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AI ANXIETY AND LIFE SATISFACTION AMONG OFFICE WORKERS: THE MEDIATING ROLE OF NEGATIVE AFFECT AND THE MODERATING ROLE OF PERCEIVED SOCIAL SUPPORT

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ABSTRACT

The rapid integration of artificial intelligence (AI) into the workplace creates new opportunities while also posing psychological challenges for employees. This study examined the relationships among AI anxiety (*AIA*), life satisfaction (*LS*), negative affect (*NA*), and perceived social support (*PSS*) among office workers in Ho Chi Minh City. Using a cross-sectional design, data were collected from 292 participants, with 288 valid responses retained for analysis. Pearson correlations and PROCESS Macro Models 4 and 14 were used to test the hypothesized relationships. Results showed that 44.79% of participants reported above-average *AIA*, particularly regarding socio-technical blindness and job replacement anxiety. *AIA* was positively associated with *NA* (r = 0.213, p < 0.001), whereas *NA* was negatively associated with *LS* (r = -0.255, p < 0.001). *NA* partially mediated the relationship between *AIA* and *LS* (B = -0.065, 95% CI [-0.114, -0.028]). However, *AIA* also showed a significant positive direct association with *LS* (r = 0.138, p = 0.019). Furthermore, *PSS* significantly moderated the relationship between *NA* and *LS* (B = 0.129, p = 0.020), weakening the negative effect of *NA* on *LS.* The indirect effect of *AIA* on *LS* through *NA* was non-significant at high levels of *PSS*. Overall, the findings suggest that *AIA* affects *LS* partly through emotional processes, while *PSS* serves as a buffering resource that mitigates the adverse effects of negative emotions. These findings highlight the importance of emotion regulation and social support in promoting employee well-being during AI-driven workplace transformation.

Keywords: AI anxiety, digital transformation, life satisfaction, negative affect, perceived social support.

1. INTRODUCTION

Over the past two decades, artificial intelligence (AI) has emerged as a central pillar of digital transformation, profoundly reshaping job structures, skill requirements, and employees' psychological experiences across various economic and social sectors [1], [2]. According to estimates by the Organization for Economic Co-operation and Development (OECD), approximately 14% of jobs in member countries are at high risk of automation within the next 15–20 years, while nearly 32% are expected to undergo significant changes in task composition, requiring large-scale reskilling and upskilling efforts [3]. Recent reports from the International Labour Organization (ILO) further indicate that the impact of AI is uneven across occupations, with administrative and office-based roles being particularly vulnerable due to the high degree of digitization in information processing, data analysis, and decision-support tasks [1], [2].

In this context of rapid and unpredictable technological change, identifying the specific psychological mechanisms that enable employees to maintain adaptive functioning and subjective well-being is critical. Grounded in the stress-appraisal and coping framework, the relationship between technological stressors and well-being is viewed as a dynamic process of emotional and cognitive evaluation [4]. Central to this process is the affect-as-information framework, which posits that individuals often rely on their current emotional states as informational cues when making global judgments about their life satisfaction [5]. Furthermore, the buffering hypothesis suggests that the detrimental impact of these emotional signals can be mitigated by protective resources, such as perceived social support [6]. In digital work contexts, these resources may function as buffering mechanisms that help employees reinterpret and regulate negative emotional experiences, thereby protecting their life satisfaction from the adverse effects of AI-related pressure.

The increasing integration of AI into the workplace is closely associated with adverse psychological responses, most notably AI anxiety (*AIA*), which refers to a state of fear, tension, and unease related to potential job displacement, continuous learning demands, and the socio-technical opacity of AI systems [7]. Y.-Y. Wang and Y.-S. Wang conceptualize *AIA* as a multidimensional construct encompassing technological learning anxiety, job replacement concerns, socio-technical uncertainty, and perceived lack of control over AI figuration, reflecting emerging psychological challenges unique to the digital transformation era compared to traditional forms of technology-related anxiety [8]. Another perspective suggests that, unlike traditional technostress, *AIA* in contemporary workplaces may be appraised at the primary level not only as a threat but also as a challenge [4]. For professionals in knowledge-intensive sectors, this anxiety may reflect an accelerated awareness of technological shifts, potentially acting as a catalyst for proactive adaptation and engagement, which may coexist with positive life evaluations.

Despite its potential as a challenge, *AIA* inevitably triggers negative affect (*NA*), reflecting emotional states such as distress and unease when demands are perceived to strain personal resources [9], [10]. According to the affect-as-information perspective, these negative emotional responses serve as unfavorable signals during cognitive judgment processes [5]. Consequently, *NA* is expected to function as a key mediating mechanism, translating the psychological strain of AI integration into diminished evaluations of overall life satisfaction (*LS*) [11].

While *NA* typically undermines well-being, the buffering hypothesis emphasizes that the presence of social resources can mitigate these adverse effects [6]. According to the buffering hypothesis, perceived social support (*PSS*) can weaken the relationship between stressors and negative outcomes by enhancing perceived control, reinforcing adaptive beliefs, and facilitating emotional regulation processes [6]. In organizational contexts, *PSS* from colleagues, supervisors, and family not only directly enhances *LS* but also contributes to the development of consequence-buffering resources by helping employees reframe their experiences and maintain a sense of meaning in the face of technological change [11], [12].

