

AI Perception Dimensions as Predictors of Employee Adaptation in Symbiotic Work Environments: Evidence from Thailand's Private Sector

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ABSTRACT. This study examines how employees' perceptions of artificial intelligence (AI) influence their adaptation to human-AI collaboration environments in Thailand, focusing on addressing the limited data resources available in developing countries. Perceptions of AI were defined in four dimensions: perceived value, perceived inevitability, acceptance readiness, and adaptive preparedness. A quantitative cross-sectional research design was used, collecting data from 387 private sector employees via a structured questionnaire. Employee adaptation was measured by work adaptation, AI-human compatibility, and collaboration based on trust. Hierarchical multiple regression analysis revealed that all four dimensions significantly predicted adaptation, explaining (adjusted R^2) 76.7% of the variance. Adaptive preparedness was the strongest predictor, followed by acceptance readiness, perceived value, and perceived inevitability, respectively. Age had a minor negative impact, while education level was insignificant. The findings indicate that effective human-AI collaboration stems from perceived, emotional, and behavioral factors, emphasizing that proactive skill development is a key pathway for adaptation.

1. INTRODUCTION

Artificial intelligence (AI) has far surpassed the limitations of specialized automation. Today's AI systems, encompassing machine learning, natural language processing, and robotics, are augmenting executive decision-making, restructuring supply chains, and creating outcomes previously thought to be solely human responsibility [1, 2]. These changes have had a significant impact: job roles are being restructured, organizational hierarchies are being challenged, and the scope of professional work is being redefined [3, 4]. The increased productivity is real, but

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concerns are also real, including issues of displacement, outdated skills, and the increasingly stressed psychological relationship between workers and the organizations that use these systems [5, 6, 7].

Whether this transition generates shared prosperity or deepens inequality depends less on algorithmic sophistication than on how employees respond to it. Employees are not passive recipients of technological change; their perceptions, attitudes, and behavioral responses actively shape whether implementation succeeds or stalls [8, 9]. Researchers have consequently turned to technology acceptance frameworks, most notably the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) to explain adoption intentions through perceived usefulness and ease of use [10, 11]. More recent AI-specific work has extended these models to include perceived autonomy, ethical concerns, and trust [12, 13].

However, a blind spot that remains in this study is geography. Most researches in behavioral and organizational technology are based on educated, industrialized, wealthy, and democratic Western populations, or Western, Educated, Industrialized, Rich, and Democratic (WEIRD) [14], TAM [9], and the Unified Theory of Acceptance and Use of Technology (UTAUT) [15] are no exception. The primary validation takes place in the context of North America and Europe [15]. This is important because organizational culture, power dynamics, and attitudes toward power and uncertainty vary significantly from society to society [16, 17]. Cultures with high power distances may respond differently to top-down AI commands; collectivized societies may prioritize group interconnection over the benefits of individual performance [18]. Whether findings from the WEIRD context can be applied elsewhere remains an open empirical question [19]. This gap is particularly pronounced in Southeast Asia. The region is digitizing rapidly, backed by substantial public and private investment in AI adoption [20], yet scholarly understanding of how employees in these countries perceive and adapt to AI at work remains thin [21]. National reform agendas, such as Indonesia's Making Indonesia 4.0 project, Singapore's Smart Nation project, and Thailand's Thailand 4.0 project, all depend significantly on the readiness of the workforce. Neglecting this aspect will have a significant impact on both national research and policy.

Thailand offers a particularly instructive case. The government's Thailand 4.0 initiative has created direct organizational pressure to integrate AI across private sector industries [22], the human capital challenges of doing so remain poorly understood [23]. Thai workplace culture is shaped by hierarchical norms, collectivist values, and relatively high uncertainty avoidance [16], may produce responses to AI that differ meaningfully from those documented in Western studies. Employees perceive AI not merely as a productivity tool but as a potential disruption to establish social and authority structures. Prior technology adoption research in Thailand has

largely focused on consumers or single sectors such as education [24, 25], leaving the private sector workforce under examined.

This study focuses on the intersection of three key issues: the global debate about AI and the future of work; the theoretical need to reduce WEIRD in technology management, industrial and academic fields; and the practical necessity of Thailand's digital transformation agenda. We argue that the fields focus on adoption. That is, the initial willingness to use the technology – obscures the more important question of how employees will adapt to working with AI over time. Adaptation involves ongoing changes in knowledge, behavior, and relationships, which adoption alone cannot cover [26]. A symbiotic framing goes further still, emphasizing that effective human–AI work requires employees to redefine roles, trust AI outputs, and develop genuine collaborative interdependence. It is not simply comply with a new tool [27].

