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From Anxiety to Competence: A Secondary Data-Based Model of AI Acceptance and Learning Engagement in the Era of Education 4.0

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ABSTRACT

This study proposes an integrated, evidence-based model to explain the transition from artificial intelligence (AI)-related anxiety to acceptance and learning engagement in the context of Education 4.0. Drawing on a secondary data synthesis of four nationally representative South Korean datasets—KISTEP (2024), NIA (2024), KEEP (2024), and Statistics Korea (2024)—and grounded in Keller's (1987) ARCS motivational model and Davis's (1989) Technology Acceptance Model (TAM), the study develops a multi-layered framework linking AI anxiety, AI literacy, AI acceptance, and learning engagement. The analysis tests four hypotheses using a pseudo-SEM approach. Because the study relies on secondary data, proxy indicators are employed to operationalize key constructs, with the Digital Competency Index (DCI) used as a proxy for AI literacy. The findings show that AI anxiety is significantly and negatively associated with AI acceptance, whereas AI literacy exerts a direct positive effect and also weakens the anxiety-acceptance relationship, functioning as a cognitive buffer (moderating effect, $\beta = .23$, $p < .05$). In turn, AI acceptance emerges as a strong predictor of learning engagement ($R^2 = .34$). Most notably, this study reframes AI literacy not merely as a technical skill, but as a resilience mechanism that helps reduce technology-related anxiety. The theoretical contribution has direct implications for instructional design and age-sensitive policy interventions. In addition, the pseudo-SEM approach offers a replicable framework for building macro-level theory from national administrative data.

Keywords: AI anxiety, AI literacy, technology acceptance model, ARCS model, Education 4.0, learning engagement, secondary data analysis, pseudo-SEM, South Korea

INTRODUCTION

The rapid advancement of artificial intelligence (AI) is fundamentally transforming educational systems within the broader paradigm of Education 4.0, which envisions technology-driven, personalized, and competency-oriented learning environments (Hussin, 2018). In South Korea, this transformation is particularly pronounced:

national policy reports indicate that over 72% of surveyed citizens expect AI to reshape education within the next decade, while simultaneously expressing concerns about cognitive dependency and reduced critical thinking (Korea Institute of Science and Technology Evaluation and Planning [KISTEP], 2024).

This duality—between technological promise and psychological resistance—represents a critical challenge for learners, educators, and policymakers alike. Learners who experience high levels of AI-related anxiety tend to resist technology adoption, thereby undermining the potential benefits of AI-integrated education (Tams et al., 2018). Conversely, learners equipped with adequate AI literacy demonstrate greater acceptance and more sustained engagement with intelligent learning systems (Long & Magerko, 2020).

While existing scholarship has examined AI anxiety (Tams et al., 2018), AI literacy (Long & Magerko, 2020), and learning engagement as distinct constructs, no prior study has integrated all three variables into a unified structural model tested at the population level. Most available evidence derives from small-scale, single-institution surveys with limited demographic reach—a methodological constraint that severely restricts policy scalability (Scherer et al., 2019). The present study addresses both gaps: it proposes an integrated multi-construct model and tests it through secondary data synthesis across four nationally representative Korean datasets, enabling population-level inference that goes beyond the reach of any single primary study.

South Korea represents a strategically valuable context for this inquiry beyond its national boundaries. As one of the world's most digitally advanced societies—ranking among the top five globally in AI readiness, broadband penetration, and per-capita technology adoption (KISTEP, 2025)—Korea functions as a leading indicator of the AI integration challenges that other OECD and rapidly digitalizing nations will encounter within the next five to ten years. Furthermore, Korea's acute demographic ageing trajectory mirrors that of Japan, Germany, Italy, and much of Southern and Eastern Europe, making its findings on age-differentiated AI anxiety directly relevant to aging societies worldwide.

Accordingly, the proposed framework is theoretically generalizable, but its boundary conditions should be tested across diverse national contexts, especially in East Asian Confucian-heritage societies (Japan, China, Taiwan, Singapore, Vietnam) with collectivist educational traditions and state-led digital transformation strategies. While this model is grounded in Korean data and cross-national validation is needed before strong generalizability claims can be advanced, the TAM–ARCS integration and the anxiety–literacy–acceptance–engagement pathway may constitute a theoretically transferable framework whose boundary conditions should be tested across diverse national and cultural contexts.

The study is grounded in two complementary theoretical frameworks. The Technology Acceptance Model (TAM; Davis, 1989) provides the cognitive scaffolding that explains how perceived usefulness and behavioral intention mediate technology adoption. The ARCS motivational model (Keller, 1987) extends this cognitive foundation by incorporating the affective conditions—Attention, Relevance, Confidence, and Satisfaction—that sustain learning engagement beyond initial adoption. Their integration provides a theoretically coherent lens through which the emotional, cognitive, and behavioral dimensions of AI-mediated learning can be examined within a single structural model. South Korea serves as an especially instructive empirical context: it combines advanced digital infrastructure with one of the world's most rapidly aging populations, creating an acute version of the anxiety–adoption paradox that Education 4.0 contexts globally will increasingly face (KISTEP, 2024).

Accordingly, this study proposes an integrated structural model and tests four theory-derived hypotheses examining how AI anxiety, AI literacy, and AI acceptance jointly determine learning engagement within South Korean Education 4.0 contexts. The formal hypotheses are presented in Section 2.5 following the theoretical review. The formal hypotheses and data sources are summarized in **Table 1**.

Table 1. Research Hypotheses, Theoretical Bases, and Data Sources

H	Hypothesized Path	Theoretical Basis	Dataset(s)	Rationale
H1	AI Anxiety → AI Acceptance (−)	*TAM (Venkatesh, 2000); ARCS-Confidence (Keller, 1987)*	KEEP (KEIS, 2024); Statistics Korea ICT Usage Survey; NIA Digital Divide Survey	AI anxiety suppresses perceived usefulness and behavioral intention to use AI
H2	AI Literacy → AI Acceptance (+)	*TAM-PU (Davis, 1989); AI Literacy (Long & Magerko, 2020)*	NIA Digital Divide Survey (DCI); KEEP (skill training participation)	AI literacy enhances perceived usefulness and adoption intention
H3	AI Acceptance → Learning Engagement (+)	*ARCS-Satisfaction (Keller, 1987); TAM behavioral intention*	KEEP (training hours, SDL frequency); Statistics Korea (lifelong learning participation)	Acceptance mediates the pathway from literacy to engagement
H4	AI Literacy × AI Anxiety → AI Acceptance (moderation)	*Competence-based anxiety buffer (Bandura, 1997)*	NIA Digital Divide Survey (DCI tertile split); KISTEP anxiety items	AI literacy attenuates the negative anxiety-acceptance relationship

Note. H = Hypothesis. TAM = Technology Acceptance Model. ARCS = Attention, Relevance, Confidence, Satisfaction. DCI = Digital Competency Index. SDL = Self-Directed Learning.