In Vietnam, particularly in Ho Chi Minh City - the country's largest economic and technological hub - digital transformation and AI adoption in organizations are accelerating rapidly, yet significant gaps remain in employees' capacity to effectively utilize AI at a deeper level [13], [14]. Surveys conducted in the Asia–Pacific region indicate that approximately 16% of employees are concerned about job displacement due to AI, while many simultaneously face pressure to acquire new skills and cope with increased workloads [15], [16]. Recent labor market reports also reveal a rapid increase in AI tool usage in Vietnam, accompanied by rising perceptions of job insecurity and work overload among office workers, who are particularly exposed to AI-related changes [17], [18].

Despite the growing body of international research on *AIA*, the literature remains fragmented regarding the psychological and social mechanisms through which *AIA* influences *LS*, especially in rapidly developing and digitally transforming contexts such as Vietnam [7], [19]. Existing domestic studies have largely focused on technical and policy aspects of digitalization, with limited attention to the psychological mechanisms governing how office workers in digitally intensive environments like Ho Chi Minh City cope with these shifts. Given that administrative and knowledge-based roles are particularly exposed to AI, there is an urgent need to examine how emotional and social factors interact to shape workforce well-being.

Against this backdrop, the present study aims to test a moderated mediation model grounded in the affect-as-information framework and the buffering hypothesis. By focusing on office employees in Ho Chi Minh City, this study seeks to elucidate the stage-specific mechanisms through which *AIA* influences *LS* via the mediating role of *NA*, and how *PSS* functions as a boundary condition. The findings are intended to provide quantitative evidence on psychological adjustment and offer practical implications for organizations to design supportive systems that mitigate the emotional consequences of AI and promote human capital sustainability.

2. THEORETICAL BACKGROUND - LITERATURE REVIEW

2.1. Theoretical background and hypotheses development

2.1.1. Stress appraisal and coping theory, technostress, and AI anxiety (AIA)

According to Stress appraisal and coping theory, stress is not a direct response to objective events but rather the result of a transactional process between individuals and their environment, where individuals evaluate the significance of events and their available coping resources [4]. During primary appraisal, a stressor such as AI can be perceived in two directions: As a threat to job security or as a challenge that stimulates personal growth.

In the context of rapid digital transformation in dynamic economic centers like Ho Chi Minh City, *AIA* - comprising concerns over job replacement, socio-technical blindness, AI configuration, and constant learning demands - can lead to contrasting consequences for *LS*. On one hand, traditional technostress perspectives suggest that *AIA* creates psychological strain and diminishes *LS* when individuals perceive a lack of coping resources to meet technological demands. On the other hand, anxiety may function as accelerated awareness, prompting employees to proactively prepare, learn, and adapt to master new technologies, which may maintain or even enhance their sense of control and overall *LS* [4]. Given the complex and multidimensional nature of *AIA* in the modern workplace, this study proposes a significant relationship between *AIA* and *LS* without pre-specifying the direction of the association.

H1: *AIA is significantly associated with LS among office workers in Ho Chi Minh City.*

Moreover, based on the stress appraisal–coping process, when AI is perceived as a threat that exceeds perceived coping resources, negative emotional reactions such as anxiety, tension, and unease are likely to intensify. Therefore, *AIA* is expected to be positively related to *NA*.

H2: AIA is positively associated with NA among office workers in Ho Chi Minh City.

2.1.2. Subjective well-being (SWB) and the affect-as-information mechanism

SWB theory conceptualizes happiness as the result of individuals' subjective evaluations of their lives, comprising two main components: (i) a cognitive component, reflected in *LS*, and (ii) an affective component, consisting of positive affect (PA) and negative affect (*NA*) [10], [20]. *LS* represents a cognitive judgment process in which individuals compare their

current life circumstances with self-defined standards and expectations [21], whereas *NA* reflects the frequency and intensity of adverse emotional experiences [9].

To explain how affective states influence cognitive evaluations such as *LS*, the affect-as-information framework proposes that individuals often rely on their current emotional states as informational cues when making global judgments about their lives [5]. When *NA* is salient, individuals tend to evaluate their overall life circumstances less favorably, partly due to the misattribution of transient emotional states to broader life judgments [5]. Extensive quantitative evidence demonstrates a robust negative association between *NA* and *LS* across cultural and occupational contexts [10].

Applied to the context of *AIA*, negative emotions arising from perceived AI-related threats - such as fear of job displacement or loss of control - may permeate the cognitive evaluation process and lower *LS* through the affect-as-information mechanism. Consequently, *NA* is expected to impair *LS* among office workers.

H3: NA is negatively associated with LS among office workers in Ho Chi Minh City.

2.1.3. The mediating role of negative affect (NA)

Integrating Stress appraisal & coping theory with SWB theory and the affect-as-information perspective reveals a clear indirect mechanism linking *AIA* to *LS*. Specifically, *AIA* activates *NA* through stress appraisal processes; subsequently, *NA* exerts a detrimental influence on *LS* via subjective evaluation mechanisms. Prior research on stress and well-being consistently supports the mediating role of negative emotions in the relationship between stressors and *LS* [4], [10].

Accordingly, *NA* is expected to function as a key psychological mechanism through which *AIA* influences *LS* in the context of digital transformation.

H4: NA mediates the relationship between AIA and LS among office workers in Ho Chi Minh City.

