# The Impacts of AI-office Assistants' Application on the Well-being of Employees: An Empirical Study

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**Abstract:** With the widespread application of Artificial Intelligence Office Assistants (AIOAs), the workplace is being reshaped, prompting debate over their impact on employees' psychological well-being. Although existing research emphasizes AI-driven efficiency gains, few studies examine the affective mechanisms linking human–AI interaction to multidimensional employee well-being. Drawing on the Artificial Intelligence Device Use Acceptance (AIDUA) model and Employee Well-being (EWB) theory, this study develops an integrated framework explaining how AI characteristics shape employees' life, workplace, and psychological well-being through cognitive appraisals and affective responses. Survey data from 230 employees of multinational companies (MNCs), collected via Credamo and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM), reveal that: (1) social influence, hedonic motivation, and anthropomorphism are positively related to performance expectancy whereas social influence is negatively associated with effort expectancy (2) hedonic motivation and anthropomorphism are not associated with effort expectancy; and (3) performance and effort expectancy shape employee well-being through the mediation of positive emotion. This study validates the appraisal–emotion–well-being pathway and the functional–affective duality of anthropomorphism in workplace settings, advising MNCs to prioritize functional utility and positive emotional design over merely anthropomorphic appearance to foster genuine employee well-being.

**Keywords**: Artificial intelligence-based office Assistants application, Employee well-being, Positive emotion, Human-ai collaboration

## 1. Introduction

The introduction of artificial intelligence (AI) into the modern workplace is one of the most significant technological changes of the twenty-first century. Within multinational companies (MNCs), the work environment is characterized by high-intensity cross-cultural communication, complex multi-time-zone collaboration, and relentless demands for cognitive agility (Marikyan et al., 2022). In this context, AI-based office assistants (AIOAs)—encompassing advanced tools for text generation, data analysis, real-time translation, and intelligent scheduling—have become more than technological utilities; they are embedded in daily operations as digital collaborators across diverse functional areas. While valued for overcoming geographic barriers and streamlining global operations, the profound reliance on AI in such high-pressure environments extends far beyond task efficiency, penetrating the psychological and emotional domains that fundamentally affect employee well-being.

Current studies report a two-sided impact of AI in the workplace. On one hand, digital assistants improve work performance (Ma et al., 2025) through functional support and enhance engagement by increasing the playfulness of work. On the other hand, AI adoption can trigger technostress and emotional exhaustion, exacerbating work-family conflict and diminishing job satisfaction. Unlike traditional static software, contemporary generative AI exhibits distinct anthropomorphic and interactive capabilities that lead employees to engage with it as a socially proximate entity rather than a conventional tool. Human–AI interaction thus transcends mere usability concerns and constitutes a complex social-emotional process mediated by psychological appraisal. This dialectical nature necessitates a theoretical approach that moves beyond the productivity metrics of the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) to illuminate the cognitive-emotional mechanisms through which employees evaluate, respond to, and are ultimately affected by AI technologies.

However, the TAM and the UTAUT) mainly focused on the prediction of behavioral intentions and application attitudes without considering the downstream psychological impacts of AI usage. The Artificial Intelligence Device Use Acceptance (AIDUA) model proposed by Gursoy et al. (2019) represents a significant advancement by delineating a three-stage cognitive-emotional process encompassing primary appraisal (social influence, hedonic motivation, and anthropomorphism), secondary appraisal (performance expectancy and effort expectancy), and emotional response. The AIDUA model is used to reveal the behavioral acceptance or rejection of an AI technique, which cannot reveal the spillover effects of cognitive-emotional dynamics on employees' well-being.

A scholarly consensus holds that employee well-being is not merely a synonym for job satisfaction but a multidimensional construct encompassing life, workplace, and psychological dimensions. The tripartite Employee Well-being (EWB) model of Zheng et al. (2015) offers a theoretically grounded and cross-culturally validated framework for capturing this multidimensionality. Yet empirical research directly bridging AI-specific cognitive appraisal variables with multidimensional well-being outcomes remains remarkably scarce: while the instrumental attributes of AI, such as efficiency gains and error reduction, are frequently emphasized, the effects of deeper psychological appraisals of AI on employee well-being are rarely examined.

## 2. Literature Review and Hypothesis Development

### 2.1 Theoretical Framework

The AIDUA model delineates a three-stage sequential process—primary appraisal, secondary appraisal, and emotional response—to explain individuals' psychological processing of and reactions to intelligent technologies (Lazarus, 1991). Whereas traditional frameworks such as TAM focus on instrumental utility, recent organizational studies highlight that AIOAs possess unique social and anthropomorphic attributes, making the cognitive-emotional lens of AIDUA particularly suitable for complex workplace contexts.