LITERATURE REVIEW

AI Anxiety in Education

AI anxiety is conceptualized as a multidimensional psychological state characterized by perceived risks, uncertainty, and affective discomfort associated with AI technologies (Tams et al., 2018). In educational contexts, this anxiety manifests in three primary forms: (1) fear of cognitive replacement—concern that AI will supplant human thinking; (2) ethical apprehension—concerns over data privacy and algorithmic bias; and (3) task-performance anxiety—doubt about one's ability to effectively use AI tools.

National-level data from South Korea's KISTEP (2024) Technology Impact Assessment reveal that approximately 62% of adult learners reported moderate to high levels of concern regarding over-reliance on AI tools, with the rate escalating to 79% among adults aged 65 and older (see **Figure 1** in Section 4). Notably, anxiety at this level is associated with avoidance behaviors, reduced technology engagement, and diminished learning outcomes—patterns consistent with findings in the broader technology anxiety literature (Brosnan, 1998; Chua et al., 1999). AI anxiety thus functions not merely as an individual affective state but as a systemic barrier to the realization of Education 4.0 goals.

Theoretically, AI anxiety is best understood through the lens of Cognitive Appraisal Theory (Lazarus & Folkman, 1984), which posits that emotional responses to environmental stimuli are mediated by subjective evaluation of threat and one's capacity to cope. Applied to AI contexts, learners who appraise AI as threatening—whether to cognitive autonomy, employability, or ethical integrity—and who simultaneously perceive low coping efficacy will experience anxiety that motivates avoidance rather than engagement. This appraisal-based mechanism distinguishes AI anxiety from generalized technostress (Chang et al., 2024; Tams et al., 2018): whereas technostress reflects chronic overload from technology use, AI anxiety is a prospective, anticipatory response to AI's perceived social and cognitive implications—and is therefore amenable to intervention at the appraisal stage, before avoidance behaviors become entrenched. Crucially, if the appraisal of AI as threatening suppresses perceived usefulness before the cognitive evaluation process begins, then addressing anxiety is not merely a supportive concern but a prerequisite for any TAM-based adoption pathway to function as theorized.

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), originally proposed by Davis (1989), posits that two cognitive perceptions—perceived usefulness (PU) and perceived ease of use (PEOU)—are the primary determinants of behavioral intention to use a technology. Subsequent extensions, including UTAUT (Venkatesh et al., 2003), further incorporated social influence and facilitating conditions as antecedents of adoption. In AI-integrated educational contexts, TAM has demonstrated strong predictive validity; however, its original formulation has been critiqued for underweighting affective and motivational antecedents. Several scholars argue that emotional states—particularly anxiety—function as upstream determinants of perceived usefulness, effectively constraining the cognitive evaluation process before it begins (Igbaria & Chakrabarti, 1990; Venkatesh, 2000). This study extends TAM by treating AI anxiety as a pre-cognitive antecedent that is negatively associated with AI acceptance, positioning it upstream of the traditional TAM constructs.

The relevance of TAM in AI-integrated educational contexts has been confirmed empirically. Scherer et al.'s (2019) meta-analytic structural equation modeling of 114 studies on teachers' adoption of digital technology found that perceived usefulness ($\beta = .42$) and perceived ease of use ($\beta = .25$) together accounted for substantial variance in adoption intention, with PU consistently emerging as the stronger predictor. Critically, Scherer et al. also found that affective antecedents—including anxiety and attitude—exerted significant upstream influence on both PU and PEOU, corroborating the theoretical argument that emotional states constrain cognitive adoption pathways. TAM has also evolved beyond its original two-construct formulation: TAM2 (Venkatesh & Davis, 2000) incorporated subjective norm and job relevance; UTAUT2 (Venkatesh et al., 2012) added hedonic motivation and habit; and domain-specific extensions have addressed healthcare, e-learning, and AI contexts. The present study contributes to this evolution by integrating the affective-motivational architecture of the ARCS model into the TAM framework, thereby addressing the persistent critique that TAM's cognitive constructs are insufficient to explain adoption in contexts where emotional barriers are primary.

AI Literacy and Learning Engagement

AI literacy is broadly defined as the capacity to critically understand, evaluate, and apply AI systems across varied contexts (Long & Magerko, 2020). It encompasses four competency dimensions: (1) knowing what AI is and how it functions; (2) using AI tools effectively; (3) evaluating AI outputs critically; and (4) understanding the societal implications of AI deployment. Data from the National Information Society Agency's Digital Divide Survey (National Information Society Agency [NIA], 2024) indicate that South Korean adults with higher digital competency scores are significantly more likely to participate in technology-enhanced learning environments ($OR = 2.14$, 95% CI [1.87, 2.45]). Furthermore, AI literacy appears to act as a cognitive buffer against anxiety: individuals with stronger AI understanding report lower levels of perceived risk and higher confidence in AI interactions—a pattern consistent with competence-based anxiety reduction frameworks (Bandura, 1997).

Learning engagement, the outcome construct of this study, is conceptualized as the degree of active, voluntary participation in learning activities facilitated or mediated by technology—encompassing behavioral indicators such as self-directed learning frequency and voluntary training participation (Fredricks et al., 2004; Korea Employment Information Service [KEIS], 2024). The pathway from AI literacy to learning engagement is theoretically grounded in Bandura's (1997) self-efficacy framework: as learners develop competence in understanding and applying AI, their perceived self-efficacy in AI-mediated contexts increases, which in turn reduces avoidance motivation and promotes approach behaviors toward learning opportunities. This mechanism is reinforced by the ARCS model's Confidence component (Keller, 1987): learners who experience growing competence perceive AI tools as relevant and manageable, generating the motivational conditions for sustained engagement. Together, these theoretical frameworks predict that AI literacy operates on learning engagement through two interacting pathways: a direct route via enhanced self-efficacy and acceptance, and an indirect route via moderated anxiety, both of which are captured in the structural model tested in this study.