2.1.4. Perceived social support (PSS) and the buffering hypothesis

The buffering hypothesis, proposed by Cohen and Wills (1985), posits that social support influences psychological health through two pathways: (i) a main effect, whereby higher levels of social support are associated with better psychological well-being regardless of stress levels; and (ii) a buffering effect, whereby social support attenuates the negative impact of stressors or adverse psychological states on mental health outcomes. The buffering effect is particularly relevant for explaining individual differences in psychological vulnerability among people exposed to similar levels of stress or *NA* [6].

A key insight from the literature is that *PSS* is often a stronger and more consistent predictor of well-being than objective or received support, as it more directly reflects individuals' subjective appraisal of resource availability in times of need [6], [22]. B. Lakey and S. Cohen argue that individuals' belief that support is available when needed directly shapes cognitive and emotional processes, including situation appraisal, emotion regulation, and global life judgments [23]. According to House's (1981) typology, social support may take the form of emotional support (empathy, reassurance), informational support (advice, guidance), or instrumental support (tangible resources), all of which can mitigate the harmful effects of negative emotions on psychological well-being [24].

When integrated with SWB theory and the affect-as-information framework, it can be argued that although *NA* typically undermines *LS* by serving as a negative informational cue during life evaluations [5], [10], this effect is not uniform across individuals. When *PSS* is high, social relationships function as psychological resources that help individuals reinterpret negative emotions (e.g., viewing anxiety as temporary rather than as a sign of failure), regulate

emotions more effectively, and maintain a sense of belonging and self-worth. These processes reduce the extent to which *NA* is incorporated into global *LS* judgments [23], [25].

In the context of digital transformation and AI adoption, office workers may frequently experience *NA* due to adaptation pressures, career uncertainty, and continuous learning demands. However, consistent with the buffering hypothesis, *PSS* from colleagues, supervisors, family, and friends is expected to weaken the negative relationship between *NA* and life satisfaction. Even under high levels of *NA*, individuals with strong *PSS* are more likely to maintain higher *LS* than those with limited support, as their life evaluations are less dominated by adverse emotional states [6], [10].

Therefore, this study proposes that *PSS* plays a moderating role in the relationship between *NA* and *LS*.

H5: PSS weakens the negative relationship between NA and LS among office workers in Ho Chi Minh City.

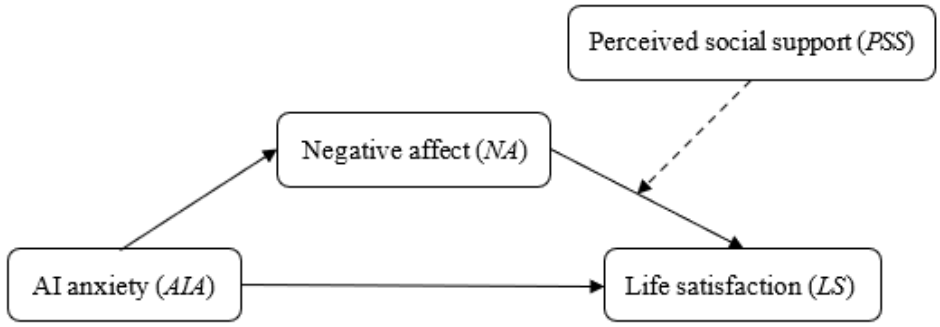

Figure 1. Conceptual model of AI anxiety, negative affect, and life satisfaction, with perceived social support as a moderator

Source: Author's illustration based on the proposed research model.

2.2. Literature review

Recent studies have increasingly examined *AIA* as a psychological response to rapid technological change. At the measurement level, *AIA* has been operationalized using the Artificial Intelligence Anxiety Scale (AIAS) developed by Y.-Y. Wang and Y.-S. Wang, comprising four dimensions: learning, job replacement, socio-technical blindness, and AI configuration [8]. Quantitative evidence across different cultural contexts - including Germany and Indonesia - has consistently demonstrated high internal reliability ($\alpha > 0.80$) and stable factor structures, supporting the robustness and cross-cultural applicability of the scale [26], [27]. Moreover, *AIA* has shown positive associations with anxiety and depression, and negative associations with *LS*, providing evidence of convergent and discriminant validity [26].

Beyond measurement, recent research has shifted toward understanding the mechanisms through which *AIA* influences psychological outcomes. In educational settings, *AIA* has been found to negatively relate to AI self-efficacy and attitudes toward AI, particularly when individuals lack hands-on experience [28], [29]. In organizational contexts, *AIA* has been linked to adverse work-related outcomes through emotional processes. Specifically, *AIA* increases emotional exhaustion, which in turn reduces work passion [19]. Extending this line of inquiry, Z. Feng et al. demonstrated that *AIA* negatively predicts *LS* indirectly through *NA*, with *NA* serving as a full mediator [11]. These findings highlight the role of those emotional responses - rather than cognitive evaluations alone - as the primary pathway linking *AIA* to well-being.

The mediating role of *NA* is further supported by the "affect-as-information" framework, which posits that individuals rely on their emotional states as informational cues when evaluating their lives [5]. Accordingly, heightened *NA* - such as stress, anxiety, and depression - can bias individuals toward more negative life evaluations. In parallel, the buffering hypothesis suggests that *PSS* can mitigate the adverse effects of stress and negative emotions on psychological well-being [6]. Quantitative studies have shown that *PSS* weakens the negative relationship between stress or *NA* and *LS*, indicating its protective role at later stages of the stress process [30], [31].