The sequential structure of the AIDUA model is rooted in the cognitive-motivational-relational theory of emotion, in which the encounter between a human and an intelligent agent is not merely a technical affair but a process of psychological meaning-making (Lazarus, 1991). During primary appraisal, the AI assistant is identified as a relevant or irrelevant stimulus within the work environment; secondary appraisal follows, as the individual evaluates their own coping resources and the potential outcomes of the interaction (Lazarus, 1991). In professional AI usage, this evaluation centers on the balance between functional utility and the cognitive effort required for mastery. By emphasizing this cognitive-to-emotional transition, the framework captures the nuanced reality that technology adoption is driven by both internal affective states and external performance metrics.

Concurrently, the EWB framework defines well-being as a tripartite construct spanning workplace, life, and psychological dimensions (Zheng et al., 2015). In MNCs, where employees constantly navigate cross-cultural communication and high-intensity tasks, the integration of AI tools profoundly disrupts traditional work boundaries. Bridging the AIDUA and EWB models therefore enables a comprehensive understanding of how employees' cognitive evaluations of AI cascade through emotional experiences to shape their multidimensional well-being (Chuang et al., 2025).

### 2.2 Primary Appraisal and Secondary Appraisal

Within the AIDUA framework, primary appraisal factors—social influence, hedonic motivation, and anthropomorphism—serve as the foundational cues employees use to initially evaluate a new technology (Gursoy et al., 2019). In the highly collaborative and interconnected environment of MNCs, social influence plays a pivotal role in shaping technological perceptions. Drawing on social learning theory, when employees observe peers and supervisors successfully endorsing AIOAs, this social validation reduces the uncertainty associated with new technologies (Fang et al., 2026). Such collective endorsement acts as a heuristic cue, signalling that the tool is effective for overcoming cross-cultural barriers and that a shared knowledge pool supports the learning curve. When peers and supervisors are perceived as readily available sources of guidance and troubleshooting, the cognitive burden of independently mastering the tool is reduced, thereby lowering effort expectancy. Therefore, we assume:

***H1a:*** *Social influence is positively related to performance expectancy.*

***H1b:*** *Social influence is negatively related to effort expectancy.*

Moving from external influences to internal drivers, hedonic motivation—the perceived enjoyment and playfulness derived from AI interaction—profoundly alters cognitive evaluations. When MNC employees find generative AI engaging or intellectually stimulating, it triggers a state of cognitive absorption (Marikyan et al., 2022). This intrinsic enjoyment mitigates initial technological resistance and reframes complex tasks as manageable challenges, making the system appear both more productive in generating novel solutions and less draining to operate. Thus, we assume:

***H2a:*** *Hedonic motivation is positively related to performance expectancy.*

***H2b:*** *Hedonic motivation is negatively related to effort expectancy.*

Furthermore, anthropomorphism—assigning human-like traits to AI—introduces a uniquely influential interaction dynamic. By mimicking human conversational norms, highly anthropomorphized interfaces tap into employees' existing social schemas. This human-like social presence fosters familiarity and trust, reinforcing users' perceived competence of the system and enhancing performance expectancy. At the same time, personification makes the interaction more natural, reducing the perceived operational friction and cognitive load (Chen et al., 2025). Therefore, we assume:5). Therefore, we assume:

***H3a:*** *Anthropomorphism is positively related to performance expectancy.*

***H3b:*** *Anthropomorphism is negatively related to effort expectancy.*

### 2.3 Secondary Appraisal and Emotional Response

Following the initial assessment, employees engage in secondary appraisal, evaluating the specific instrumental values and costs of the technology. Under the cognitive-motivational-relational theory of emotion, these rational appraisals are not formed in a vacuum but directly trigger emotional states (Lazarus, 1991). When MNC employees hold high performance expectations—firmly believing that AI assistants will streamline cross-time-zone communication or accelerate complex data analysis—this cognitive validation fulfils their fundamental psychological need for competence. The anticipation of mastering one's workload in a high-pressure environment elicits profound positive emotional responses such as relief, engagement, and technological empowerment (Chuang et al., 2025). Therefore, we assume:

***H4:*** *Performance expectancy is positively related to employees' positive emotional response.*

Conversely, effort expectancy reflects the perceived difficulty and cognitive load required to operate the AI. Recent research on technostress indicates that steep learning curves and high effort requirements rapidly deplete employees' limited cognitive resources (Fang et al., 2026). When an AI tool is perceived as poorly optimized or excessively demanding to operate, it functions as a hindrance stressor: the resulting friction impedes goal attainment and fuels AI anxiety and emotional exhaustion, inevitably suppressing positive emotional experiences (Ali et al., 2026). Consequently, we assume:

***H5:*** *Effort expectancy is negatively related to employees' positive emotional response.*

### 2.4 Emotional Response and Multidimensional Employee Well-being

Emotions experienced during workplace interactions possess inherent spillover effects on broader psychological and physiological states far beyond the immediate task. According to the job demands-resources (JD-R) model and the broaden-and-build theory, a positive emotional response to AI serves as a vital personal resource that buffers against the chronic demands of workplace environments (Chuang et al., 2025). At the workplace level, positive affect generated through effective human–AI collaboration is theorized to enhance professional competence and task engagement, improving job satisfaction and organizational commitment by reducing the cognitive burden of routine tasks and facilitating the execution of complex ones (Zirar et al., 2023). Thus, we assume:

***H6a:*** *Positive emotional response to AI office assistants is positively related to employee workplace well-being.*

Psychologically, experiencing positive emotions during AI usage actively mitigates feelings of inadequacy and the digital self-efficacy deficits commonly associated with rapid technological change. It fosters a stronger sense of creative self-efficacy and builds enduring psychological resilience, enabling employees to navigate workplace complexity with a healthier mindset (Ali et al., 2026). Therefore, we assume:

***H6b:*** *Positive emotional response to AI office assistants is positively related to employee psychological well-being.*

Finally, in the non-work domain the spillover effect becomes paramount. The conservation of cognitive energy afforded by emotionally positive and efficient AI use prevents the severe depletion of cognitive resources during working hours. Consequently, employees retain more emotional bandwidth for their personal lives, which significantly alleviates work-family conflict and enhances overall life satisfaction (Zhang et al., 2024). Thus, we assume:

***H6c:*** *Positive emotional response to AI office assistants is positively related to employee life well-being.*

# 3. Research Method

## 3.1 Sample and Data Collection

In order to examine the proposed research model, data were obtained from an online survey conducted via Credamo, a professional survey platform widely used in academic research in China. The target population comprised employees of MNCs who use AIOAs on a daily basis.

Prior to empirical analysis, the raw dataset underwent systematic pre-processing. This involved converting Likert item responses to numerical values, identifying and removing outliers, and addressing missing data. Attention-check and validity-check questions were embedded in the online form. Of the 264 initial questionnaires collected, those that failed the attention checks or contained clearly unreasonable responses were excluded. A final sample of 230 valid questionnaires was retained, valid sample retention rate of 87.12%. Descriptive statistics of respondents can be found in Table 1.

**Table 1: Descriptive statistics of respondents**

| Items | Category | Distribution |
|---|---|---|
| **Age** | 18–25 | 20.43% |
| | 26–35 | 54.35% |
| | 36–45 | 20.43% |
| | 46–55 | 2.17% |
| | 56–65 | 2.17% |
| | Over 66 | 0.43% |
| **Headquarters of the MNC** | Foreign Headquarters | 20.43% |
| | Domestic Headquarters | 79.57% |
| **Type of AIOA used (Multiple responses)** | Text generation | 90.87% |
| | Data analysis | 93.48% |
| | Translation tool | 94.78% |
| | Design & drawing | 22.61% |
| | Programming assistance | 20% |

## 3.2 Measures

The survey instrument was divided into two parts: demographics and measurement items of the key constructs. The central measurement part included the nine latent variables of the proposed theoretical model. Each item was adapted from an existing validated scale to achieve content validity. Items based on the scale created by Gursoy et al. (2019) were modified to represent the AI acceptance antecedent variables, including social influence (SI), hedonic motivation (HM), anthropomorphism (ANT), performance expectancy (PE), effort expectancy (EE), and emotional response (EMO). For the employee well-being variables — life well-being (LWB), workplace well-being (WWB), and psychological well-being (PWB) — the cross-cultural multidimensional well-being scale developed by Zheng et al. (2015) was used.