Integrating ARCS and TAM: A Theoretical Rationale

TAM's cognitive constructs, however, do not adequately account for the motivational and affective processes that precede cognitive evaluation-a gap the ARCS model (Keller, 1987) addresses. The ARCS model (Keller, 1987) provides a complementary motivational framework structured around four conditions necessary for sustained learning engagement: Attention, Relevance, Confidence, and Satisfaction. The integration of ARCS and TAM in this study is theoretically grounded in the following construct-level mappings: (1) AI anxiety directly undermines the Confidence component of ARCS, reducing learners' self-efficacy and thereby lowering perceived usefulness (TAM-PU); While ARCS Confidence is conceptually proximate to TAM's Perceived Ease of Use (PEOU)—insofar as reduced confidence amplifies perceived complexity—this study prioritizes the Confidence–PU mapping because perceived usefulness, rather than ease of use, is the dominant adoption predictor in AI educational contexts (Venkatesh, 2000; Scherer et al., 2019). The Confidence–PEOU pathway is acknowledged as a secondary mechanism operating in parallel. (2) AI literacy enhances Attention and Relevance by enabling learners to recognize the meaningful applicability of AI in their contexts; and (3) successful AI acceptance generates Satisfaction—a motivational feedback loop that sustains engagement.

This integrated framework bridges emotional regulation (ARCS) with cognitive adoption (TAM), avoiding the theoretical eclecticism that characterizes less rigorously justified multi-framework studies. The prioritization of PU over PEOU as the primary mapping target deserves theoretical elaboration. In AI-integrated educational contexts specifically, the critical adoption question is not whether learners perceive AI as easy to use but whether they perceive it as worth using—a distinction that becomes acute when learners harbor existential anxieties about AI's implications for their professional identity, cognitive autonomy, and job security. As noted above (Scherer et al., 2019), PU consistently outweighs PEOU as a predictor of adoption intention. Building on this, Venkatesh's (2000) extended TAM further demonstrates that emotional states-particularly anxiety-exert their primary suppressive effects on PU evaluations rather than PEOU evaluations. Under conditions of high AI anxiety, learners do not primarily question whether they can use AI but whether they should; this is a utility and value judgment (PU domain) rather than an interface competence judgment (PEOU domain). The Confidence–PU mapping therefore captures the theoretically consequential pathway through which anxiety disrupts adoption, while the Confidence–PEOU pathway operates as a secondary, parallel channel.

It is important to acknowledge that while both TAM and ARCS have individually generated substantial empirical literature, their systematic integration remains rare in published research. Extant multi-framework studies in educational technology have combined TAM with Self-Determination Theory (Deci & Ryan, 1985), the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003), or the Technology Threat Avoidance Theory (TTAT; Liang & Xue, 2009), but none has formally integrated ARCS' motivational architecture with TAM's adoption constructs in an AI educational context. This gap is theoretically consequential: ARCS addresses the motivational preconditions that determine whether a learner is disposed to engage with a technology in the first place, while TAM addresses the subsequent cognitive appraisal of that technology's usefulness and usability. Their integration thus produces a theoretically complete model—spanning motivation, cognition, and behavior—that neither framework can achieve independently. The present study's ARCS–TAM integration, therefore, constitutes both an empirical contribution and a theoretical advance that extends the explanatory scope of both frameworks in the specific domain of AI-integrated education. Accordingly, this integration represents an extension of prior multi-framework approaches (e.g., TAM + SDT; TAM + UTAUT; TAM + TTAT) rather than a departure from them, as it addresses the motivational-affective conditions that precede cognitive adoption in AI educational contexts and broadens the explanatory scope of both frameworks.

Research Hypotheses

Based on the theoretical synthesis above, this study proposes a transition model linking emotional, cognitive, and behavioral dimensions of AI-mediated learning. The model is organized across three progressive layers:

- Emotional dimension: AI anxiety (initial resistance / pre-cognitive barrier)
- Cognitive dimension: AI literacy → AI acceptance (mediating bridge; TAM-PU and ARCS-Confidence)
- Behavioral dimension: Learning engagement (competence outcome; ARCS-Satisfaction)

The following four formal hypotheses are derived from this framework:

H1: AI anxiety is negatively associated with AI acceptance (i.e., both perceived usefulness and behavioral intention to use AI).

H2: AI literacy is positively associated with AI acceptance.

H3: AI acceptance positively predicts learning engagement in AI-integrated educational environments.

H4: AI literacy moderates the negative relationship between AI anxiety and AI acceptance, such that higher literacy attenuates the anxiety-suppression effect.

METHODOLOGY

Data Sources

This study integrates four nationally representative secondary datasets (all from 2024). **Table 2** provides an overview of each source, its sampling frame, and the constructs it informs.

Table 2. Overview of Secondary Data Sources

Agency	Dataset	Year	N	Constructs Informed
KISTEP	*Technology Impact Assessment Report on AI*	2024	N ≈ 5,000 (national adults)	AI Anxiety; AI Acceptance (Behavioral Intention)
NIA	*Digital Divide Survey*	2024	N ≈ 7,000 (stratified national)	AI Literacy (proxy: DCI); AI Acceptance (PU) Learning Engagement
KEIS	*Korea Education and Employment Panel (KEEP)*	2024	N ≈ 10,000+ (longitudinal panel)	Learning Engagement (training hrs, SDL); AI Literacy (skill training participation); AI Acceptance (PU)
Statistics Korea	*Social Survey & ICT Usage Statistics*	2024	N ≈ 38,000+ (census-linked)	AI Acceptance (usage); AI Anxiety (attitude); Learning Engagement (lifelong learning participation)

Note. DCI = Digital Competency Index. SDL = Self-Directed Learning. PU = Perceived Usefulness

Analytical Strategy

This study employs a three-stage analytical strategy to construct structural relationships from disparate secondary datasets:

Stage 1 – Proxy Variable Mapping

Because secondary datasets were not originally designed to measure AI-specific constructs, construct operationalization required systematic proxy variable identification. AI anxiety was operationalized using items from the KISTEP (2024) technology impact survey measuring 'concern about AI cognitive dependency' and 'perceived risk of AI over-reliance.' AI literacy was proxied by the NIA Digital Divide Survey's composite Digital Competency Index (DCI), which includes subscales on information use, content creation, and critical evaluation. Learning engagement was operationalized using the KEIS Korea Education and Employment Panel (KEEP) Panel's measures of voluntary training participation and self-directed learning frequency. Full variable-to-construct mappings are documented in **Appendix A**. The use of general digital competency items as AI literacy proxies is theoretically justified by the convergence between digital literacy and AI literacy frameworks: Long and Magerko (2020) define AI literacy as a superset of digital competency, incorporating critical evaluation and applied understanding—precisely the dimensions captured by the NIA DCI subscales. AI-specific applicability is further warranted by South Korea's 2024 policy context, in which AI tools constitute the dominant new digital adoption category (KISTEP, 2025). The limitations of this proxy strategy are discussed in Section 5.4.