Taken together, the existing literature supports a coherent mechanism in which *AIA* increases *NA*, which subsequently reduces *LS*, while *PSS* serves as a protective factor that can attenuate the detrimental impact of negative emotions. However, several important gaps remain. First, most prior studies have been conducted in non-Vietnamese contexts, limiting the generalizability of findings to rapidly developing labor markets such as Vietnam. Second, although the mediating role of *NA* is well established, the moderating role of *PSS* has primarily been examined at earlier stages (e.g., stressor → emotion), with limited attention to its role in buffering the impact of *NA* on *LS*. Third, existing research has paid relatively limited attention to office workers as a distinct occupational group, despite their heightened exposure to AI-driven task changes and digital transformation in contemporary workplaces.

To address these gaps, the present study proposes a moderated mediation model in which *AIA* influences *LS* through *NA*, while *PSS* moderates the relationship between *NA* and *LS*. By focusing on office workers in Vietnam, this study aims to extend existing theoretical frameworks and provide context-specific evidence for the psychological impact of AI in emerging economies.

3. METHODOLOGY

3.1. Research design

This study employed a quantitative, cross-sectional design to examine the relationships between artificial intelligence anxiety (*AIA*), negative affect (*NA*), perceived social support (*PSS*), and life satisfaction (*LS*). Data were collected at a single time point from office workers in Ho Chi Minh City who had at least minimal exposure to AI tools in their work.

3.2. Participants and procedure

Participants were full-time office workers (aged ≥ 18) currently working in Ho Chi Minh City and reporting at least occasional use of AI tools for work purposes. A non-probability convenience sampling approach was adopted, which is commonly used in organizational and behavioral research when access to a comprehensive sampling frame is limited within practical time and resource constraints. Data were collected via an online survey distributed through professional networks, social media platforms, and workplace communities, ... A total of 292 responses were received, of which 288 valid responses were retained after data screening.

3.3. Measures

All variables were measured using validated self-report scales on Likert-type responses. All scales demonstrated good internal consistency in the present study, with Cronbach's alpha coefficients as follows: *AIA* ($\alpha = 0.95$), *NA* ($\alpha = 0.92$), *LS* ($\alpha = 0.87$), and *PSS* ($\alpha = 0.93$), all exceeding the recommended threshold of 0.70.

Artificial intelligence anxiety (*AIA*) was measured using the 21-item Artificial Intelligence Anxiety Scale (AIAS), covering four dimensions: learning, job replacement, socio-technical blindness, and AI configuration [8]. All items were rated on a 7-point Likert

scale, ranging from 1 = Strongly disagree to 7 = Strongly agree. Higher scores indicate higher levels of *AIA*.

Negative affect (*NA*) was assessed using the 10-item negative affect subscale of the Positive and Negative Affect Schedule (PANAS) [9]. Respondents were asked to indicate the extent to which they had experienced various negative emotions (e.g., anxious, distressed, upset) over past 2 weeks. Items were rated on a 5-point Likert scale, ranging from 1 = Very slightly or not at all to 5 = Extremely. Higher scores reflect greater levels of *NA*.

Life satisfaction (*LS*) was measured using the 5-item Satisfaction With Life Scale (SWLS) [32]. The scale captures individuals' global cognitive evaluation of their overall quality of life. Items were rated on a 7-point Likert scale, ranging from 1 = Strongly disagree to 7 = Strongly agree. Higher scores indicate greater *LS*.

Perceived social support (*PSS*) was measured using the 12-item Multidimensional Scale of Perceived Social Support (MSPSS), which assesses perceived support from family, friends, and significant others [33]. Items were rated on a 7-point Likert scale, ranging from 1 = Very strongly disagree to 7 = Very strongly agree. Higher scores indicate stronger *PSS*.

3.4. Data analysis

Data were analyzed using SPSS version 27 and the PROCESS Macro version 5.0. Descriptive statistics and Pearson correlations were first computed for all variables. To test the hypothesized relationships, mediation analysis was conducted using PROCESS Model 4, examining whether *NA* mediated the relationship between *AIA* and *LS*. Moderated mediation analysis was then performed using PROCESS Model 14 to examine whether *PSS* moderated the relationship between *NA* and *LS*. Bootstrapping with 5,000 resamples was used to estimate indirect effects and confidence intervals. All analyses used a significance level of $\alpha = 0.05$.

3.5. Ethical considerations

Participation was voluntary and anonymous. Informed consent was obtained prior to data collection. All data were used solely for research purposes and handled in accordance with ethical research standards.

4. RESULTS AND DISCUSSION

4.1. Results

4.1.1. Sample characteristics

Table 1. Demographic characteristics of the sample ($N = 288$)

Variable	$M \pm SD$ / n (%)
Age (years)	30.67 ± 6.75
Gender	
Male	78 (27.08)
Female	210 (72.92)
Highest level of education	
Vocational intermediate degree	6 (2.08)
College/University degree	209 (72.57)
Postgraduate degree	73 (25.35)
Work tenure	
< 2 years	125 (43.40)

≥ 2 years - < 5 years	72 (25.00)
≥ 5 years	91 (31.60)
Occupational sector	
Commercial and communications	71 (24.65)
Corporate and financial services	82 (28.47)
Technical, legal and research	67 (23.26)
Public services and others	68 (23.61)
Job position	
Staff	190 (65.97)
Team leader/Supervisor	35 (12.15)
Middle management	46 (15.97)
Senior management/Director	17 (5.90)
Frequency of AI usage	
1–3 times/month	52 (18.06)
Weekly	78 (27.08)
Daily	158 (54.86)

Note: M = mean, SD = standard deviation; n = number of participants.