The original scales were adapted in two methodological respects. First, all items were assessed on a 7-point Likert scale (1 = strongly disagree to 7 = strongly agree), rather than the 5-point scale of the original AIDUA measure. This was done to ensure consistency with the EWB measurement instrument, which employs a 7-point format, thereby facilitating construct comparison and enhancing statistical variance in responses. Second, emotional response (EMO) was measured on a 7-point semantic differential scale (e.g., 1 = Bored, 7 = Relaxed) to capture the bipolarity of affective states, consistent with the original AIDUA measurement design.

## 4. Results

### 4.1 Measurement Model

The measurement model was assessed across internal consistency reliability, convergent validity, discriminant validity, model fit, and common method bias to ensure measurement robustness, with key results summarized in Tables 2 and 3.

For internal consistency, Cronbach's alpha values range from 0.627 to 0.892 across constructs. Five constructs (SI, HM, PE, EMO, PWB) report alpha values between 0.6 and 0.7, which are acceptable for exploratory research given Cronbach's alpha's conservative nature and sensitivity to item count (all constructs use 3 items). All constructs meet the 0.70 composite reliability (CR) threshold and satisfy Dijkstra-Henseler's rho_A criterion, confirming satisfactory internal consistency.

For convergent validity, most standardized factor loadings exceed 0.6 and are significant at $p < 0.001$. Only item PWB2 has a loading of 0.524; it is retained as it stays above the 0.5 PLS-SEM cutoff and holds theoretical relevance. All average variance extracted (AVE) values surpass 0.50, verifying acceptable convergent validity.

Discriminant validity is supported by both the Fornell-Larcker criterion and HTMT ratios. The model yields an SRMR of 0.072, below the 0.08 benchmark, indicating acceptable fit. Construct-level VIF values (1.000–1.210) are well below the 3.3 threshold per Kock's (2015) full collinearity test, ruling out severe common method bias.

**Table 2: Reliability and validity test**

| Constructs/items | Item loadings | VIF | Cronbach's alphas | Composite Reliability | AVE |
|---|---|---|---|---|---|
| **Social influence (SI)** | | 1.113 | 0.67 | 0.822 | 0.58 |
| **SI1** | 0.84 | | | | |
| **SI2** | 0.69 | | | | |
| **SI3** | 0.80 | | | | |
| **Hedonic motivation (HM)** | | 1.210 | 0.63 | 0.815 | 0.58 |
| **HM1** | 0.77 | | | | |
| **HM2** | 0.76 | | | | |
| **HM3** | 0.79 | | | | |
| **Anthropomorphism (Ant)** | | 1.113 | 0.89 | 0.931 | 0.82 |
| **ANT1** | 0.87 | | | | |
| **ANT2** | 0.95 | | | | |
| **ANT3** | 0.89 | | | | |
| **Performance expectancy (PE)** | | 1.048 | 0.66 | 0.818 | 0.59 |
| **PE1** | 0.82 | | | | |
| **PE2** | 0.74 | | | | |
| **PE3** | 0.76 | | | | |
| **Effort expectancy (EE)** | | 1.048 | 0.75 | 0.854 | 0.67 |
| **EE1** | 0.88 | | | | |
| **EE2** | 0.72 | | | | |
| **EE3** | 0.83 | | | | |
| **Emotion (Emo)** | | 1.000 | 0.63 | 0.801 | 0.57 |
| **EMO1** | 0.79 | | | | |
| **EMO2** | 0.69 | | | | |
| **EMO3** | 0.79 | | | | |
| **Life Well-being (LWB)** | | | 0.73 | 0.849 | 0.65 |
| **LWB1** | 0.81 | | | | |

| Constructs/items | Item loadings | VIF | Cronbach's alphas | Composite Reliability | AVE |
|---|---|---|---|---|---|
| LWB2 | 0.83 | | | | |
| LWB3 | 0.78 | | | | |
| Workplace Well-being (WWB) | | | 0.73 | 0.846 | 0.65 |
| WWB1 | 0.73 | | | | |
| WWB2 | 0.85 | | | | |
| WWB3 | 0.83 | | | | |
| Psychological Well-being (PWB) | | | 0.65 | 0.785 | 0.56 |
| PWB1 | 0.80 | | | | |
| PWB2 | 0.52 | | | | |
| PWB3 | 0.88 | | | | |