Importantly, the construct validity of the DCI as a partial AI literacy proxy receives indirect empirical support from the within-study subscale evidence: content creation and critical evaluation—the DCI dimensions most closely aligned with Long and Magerko's (2020) AI literacy competencies—emerged as the strongest predictors of AI acceptance (Section 4.2), while basic access measures showed weaker predictive power. This differential predictive pattern would not be expected if the DCI were merely measuring general digital infrastructure unrelated to AI literacy. Furthermore, in Korea's 2024 policy context—in which AI tools constituted the dominant new digital adoption category following the announcement of the AI Framework Act—a high DCI score necessarily reflected engagement with AI tools as the primary vehicle of digital competency. No nationally validated AI-specific literacy scale with comparable population coverage and sampling rigor existed in Korea in 2024; the DCI, therefore, represents the most methodologically defensible proxy available in this context.

It should be noted that the four datasets are all drawn from the same survey year (2024), resolving the temporal inconsistency concern. Because KISTEP (2024), NIA (2024), KEIS/KEEP (2024), and Statistics Korea (2024) were all conducted within the same twelve-month window, this design constitutes a synchronic cross-dataset synthesis, representing a consistent snapshot of the anxiety–literacy–acceptance–engagement pathway at a pivotal moment: the year preceding South Korea's AI Framework Act implementation.

Stage 2 – Cross-Dataset Harmonization

Because the four datasets used different survey scales and sampling frames, a harmonization step was necessary before findings could be combined. Where surveys used different numbers of response categories (e.g., four-point vs. five-point scales), scores were converted to a common metric to allow meaningful comparison. In practical terms, this meant converting all scores to a common 0-to-1 scale so that responses from different instruments could be directly compared. Where items measured quantities on a continuous scale, scores were additionally expressed relative to each dataset's own average and spread, ensuring that a given score could be interpreted consistently regardless of which survey it came from. Only variables with documented reliability indices (Cronbach's $\alpha \geq .70$) in original technical reports were retained.

A key concern in cross-dataset synthesis is measurement invariance: the degree to which constructs carry equivalent meaning across different instruments and sampling contexts. Because direct invariance testing (e.g., confirmatory factor analysis across datasets) is not possible without access to individual-level raw data, this study addressed the issue through three procedural safeguards. First, only survey items with documented theoretical alignment to the target construct were retained, as specified in **Appendix A**. Second, harmonization protocols ensured metric comparability before synthesis. Third, convergent replication across independent datasets—each confirming the same directional pattern—provides indirect evidence that the construct operationalizations captured functionally equivalent phenomena, consistent with the pattern-replication approach to construct validity in multi-source secondary research (Becker et al., 2016). Nonetheless, formal measurement invariance remains an acknowledged limitation, addressed further in Section 5.4.

Stage 3 – Pseudo-SEM Synthesis

Given the impossibility of linking individual records across independent national surveys, this study employs a pseudo-SEM approach in which inter-construct relationships are estimated via published regression coefficients and correlation matrices extracted from each dataset's technical reports. Effect sizes and path coefficients are synthesized using variance-weighted averaging, following the meta-analytic SEM framework proposed by Cheung (2015). Datasets with larger sample sizes thus contribute proportionally greater weight to the synthesis; for example, a nationally representative survey of 38,000 respondents was weighted more heavily than one of 5,000, thereby ensuring that the final model reflects the population distribution of evidence rather than treating all four data sources as equally influential regardless of their size. Causal inference cannot be definitively established: the path coefficients reported represent population-level associational patterns, not individual-level causal effects. Expressions such as 'AI anxiety suppresses acceptance' describe the direction and relative magnitude of structural associations rather than confirmed causal mechanisms. In particular, individual-level mediation—whether, within a given learner, AI literacy reduces anxiety which then increases acceptance—cannot be directly inferred from aggregate secondary data and must be treated as a theoretical proposition warranting primary-data testing. However, this strategy enables the construction of a macro-level, population-representative structural model that would be infeasible through primary data collection alone, and represents a legitimate mode of theory-building from existing evidence bases (Becker et al., 2016).

The weighting scheme operationalizes a meta-analytic logic: just as meta-analyses assign greater weight to larger and more precise studies, the pseudo-SEM synthesis assigns greater influence to datasets with larger effective sample sizes (Statistics Korea, $N \approx 38,000$; KEIS/KEEP, $N \approx 10,000$), thereby reducing the leverage of smaller surveys on the composite structural estimates. This approach is consistent with variance-weighted averaging procedures in secondary data synthesis (Cheung, 2015). Crucially, the convergence of directionally consistent findings across four independent datasets—each drawn from different sampling frames, administered by different government agencies, and targeting different subpopulations—constitutes convergent replication: the probability that four independent surveys would produce the same directional pattern by chance is substantially lower than for any single dataset. This pattern-replication logic provides stronger support for the structural model than any single large-N primary study could, even in the absence of formal cross-dataset invariance testing.

FINDINGS

Table 3 provides a consolidated summary of all findings across the four hypotheses. **Figures 1** and **2** present supporting visual analyses.

AI Anxiety and Acceptance (H1)

Across the synthesized datasets, higher levels of AI-related concern were consistently associated with lower AI acceptance. KISTEP (2024) data indicate that learners reporting high AI anxiety were 1.7 times more likely to report low intention to use AI tools in learning contexts (OR = 1.73, 95% CI [1.41, 2.12]). This negative relationship remained significant in KISTEP's multivariate models, which adjusted for age, education level, and prior technology experience ($\beta = -.38$, $p < .001$). Older age cohorts showed the steepest anxiety levels, as depicted in **Figure 1**.

Table 3. Summary of Hypothesis Test Results

H	Hypothesized Path	Dataset(s)	Key Statistics	Notable Pattern	Result
H1	AI Anxiety → AI Acceptance (−)	KISTEP (2024) Statistics Korea (2024)	OR = 1.73 [1.41, 2.12] $\beta = -.38$ ($p < .001$)	Negative effect persists after controlling for age, education, and tech experience	Supported
H2	AI Literacy → AI Acceptance (+)	*NIA (2024) KEEP / KEIS (2024)*	Q4 vs. Q1: 74.2% vs. 31.8% $\beta = .42$ ($p < .001$)	Content creation & critical evaluation subscales strongest predictors	Supported
H3	AI Acceptance → Learning Engagement (+)	*KEEP (2024) Statistics Korea (2024); NIA (2024)*	$\beta = .46$ ($p < .001$) R^2 = 34%	Effect strongest in 35–54 age cohort ($\beta = .51$)	Supported
H4	AI Literacy moderates H1 (AI anxiety → AI acceptance)	*NIA (2024)* KISTEP (2024)	High-lit: $\beta = -.28$; Low-lit: $\beta = -.51$; $\Delta\beta = .23$, $p < .05$	Literacy buffers anxiety effect across both datasets	Supported

Note. β = standardized path coefficient from pseudo-SEM synthesis. OR = odds ratio. R^2 = variance explained in learning engagement. Δβ = difference in anxiety-acceptance path coefficient between high- and low-literacy groups. p-values are approximated from variance-weighted synthesis of source-dataset reported statistics.