Source: Author's calculation based on survey data.

Table 1 presents the demographic characteristics of the sample. The mean age of participants was 30.67 years (*SD* = 6.75). Female participants accounted for 72.92% of the sample. Most respondents held a college or university degree (72.57%), followed by postgraduate qualifications (25.35%). Regarding occupational distribution, the sample was relatively evenly spread across corporate and financial services (28.47%), commercial and communications (24.65%), public services and others (23.61%), and technical, legal, and research sectors (23.26%). This industry variety represents a broad cross-section of knowledge-intensive roles in Ho Chi Minh City, particularly those characterized by high digitization and significant exposure to AI-driven changes in information processing and decision-support tasks. Such a diverse professional background provides a robust context for examining how digital transformation pressures influence across different workplace environments. Regarding work tenure, 43.40% had less than two years of tenure. The majority of participants were in staff positions (65.97%). More than half of the participants (54.86%) reported using AI on a daily basis.

4.1.2. Reliability and common method bias

Table 2. Reliability of the scales used in the study (*N* = 288)

Scale	Number of items	Cronbach's alpha
AI Anxiety (AIAS)	21	0.95
Negative Affect (PANAS-NA)	10	0.92
Life Satisfaction (SWLS)	5	0.87
Perceived Social Support (MSPSS)	12	0.93

Source: Author's calculation based on survey data.

As shown in Table 2, all measurement scales demonstrated high internal consistency, with Cronbach's alpha values ranging from 0.87 to 0.95. These results indicate good to excellent reliability, supporting their use in subsequent analyses.

Besides, to assess potential common method bias (CMB) resulting from the self-reported nature of the data, Harman's single-factor test was conducted. The results indicated that the single factor explained 22.96% of the total variance, which is well below the recommended 50% threshold. This suggests that common method bias does not pose a significant concern in the present study.

4.1.3. Descriptive statistics and correlations

Table 3. Descriptive statistics and Pearson correlations among study variables

Variables	*M* ± *SD*	*AIA*	*NA*	*LS*	*PSS*
AI anxiety (*AIA*)	3.89 ± 1.14	1	0.213***	0.138*	0.236***
Negative affect (*NA*)	2.36 ± 0.85		1	-0.255***	-0.174**
Life satisfaction (*LS*)	4.54 ± 1.16			1	0.585***
Perceived social support (*PSS*)	4.66 ± 1.24				1

*Note: * (p < 0.05); ** (p < 0.01); *** (p < 0.001).*

Source: Author's calculation based on survey data.

Table 3 presents the descriptive statistics and Pearson correlation coefficients among the study variables. The mean level of *AIA* was moderate ($M = 3.89$, $SD = 1.14$), with 44.79% of participants reporting above-average levels of *AIA*. *NA* was reported at a relatively low level ($M = 2.36$, $SD = 0.85$), whereas *LS* ($M = 4.54$, $SD = 1.16$) and *PSS* ($M = 4.66$, $SD = 1.24$) were above the midpoint of their respective scales. Regarding the hypothesized relationships, *AIA* was positively and significantly correlated with *NA* ($r = 0.213$, $p < 0.001$), providing support for H2. Consistent with H3, *NA* was negatively and significantly associated with *LS* ($r = -0.255$, $p < 0.001$). Furthermore, a significant positive association was observed between *AIA* and *LS* ($r = 0.138$, $p = 0.019 < 0.05$). This result provides quantitative support for the two-tailed H1, confirming that *AIA* is significantly linked to individuals' *LS* within this occupational context. Given significant relationships among *AIA*, *NA*, and *LS*, subsequent analyses were conducted to examine the mediating role of *NA* using PROCESS Model 4.

In addition, *PSS* was positively and significantly correlated with *LS* ($r = 0.585$, $p < 0.001$), negatively and significantly correlated with *NA* ($r = -0.174$, $p < 0.01$). A positive association was also observed between *PSS* and *AIA* ($r = 0.236$, $p < 0.001$). These findings indicate that *PSS* is meaningfully related to the focal variables and justify its inclusion in subsequent moderation analyses.

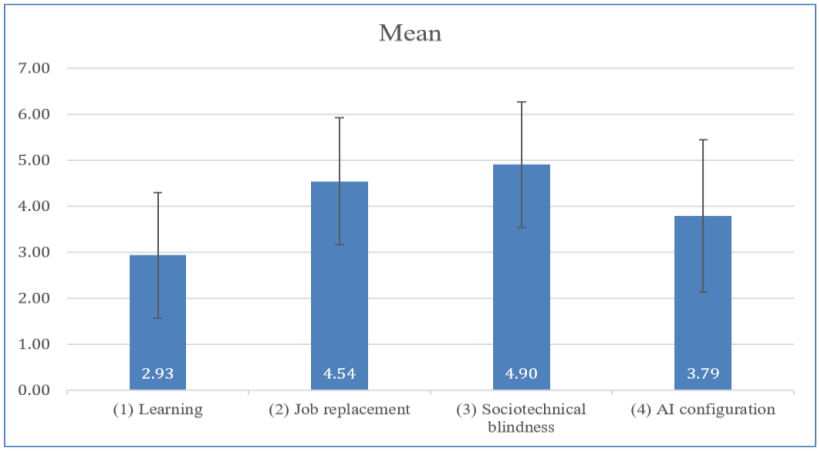

Figure 2. Mean scores of AI anxiety dimensions among office workers

Source: Author's illustration based on survey data.