**Table 3: Discriminant validity (HTMT ratios) and average variance extracted (AVE)**

| | SI | HM | Ant | PE | EE | EMO | LWB | WWB | PWB |
|---|---|---|---|---|---|---|---|---|---|
| SI | 0.748 | 0.330 | 0.176 | 0.513 | -0.206 | 0.245 | 0.235 | 0.266 | 0.069 |
| HM | 0.484 | 0.814 | 0.309 | 0.656 | -0.195 | 0.213 | 0.547 | 0.474 | 0.257 |
| Ant | 0.218 | 0.389 | 0.905 | 0.316 | 0.150 | 0.245 | 0.189 | 0.276 | 0.078 |
| PE | 0.736 | 0.437 | 0.272 | 0.757 | -0.214 | 0.308 | 0.258 | 0.290 | 0.259 |
| EE | 0.282 | 0.274 | -0.124 | 0.295 | 0.771 | 0.310 | 0.366 | 0.360 | 0.377 |
| EMO | 0.370 | 0.335 | 0.183 | 0.467 | -0.218 | 0.780 | 0.237 | 0.405 | 0.261 |
| LWB | 0.318 | 0.386 | 0.157 | 0.356 | -0.279 | 0.165 | 0.775 | 0.783 | 0.532 |
| WWB | 0.189 | 0.335 | 0.226 | 0.197 | -0.268 | 0.285 | 0.581 | 0.805 | 0.283 |
| PWB | 0.140 | 0.162 | 0.023 | 0.175 | -0.231 | 0.184 | 0.332 | 0.458 | 0.807 |

*Note.* SI = Social Influence; HM = Hedonic Motivation; ANT = Anthropomorphism; PE = Performance Expectancy; EE = Effort Expectancy; EMO = Positive Emotion; WWB = Workplace Well-being; PWB = Psychological Well-being; LWB = Life Well-being. The lower left part of the diagonal represents the Fornell-Larcker criterion, while the diagonal itself shows the square roots of the AVE (i.e., the square roots of the average variance extracted) of each latent variable. The upper right part of the diagonal represents the HTMT criterion, which is the HTMT ratio value between each variable.

### 4.2 Hypothesis Testing

The structural model was estimated using the PLS algorithm, and the statistical significance of all path coefficients was verified via a bias-corrected and accelerated bootstrap procedure with 5000 resamples and a fixed seed. Detailed results of path coefficients, standard errors, t-values, p-values, and hypothesis outcomes are summarized in Table 4.

Regarding primary appraisal effects on cognitive appraisals, social influence exerted the strongest positive predictive effect on performance expectancy ( $\beta$ = 0.404, p < 0.001), followed by hedonic motivation ( $\beta$ = 0.267, p = 0.001) and anthropomorphism ( $\beta$ = 0.119, p = 0.049). Thus, Hypotheses H1a, H2a, and H3a were all supported. For effort expectancy, only social influence showed a significant negative effect ( $\beta$ = −0.154, p = 0.013), supporting H1b. The effects of hedonic motivation ( $\beta$ = −0.126, p = 0.118) and anthropomorphism ( $\beta$ = −0.058, p = 0.430) failed to reach the 0.05 significance level, so H2b and H3b were not supported.

For cognitive appraisal effects on positive emotion, performance expectancy exerted a significant positive effect ( $\beta$ = 0.273, p < 0.001), while effort expectancy had a significant negative effect ( $\beta$ = −0.160, p = 0.010). Hypotheses H4 and H5 were therefore supported, consistent with the core logic of cognitive appraisal theory.

Positive emotion significantly and positively predicted all three well-being dimensions, with the strongest effect on workplace well-being ( $\beta$ = 0.285, p < 0.001), followed by psychological well-being ( $\beta$ = 0.184, p = 0.007) and life well-being ( $\beta$ = 0.165, p = 0.009). Hypotheses H6a, H6b, and H6c were all supported.

**Table 4: Structural model path coefficients and hypothesis testing results**

| Hypothesis | Path | Standardized β | Standard Error (SE) | t-value | p-value | Result |
|---|---|---|---|---|---|---|
| **H1a** | SI → PE | 0.404 | 0.065 | 6.19 | < 0.001 | Supported*** |
| **H1b** | SI → EE | −0.154 | 0.062 | 2.48 | 0.013 | Supported** |
| **H2a** | HM → PE | 0.267 | 0.077 | 3.471 | 0.001 | Supported** |
| **H2b** | HM → EE | −0.126 | 0.081 | 1.564 | 0.118 | Not Supported |
| **H3a** | ANT → PE | 0.119 | 0.06 | 1.971 | 0.049 | Supported* |
| **H3b** | ANT → EE | −0.058 | 0.073 | 0.789 | 0.43 | Not Supported |
| **H4** | PE → EMO | 0.273 | 0.07 | 3.901 | < 0.001 | Supported*** |
| **H5** | EE → EMO | −0.160 | 0.062 | 2.579 | 0.01 | Supported** |
| **H6a** | EMO → WWB | 0.285 | 0.074 | 3.837 | < 0.001 | Supported*** |
| **H6b** | EMO → PWB | 0.184 | 0.069 | 2.687 | 0.007 | Supported** |
| **H6c** | EMO → LWB | 0.165 | 0.063 | 2.62 | 0.009 | Supported** |

*Note.* Standardized path coefficients are reported. *p < .05. **p < .01. ***p < .001.