Based on the above, this study aims to answer three research questions concerning employees in the Thai private sector: First, what are the levels and dimensional structures of employees' perception and adaptation to artificial intelligence (AI)? Second, how do demographic and occupational factors relate to changes in these structures? And third, which dimension of perception towards AI can most effectively predict adaptation within a collaborative work environment?

This study contributes in two points of view. (1) Theoretically, it tests and contextualizes the structure of technology adoption in non-WEIRD environments [28], examining whether culturally embedded factors such as social influence, perceived job security, and hierarchical attitudes toward change carry more weight to explain than the principal effective drivers in Western models. It also extends the dependent variable from behavioral intention to reported behavioral adaptation and perception. And (2) practically, the findings provide evidence for human resource practitioners and policymakers in Thailand for designing change management programs, skills development programs, and national workforce development policies that go beyond infrastructure investments to address the human dimension of AI integration in developing countries.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1 Conceptual Framework: From Attitude to Symbiosis

Rather than treating employee attitudes toward AI as a fixed endpoint, this study conceptualizes human–AI integration as an ongoing, dyadic process of mutual adjustment. Two constructs anchor this framework: AI Perception—how employees cognitively and affectively interpret AI in their work context—and Employee Adaptation in Symbiotic Work Environments—the behavioral, cognitive, and relational changes through which effective collaboration with AI is achieved. This distinction is important, while attitudes can remain static,

adaptation by definition requires change, and while acceptance describes a turning point, interdependent coexistence describes the path of change [6, 26].

AI Perception draws on technology acceptance theory [10], change management scholarship [29], and futures reasoning literature to capture how employees make sense of AI as it enters their professional lives. Four dimensions constitute the construct:

Perceived Value of AI (PVA): which is based on the perceived benefits structure of TAM [10], records an assessment of employees' usefulness to AI, whether it enhances dignified work performance, expands capabilities, or provides practical competitive advantage [30, 31].

Perceived Inevitability of AI (PIA): based on the principle of technology identification, PIA reflects the degree to which employees perceive AI-driven change as inevitable—a macroeconomic force restructuring industries regardless of individual preferences [3]. This perception of external pressure will determine whether employees respond proactively or reactively [32].

Acceptance Readiness (AR): AR moves beyond the passive acceptance of AI to proactive psychological preparation, meaning a willingness to engage with change, coupled with emotional commitment and confidence in the organization's ability to successfully implement it [33, 34].

Adaptive Preparedness (AP): based on the theory of proactive behavior [35], demonstrates the efforts employees make to themselves to bridge the gap between current skills and future needs by seeking training, acquiring knowledge, and building the competencies necessary to work effectively with AI. [36].

Employee adaptation refers to tangible changes in behavior, perception, and relationships that enable employees to work effectively and sustainably with AI. Interdependence here does not simply refer to coexistence, but describes a mutually dependent partnership where human and AI capabilities complement each other [37]. Three dimensions make this concept tangible as:

Work Adaptation (WA): WA records behavioral changes employees make regarding workflows, daily routines, and role boundaries, such as job restructuring, adopting new skills, and customizing tasks, as AI tools are increasingly integrated into daily life [38, 39].

AI-Human Compatibility (AHC): based on the compatibility structure of [40], AHC evaluates how well the AI system's functions, interfaces, and outcomes align with the employees' work patterns and values. Achieving a good balance will lead to smoother integration into daily operations and reduce conflicts.

Trust-based Collaboration (TC): TC reflects a willingness to rely on AI results, accept recommendations, and delegate important tasks to AI, based on a perception of the system's reliability, transparency, and consistency [41]. In the absence of such trust, collaboration is likely to remain insincere, regardless of the technical complexity of the AI system.

The framework treats PVA, PIA, AR, and AP as antecedent perceptual conditions that shape employees’ capacity to achieve symbiotic adaptation across WA, AHC, and TC. A key empirical question is: which of these cognitive dimensions carries the most predictive weight, and does the model remain applicable in the context of non-Western emerging economies?

Figure 1 presents a theoretical crosswalk that traces each construct in the present framework to its disciplinary origin. Rather than positioning the seven constructs as novel inventions, the framework synthesizes and extends established theory. On the perception side, Perceived Value of AI is rooted in the perceived-usefulness logic of the Technology Acceptance Model [10]; Perceived Inevitability of AI draws on the facilitating-conditions component of UTAUT [9] together with perceptions of external technological pressure captured by the STARA construct [32]; Acceptance Readiness derives from change-readiness theory [29, 33]; and Adaptive Preparedness is grounded in proactive behavior theory [35]. On the adaptation side, Work Adaptation builds on work-design theory [38, 39], AI-Human Compatibility on the compatibility dimension of Diffusion of Innovations [40], and Trust-based Collaboration on research into human trust in AI [41]. Making this lineage explicit clarifies that the contribution of the present study lies not in the individual constructs but in their integration into a single, adaptation-centric model suited to examining human–AI symbiosis in a non-WEIRD emerging-economy context.