Figure 2 illustrates the mean scores of the four dimensions of *AIA*. Among the dimensions, socio-technical blindness showed the highest mean level ($M = 4.90$, $SD = 1.37$), followed by job replacement concerns ($M = 4.54$, $SD = 1.38$). In contrast, anxiety related to learning demands was reported at the lowest level ($M = 2.93$, $SD = 1.36$).

4.1.4. Mediation analysis: The mediating role of negative affect

Table 4. Mediation analysis results (PROCESS Model 4)

Path	*B*	*SE*	*t*	95% CI	*p*
AIA → *NA*	0.159	0.043	3.683	[0.074, 0.243]	< 0.001
NA → *LS*	-0.408	0.079	-5.185	[-0.563, -0.253]	< 0.001
Direct effect (*AIA* → *LS*)	0.205	0.059	3.504	[0.090, 0.321]	< 0.001
Indirect effect (*AIA* → *NA* → *LS*)	-0.065	0.022	-	[-0.114, -0.028]	-

Note: AIA = AI anxiety; NA = negative affect; LS = life satisfaction; SE = standard error; CI = confidence interval. Unstandardized coefficients (B) are reported. Bias-corrected bootstrapping with 5,000 resamples was used. A 95% confidence interval that does not include zero indicates a significant indirect effect.

Source: Author's calculation based on survey data.

A mediation analysis using PROCESS Model 4 was conducted to examine whether *NA* mediates the relationship between *AIA* and *LS*. As shown in Table 4, *AIA* was a significant positive predictor of *NA* ($B = 0.159$, $SE = 0.043$, $p < 0.001$). *NA*, in turn, was a significant negative predictor of *LS* ($B = -0.408$, $SE = 0.079$, $p < 0.001$). The indirect effect of *AIA* on *LS* via *NA* was significant ($B = -0.065$, 95% CI [−0.114, −0.028]). The direct effect of *AIA* on *LS* also remained significant ($B = 0.205$, $SE = 0.059$, $p < 0.001$), indicating partial mediation. Taken together, these findings support H4 by demonstrating a significant indirect effect of *AIA* on *LS* via *NA*.

4.1.5. Moderated mediation analysis

Table 5. Moderation analysis results (PROCESS Model 14)

Predictors	*B*	*SE*	*t*	*p*
Negative affect (*NA*)	-0.235	0.068	-3.472	< 0.001
Perceived social support (*PSS*)	0.522	0.047	11.169	< 0.001
NA x *PSS*	0.129	0.055	2.342	0.020
AI anxiety (*AIA*)	0.044	0.051	0.863	0.389

Note: SE = standard error. Unstandardized coefficients (B) are reported. Bias-corrected bootstrapping with 5,000 resamples was used.

Source: Author's calculation based on survey data.

Results from PROCESS Model 14 indicated a significant interaction between *NA* and *PSS* in predicting *LS* ($B = 0.129$, $SE = 0.055$, $p = 0.020 < 0.05$), as shown in Table 5. This finding suggests that *PSS* moderates the relationship between *NA* and *LS*, such that the negative association between *NA* and *LS* is weakened at higher levels of *PSS*. Thus, H5 was supported.

Table 6. Conditional indirect effects of AI anxiety on life satisfaction via negative affect at perceived social support levels (Model 14)

Level of *PSS*	Indirect effect	Boot*SE*	Boot 95% CI
Low (-1 *SD*)	-0.063	0.025	[-0.123, -0.023]

Moderate (Mean)	-0.037	0.015	[-0.077, -0.013]
High (+1 *SD*)	-0.012	0.016	[-0.048, 0.015]

Note: PSS = perceived social support; BootSE = bootstrap standard error; CI = confidence interval. Conditional indirect effects were estimated using bias-corrected bootstrapping with 5,000 resamples. A 95% confidence interval that does not include zero indicates a significant conditional indirect effect. Low and high levels of perceived social support represent −1 SD and +1 SD from the mean, respectively.

Source: Author's calculation based on survey data.

As shown in Table 6, the indirect effect of *AIA* on *LS* via *NA* was significant at low and average levels of *PSS* but became nonsignificant at high levels of *PSS*. Specifically, the conditional indirect effect decreased as *PSS* increased and was no longer significant when *PSS* was high. This pattern suggests that *PSS* buffers the indirect effect of *AIA* on *LS* through *NA*.

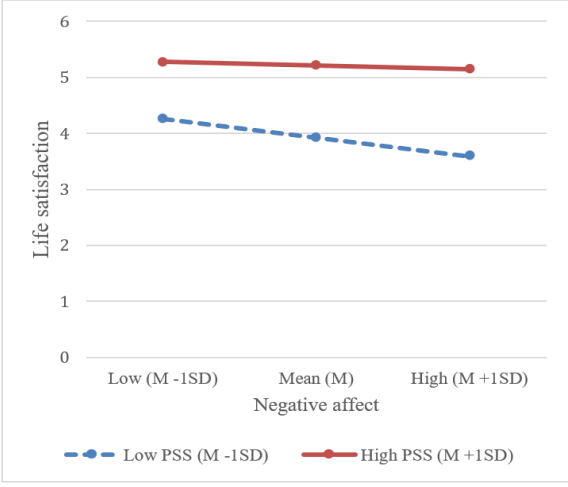

Figure 3. Moderating effect of perceived social support on the relationship between negative affect and life satisfaction

Source: Author's illustration based on calculations from the survey data.

