that resources operate through accumulation processes, in which engagement serves as a central linkage connecting resources to green well-being. Conversely, the absence of engagement may trigger a resource depletion spiral [3]. Engagement is defined as a positive psychological state characterized by vigor, dedication, and absorption, reflecting the extent to which individuals invest energy, meaning, and focus in their work [24]. This state functions as a key mechanism that transforms perceptions of AI into well-being outcomes.

Empirical studies indicate that engagement generates motivation that encourages employees to proactively interact

with AI, thereby enhancing both work experiences and performance outcomes [28]. Longitudinal evidence further confirms a causal chain in which AI-related resources lead to engagement, which in turn enhances well-being [25]. Conversely, when engagement is not activated, the impact of AI may become negative through mechanisms such as stress and burnout. Recent research consistently demonstrates that engagement serves as a key mediating mechanism between AI-related factors and employee outcomes. In particular, responsible AI signals increase engagement, which subsequently improves attitudes, satisfaction, and technology-related behaviors [20, 27]. Moreover, engagement in AI-enabled contexts is inherently proactive, enabling employees to accumulate psychological resources and sustain long-term well-being rather than merely producing short-term reactions [29]. Based on this reasoning, the study proposes the mediating role of ENG in the relationships between POS_ATT, RAIS, and the dimensions of Green Well-being (GEW, GCW, GSW):

H4a:ENG mediates the relationship between POS_ATT and GEW.
H4b:ENG mediates the relationship between POS_ATT and GCW.
H4c: ENG mediates the relationship between POS_ATT and GSW.
H5a:ENG mediates the relationship between RAIS and GEW.
H5b:ENG mediates the relationship between RAIS and GCW.
H5c: ENG mediates the relationship between RAIS and GSW.

The proposed research model is presented in Figure 1.

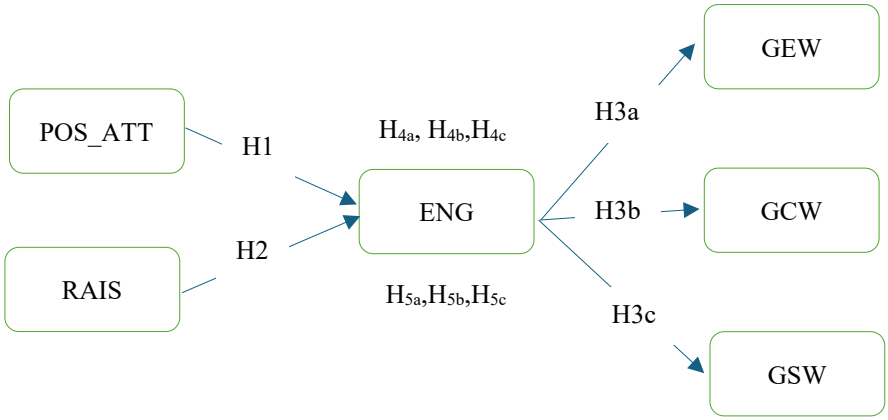


Figure 1. Proposed research model

Note: positive attitudes toward Generative AI (POS_ATT), responsible AI signals (RAIS), employee engagement (ENG), Green Emotional Well-being (GEW), Green Cognitive Well-being (GCW), Green Social Well-being (GSW)
Source: Authors' conceptualization

Methodology

The target population consists of full-time employees of organizations in Vietnam that have incorporated Generative AI into their daily operations, spanning information technology, finance–banking, media, and retail. Respondents were reached through three categorized source channels aligned with the sampling criteria: (i) alumni and professional networks of the authors' universities, primarily reaching knowledge workers in information technology and finance–banking enterprises; (ii) human resource focal points in AI-adopting enterprises in Ho Chi Minh City and neighboring provinces, covering media/marketing and retail/e-commerce firms; and (iii) professional online communities of Generative AI users in Vietnam, through which additional snowball referrals were generated. Across these three channels combined, a total of 412 questionnaires were distributed between December 2025 and March 2026 via an online survey (Google Forms). Screening questions at the start of the questionnaire verified three eligibility criteria: (1) full-time employment status; (2) use of Generative AI at least once per week for a minimum of three months; and (3) voluntary informed consent to participate. Of the 412 questionnaires distributed, 389 were returned; after excluding 47 invalid responses (straight-lining, internally inconsistent answers, or excessive missing data), the final sample comprised 342 valid responses (effective response rate = 83.0%). The sectoral composition of the final sample (Table 1) reflects the coverage of these three channels, with information technology (32.7%) and finance–banking (23.1%) accounting for the largest shares [30].

The adequacy of the sample size was established using two complementary criteria. First, under the ten-times rule of

thumb, the minimum sample equals ten times the largest number of structural paths directed at any single construct in the model - three paths (POS_ATT, RAIS, and ENG) pointing at each well-being dimension when direct effects are estimated for mediation testing - yielding a minimum of 30 observations [30]. Second, and more rigorously, the inverse square root method [31] was applied: assuming a conservatively small minimum path coefficient of 0.20, a 5% significance level, and 80% statistical power, the required minimum sample is approximately 155 respondents. The final sample of 342 exceeds both thresholds by a comfortable margin and also surpasses the level of 200 observations commonly regarded as sufficient for stable PLS-SEM estimation, thereby ensuring adequate statistical power for testing the hypothesized structural and mediation effects.