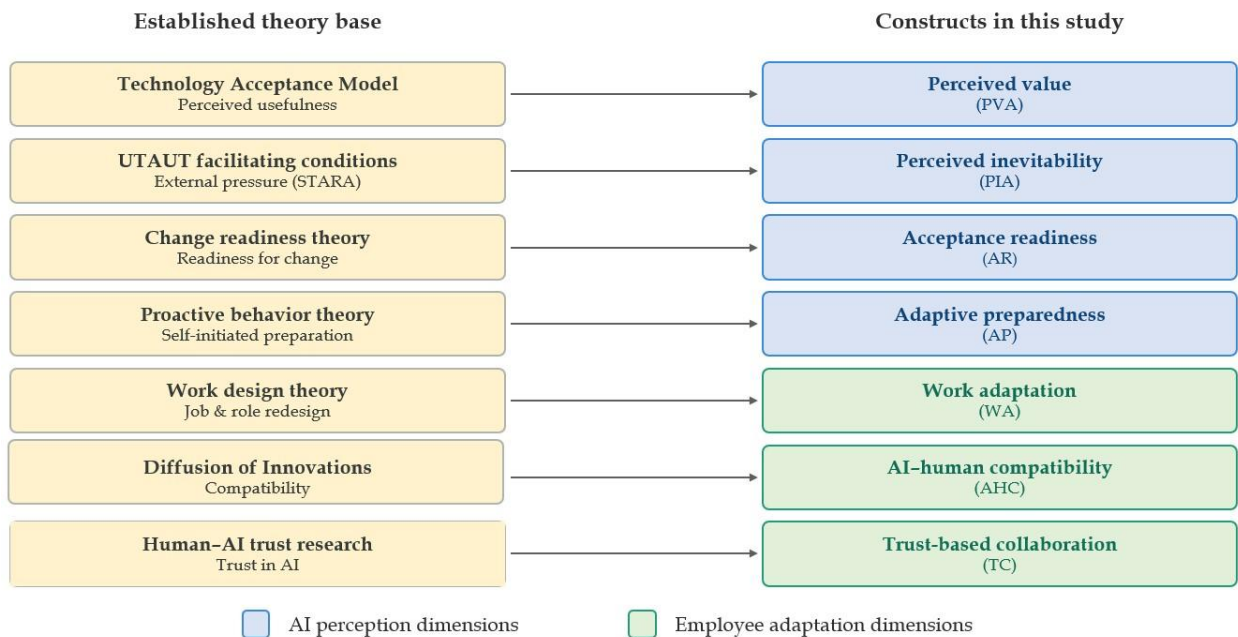


Figure 1. Theoretical Crosswalk Linking Established Theories to the Constructs Examined in This Study

2.2 Related Research and Hypothesis Development

Building on this theoretical foundation, Figure 2 specifies the research model tested in this study. The four AI Perception dimensions (PVA, PIA, AR, and AP) are modeled as independent predictors of Employee Adaptation, which is operationalized as a second-order construct reflected by three dimensions (WA, AHC, and TC) and analyzed as a composite criterion (ADAPT_TOTAL). Demographic characteristics are entered as statistical controls. TAM establishes perceived usefulness as a primary adoption driver [10], and AI-specific research confirms that positive capability beliefs reduce threat perceptions and increase engagement [42]. Applied to the adaptation context:

H1: Perceived Value of AI (PVA) is positively related to Employee Adaptation.

Within UTAUT, facilitating conditions, including the perceived inevitability of a technology, prompt cognitive preparation for change [9]. Change management research further establishes readiness as a prerequisite for successful adaptation rather than a byproduct of it [29]:

H2: Perceived Inevitability of AI (PIA) is positively related to Employee Adaptation.

H3: Acceptance Readiness (AR) is positively related to Employee Adaptation.

Proactive behavior theory holds that individuals who self-initiate skill development are better equipped to absorb and navigate change [35], a pattern reinforced by research on digital competency and employability [43]:

H4: Adaptive Preparedness (AP) is positively related to Employee Adaptation.

Given mixed evidence on demographic influences in technology acceptance research [44], this study also examines gender, age, education, income, work experience, and region as exploratory research questions rather than directional hypotheses.