Figure 3 illustrates the moderating effect of *PSS* on the relationship between *NA* and *LS*. Specifically, the negative association between *NA* and *LS* was stronger at lower levels of *PSS*, whereas this association was weakened when *PSS* was high.

4.2. Discussion

4.2.1. Relationships among AI anxiety, negative affect, and life satisfaction

The present study indicated that *AIA* was positively associated with *NA*, providing support for H2. This finding is consistent with prior international research conceptualizing *AIA* as a novel form of technostress, which is capable of eliciting negative emotional responses such as anxiety, stress, and insecurity [28], [29], [34]. From the perspective of Stress appraisal and coping theory, when individuals appraise the rapid integration of AI as a demand that potentially exceeds their current coping resources, *NA* emerges as a primary psychological response [4].

Besides, the research found a weak but statistically significant positive association between *AIA* and *LS*, supporting H1 two-tailed hypothesis. This result differs from the findings of Z. Feng et al., who observed a negative association between *AIA* and *LS* [11]. Nevertheless, both studies converge in identifying *NA* as a mediating mechanism linking *AIA* and *LS* [11]. Theoretically, this divergence highlights that *AIA* may not function solely as a detrimental stressor but can be appraised as a challenge rather than a threat.

Differences in occupational context may partially account for the variation in the strength and direction of these relationships. In the study by Z. Feng et al. [11], the sample comprised full-time employees in the service sector, where emotional labor, performance evaluation, and work-related experiences are more directly tied to SWB. In contrast, among office workers in Ho Chi Minh City, particularly those in knowledge-intensive sectors like Marketing, IT, Finance, Education…, *AIA* may reflect an accelerated awareness of ongoing technological changes. In such a dynamic environment, this heightened awareness can coexist with a willingness to adapt rather than resistance or avoidance

Importantly, contemporary office workers in this study do not perceive AI primarily as an abstract threat. Instead, the increasing integration of AI applications has positioned it as a practical and supportive tool that enhances task performance. As employees gain experience, AI-related concerns may shift from fear of the unknown toward an instrumental and pragmatic orientation. Consequently, *AIA* in this context may stimulate adaptive coping and proactive engagement, explaining why individuals with higher awareness (and thus higher *AIA*) might also report higher life evaluations.

An examination of the components of *AIA* further supports this interpretation. Socio-technical blindness and job replacement anxiety were the most salient components, whereas learning anxiety was reported at the lowest level. This pattern confirms the readiness of current office workers to learn and adapt, viewing the anxiety as a functional drive to remain competitive in the digital labor market.

Furthermore, discrepancies with prior studies may stem from measurement differences. While this study used the full 21-item AIAS covering four dimensions, Z. Feng et al. [11] used a 6-item version, only focusing on AI learning anxiety and job replacement anxiety. This narrower operationalization, emphasizing more immediate and personally salient threats of service labor, may render the construct of *AIA* more closely aligned with evaluations of *LS*, thereby strengthening the observed associations.

Finally, consistent with H3, *NA* was negatively associated with *LS*. This finding is well aligned with established theories of SWB, which conceptualize *LS* as the cognitive component of well-being that is strongly influenced by affective signals [5], [10], [35]. According to the affect-as-information framework, this also confirms that while *AIA* can drive proactive adaptation, the resulting negative emotional states still serve as unfavorable informational cues that lower global life judgments.

4.2.2. The mediating role of negative affect

The mediation analysis demonstrated that *NA* partially mediates the relationship between *AIA* and *LS*, thereby supporting H4. Specifically, higher levels of *AIA* were associated with increased *NA*, which in turn was negatively related to *LS*. Although the indirect effect of *AIA* on *LS* through *NA* was statistically significant, the direct effect remained significant. This pattern indicates that *AIA* influences *LS* through both emotional and non-emotional pathways.

Theoretically, these findings reinforce and extend the Stress appraisal and coping theory by clarifying the dual-processing nature of technological stress. While stressors such as AI-related job displacement and socio-technical blindness initially elicit affective responses, the partial mediation suggests that the cognitive-evaluative path remains distinct. This contributes to the literature by showing that employees in Ho Chi Minh City do not just feel the stress of AI; they also cognitively process it. As argued in section 4.2.1, the direct path might represent a challenge appraisal where individuals recognize the necessity of AI for professional survival even while experiencing situational emotional strain.

The present findings are broadly aligned with those of Z. Feng et al., identifying *NA* as a key mediating mechanism [11]. However, whereas Z. Feng et al. reported a fully mediated

relationship, the current study revealed a partial mediation pattern. This divergence offers a significant theoretical refinement: It suggests that the emotional toll of AI anxiety is context dependent. In the highly dynamic and emerging digital economy of Vietnam, the direct cognitive awareness of AI as a functional tool may bypass emotional filters more than in the service sectors studied by Z. Feng et al., where emotional labor is more central to life evaluations.

Notably, this convergence emerges despite differences in the operationalization of *NA*. While Z. Feng et al. [11] used DASS-21 to capture enduring psychological distress, the present study utilized the PANAS-*NA* to reflect situational emotional states. The robustness of the *AIA* → *NA* → *LS* pathway across different measures suggests that both chronic and transient emotional states serve as informational signals in the evaluation of SWB.