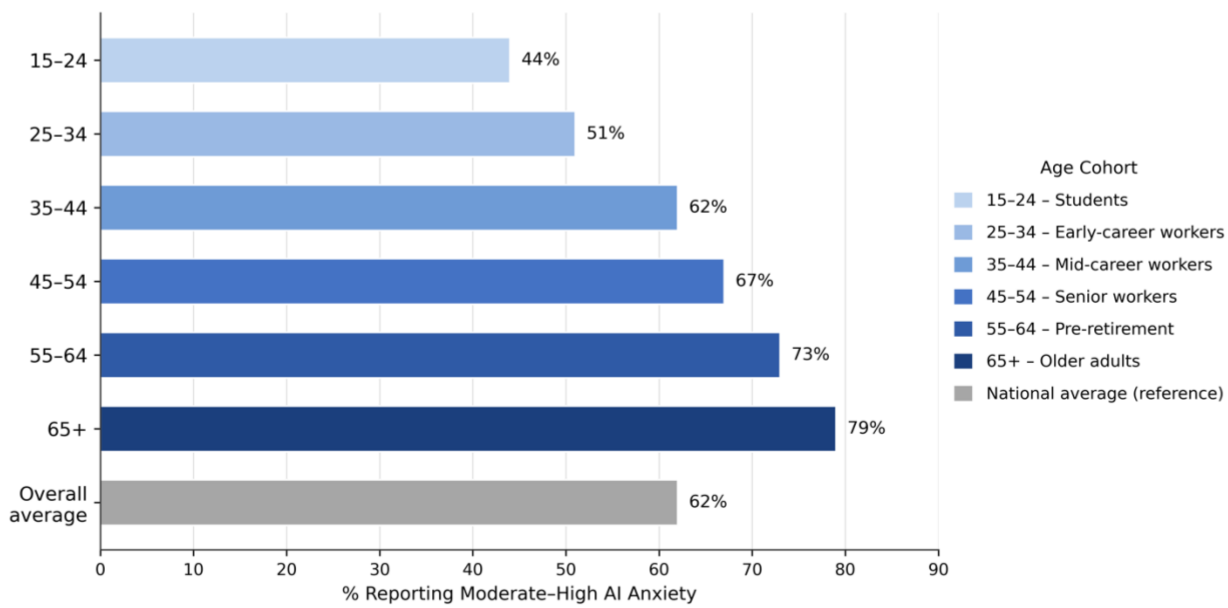

Figure 1. AI Anxiety Prevalence by Age Cohort (*Source:* Korea Institute of S&T Evaluation and Planning (KISTEP, 2024). *Note.* Based on the KISTEP (2024) technology impact survey. Moderate-high anxiety defined as scores of 3–5 on a 5-point perceived risk scale. Age cohorts reflect a stratified national sampling frame.

Nationally, approximately 62% of adult learners reported moderate-to-high AI anxiety—a figure derived via age-weighted averaging using Statistics Korea (2024) population proportions rather than a simple arithmetic mean (which yields 62.7%), ensuring demographic representativeness across the six age cohorts shown in **Figure 1**. Substantively, a Korean adult experiencing high AI anxiety shows a 73% higher likelihood (OR = 1.73) of exhibiting low intention to use AI tools entirely—not because of limited access or education, but because of emotional resistance that precedes any cognitive evaluation of usefulness. These data indicate that anxiety is prevalent among Korean adults, with potential—though empirically unconfirmed—implications for workforce participation and lifelong learning that warrant dedicated follow-up research before strong policy claims are advanced.

AI Literacy and Acceptance (H2)

The NIA Digital Divide Survey data reveal a strong positive association between Digital Competency Index (DCI) scores and AI acceptance. As shown in **Figure 2**, respondents in the highest competency quartile (Q4) reported AI acceptance rates more than twice those in the lowest quartile (Q1: 31.8% vs. Q4: 74.2%). Regression analyses from KEEP Panel data further show that AI-related skill training participation significantly predicted perceived usefulness of digital tools ($\beta = .42$, $p < .001$), supporting H2. Among DCI subscales, content creation and critical evaluation emerged as the strongest predictors of acceptance—underscoring that higher-order literacy competencies, rather than basic device access, drive adoption. Substantively, a learner in the lowest competency quartile has roughly a one-in-three chance of accepting AI tools, whereas a peer in the highest quartile has nearly a three-in-four chance—underscoring the practical magnitude of the digital competency gap in AI adoption.