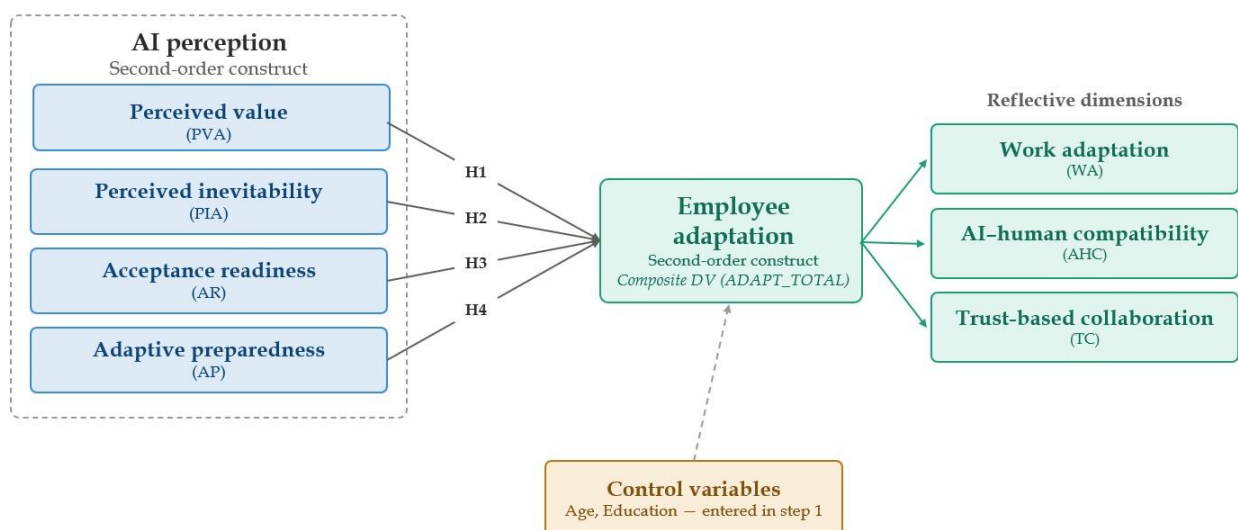


Figure 2. Research Model and Hypothesized Relationships (H1-H4)

3. METHODOLOGY

3.1 Design & Sample

The study adopted a quantitative cross-sectional design, appropriate for examining correlational relationships among variables at a single point in time [45]. The target population was private sector employees across Thailand.

A sample size of 400 was calculated using the [46]'s formula at a 95% confidence level and 5% margin of error, based on Thailand's estimated private-sector workforce of 24.47 million. Data was collected over a one-month period through self-administered online questionnaires distributed through simple random sampling across professional social media networks and industry-specific forums relevant to Thai employees in the manufacturing, service, freelance, and general employment sectors [47].

Screening for completeness and response consistency yielded 387 usable responses from the initial 400 submissions (response rate: 96.75%). Online convenience sampling introduces the possibility of self-selection bias, though this response rate falls within accepted parameters for web-based social science surveys [48]. The sample profile, summarized in Table 1, represents a cross-section of private sector employees across gender, age, education level, region of workplace, monthly income, and work experience.

Table 1. Sample Characteristics

Characteristic	Category	Frequency	Percentage
Gender	Male	117	30.2
	Female	270	69.8
Age	Under 25 years	97	25.1
	25-30 years	112	28.9
	31-40 years	86	22.2
	41-50 years	57	14.7
	Over 50 years	35	9.0
Education	Below Bachelor's Degree	108	27.9
	Bachelor's Degree	224	57.9
	Postgraduate Degree	55	14.2

Characteristic	Category	Frequency	Percentage
Work Region	Bangkok Metropolitan	164	42.4
	Northeast	75	19.4
	Central	84	21.7
	Eastern	35	9.0
	South	15	3.9
	North	14	3.6
Monthly Income	< 475 USD	97	25.1
	475-790 USD	162	41.9
	791-1,100 USD	75	19.4
	> 1,100 USD	53	13.7
Work Experience	< 5 years	102	26.4
	5-10 years	130	33.6
	10-15 years	91	23.5
	> 15 years	64	16.5

n = 387

3.2 Measures and Instrumentation

The survey instrument comprised three sections: demographics, AI Perception items, and Employee Adaptation items. All constructs were measured using reflective multi-item scales on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), consistent with standard practice in organizational attitude research [47].

AI Perception was modeled as a second-order construct with four dimensions, drawing on recent work decomposing employee AI attitudes into cognitive and affective components [49, 50]. Twenty items were developed across the four dimensions: PVA (5 items) captured utilitarian assessments of AI's performance benefits [51]; PIA (5 items) measured the perceived inevitability of AI-driven workplace change [52]; AR (5 items) assessed psychological preparedness and

willingness to engage with that change [53]; and AP (5 items) gauged proactive skill and knowledge acquisition efforts ahead of AI integration [54].