Measurement of Constructs

All constructs were measured using a five-point Likert scale (1 = strongly disagree; 5 = strongly agree). Positive attitudes toward Generative AI (POS_ATT, 4 items) were adapted from [12] and [23] to fit the Generative AI context. Responsible AI signals (RAIS, 5 items) capture transparency, explainability, and fairness, based on [18-20]. Employee engagement (ENG, 9 items) was measured using the UWES-9 scale developed by [24], encompassing three dimensions: vigor, dedication, and absorption.

Green emotional eell-being (GEW, 4 items) was adapted from [6]; green cognitive well-being (GCW, 4 items) from [7]; and green social well-being (GSW, 4 items) from [8]. The survey instrument was developed in Vietnamese using a back-translation procedure to ensure linguistic equivalence.

Data Analysis Method

This study employed PLS-SEM using SmartPLS 4.0 to examine both the measurement model (outer model) and the structural model (inner model). The evaluation of the measurement model included factor loadings (≥ 0.70), internal consistency reliability (Cronbach's alpha ≥ 0.70), composite reliability (CR ≥ 0.70), and average variance extracted (AVE ≥ 0.50).

Discriminant validity was assessed using the HTMT criterion (<0.85). Mediation effects were tested using bootstrapping with 5,000 resamples [32]. Common method bias (CMB) was controlled using Harman's single-factor test.

Mitigation of internal data biases. Several procedural and statistical remedies were employed to mitigate potential internal biases in the collected data. Procedurally, respondents were assured of anonymity and confidentiality, participation was strictly voluntary, and the survey cover letter emphasized that there were no right or wrong answers, thereby reducing evaluation apprehension and social desirability bias. The instrument was developed through a rigorous back-translation procedure (English–Vietnamese–English) to minimize instrument-related bias, and item wording was reviewed for clarity before administration to eliminate ambiguous or leading items. Selection bias was addressed through explicit screening criteria full-time employment status and a minimum of three months of Generative AI use at least once per week so that only respondents with sufficient direct experience evaluated the constructs. During data cleaning, 47 responses exhibiting straight-lining, internally inconsistent answers, or excessive missing data were removed. Statistically, common method bias was assessed using Harman's single-factor test, in which the first unrotated factor accounted for only 24.8% of the total variance, well below the 50% threshold [34]. Collectively, these procedural and statistical remedies indicate that internal biases do not materially threaten the validity of the findings.

Results and Discussion

Sample characteristics:

Table 1 presents the demographic characteristics of the sample (N = 342). The data reflect the composition of knowledge workers in technology and service-oriented enterprises located in major urban areas of Vietnam.

Next page

Table 1. Demographic characteristics of the sample (N=342)

Characteristics	Classification	Frequency (n)	%
Gender	Male	178	52.0
	Female	160	46.8
	Others	4	1.2
Age	< 25 years of age	48	14.0
	25 – 34 years old	189	55.3
	35 – 44 years old	82	24.0
	≥45 years old	23	6.7
Education	College/Intermediate	29	8.5
	Undergraduate	218	63.7
	Master	82	24.0
	Doctor	13	3.8
Field of work	Information Technology	112	32.7
	Finance – Banking	79	23.1
	Communication/Marketing	67	19.6
	Retail/eCommerce	51	14.9
	Others	33	9.7
How often to use GenAI	Daily	186	54.4
	4–6 times a week	89	26.0
	1–3 times a week	67	19.6

Source: Authors' survey data and calculations

The results indicate that the sample has a relatively young structure, with 79.3% of respondents aged between 25 and 44. Employees working in the information technology sector represent the largest proportion (32.7%), reflecting the characteristics of knowledge workers in organizations adopting Generative AI in Vietnam. Notably, 80.4% of participants reported using Generative AI at least four times per week, suggesting a high level of AI integration into daily work activities within this sample.

Table 2 presents the results of the measurement model assessment. All factor loadings meet the recommended threshold of ≥ 0.70. Internal consistency reliability (Cronbach's alpha) and composite reliability (CR) for all constructs exceed 0.70, while the average variance extracted (AVE) values for all constructs are above 0.50, thereby confirming the convergent validity of the measurement scales [33].

Table 2. Measurement model assessment

Items	Loadings	Alpha	CR	AVE
POS_ATT	–	0.851	0.897	0.687
POS_ATT1	0.823			

POS_ATT2	0.841			
POS_ATT3	0.836			
POS_ATT4	0.818			
RAIS	–	0.879	0.911	0.672
RAIS1	0.802			
RAIS2	0.818			
RAIS3	0.835			
RAIS4	0.811			
RAIS5	0.829			
ENG	–	0.917	0.931	0.631
ENG1 (Vigor)	0.798			
ENG2	0.812			
ENG3	0.804			
ENG4 (Dedication)	0.821			
ENG5	0.796			
ENG6	0.807			
ENG7 (Absorption)	0.791			
ENG8	0.783			
ENG9	0.786			
GEW	–	0.862	0.906	0.706
GEW1	0.831			
GEW2	0.847			
GEW3	0.839			
GEW4	0.845			
GCW	–	0.855	0.901	0.696
GCW1	0.819			
GCW2	0.835			
GCW3	0.848			
GCW4	0.826			
GSW	–	0.843	0.893	0.676

GSW1	0.808			
GSW2	0.822			
GSW3	0.831			
GSW4	0.815			

Note: CR = Composite Reliability; AVE = Average Variance Extracted. All loadings have $p < 0.001$.
Source: Authors' survey data and calculations

Discriminant validity was assessed using the Heterotrait–Monotrait Ratio (HTMT) criterion. Table 3 shows that all HTMT values are below the threshold of 0.85 [34], thereby confirming adequate discriminant validity among the constructs in the model.