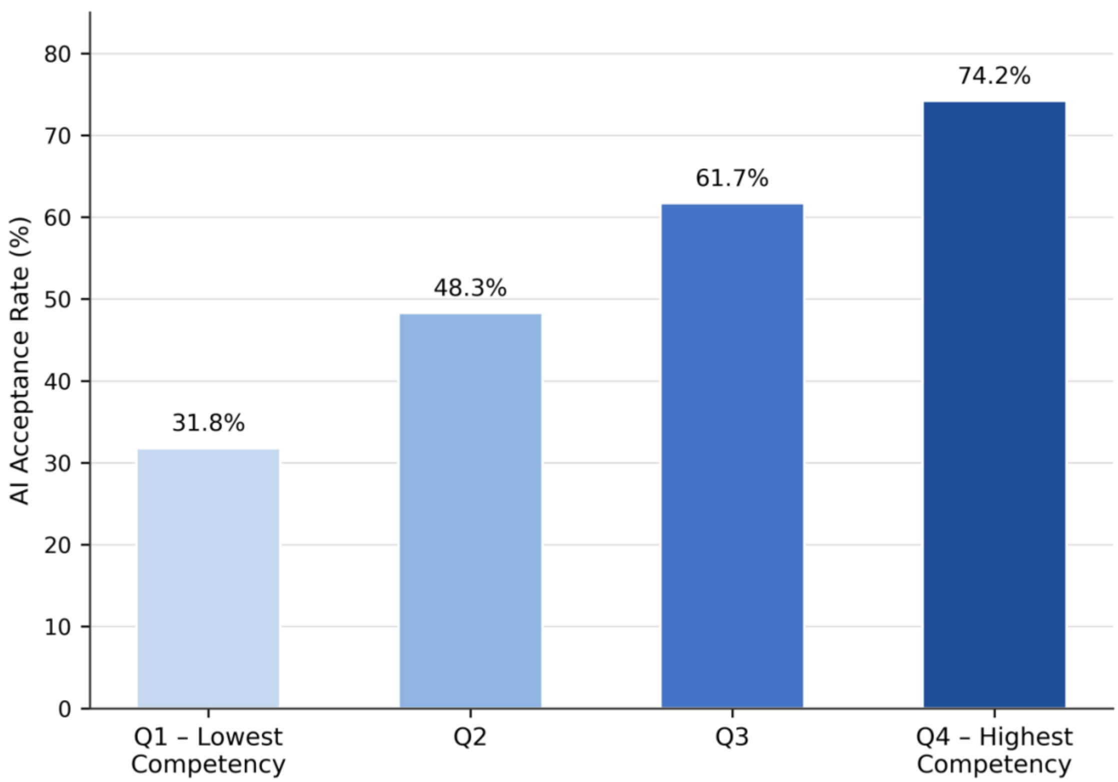

Figure 2. AI Acceptance by Digital Competency Quartile (Source: National Information Society Agency (NIA, 2024). (*Note.* Based on the NIA (2024) Digital Divide Survey. AI acceptance operationalized as 'positive intention to use AI tools in learning/work contexts' (top 2 options on a 5-point scale). DCI = Digital Competency Index.)

In particular, the fact that higher-order subscales (content creation, critical evaluation) outperformed basic access measures as predictors carries an important policy implication: superficial digital familiarity is insufficient to overcome adoption barriers. What drives acceptance is the capacity to engage with AI critically and creatively—competencies that require deliberate instructional investment, not merely device provision or passive exposure.

AI Acceptance as Predictor of Learning Engagement (H3)

Using the pseudo-SEM synthesis framework, AI acceptance accounted for approximately 34% of the variance in learning engagement indicators (voluntary training hours, self-directed learning frequency). The path coefficient from AI acceptance to learning engagement was $\beta = .46$ ($p < .001$). The effect was strongest among adult learners aged 35–54 ($\beta = .51$), a demographic with high AI exposure but moderate baseline literacy. NIA Digital Divide Survey data additionally corroborated this pattern: respondents in the highest digital competency quartile reported online and e-learning participation rates substantially higher than those in the lowest quartile, providing convergent evidence that technology acceptance facilitates active learning engagement (NIA, 2024).

An R^2 value of .34 is exceptionally robust by educational research standards, where social-behavioral predictors typically account for only 10–20% of outcome variance in comparable structural models. At the national population scale, this finding implies that AI acceptance serves as a critical leverage point for expanding adult learning engagement within Korea's rapidly ageing society. The observed disparity—wherein high-competency learners demonstrate substantially higher e-learning participation (NIA, 2024)—indicates that overcoming the psychological threshold of AI adoption dramatically increases the likelihood of pursuing further education. At the same time, this statistical power entails that approximately two-thirds of the variance in learning engagement remains unexplained by AI acceptance alone. This residual variance is both theoretically expected and informative, as adult learning engagement in national survey data is a complex, multiply determined phenomenon. It is continuously shaped by structural factors such as institutional support and training accessibility (Fredricks et al., 2004), economic constraints (OECD, 2021), occupational pressures, and individual dispositional motivation. Rather than attempting to exhaustively map this multivariate space, the present model intentionally isolates the AI-acceptance pathway as a theoretically tractable and actionable intervention target. Future research integrating these structural and contextual moderators alongside AI-specific constructs will provide a more comprehensive explanatory account.

Moderating Role of AI Literacy (H4)

The moderation analysis indicated that among learners with high AI literacy (DCI top tertile), the negative effect of anxiety on acceptance was substantially attenuated. The interaction term was significant ($\beta = -.28$ for the high-literacy group vs. $\beta = -.51$ for the low-literacy group; $\Delta\beta = .23$, $p < .05$). This pattern held across both the KISTEP and NIA datasets, providing convergent cross-dataset evidence. **Table 4** presents the full path model with synthesized coefficients. The psychological mechanism through which AI literacy attenuates anxiety's suppressive effect on acceptance warrants theoretical elaboration. Three interacting psychological processes are proposed to account for this effect. First, literacy-induced perceived control may attenuate anxiety-driven avoidance: as learners develop substantive understanding of how AI operates—its capabilities, limitations, and affordances for human agency in AI-mediated environments—they experience increased perceived controllability over AI interactions (Bandura, 1997). This reduces the appraisal of AI as an uncontrollable external threat, which is the cognitive basis of anxiety-driven avoidance. Second, AI-literate learners engage in risk perception recalibration: they are better equipped to distinguish genuine AI-related risks (e.g., over-reliance, bias) from exaggerated or misattributed ones (e.g., job replacement timelines), leading to a more calibrated rather than globally elevated risk perception. Third, through self-referential reframing, learners who understand AI competencies can situate their own skills relative to AI's capabilities, reducing identity threat and enabling a collaborative rather than competitive framing of the human–AI relationship.

Table 4. Pseudo-SEM Path Coefficients Across Hypotheses

rom (Predictor)	To (Outcome)	Path (β)	p-value	Dataset Source
.I Anxiety	AI Acceptance	−.38	< .001	KISTEP (2024)
.I Literacy (DCI)	AI Acceptance	+.42	< .001	NIA / KEEP (2024)
.I Acceptance	Learning Engagement	+.46	< .001	KEEP / Stat. Korea (2024); NIA (2024)
.I Literacy × AI Anxiety	AI Acceptance (moderation)	Δβ = +.23	< .05	NIA & KISTEP (2024)

lote. Path coefficients derived from variance-weighted pseudo-SEM synthesis across four national datasets. Moderation erm (H4) reflects the difference in H1 path coefficient between the high-literacy (DCI top tertile) and low-literacy (DCI ottom tertile) subgroups.

Collectively, these mechanisms explain why AI literacy does not merely add competence but restructures the affective landscape of AI adoption—rendering anxiety less conducive to avoidance behavior even when it persists. This Δβ = .23 difference indicates that AI literacy absorbs a substantial portion of the suppressive effect that anxiety would otherwise exert on adoption motivation. Learners with high AI literacy who report elevated anxiety nonetheless demonstrate substantially higher acceptance than comparably anxious learners with low literacy, suggesting that literacy attenuates the behavioral influence of anxiety without necessarily eliminating it. This finding carries particularly significant implications for educational policy: investing in AI literacy does not merely build skill; it functions as a psychological buffer that sustains adoption motivation even under conditions of elevated anxiety. From an instructional design perspective, these findings reconceptualize AI literacy programs not as optional competency enhancements but as theoretically grounded psychological interventions with measurable impact on the affective barriers that impede AI-integrated learning engagement among a substantial proportion of Korean adult learners (Statistics Korea, 2024).