Employee Adaptation was similarly modeled as a second-order construct with three dimensions across 15 items [26]: WA (5 items) captured modifications to work routines and role definitions [55]; AHC (5 items) assessed perceived fit between AI system functions and individual work styles [56]; and TC (5 items) measured reliance on and confidence in AI as a collaborative partner [57, 58].

To establish cross-cultural validity, all items were translated into Thai using [59]'s back-translation protocol. Three scholars in organizational behavior and management information systems reviewed the translated items for content validity. A pilot test with 30 respondents confirmed item clarity and preliminary scale reliability, with minor wording adjustments made prior to full deployment [48].

3.3 Data Analysis

All analyses were conducted in IBM SPSS Statistics (Version 28). Descriptive statistics – frequencies, percentages, means, and standard deviations – were calculated to characterize the sample groups and summarize the principal variables [60]. Differences between groups based on demographic factors were examined using t-tests for binary variables and one-way ANOVA with Tukey post-analysis tests for multiple variables [61]. Pearson correlation assessed the binary relationship between the AI perception dimensions and employee adaptation. To identify the unique predictive contributions of each AI perception dimension, a multilevel regression was performed: demographic control variables were entered in block 1, followed by the four AI perception dimensions in block 2, with overall employee adaptation as the criterion variable [62].

To address the potential threat of common method bias (CMB) arising from the single-source, self-reported cross-sectional design, both procedural and statistical approaches were adopted [63]. Procedurally, respondent anonymity was guaranteed, and predictor and criterion items were positioned in separate sections of the questionnaire to reduce demand characteristics and evaluation apprehension [64]. To assess common method bias, Harman's single-factor test was conducted by entering all study items into an exploratory principal component analysis. The single extracted component accounted for 40.49% of the total variance, which falls below the conventional 50% threshold [63], suggesting that common method bias is unlikely to be a serious concern in this study.

This finding is acknowledged as a limitation of the cross-sectional, self-report design. However, it is worth noting that Harman's test is widely regarded as a conservative and limited diagnostic tool [63, 64], and the high loading on a single component is partly attributable to the theoretically coherent and inter-related nature of the constructs under investigation – namely, dimensions of AI perception and employee adaptation – which are expected to covary

meaningfully. Future research employing longitudinal designs or independent data sources for predictor and criterion variables would more rigorously address this concern.

4. RESULTS

4.1 Descriptive Statistics and Preliminary Analyses

Table 2 presents descriptive statistics and reliability estimates for all constructs. Mean scores indicate generally positive orientations toward AI across the sample: overall AI Perception ($M = 3.87$, $SD = 0.62$) and Employee Adaptation ($M = 3.77$, $SD = 0.71$) both fell in the moderate-to-high range. Among the AI Perception dimensions, Perceived Inevitability registered the highest mean ($M = 4.01$, $SD = 0.68$), suggesting that employees widely recognize AI as an unavoidable workplace force even where preparedness lags. Adaptive Preparedness returned the lowest score ($M = 3.62$, $SD = 0.82$), a gap with practical implications explored in the Discussion. On the adaptation side, Work Adaptation ($M = 3.92$) outpaced Trust-based Collaboration ($M = 3.65$), indicating that behavioral adjustment to AI precedes the deeper relational trust required for genuine collaboration. All scales demonstrated strong internal consistency (Cronbach's alpha $> .85$). This means that the measurement items within each scale have a high degree of consistency in measuring the same underlying structure, or respondents answered the questions in a similar and consistent manner, demonstrating the reliability of the scale [65].

Table 2. Descriptive Statistics and Scale Reliabilities

Construct/Dimension	Mean (M)	Standard Deviation (SD)	Cronbach's Alpha (α)
AI Perception (Total)	3.87	0.62	.92
Perceived Value (PVA)	3.95	0.67	.87
Perceived Inevitability (PIA)	4.01	0.68	.89
Acceptance Readiness (AR)	3.91	0.71	.88
Adaptive Preparedness (AP)	3.62	0.82	.85
Employee Adaptation (Total)	3.77	0.71	.94
Work Adaptation (WA)	3.92	0.73	.91
AI-Human Compatibility (AHC)	3.73	0.82	.93
Trust-based Collaboration (TC)	3.65	0.78	.89

4.2 Group Differences Based on Demographic Factors

Independent samples t-tests yielded no significant differences by gender, income, or work region on either AI Perception or Employee Adaptation. One-way ANOVA, however, identified significant variation by age and education level, summarized in Table 3. On age, Tukey HSD post-hoc tests revealed that the 25–30 cohort scored significantly higher on both Acceptance Readiness and Adaptive Preparedness than employees under 25 and those over 50—a pattern suggesting that mid-early career professionals may occupy a distinctive preparedness advantage relative to both newer entrants and longer-tenured workers. On education, postgraduate-qualified employees reported significantly higher PVA, PIA, and AR than bachelor's degree holders and those with sub-degree qualifications, consistent with the view that higher education fosters both awareness of and readiness for technological change.