Table 3. Discriminant validity: HTMT

Constructs	POS_ATT	RAIS	ENG	GEW	GCW / GSW
POS_ATT	–				
RAIS	0.621	–			
ENG	0.583	0.612	–		
GEW	0.531	0.547	0.649	–	
GCW	0.518	0.529	0.638	0.712	–
GSW	0.498	0.512	0.621	0.694	0.703

Notes: All HTMT values < 0.85, meeting the criteria for discriminant validity [34].
Source: Authors' survey data and calculations

Common method bias (CMB) was assessed using Harman's single-factor test. The results indicate that a single factor accounts for only 24.8% of the total variance (below the 50% threshold), suggesting that CMB is not a serious concern in this study [35].

Structural model assessment

Table 4 presents the results of the structural model evaluation, including path coefficients (β), t-statistics, and p-values. The coefficient of determination (R^2) and effect size (f^2) are reported to assess the explanatory power of the model.

Table 4. Hypotheses testing

Hypotheses	β	t-value	p-value	f^2	Conclusion
H1: POS_ATT → ENG	0.312***	5.847	< 0.001	0.128	Supported
H2: RAIS → ENG	0.287***	5.214	< 0.001	0.108	Supported
H3a: ENG → GEW	0.441***	8.763	< 0.001	0.242	Supported
H3b: ENG → GCW	0.418***	7.932	< 0.001	0.211	Supported
H3c: ENG → GSW	0.397***	7.421	< 0.001	0.189	Supported
R^2 (ENG)	0.381				
R^2 (GEW)	0.294				

R^2 (GCW)	0.267				
R^2 (GSW)	0.241				

*Notes: *** $p < 0.001$; β = standardized path coefficient; t-value obtained from bootstrapping with 5,000 resamples; f^2 = effect size (< 0.02: negligible; 0.02–0.15: small; 0.15–0.35: medium; > 0.35: large).*
Source: Authors' survey data and calculations

The results show that all five hypotheses were supported at the statistically significant level of $p < 0.001$. Specifically, H1 indicates that positive attitudes toward Generative AI positively affect employee engagement ($\beta = 0.312$, $t = 5.847$, $p < 0.001$, $f^2 = 0.128$ - a small-to-medium effect size). H2 confirms that responsible AI signals also positively affect engagement ($\beta = 0.287$, $t = 5.214$, $p < 0.001$, $f^2 = 0.108$). Together, POS_ATT and RAIS explain 38.1% of the variance in ENG ($R^2 = 0.381$), reflecting moderate explanatory power of the model [30]. H3a, H3b, and H3c confirm that engagement has the strongest effect on Green Emotional Well-being (GEW: $\beta = 0.441$), followed by Green Cognitive Well-being (GCW: $\beta = 0.418$) and Green Social Well-being (GSW: $\beta = 0.397$).