Bootstrap mediation analysis further verified the "cognitive appraisal‑positive emotion‑employee well-being" mechanism (Table 5). Positive emotion significantly mediated the relationships between performance expectancy and both workplace well-being ( $\beta$ = 0.078, p = 0.012) and psychological well-being ( $\beta$ = 0.050, p = 0.039), while the indirect effect on life well-being was marginally significant ( $\beta$ = 0.045, p = 0.065). For the effort expectancy pathway, the negative mediation effect was significant only for workplace well-being ( $\beta$ = −0.046, p = 0.044). Among serial mediation pathways, the social influence → performance expectancy → positive emotion chain showed the strongest effect ( $\beta$ = 0.111, p = 0.001). Overall, positive emotion partially mediates the appraisal‑well-being relationship, with the most robust effects observed for workplace well-being.

**Table 5: Bootstrap Test Results of Specific Indirect Effects (Mediation Analysis)**

| | Original Sample O | （M） | (STDEV) | T-value | P-value |
|---|---|---|---|---|---|
| **EE → EMO → LWB** | -0.026 | -0.031 | 0.017 | 1.547 | 0.122 |
| **EE → EMO → PWB** | -0.029 | -0.035 | 0.019 | 1.56 | 0.119 |
| **EE → EMO → WWB** | -0.046 | -0.049 | 0.023 | 2.013 | 0.044 |
| **PE → EMO → LWB** | 0.045 | 0.052 | 0.025 | 1.844 | 0.065 |
| **PE → EMO→ PWB** | 0.05 | 0.058 | 0.024 | 2.06 | 0.039 |
| **PE → EMO → WWB** | 0.078 | 0.083 | 0.031 | 2.5 | 0.012 |

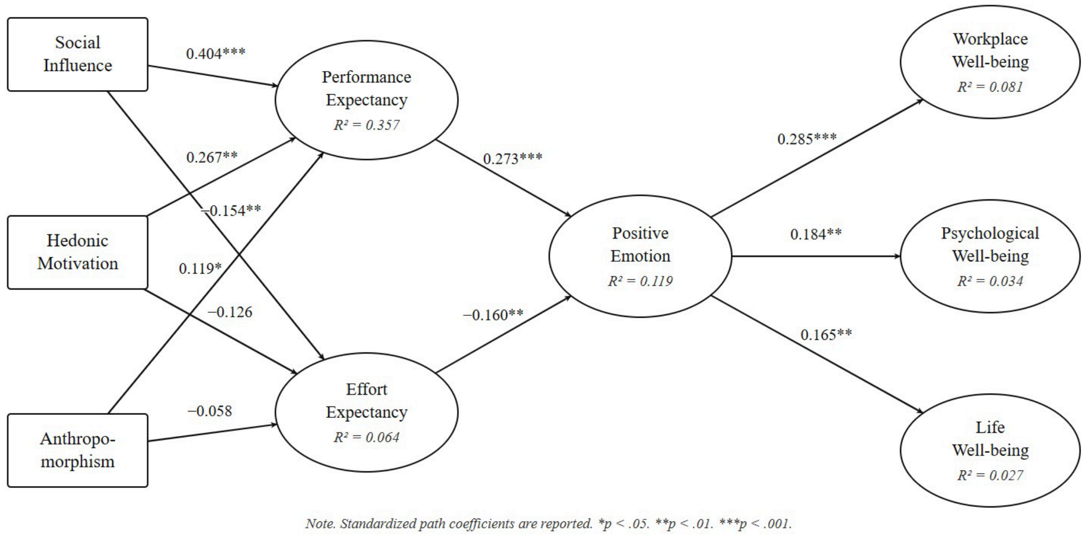


**Figure 1: Structural Equation Model with Standardized Estimates**

# 5. Conclusion

## 5.1 Key Findings

This study examines the psychological and affective impacts of AIOAs ' application on employee well-being in MNCs. Whereas previous research has predominantly highlighted the efficiency and productivity gains of AI, its emotional consequences and spillover effects on overall well-being have received limited attention. Using an integrated framework that bridges the cognitive-emotional appraisal components of the AIDUA architecture with multidimensional employee well-being, this paper maps the theoretical mechanisms through which AI tools shape workers' professional and personal lives.