Table 3. Summary of Significant ANOVA Results

Dependent Variable	Factor	F-value	p-value	η^2	Significant Post-Hoc Contrasts (Tukey HSD)
Acceptance Readiness (AR)	Age	2.69	.032	.045	25-30 > Under 25; 25-30 > Over 50
Adaptive Preparedness (AP)	Age	2.49	.044	.042	25-30 > Under 25; 25-30 > Over 50
Perceived Value (PVA)	Education	7.40	.001	.060	Postgrad > Bachelor's; Postgrad > Below Bachelor's
Perceived Inevitability (PIA)	Education	4.33	.014	.036	Postgrad > Bachelor's
Acceptance Readiness (AR)	Education	7.31	.001	.060	Postgrad > Bachelor's; Postgrad > Below Bachelor's

4.3 Correlation and Regression Analyses

Table 4 reports Pearson correlations among all study variables. Every AI Perception dimension correlated positively and significantly with every Employee Adaptation dimension (all $p < .01$), with coefficients ranging from moderate to strong. Two patterns warrant particular attention ahead of the regression analysis. First, Acceptance Readiness showed the strongest

association with Work Adaptation ($r = .77$), suggesting a tight coupling between psychological preparedness and behavioral adjustment at the task level. Second, Adaptive Preparedness registered equally strong correlations with both AI-Human Compatibility and Trust-based Collaboration ($r = .79$ for each), pointing to proactive skill-building as a common foundation for both fit perception and collaborative trust. These intercorrelations justified proceeding to hierarchical regression to disentangle the independent predictive contributions of each dimension.

Table 4. Intercorrelations among Study Variables (Pearson's r)

Variable	1	2	3	4	5	6	7	8
1. PVA	1							
2. PIA	.60**	1						
3. AR	.73**	.72**	1					
4. AP	.66**	.62**	.76**	1				
5. WA	.66**	.64**	.77**	.61**	1			
6. AHC	.68**	.57**	.75**	.79**	.70**	1		
7. TC	.65**	.55**	.69**	.79**	.68**	.74**	1	
8. ADAPT_TOTAL	.72**	.67**	.85**	.83**	.91**	.92**	.90**	1

Note. ** $p < .01$. PVA=Perceived Value, PIA=Perceived Inevitability, AR=Acceptance Readiness, AP=Adaptive Preparedness, WA=Work Adaptation, AHC=AI-Human Compatibility, TC=Trust-based Collaboration, ADAPT_TOTAL=Employee Adaptation Total Score.

4.4 Regression Analysis

Table 5 presents the hierarchical regression results. Demographic controls entered in Step 1 explained 8.3% of variance in Employee Adaptation ($R^2 = .083$), with age ($\beta = -.230$, $p < .001$) and education ($\beta = .181$, $p < .001$) both significant at this stage. The addition of the four AI Perception dimensions in Step 2 produced a substantial improvement in model fit ($\Delta R^2 = .688$, $p < .001$), with the full model accounting for 77.1% of variance (Adjusted $R^2 = .767$, $F(6, 380) = 284.979$, $p < .001$).

With demographics controlled, all four AI Perception dimensions emerged as independent significant predictors. Adaptive Preparedness carried the largest effect ($\beta = .424$, $p < .001$), followed by Acceptance Readiness ($\beta = .233$, $p < .001$), Perceived Value ($\beta = .211$, $p < .001$), and Perceived Inevitability ($\beta = .155$, $p < .001$) – supporting H1 through H4. Among the controls, age retained a small but significant negative effect in the full model ($\beta = -.063$, $p = .013$), while education was no longer significant ($\beta = -.006$, $p = .829$), suggesting its influence on adaptation operates primarily through shaping AI perceptions rather than directly. All VIFs fell below 3.0 (highest: AR = 2.911), indicating multicollinearity was not a concern [66].