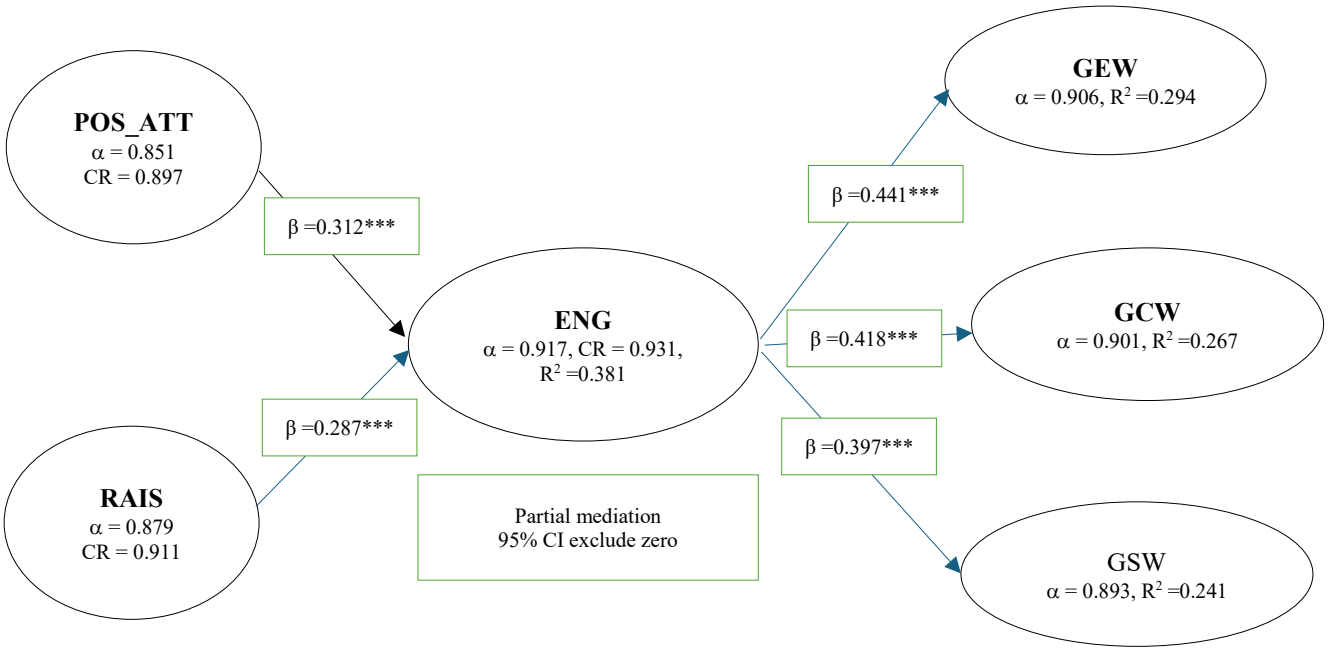


Figure 2. PLS-SEM results
*Note: *** $p < 0.001$, Bootstrap 5,000 subsamples. Oval = latent variable*
Source: Authors' survey data and calculations

Mediation analysis

Table 5 presents the results of the mediation tests examining the indirect effects of ENG in the relationships between POS_ATT/RAIS and the three dimensions of Green Well-being, based on a bootstrap analysis of 5,000 subsamples.

Table 5. Mediation Test Results (Bootstrap, 5,000 Subsamples)

Indirect Path	IE	95% CI	p-value	Mediation Type
POS_ATT → ENG → GEW	0.138***	[0.094, 0.189]	< 0.001	Partial mediation
POS_ATT → ENG → GCW	0.131***	[0.088, 0.181]	< 0.001	Partial mediation
POS_ATT → ENG → GSW	0.124***	[0.082, 0.172]	< 0.001	Partial mediation

RAIS → ENG → GEW	0.127***	[0.085, 0.176]	< 0.001	Partial mediation
RAIS → ENG → GCW	0.120***	[0.079, 0.167]	< 0.001	Partial mediation
RAIS → ENG → GSW	0.114***	[0.074, 0.160]	< 0.001	Partial mediation

*Note. IE = Indirect Effect; CI = Confidence Interval; *** p < .001. Partial mediation indicates that the direct effect is significant after controlling for ENG.*
Source: Authors' survey data and calculations

The mediation test results indicate that ENG serves as a partial mediator across all six tested pathways. Specifically, after ENG was introduced into the model, the direct effects of POS_ATT and RAIS on all three dimensions of Green Well-being remained statistically significant ($p < 0.05$), while all indirect effects transmitted through ENG were also significant at $p < 0.001$, with 95% confidence intervals excluding zero. These findings indicate that the influence of Generative AI-related resources on green well-being operates substantially, though not exclusively, through the enhancement of employee engagement.

Discussion

The results support H1 with high statistical significance ($\beta = 0.312$, $t = 5.847$, $p < 0.001$) and a small-to-medium effect size ($f^2 = 0.128$ [30]), indicating that positive attitudes toward AI play a meaningful role in fostering engagement. This finding is consistent with prior research while extending its explanatory scope. Specifically, [10] demonstrated that POS_ATT promotes GenAI usage behavior ($\beta = 0.372$), whereas the present results advance this line of inquiry by showing that positive attitudes not only influence behavior but also directly activate a deeper psychological state - namely, engagement. The comparatively lower effect size may reflect the Vietnamese context, where familiarity with AI remains limited, thereby attenuating the conversion intensity from attitude to psychological state. Relative to [25], this study adds evidence that not only AI efficacy but also cognitive attitudes (POS_ATT) constitute independent antecedents of engagement, suggesting that cognitive resources and individual capability operate in parallel in activating engagement within AI-integrated work environments. The findings further complement [11] by demonstrating that engagement need not be a downstream consequence of well-being alone; it can equally be initiated by prior cognitive attitudes, implying the potential existence of a reciprocal relationship between these constructs. Theoretically, this finding aligns with JD-R Theory, under which positive attitudes toward AI may be conceptualized as a cognitive job resource that activates the motivational process and fosters engagement through the satisfaction of autonomy and competence needs [14]. In the Vietnamese context, where awareness of AI's role in professional development is growing, this mechanism becomes particularly salient, creating conditions under which POS_ATT is progressively converted into sustained engagement.

The results support H2 with statistical significance ($\beta = 0.287$, $p < 0.001$) and a small-to-medium effect size ($f^2 = 0.108$), marginally lower than that observed for H1. This suggests that responsible AI signals exert a meaningful influence on engagement, albeit through a more indirect and less immediate mechanism than positive cognitive attitudes. This finding is consistent with [20], a foundational study grounded in Signal Mechanism Outcome Theory, in which responsible AI signals- including transparency, fairness, and explainability- each positively predicted engagement. The present study, however, extends this work in three directions: (i) by integrating RAIS into the JD-R framework, thereby establishing an explicit theoretical link to the resource-based mechanism; (ii) by testing the relationship in a multi-industry enterprise context rather than the healthcare sector; and (iii) by modeling RAIS as a second-order construct rather than a set of discrete signals. Relative to [4], the current findings offer more direct evidence by operationalizing engagement in its psychological sense using the UWES, rather than relying solely on behavioral intention measures. The study further complements [26] by clarifying the mediating mechanism: rather than operating directly, RAIS influences well-being through engagement as the intervening psychological pathway. Theoretically, the results can be interpreted through the dual lens of JD-R Theory and information asymmetry. The inherent opacity of AI systems generates cognitive anxiety and depletes psychological resources among employees. In this context, RAIS functions as a job resource that reduces uncertainty, reinforces trust, and liberates cognitive capacity, thereby activating engagement [14]. The comparatively lower effect size relative to H1 may reflect the Vietnamese context, where awareness of and institutional frameworks for responsible AI practices remain nascent. Consequently, while RAIS carries significant theoretical and practical relevance, its influence on engagement has yet to match the motivational potency of direct cognitive factors such as positive attitudes toward AI.