The empirical analysis, conducted via PLS-SEM, validates the sequential cognitive-emotional process within the MNC context. First, the AIDUA sequence is confirmed: cognitive appraisals serve as the necessary prerequisites for emotional responses, with social influence emerging as the most dominant driver, significantly enhancing perceived utility while concurrently reducing the perceived difficulty of AI usage. Second, positive emotion plays a mediating role in the relationship between AI cognitive evaluations and employee well-being. Finally, AI's impact is inherently multidimensional, exerting its most substantial influence on workplace well-being, followed by significant spillover into psychological and life well-being.

The alignment of these results with the tripartite EWB model (Zheng et al., 2015) indicates that AI functions as a critical psychological resource that helps employees navigate job-related demands. The strongest effect on workplace well-being ($\beta = 0.285$) suggests that the functional support provided by AI primarily mitigates professional stressors. In the rigorous, task-oriented culture of MNCs, hedonic and anthropomorphic features may provide intellectual stimulation, yet they do not reduce the inherent complexity of professional AI prompting or cross-cultural reporting tasks. This directly explains why H2b and H3b were not supported: neither the playfulness of AI nor its human-like interaction style can substitute for the rigorous cognitive effort required to operate the system effectively in a professional context. These findings diverge from the consumer-centric focus of the original AIDUA model (Gursoy et al., 2019), implying that workplace technological acceptance is driven more by social validation and functional mastery than by mere playfulness. Consistent with conservation of resources theory, when AI conserves cognitive energy during work hours, the resulting resource surplus enables employees to experience improved life satisfaction beyond the office environment.

## 5.2 Research Implications

This study examines the mechanisms through which employees' cognitive appraisals of AI-office assistants foster positive emotions and multidimensional well-being, together with the applicability of these mechanisms within the highly structured context of MNCs. Drawing on the AIDUA framework and cognitive appraisal theory, it reveals that although the functional and social attributes of AI shape initial usage expectations, their value ultimately lies in generating positive emotional responses. These emotions, in turn, serve as a pivotal psychological mechanism that promotes workplace, psychological, and life well-being in a cascading manner.

In the MNC context, employees' cognitive appraisals exhibit unique dynamics that challenge traditional technology acceptance assumptions. Anthropomorphism, often viewed as a double-edged sword or an identity threat in consumer service settings, is shown here to serve as a performance-enhancing cue: because MNC employees prioritize task efficiency and complex cross-border communication, the human-like conversational ability and contextual responsiveness of AI assistants actively bolster their performance expectancy. Yet anthropomorphism fails to mitigate the cognitive burden of adopting the tool—endowing AI with human traits does not lower users' expectations regarding the mental effort required. This indicates that in professional settings, the appraisal of technological difficulty is fundamentally a socially embedded process driven by peer dynamics and organizational norms, rather than by the intrinsic design of the tool itself.

Although the original AIDUA model effectively explains the mechanisms of behavioral acceptance, the current study advances this theoretical framework. Its primary contribution lies in integrating the multidimensional employee well-being (EWB) model with the AIDUA model, deepening understanding of technostress within the human–AI collaboration process. This is also among the first empirical studies to examine how cognitive evaluations of AI influence multidimensional well-being through emotional mechanisms in the MNC context, advancing existing theory beyond productivity and adoption metrics and opening new avenues for understanding the psychological spillover effects of human–AI collaboration in the modern workplace.

### 5.3 Practical Implications

This study offers actionable recommendations for MNC managers and technical personnel striving to facilitate seamless AI adoption in remote offices while proactively safeguarding the well-being of their workforce.

The robust dual effect of social influence—which simultaneously bolsters performance expectations and significantly alleviates the perceived effort of using AI—highlights that digital transformation is a socially embedded process, not merely an IT initiative. MNCs should not simply deploy AI software and expect organic, seamless adoption; instead, managers must actively orchestrate a supportive social climate, identifying and empowering "AI champions" or early adopters across departments to serve as peer mentors.