Table 5. Hierarchical Multiple Regression

Predictor	Step 1(β)	Step 2(β)	t	p-value	VIF
Age Group	-.230*	-.063	-2.498	.013	1.058
Education Level	.181*	-.006	-.217	.829	1.084
Perceived Value (PVA)		.211	5.495	<.001	2.436
Perceived Inevitability (PIA)		.155	4.575	<.001	1.898
Acceptance Readiness (AR)		.233	5.549	<.001	2.911
Adaptive Preparedness (AP)		.424	13.025	<.001	1.756
R^2	.083	.771			
Adjusted R^2	.078	.767			
ΔR^2	-	.688			
F for ΔR^2	17.329**	284.979**			

Note. * $p < .05$, ** $p < .001$. Step 1 $R^2 = .083$; Final Model $R^2 = .771$

5. DISCUSSION

The findings position this study among the first quantitative investigations of human-AI symbiosis in a non-WEIRD Southeast Asian context, and the results both confirm and complicate

established theory. What follows unpacks the key empirical patterns, their theoretical significance, and their practical bearing for organizations navigating AI integration in emerging economies.

5.1. Interpretation of Key Findings

The most significant finding was that the four perceptual AI dimensions—PVA, PIA, AR, and AP—could independently predict employee adaptation after controlling for demographic variables, supporting hypotheses H1 through H4, which differs from the more selective model typical of TAM-derived research where perceived benefit often masks other predictors [10]. In the Thai private sector, no single perceptual dimension is the dominant factor: perceived value, perceived inevitability, acceptance readiness, and adaptive preparedness, all contribute to varying outcomes of adaptation.

Adaptive preparedness is appeared to be the strongest predictor ($\beta = .424$), followed by acceptance readiness ($\beta = .233$), perceived value ($\beta = .211$), and perceived inevitability ($\beta = .155$). The gap between AP and AR needs careful consideration. Both concepts relate to employees' attitudes towards AI-driven change, but AR reflects a psychological state which is a feeling of readiness, while AP reflects behavioral patterns including proactive preparation. The emphasis on action over feelings in this context clearly demonstrates that in environments where AI adoption is rapid and largely top-down, such as Thailand's Thailand 4.0 development path, attitudinal willingness alone is insufficient without investment in capabilities. Employees who consistently seek training, including acquiring new skills and building self-confidence before it's necessary, will be better positioned to adapt attitudes and build the relationships essential for effective collaboration [26, 35].

The significant contributions of PVA and PIA, along with AR and AP, point to a hierarchical logic worth explaining. Employees appear to first consider the instrumental value of AI and accept the structural inevitability, which are cognitive orientations that create the preconditions for motivation for change. Then, readiness and preparation decode those orientations into adaptive behaviors. This multi-layered model is consistent with change management theory [29, 34] and extends TAM and UTAUT to the adaptive domain: awareness of benefit and inevitability is also significant, but neither alone is sufficient to create the ongoing behavioral and relational modifications that interdependent work requires [6].

5.2. Demographic Influences and Cultural Contextualization

Demographic analyses yield several noteworthy patterns. At the bivariate level, ANOVA results confirmed significant group differences by age and education in key AI Perception dimensions (Table 3). More importantly, the regression analysis revealed that age retained a small but statistically significant negative effect on Employee Adaptation in the full model ($\beta = -.063$, $p = .013$), even after controlling for AI Perception dimensions. This finding suggests that beyond

perceptual differences, age carries an independent constraining influence on adaptation—a pattern consistent with research linking cognitive flexibility and technological learning agility to earlier career stages [44]. Older employees may face greater obstacles in restructuring existing workflows and developing trust-based collaboration with AI systems, regardless of how much they perceive the value or necessity of AI. On the other hand, education level was not significantly important across all models ($\beta = -.006$, $p = .829$), suggesting that the influence of education level on adaptation occurred more through the determination of perspectives toward AI rather than directly.

This result has further significance when considered within the cultural context of Thailand. The norm of high power distance may explain why PIA scores are higher in the sample—organizational AI requirements are recognized as inevitable—but this recognition of inevitability does not automatically translate into adaptation. The data suggest that true adaptation relies on intrinsic readiness and self-directed preparation, which hierarchical adherence alone cannot construct. The inclusive focus in the Thai workplace may mean that the promotion of AR and AP is not solely an individual project: peer influence, team-level support, and the organizational atmosphere are likely to modify how these attributes develop and translate into behavior.[18] These contextually significant dynamics illustrate why reducing weird in the literature is important—proactive work occurs in this context, but its expression is determined by institutional and social conditions that Western models fail to capture [14, 23].