Integrating these results with the affect-as-information framework provides a deeper explanation for H4. *NA* states function as unfavorable informational cues that bias individuals toward less positive assessments of their overall life. By confirming this mechanism, the study demonstrates that the stress of the future (*AIA*) impacts the judgment of the present (*LS*) primarily by coloring the individual's current emotional lens. However, the remaining direct effect indicates that office workers are capable of partitioning some of their technological anxiety as a professional reality that does not fully dictate their overall LS.

4.2.3. The moderating role of perceived social support at the emotional outcome stage

Beyond the mediating role of *NA*, the present study demonstrates that *PSS* moderates the relationship between *NA* and *LS*. Results from PROCESS Model 14 indicate that the detrimental effect of *NA* on *LS* diminishes as levels of *PSS* increase. Theoretically, this finding provides robust evidence for the buffering hypothesis of Cohen & Wills (1985), clarifying that social support functions not by preventing the emergence of technostress-induced emotions, but by mitigating their adverse consequences for cognitive well-being [6]. In the context of office workers in Ho Chi Minh City, while *NA* inevitably emerges in response to *AIA*, individuals with high *PSS* are better equipped to maintain positive life evaluations, thereby weakening the *NA–LS* link. This pattern aligns with prior research demonstrating that social support buffers the harmful effects of stress and negative emotions on well-being [30], [31].

A significant theoretical contribution of this study lies in verifying the moderating role of *PSS* at a later stage of the psychological process. This differs from Z. Feng et al., who found that *PSS* moderated the earlier relationship between *AIA* and *NA* [11]. This divergence allows for a critical refinement of existing models: The primary function of *PSS* in digital transformation contexts may lie in helping individuals cope with and reinterpret negative emotional experiences rather than acting as a preventive barrier against anxiety itself.

One plausible explanation for this stage-specific moderation relates to the nature of the affective experience. While Z. Feng et al. measured intense, enduring symptoms via the DASS-21, the present study captured everyday situational emotions using the PANAS-*NA* [11]. Under conditions of transient emotional strain, *PSS* facilitates emotional regulation and cognitive reappraisal, effectively protecting *LS* from being unduly shaped by passing *NA*. From the perspective of the affect-as-information framework, *PSS* acts as a buffer that prevents individuals from using negative emotional signals as the primary basis for their global life judgments.

Taken together, these findings reconceptualize *PSS* as a consequence-buffering resource rather than a preventive factor in the era of *AIA*. While social support may not directly reduce *AIA* or fully inhibit *NA*, it substantially limits the translation of negative emotional states into diminished *LS*. This distinction extends the buffering framework in digital work contexts by clarifying the timing and functional role of social support. Practically, it suggests that organizational interventions in Vietnam should prioritize strengthening social support

networks as a consequence-buffering resource to help employees manage the emotional downstream of technological change.

Furthermore, the strong moderating effect of *PSS* observed in this study may be partially attributable to the sample's gender composition, which was predominantly female (72.92%). Extant literature suggests that gender differences exist in social support dynamics, with women often reporting higher levels of perceived emotional support and utilizing social networks more effectively as a coping mechanism compared to men. Therefore, the robust buffering role of *PSS* in mitigating the negative impact of *NA* on *LS* found here may reflect these gender-specific socialization patterns. While a formal subgroup analysis was limited by the smaller male subsample, these results highlight the importance of considering gender as a potential moderator in future technostress research.

5. CONCLUSION

This study investigated the relationships among *AIA*, *NA*, and *LS*, as well as the role of *PSS*, among office workers in Ho Chi Minh City. The findings provide quantitative evidence for the proposed moderated mediation model, highlighting the central role of emotional processes in explaining the association between *AIA* and *LS*. Specifically, supporting the H1 and Stress appraisal theory, *AIA* exhibited a significant positive association with *LS*, suggesting that in dynamic digital hubs, AI-related anxiety may be appraised as a challenge that motivates adaptation. However, *AIA* simultaneously increased *NA*, which in turn lowered *LS*, confirming *NA* as a key psychological mechanism linking technological concerns to well-being through the affect-as-information framework.

Importantly, *PSS* emerged as a consequence-buffering factor at a later stage of the emotional process. While *PSS* did not reduce the emergence of *NA* in response to *AIA*, it significantly weakened the negative association between *NA* and *LS*. This suggests that *PSS* functions primarily as a protective resource that mitigates the consequences of negative emotional experiences, rather than as a preventive factor that helps employees reinterpret and regulate such experiences.

These findings contribute to the growing literature by clarifying the stage-specific role of social support and the dual-pathway influence of *AIA* on employee well-being. Practically, organizations should prioritize strengthening social support systems to help employees manage the emotional consequences of technological change.

Several limitations should be acknowledged. First, the cross-sectional design of the study precludes causal inference regarding the observed relationships. Second, while the reliance on self-report measures may introduce common method bias, Harman’s single-factor test revealed that the first factor accounted for only 22.96% of the variance, suggesting that CMB was not a pervasive issue in this dataset. Third, the strong female skew (72.92%) of the sample may limit generalizability and could moderate the perceived effects of social support. Finally, the use of convenience sampling limits the generalizability of the findings, as the sample may not be fully representative of the broader population of office workers. Future research would benefit from employing probability sampling methods, as well as longitudinal or experimental designs, to enhance representativeness and strengthen causal interpretations. In addition, future studies could examine other personal and organizational resources that may buffer the effects of *AIA*.

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