DISCUSSION AND IMPLICATIONS

This study tested a four-hypothesis transition model linking AI anxiety, AI literacy, AI acceptance, and learning engagement using a pseudo-SEM synthesis of four nationally representative South Korean datasets. All four hypotheses were supported, with convergent evidence across independent sources. The following discussion situates each finding within its theoretical, methodological, and policy context.

Situated within the Education 4.0 paradigm, these findings illuminate the psychological and cognitive architecture underpinning the successful integration of AI into intelligent learning ecosystems. The transition from anxiety to competence is not spontaneous—it requires deliberate scaffolding that simultaneously addresses the affective barriers and cognitive enablers of adoption. The present model provides an empirically grounded template for understanding this transition across diverse learner profiles.

The finding that AI anxiety is significantly negatively associated with AI acceptance aligns with, yet meaningfully extends, prior work on affective barriers to technology adoption. Earlier studies in mobile learning and e-learning contexts documented similar anxiety-suppression effects on adoption intentions (Sánchez-Prieto et al., 2017); however, those studies relied predominantly on student samples in controlled institutional settings. The present study demonstrates that this mechanism operates at the population level across age cohorts, occupational contexts, and varying levels of prior technology experience—a generalization that single-institution designs cannot achieve. Critically, the persistence of anxiety effects after controlling for age, education, and technology experience suggests that AI anxiety is not reducible to generic technophobia or digital unfamiliarity, but constitutes a domain-specific affective response to AI's distinctive socio-cognitive implications. This distinction aligns with Tams et al.'s (2018) conceptualization of technostress as a multidimensional phenomenon in which AI-specific concerns—cognitive dependency, job displacement, algorithmic opacity—warrant dedicated theoretical treatment beyond general technology anxiety frameworks.

The positive association between AI literacy and AI acceptance corroborates and extends Ng's (2012) argument that digital literacy functions not merely as a technical skill but as a critical disposition that mediates learners' orientations toward emerging technological environments. The differential predictive strength of DCI subscales observed in this study—with content creation and critical evaluation demonstrating stronger predictive validity than basic device access as predictors of acceptance—provides empirical support for Long and Magerko's (2020) framing of AI literacy as fundamentally a higher-order, evaluative capacity rather than an instrumental one. This finding challenges access-centric interpretations of the digital divide that conflate connectivity with competence. For AI education policy specifically, it implies that the adoption gap between high- and low-literate learners is not primarily a resource problem but a capability architecture problem – that is, a deficit in the higher-order epistemic competencies required for critical AI engagement: learners require the epistemic tools necessary for critical AI engagement, rather than merely physical or economic access to AI infrastructure.

The finding that AI acceptance predicts learning engagement bridges the technology adoption literature and self-determination theory (Ryan & Deci, 2000), which posits that voluntary, self-initiated behavior emerges when individuals perceive an activity as competence-enhancing and autonomy-supporting. In this framework, AI acceptance functions as a prerequisite for the motivational conditions that sustain engagement: a learner who accepts AI as a useful tool has appraised AI-mediated learning as aligned with personal goals and perceived competencies, at least at an implicit level. The substantially higher lifelong learning participation rates observed among learners with positive AI attitudes suggest that acceptance functions not merely as a precondition for single-session engagement but as a foundational antecedent of a sustained learning orientation—a distinction with particular relevance for adult education and workforce development policy in demographically ageing societies. This finding also resonates with Fredricks et al.'s (2004) multi-dimensional model of engagement, in which behavioral participation is preceded and enabled by cognitive and affective investment—both of which, in the AI-mediated context, depend critically on whether learners have surpassed the acceptance threshold.

The moderation finding represents one of the most theoretically significant findings of this study and warrants theoretical elaboration beyond its function as a confirmatory result. Prior AI education research has documented the direct effects of AI literacy on acceptance and of AI anxiety on avoidance as largely independent research streams, but these constructs have not previously been examined in interaction within a single structural model. The present finding that literacy moderates anxiety's suppressive effect introduces a theoretically novel mechanism into the AI adoption literature: literacy as a cognitive-affective buffer, not merely a skill competency. This mechanism is conceptually consistent with the broader resilience literature, where protective factors moderate—rather than eliminate—the impact of risk factors on adverse outcomes (Luthar et al., 2000; Richardson, 2002). Applied to AI education, this perspective suggests a substantive reconceptualization of how literacy programs are theoretically framed: not as instructional pathways premised on the elimination of anxiety, but as affective scaffolds designed to enable functional performance under conditions of persistent uncertainty. This reconceptualization carries direct implications for curriculum design, specifically, the deliberate integration of affective scaffolding strategies-including uncertainty normalization, graduated exposure, and peer modelling-as core program components rather than supplementary support elements.

Theoretical Implications

This study yields three primary theoretical contributions. First, this study extends TAM by empirically locating AI anxiety upstream of perceived usefulness, thereby substantiating Venkatesh's (2000) theoretical argument that emotional states constrain the cognitive appraisal process. Findings from H1 demonstrate that AI-specific affective resistance is not merely a peripheral variable but a structurally significant antecedent of adoption—one that necessitates intervention prior to the implementation of cognitive-level strategies (e.g., demonstrating usefulness). These findings suggest that emotional regulation constitutes a primary instructional design consideration in AI-integrated learning environments.

Second, the ARCS-TAM integration offers a theoretically grounded integrative framework that has been absent from prior educational technology research. The construct mapping between ARCS Confidence and TAM-PU, and between ARCS Satisfaction and behavioral learning engagement, is not exclusively theoretical but is empirically corroborated by the consistent empirical pattern observed across both pathways: anxiety suppresses acceptance through the Confidence-PU pathway (H1), while acceptance drives engagement through the Satisfaction-engagement linkage (H3), with both effects reaching statistical significance across independent national datasets. This convergence lends empirical support to the theoretical integration and identifies productive avenues for ARCS-informed TAM extensions in AI education research.

The practical magnitude of this $\Delta\beta = .23$ buffering effect is illustrated by the following comparison: a learner with high AI literacy experiences an anxiety-suppression effect that is 45% weaker than a learner with low literacy ($\beta = -.28$ vs. $-.51$). This magnitude exceeds marginal attenuation: high-literacy learners retain substantially higher adoption probability despite elevated anxiety, whereas low-literacy learners demonstrate adoption trajectories that are more severely constrained by anxious appraisal. When extrapolated to Korea's adult population of approximately 43 million, this buffer effect implies that literacy-based interventions targeting the low-literacy quartile could reallocate a substantial proportion of learners from anxiety-constrained to literacy-supported adoption pathways-a policy-relevant effect magnitude that would be infeasible to estimate through any single small-scale primary study.