5.3. Theoretical Implications

Three theoretical contributions emerge from these findings. First, this study extends technology acceptance theory by demonstrating that symbiotic adaptation—unlike initial acceptance—requires a broader perceptual portfolio than perceived usefulness alone. Modeling human–AI collaboration in emerging economies calls for integrating behavioral self-regulation constructs [35] and change readiness frameworks [29] alongside TAM and UTAUT, rather than treating the latter as sufficient. Second, the study provides quantitative validation of the symbiotic adaptation construct, offering a measurable, multi-dimensional framework that future research can replicate, extend, or test in comparative designs. Third, by generating empirical evidence from Thailand rather than a Western setting, the study adds to the growing body of work challenging the geographical assumptions embedded in mainstream management theory [14, 28]—demonstrating that the drivers of human–AI collaboration, while recognizable across contexts, carry different relative weights depending on the institutional and cultural environment.

5.4. Practical Implications

For HR practitioners and organizational leaders managing AI integration in Thailand and comparable economies, the central message is that demonstrating AI's utility—however

convincingly – is not enough. The strongest predictor of adaptation is what employees do before and during implementation, not merely what they think about it.

Three priorities follow from this. Change communication programs should be designed not only to inform but to build genuine psychological readiness – creating space for employees to process uncertainty, ask questions, and develop confidence in the organization's implementation capacity [49]. Structured upskilling and reskilling initiatives should be treated as strategic infrastructure rather than optional add-ons, with particular emphasis on self-directed learning cultures that reward proactive skill acquisition [36]. Age-differentiated support is also warranted: given the independent negative effect of age on adaptation in the full model, older employees merit targeted mentorship, simplified onboarding pathways, and stronger peer support structures that reduce the inertia costs of behavioral change.

For policymakers, the data expose a gap in Thailand's current AI strategy. Investment in digital infrastructure is necessary but insufficient if the workforce lacks the readiness and preparedness to leverage it. National lifelong learning ecosystems and public communication campaigns that demystify AI – particularly for older and regionally distributed workers – represent the complementary human capital investments that Thailand 4.0 requires.

5.5. Limitations and Future Research Directions

Three limitations bear on the interpretation of these findings. The cross-sectional design supports associational but not causal inference; the temporal sequencing implied by the cognitive-behavioral model proposed here requires longitudinal verification. Online convenience sampling produced a sample concentrated in the Bangkok Metropolitan (42.4%), with limited representation from Southern and Northern regions where AI adoption trajectories and workplace cultures may differ. Self-report data introduce the possibility of common method bias; while Harman's test and procedural controls were applied, the 69.84% single-factor variance warrants caution in interpreting effect size.

Three limitations bear on the interpretation of these findings. First, the cross-sectional design supports associational but not causal inference; the temporal sequencing implied by the cognitive-behavioral relationships proposed here requires longitudinal verification. Second, the use of online convenience sampling resulted in a sample concentrated in the Bangkok Metropolitan area (42.4%), with limited representation from Southern and Northern regions (3.9% and 3.6%, respectively), where AI adoption trajectories and workplace cultures may differ meaningfully from those in major urban centers. Accordingly, the generalizability of findings to employees in these underrepresented regions should be approached with caution. Third, the reliance on self-reported data introduces the possibility of common method bias; however, Harman's single-factor test indicated that one component accounted for only 40.49% of the total variance which is falling below the conventional 50% threshold [63], suggesting that common

method bias is unlikely to pose a serious threat to the validity of the findings, though this limitation should be acknowledged given the monomethod design

Future research should address these constraints on multiple fronts. Longitudinal designs would allow researchers to trace how AI perceptions and adaptive behaviors co-evolve as implementation matures. Mixed-method approaches would deepen understanding of the cultural and organizational factors, which are leadership style, team dynamics, institutional support, that moderate the AR and AP pathways identified here [49]. Replication across other Southeast Asian nations would enable the comparative analysis needed to distinguish Thailand-specific patterns from broader regional dynamics. Finally, organizational-level variables such as high-performance work systems and transformational leadership represent promising moderator candidates that individual-level survey data cannot adequately capture

5.6. Conclusion

This study examines the human pathway to a collaborative work environment in contexts overlooked by mainstream research. Data from 387 Thai private sector employees informs a consistent statement: adaptation to AI is not dependent on how employees evaluate the technology, but rather on what they do with it. Adaptability (proactive and self-directed investment in skills and knowledge) appears as the most significant predictor, with readiness, perceived value, and acceptance as inevitable, and free participation, age (not education), still having a direct impact when controlling for perception. Overall, these findings suggest that organizations and policymakers in Thailand and similar economies especially in the developing countries cannot simply leave workforce readiness as a consequence of AI adoption. This readiness must be intentionally cultivated, both before and during adoption, for human-AI collaboration to be truly realized.

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