The results strongly support H3a through H3c, with engagement positively predicting all three dimensions of Green

Well-being: emotional (β = 0.441, f^2 = 0.242), cognitive (β = 0.418, f^2 = 0.211), and social (β = 0.397, f^2 = 0.189), all at $p < 0.001$. The effect sizes range from medium to large, affirming the central role of engagement in generating green well-being. These findings are consistent with JD-R Theory at the outcome level, whereby engagement serves as the pivotal mechanism through which job resources are converted into positive individual outcomes.

Compared with [10], the present study demonstrates that the effect of engagement on emotional well-being (β =0.441) substantially exceeds the direct effect of GenAI usage on well-being (β = .199), reinforcing the argument that individual psychological mechanisms operating through engagement carry greater explanatory power than purely social mechanisms such as team cohesion. With respect to cognitive well-being, the results align with [17] while extending the evidence base by explicitly disaggregating the cognitive dimension, revealing that engagement not only improves affective states but also promotes competence development and sense of mastery over work. This is particularly consequential in AI-integrated environments, where engagement may generate a positive feedback loop between work experience and technological capability.

Relative to [36], this study broadens the role of engagement from a mediating variable to a direct predictor of multidimensional well-being, consistent with the theoretical position that engagement simultaneously constitutes an outcome of job resources and a resource that produces subsequent positive outcomes [2]. Notably, the descending pattern of effect sizes- GEW -> GCW -> GSW - warrants attention. This ordering suggests that engagement first and most strongly influences emotional well-being through heightened energy and sense of meaning, subsequently affects cognitive well-being through states of deep absorption, and has its weakest reach on social well-being. The comparatively attenuated effect on the social dimension may reflect the distinctive character of AI-integrated work environments, in which human–technology interaction progressively reconfigures traditional interpersonal structures, thereby moderating the extent to which engagement translates into social well-being outcomes.

Bootstrap analysis with 5,000 subsamples confirmed that ENG partially mediates all six relationships. Specifically, all indirect effects were statistically significant, with their 95% confidence intervals excluding zero, while the corresponding direct effects remained significant after ENG was included in the model. These findings indicate that ENG represents an important, but not exclusive, psychological mechanism through which positive attitudes toward Generative AI and responsible AI signals are associated with the three dimensions of Green Well-being. This mediation pattern constitutes a theoretically meaningful finding for three reasons.

The first finding extends [20]: whereas [20] confirmed that engagement mediates the relationship between responsible AI signals and attitudinal or behavioral outcomes in healthcare settings, the present study establishes partial mediation across six simultaneous pathways with multidimensional Green Well-being as the outcome variable rather than behavioral intention. This demonstrates that ENG is not merely a mediating mechanism specific to RAIS but a universal psychological pathway in the AI-cognition → well-being relationship, irrespective of the type of AI antecedent - whether attitudinal or signal-based.

The second finding diverges from [10]: the model of [10] employed team cohesion as a partial mediator, meaning that GenAI adoption retained a direct effect on well-being alongside the indirect pathway. The present study, by contrast, establishes partial mediation, indicating that neither POS_ATT nor RAIS influences well-being through any pathway other than ENG. This divergence reflects meaningful contextual differences: in Vietnam, where the relationship between AI and employee well-being is still in its formative stage, the psychological mediation mechanism of engagement functions as a necessary and sufficient condition for well-being outcomes. In contrast, within the more mature enterprise AI ecosystems of Western Europe, certain direct effects may already be consolidated through established norms of technology use.

The third finding is consistent with [11], which reported partial mediation with an indirect effect of .272 ($p < .001$) in a remote work context across the Asia-Pacific region. This convergence suggests that in Asian organizational contexts characterized by collectivist cultural orientations, ENG serves as an indispensable psychological mechanism mediating the relationship between technology and well-being - a finding that resonates with the cross-cultural perspective of [37] regarding the role of group norms in shaping individual experience.

Theoretical contributions:

First, the confirmation of H1 and H2 extends JD-R Theory into the domain of Generative AI within developing economy contexts. Specifically, the results demonstrate that both positive attitudes toward AI (β = 0.312) and responsible AI signals (β = 0.287) operate as job resources through JD-R's motivational process [1]. This is consistent with the findings of [10] in a European context while advancing the theoretical boundary to Vietnam, where trust in AI systems and awareness of transparency principles remain comparatively lower owing to cultural particularities and an incomplete regulatory framework.