By fostering visible leadership endorsement and showcasing peer-to-peer success stories, companies can leverage social norms to reduce the intimidating learning curve of new AI tools and build collective confidence in their utility. Furthermore, since human-like attributes and interactive enjoyment significantly elevate employees' performance expectations, MNCs should prioritize procuring AI assistants equipped with natural conversational interfaces and engaging user experiences.

A critical caveat, however, is revealed by the present data: making an AI tool "fun" or "human-like" does not statistically reduce the actual cognitive effort required to master it for complex, cross-border tasks. Investing in advanced, user-friendly interfaces therefore cannot replace rigorous, structured technical onboarding. Companies must provide targeted training that addresses the practical complexities of the system, rather than assuming an intuitive interface alone will guarantee frictionless adoption.

### 5.4 Social Implications

The societal impact of deploying AI office assistants extends far beyond corporate productivity metrics, fundamentally reshaping the psychological landscape of the modern workforce. One of the most critical insights of this study is the empirical validation of the spillover effect, which implies that the transition to an AI-augmented economy is not strictly an economic or technological issue but a profound public health and societal well-being imperative. As AI becomes ubiquitous, society must consciously shift the dominant narrative from "AI as a threat to employment" to "AI as a catalyst for human flourishing." Ensuring that employees experience positive affective states during human–AI collaboration is essential for cultivating a healthy, sustainable, and psychologically resilient digital society.

Furthermore, this study sheds light on the hidden cognitive toll of the digital era. The findings reveal that while anthropomorphic and hedonic features make AI systems appear more competent, they fail to alleviate the actual cognitive effort required to master these tools. On a societal level, this exposes a dangerous misconception: the assumption that "smart" or "conversational" technology is inherently effortless to adopt. If the rapid deployment of advanced AI outpaces workers' cognitive adaptation, and intuitive design is falsely assumed to replace structured learning, society risks exacerbating "digital burnout" and technological anxiety among the white-collar demographic.

Finally, the profound capacity of social influence to mitigate perceived effort and boost performance expectations testifies to the enduring importance of human connection in an automated world. The data underscore that human-to-human social support remains the most effective buffer against technological intimidation. As society advances further into the digital age, collaboration among policymakers, educational institutions, and corporate entities is essential to build socially supportive ecosystems that leverage human communities and peer networks to foster collective technological empowerment and social cohesion.

### 5.5 Limitations and Future Research Directions

Although this study has theoretical and practical contributions, several limitations should be acknowledged and addressed in future research.

First, the use of cross-sectional survey data precludes definitive causal inferences regarding the relationships among cognitive AI appraisals, emotional states, and workplace well-being. Although the proposed pathways are firmly grounded in cognitive appraisal theory, future studies could employ longitudinal designs or experimental methods to elucidate the dynamic process of human–AI interaction and its long-term consequences for psychological well-being.

Second, the empirical data were collected exclusively from employees of MNCs operating in China. While this provides a highly relevant sample for assessing the adoption of cutting-edge AI technologies, it constrains the generalizability of the findings. Cultural dimensions such as power distance and collectivism (Liu et al., 2022) may strongly affect the perceived influence of social factors and anthropomorphic characteristics; future studies are therefore encouraged to conduct cross-cultural comparisons (e.g., Eastern versus Western MNCs) to validate the boundary conditions of the proposed model.

Third, to align with the positive-psychology perspective of the EWB framework, the current conceptual model focuses exclusively on the mediating role of positive emotions. However, interacting with AI can also induce negative affective states such as technostress, algorithm aversion, and fear of replacement. Future research should develop a dual-pathway model to examine simultaneously the triggering and mitigating mechanisms of negative emotions and their potentially destructive impact on employee well-being.

Finally, although the statistical analysis indicated that common method bias (CMB) is unlikely, the reliance on self-reported data is acknowledged as a limitation. Future studies could incorporate objective behavioral data, such as real AI system usage logs or physiological indicators of stress, to enrich understanding of the psychological dynamics of AI deployment. Exploring the impact of AIOAs' adoption on knowledge management, such as knowledge transfer in MNCs (Liu et al., 2024), also offers a promising avenue.

**Ethics declaration:** This study is based on primary data involving human participants, but no sensitive personal information was collected. It is also approved by the SZTU research committee.

**AI declaration:** During the preparation of this paper, the authors used ChatGPT-4 (OpenAI) and Grammarly to assist with language polishing, grammar checking, and sentence structure refinement. The AI-generated content was carefully reviewed, edited, and verified by the authors to ensure accuracy, originality, and consistency with the research objectives. The authors take full responsibility for the final content of this paper.

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