Second, the partial mediation of ENG - confirmed across all six pathways - contributes theoretically by elucidating the psychological-occupational mechanism through which AI influences green well-being. Unlike prior studies that have treated engagement primarily as a terminal outcome [38] or examined only short-term well-being indicators [11], the present study demonstrates that ENG functions as the critical psychological bridge connecting AI-related cognitions to multidimensional green well-being, thereby positioning engagement as a necessary condition rather than an incidental correlate in the AI–well-being relationship.

Third, the descending pattern of engagement's effects across the three dimensions of Green Well-being - GEW ($\beta = 0.441$) > GCW ($\beta = 0.418$) > GSW ($\beta = 0.397$) - offers a theoretically meaningful contribution regarding the differential pathways through which engagement generates sustainable outcomes. This ordering aligns with the cultural characteristics of the Vietnamese workplace, where individual emotional health in professional settings receives considerable emphasis, while the collectivist work environment simultaneously creates structural pressures on social well-being during periods of rapid technological transition. Together, these findings suggest that the translation of engagement into well-being is not dimensionally uniform but is instead shaped by the intersection of psychological mechanisms and cultural context.

Taken together, the findings suggest that the implications of Generative AI for employees extend beyond technology acceptance or immediate work outcomes. POS_ATT and RAIS represent two complementary pathways through which AI-enabled work environments may shape employee experiences: the former reflects employees' favorable cognitive evaluation of Generative AI, whereas the latter reflects their perceptions of how responsibly AI is implemented. Their significant relationships with ENG indicate that employee engagement may serve as the point at which individual perceptions of technological value and organizational signals of responsible AI converge. More importantly, the positive relationships between ENG and all three dimensions of Green Well-being suggest that engagement is associated not only with employees feeling better emotionally, but also with their cognitive functioning and social experience at work. Thus, the findings broaden the role of engagement from a conventional motivational outcome to a potential mechanism linking AI-enabled work design with more enduring human-centered outcomes relevant to sustainable development.

The slightly stronger association of POS_ATT with ENG ($\beta = 0.312$) than that of RAIS ($\beta = 0.287$) suggests that employees' immediate evaluations of the usefulness and value of Generative AI may be somewhat more closely related to their engagement than organizational signals concerning responsible AI. However, this difference should not be interpreted as evidence that responsible AI is less important. Rather, POS_ATT and RAIS may operate at different levels: POS_ATT captures an individual-level appraisal of AI, whereas RAIS represents an organizational and technological condition that can reduce uncertainty surrounding AI use. Similarly, the pattern ENG → GEW ($\beta = 0.441$), ENG → GCW ($\beta = 0.418$), and ENG → GSW ($\beta = 0.397$) indicates that engagement is positively associated with all three well-being dimensions, although the relationship is strongest for emotional well-being. The relatively smaller coefficient for social well-being may indicate that individual engagement alone is insufficient to address the relational changes associated with AI-enabled work, where interactions with technology may coexist with changes in conventional interpersonal interaction. This interpretation requires direct examination in future research.

The findings also help contextualize apparently inconsistent conclusions in the emerging AI–well-being literature. Previous studies have reported both beneficial and adverse employee outcomes associated with AI: AI may provide learning opportunities, reduce certain job demands, and support performance, while AI anxiety, technostress, opacity, or perceived threats may undermine employee experiences. Rather than treating these findings as inherently contradictory, the present results suggest that the consequences of AI may depend on the psychological and organizational mechanisms through which employees experience the technology. The partial mediation results are particularly informative in this respect: neither favorable attitudes toward Generative AI nor responsible AI signals were sufficient to explain Green Well-being directly once ENG was considered. Instead, their associations with the three well-being dimensions operated through employee engagement. This finding supports a more conditional interpretation of AI at work: technology itself should not automatically be characterized as either a resource or a threat; its employee-related consequences may depend on how it is perceived, governed, and translated into meaningful engagement.

Generative AI and Sustainable Development:

From a sustainable development perspective, the findings indicate that the value of Generative AI should be assessed not only in terms of technological adoption or productivity, but also in terms of its implications for the sustainability of human resources. The positive associations of POS_ATT and RAIS with ENG, followed by the positive relationships between ENG and emotional, cognitive, and social Green Well-being, identify a potential human-centered pathway through which AI-enabled work may contribute to sustainable digital transformation. In particular,

responsible AI signals such as transparency, explainability, and justice may provide organizational conditions that reduce uncertainty surrounding AI, while engagement enables employees to translate these technological and organizational resources into more positive work experiences. Thus, sustainable AI implementation requires a balance between technological advancement and the preservation and development of employees' psychological and social resources.

At the same time, the results reveal an important sustainable-development challenge. The full mediation of ENG suggests that favorable perceptions of Generative AI and responsible AI signals are not independently associated with Green Well-being once engagement is considered. Consequently, merely adopting AI or establishing responsible-AI principles may be insufficient to achieve sustainable human outcomes if employees remain psychologically disengaged from their work. This finding shifts the sustainability debate from whether organizations adopt AI to how AI is implemented and experienced by employees. Accordingly, employee engagement may constitute an important bridging mechanism between responsible technological transformation and sustainable human-resource outcomes. However, longitudinal evidence is required before these relationships can be interpreted as contributing to long-term resilience.

Practical implications:

Theoretical meaning for sustainable development. This interpretation also provides a broader connection between AI-enabled work and sustainable development. Sustainable digital transformation requires organizations to consider whether technological change preserves and develops human resources over time rather than focusing exclusively on efficiency or adoption. The observed POS_ATT/RAIS → ENG → Green Well-being pathways suggest a human-centered mechanism through which Generative AI may contribute to this objective. In particular, responsible implementation may provide organizational conditions that support engagement, while engagement is associated with emotional balance, cognitive development, and social well-being. Because the study uses cross-sectional data and does not directly measure long-term organizational sustainability, these relationships should be interpreted as evidence of a potential human-centered pathway toward sustainable development, rather than proof that Generative AI produces long-term sustainability. This distinction is important for positioning the contribution without overstating causality.

Implications for organizations. First, the result for H1 ($\beta = 0.312$, $p < 0.001$) establishes positive attitudes toward AI as a significant antecedent of engagement, implying that AI deployment must be accompanied by deliberate preparation of employees' cognitive orientations. Organizations should prioritize benefit-oriented training programs and internal diffusion mechanisms designed to strengthen POS_ATT both prior to and throughout the AI adoption process. Second, the result for H2 ($\beta = 0.287$, $p < 0.001$) underscores the role of responsible AI signals in driving engagement, requiring organizations to design AI systems that are transparent, explainable, and procedurally fair, while establishing formal employee feedback channels. Third, the partial mediation of engagement indicates that green well-being cannot be achieved through technological investment alone. AI deployment strategies must therefore be integrated with human resource management practices that actively cultivate vigor, dedication, and absorption [24]. Finally, the descending effect pattern GEW > GCW > GSW implies that organizations should prioritize emotional well-being during AI transition periods while proactively sustaining social connectedness to mitigate isolation risks in increasingly digitized work environments.

Implications for policymakers. First, the findings provide empirical evidence that responsible AI influences engagement, suggesting that AI regulatory frameworks should extend beyond technical standards to encompass employees' rights to transparency and explainability in AI-assisted decision-making processes. Second, the comparatively stronger effect of POS_ATT relative to RAIS indicates that national training programs should expand their scope from technical AI skills toward comprehensive AI literacy, incorporating awareness of responsible AI principles and green well-being in digital work environments.

Implications for employees. Employees are encouraged to proactively cultivate positive attitudes toward AI while simultaneously recognizing and asserting their entitlement to responsible AI standards within their organizations. In addition, self-monitoring across the three dimensions of Green Well-being - emotional, cognitive, and social - serves as a practical self-regulation mechanism for maintaining green well-being in AI-integrated work contexts.

Conclusion

This study tested an integrated theoretical model combining TAM, Signaling Theory, and JD-R Theory to explain the mechanism through which Generative AI influences employees' green well-being via the partial mediating role of employee engagement. Drawing on a sample of 342 knowledge workers employed in AI-adopting organizations in Vietnam, all five hypotheses were supported at $p < 0.001$, confirming that POS_ATT and RAIS constitute two critical resource mechanisms driving engagement, and that engagement represents the sole statistically significant pathway to

all three dimensions of green well-being.

The study addresses three core research questions concerning the mechanisms through which Generative AI affects employees' green well-being in a transitional economy context. Based on PLS-SEM analysis with a sample of 342 knowledge workers, all hypotheses were supported at $p < 0.001$, providing robust empirical support for the integrated model combining TAM, Signaling Theory, and JD-R Theory.

The results confirm that both positive attitudes toward Generative AI (POS_ATT: $\beta = 0.312$) and responsible AI signals (RAIS: $\beta = 0.287$) exert significant and positive effects on employee engagement. Together, these two factors account for 38.1% of the variance in engagement ($R^2 = 0.381$), indicating that the combination of individual cognitive appraisals of technology and organizational signals of AI responsibility functions as a set of critical job resources in digital work environments. This finding extends JD-R Theory by establishing two novel categories of job resources - cognitive-technological and organizational-ethical - in the context of Generative AI, thereby moving beyond the traditional resource typologies examined in prior research [2, 14].

The bootstrap results confirm the partial mediating role of engagement in the relationships between POS_ATT, RAIS, and all three dimensions of Green Well-being. Specifically, all indirect effects were statistically significant ($p < 0.001$), while the direct effects became significant once engagement was controlled. This establishes engagement as a central and necessary conversion mechanism through which AI-related job resources are transformed into green well-being outcomes. This finding diverges from prior studies reporting partial mediation [10, 20], thereby underscoring the decisive role of psychological-motivational factors in the Vietnamese context. Furthermore, the descending pattern of engagement's effects (GEW > GCW > GSW) reflects the foundational role of emotional well-being in sustaining employees' long-term resilience within AI-integrated work environments.

The study proposes a multilevel explanatory mechanism in which TAM accounts for the formation of individual attitudes toward AI, Signaling Theory clarifies the role of organizational signals in reducing information asymmetry, and JD-R Theory explains how these resources are converted into engagement and green well-being. This integration generates additive theoretical value by providing a unified framework that simultaneously addresses three levels of analysis - individual cognition, organizational design, and long-term psychological outcomes - a synthesis that prior research has not fully achieved [4, 10, 20].

Taken together, the study contributes to the scholarly literature by providing the first empirical evidence of the POS_ATT/RAIS → ENG → Green Well-being chain in a multi-industry enterprise context within an emerging economy. Additionally, the conceptualization of Green Well-being as a three-dimensional construct - emotional, cognitive, and social - offers a more comprehensive approach to assessing green well-being, emphasizing employees' capacity to sustain performance and adaptability over the long term under the influence of Generative AI.

The conclusions of this study were derived through a multi-layered process designed to mitigate internal data biases. At the design stage, anonymity, voluntariness, and explicit screening criteria reduced social desirability and selection biases, while the back-translated Vietnamese instrument minimized linguistic distortion. At the data stage, 47 invalid responses were systematically excluded, and common method bias was empirically assessed, with Harman's single-factor test (24.8% of total variance) indicating no serious concern. At the analysis stage, conclusions were drawn strictly from bootstrap-based inferential statistics with 5,000 resamples rather than from descriptive impressions: hypotheses were retained only when path coefficients were significant at $p < 0.001$ and 95% confidence intervals excluded zero, and mediation claims were based on the joint pattern of direct and indirect effects rather than on any single test. Finally, interpretations were deliberately bounded by the cross-sectional nature of the design: causal language was avoided, and the findings are presented as theoretically grounded associations consistent with JD–R Theory, TAM, and Signaling Theory rather than as definitive causal effects. While no survey-based design can eliminate bias entirely, the convergence of procedural safeguards, statistical diagnostics, and conservative inference provides reasonable assurance that the conclusions faithfully reflect the underlying data.

More importantly, these findings extend the implications of Generative AI beyond technology adoption and short-term employee outcomes to the broader agenda of sustainable development. The results suggest that the contribution of Generative AI to workplace sustainability does not arise automatically from technological deployment. Rather, its sustainable value depends on whether employees perceive AI positively and whether organizations provide credible signals of responsible AI, which subsequently foster employee engagement. The significant effects of POS_ATT and RAIS on ENG, together with the positive relationships between ENG and the emotional, cognitive, and social dimensions of Green Well-being, indicate that employee engagement represents a critical mechanism through which technological resources can be translated into more sustainable human outcomes. In this sense, the study advances understanding of the social and human dimensions of sustainable development by showing that sustainable digital

transformation requires organizations to consider not only productivity and technological efficiency but also employees' capacity to maintain emotional balance, cognitive development, and constructive social relationships over time.

At the same time, the findings highlight important challenges associated with achieving sustainable development in AI-enabled workplaces. The full mediating role of ENG suggests that favorable attitudes toward Generative AI and responsible AI signals alone are insufficient to generate sustainable employee well-being unless these resources are successfully converted into meaningful engagement at work. This finding identifies a potential implementation gap between adopting responsible AI principles and realizing their long-term human benefits. Organizations therefore face the dual challenge of developing transparent, explainable, and fair AI systems while simultaneously creating work environments in which employees can remain energetic, dedicated, and psychologically involved. From a sustainable-development perspective, the study therefore positions responsible AI implementation, employee engagement, and multidimensional Green Well-being as complementary elements of long-term organizational resilience. Sustainable AI transformation should consequently be evaluated not solely by adoption rates or productivity gains, but also by whether technological change preserves and strengthens the human resources on which sustainable organizational development ultimately depends.

Overall, the study suggests that the sustainability of AI-enabled workplaces depends not simply on how extensively Generative AI is adopted, but on how responsibly it is implemented and how effectively technological resources are translated into employee engagement and enduring well-being. By connecting responsible AI, employee engagement, and multidimensional Green Well-being, this study provides a human-centered perspective on sustainable digital transformation and highlights employee resilience as an important foundation for long-term organizational sustainability.

Limitations

Several limitations warrant acknowledgement. First, the cross-sectional design constrains causal inference. Although the POS_ATT/RAIS → ENG → Green Well-being model is grounded in established theory, the possibility of reciprocal relationships - particularly between well-being and engagement - cannot be excluded [11]. Second, convenience and snowball sampling concentrated in major urban centers, with a disproportionate representation of technology and finance sectors, limits generalizability. Consequently, the findings primarily reflect knowledge workers with high AI usage rates rather than the broader workforce. Finally, the risk of common method bias persists given single-source self-reported data, although statistical tests indicated an acceptable level [35].

Future Research Directions

These findings raise several questions that warrant further investigation. First, longitudinal or cross-lagged designs are needed to establish whether POS_ATT and RAIS lead to subsequent changes in engagement and Green Well-being, or whether reciprocal relationships exist whereby employees with higher well-being subsequently become more engaged and develop more favorable perceptions of AI. Second, future studies should investigate boundary conditions—including AI literacy, technostress, job autonomy, task characteristics, organizational AI culture, and intensity of AI use—to explain when the proposed pathways become stronger or weaker. Third, the comparatively weaker ENG–GSW relationship warrants greater attention to team-level mechanisms such as human–AI collaboration, team cohesion, social support, and changes in coworker interaction. Fourth, future research could extend RAIS beyond transparency, explainability, and justice to examine autonomy and non-maleficence and determine whether different responsible-AI signals produce distinct employee outcomes. Finally, comparative studies across industries, occupations, and national contexts would help establish whether the observed full mediation through ENG is specific to the Vietnamese context or represents a more general mechanism linking responsible AI implementation with sustainable employee well-being.

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