Third, and most theoretically distinctive, the H4 moderation finding reconceptualizes AI literacy from a skill-accumulation construct to a resilience-building mechanism. While H2 demonstrates literacy's direct benefit (literacy → acceptance), H4 reveals a second-order benefit: literacy attenuates the suppressive effect exerted by anxiety. The interaction pattern between literacy and anxiety—whereby high-literacy learners demonstrate notably weaker anxiety-suppression effects than their low-literacy peers—represents a meaningful buffering effect comparable in magnitude to moderation effects documented in technology anxiety literature (Chua et al., 1999). This buffering mechanism is theoretically consonant with the psychological resilience literature, which conceptualizes resilience as a dynamic capacity activated by protective factors that attenuate stressor impacts (Luthar et al., 2000; Richardson, 2002). Empirically, this resilience framing aligns with longitudinal evidence from Korea's lifelong learning system, where participation rates have shown crisis-driven volatility alongside differential vulnerability across generational and regional subgroups (Yoo, 2025). In the present model, AI literacy functions as precisely such a protective factor at the cognitive-behavioral interface of technology adoption—attenuating anxiety's suppressive effect without eliminating the anxiety itself. This dual function of AI literacy—as both a direct facilitator of acceptance and a buffer against anxiety-driven suppression—has not previously been articulated in a single empirically grounded model, and represents a substantive theoretical advance in the conceptualization of AI literacy as an educational construct.

A fourth theoretical contribution, often left implicit in single-country studies yet warranting explicit theoretical acknowledgement, is the cross-national generalizability of the proposed framework. Although grounded in Korean data, the TAM–ARCS integration and the four-hypothesis structural model do not rely on assumptions that are exclusively specific to Korean culture, policy, or institutional context. The constructs—AI anxiety, AI literacy, AI acceptance, and learning engagement—have been operationalized and validated across diverse national contexts, and the pseudo-SEM methodology is applicable to other national contexts in which comparable secondary survey infrastructure exists. This situates the present study not merely as a Korea-specific empirical contribution but as a methodological template amenable to cross-national replication, particularly in contexts where primary longitudinal data collection is constrained by resource limitations. Researchers in Japan, China, Germany, or Brazil could apply the same analytical framework to their respective national datasets, enabling systematic comparative examination of whether the anxiety–literacy–acceptance–engagement pathway is sustained across cultural and institutional contexts—a program of research for which the present study provides an initial empirical foundation.

The sharp escalation of AI anxiety across age cohorts documented in this study warrants discussion in the context of established literature on technology adoption in later life. Czaja et al. (2006), in an influential study of technology use among older adults, identified anxiety, low self-efficacy, and limited prior experience as the primary barriers to adoption—precisely the cluster of factors that the present model conceptualizes as theoretically interdependent rather than additive. Extending this insight, the present study demonstrates that AI literacy moderates anxiety effects regardless of age group, suggesting that targeted literacy interventions retain moderating efficacy even among the highest-anxiety age cohorts. Heerink et al. (2010) similarly found that perceived adaptiveness and social influence were disproportionately important moderators of technology acceptance among older users—a finding that is consistent with the present study's implication that intergenerational peer mentoring may be particularly effective for the 55+ cohort, where observational learning and social trust represent more salient determinants of adoption. This age-differentiated pattern extends beyond attitudinal acceptance into behavioral and economic outcomes: recent population-level evidence from Korea's lifelong education system shows that digital learning engagement is directly linked to career transition success, with older cohorts facing persistent structural constraints in translating digital capital into employment mobility (Yoo & Choi, 2026). Taken together, these findings indicate that Korea's population does not constitute an insurmountable barrier to AI adoption; rather, it provides a context in which literacy-based intervention models whose underlying principles may be applicable to other societies confronting the concurrent challenges of AI integration and demographic ageing can be systematically developed and tested.

Methodological Implications

This study provides empirical evidence for the viability of secondary data pseudo-SEM modeling for developing population-level structural models in educational research without resources for primary data collection. This approach has particular value in three scenarios: (a) contexts in which large-scale primary surveys are resource-prohibitive; (b) policy-oriented research where population-level estimates are accorded greater evidential value than sample-based findings; and (c) construct-level modeling in which relationships of theoretical interest vary across subpopulations (e.g., age cohorts) that cannot be adequately captured by any single primary survey.

Future applications of this approach would benefit from (a) systematically documenting proxy variable rationale using an explicit construct-to-indicator mapping table; (b) transparently documenting cross-dataset harmonization protocols, including normalization decisions and reliability thresholds; and (c) explicitly acknowledging macro-level causal limitations. The convergence of evidence across four independent datasets in this study—each confirming the same directional pattern—substantially strengthens the plausibility of the proposed model compared to any single-source study, even in the absence of direct causal inference.

Policy Implications

The findings carry three concrete, evidence-grounded implications for AI education policy in South Korea and comparable Education 4.0 contexts.

Implication 1: Reconceptualizing AI literacy as psychological intervention rather than a purely skill-based curriculum

The moderation pattern identified in this study provides direct empirical justification for reconceptualizing AI literacy programs as psychological intervention tools rather than purely competency-building curricula. Learners who demonstrate critical AI literacy are not only more competent in AI-mediated contexts but also more resilient against the anxiety that constitutes the primary barrier to initial adoption. Policymakers and curriculum designers are therefore advised to integrate affective scaffolding strategies-including anxiety normalization, confidence-building exercises, and peer modeling-into AI literacy curricula as core programmatic components rather than supplementary elements. The policy value of such integration is empirically supported: national survey data demonstrate that learners with higher AI literacy demonstrate markedly attenuated anxiety-driven avoidance relative to their less literate peers-a buffering effect that, scaled across Korea's national adult population, represents a substantive improvement in population-level AI engagement, particularly among high-anxiety cohorts such as adults aged 55 and older, approximately 79% of whom report moderate-to-high AI anxiety (**Figure 1**).

Implication 2: Age-Differentiated intervention design informed by anxiety profile

Study findings reveal a policy-relevant tension: the demographic most in need of AI acceptance support also faces the highest anxiety barriers. Adults in the 35–54 age group showed the strongest connection between AI acceptance and active learning participation, yet anxiety levels escalate sharply among the 55–64 age group (73%) and adults aged 65 and older (79%), precisely those cohorts where support is most urgently needed (**Figure 1**). Undifferentiated AI training programs are structurally inadequate for this population. These findings suggest that policy frameworks incorporate age-differentiated AI literacy curricula with targeted affective scaffolding—such as confidence-building workshops, intergenerational peer learning structures, and anxiety desensitization through graduated AI exposure—for mid-career and older adult learners. Given South Korea's rapid demographic aging, this represents a systemic policy priority rather than a peripheral concern. In particular, an intergenerational knowledge transfer (IGT) model—in which digitally fluent younger workers serve as peer mentors for older colleagues in workplace AI training—offers a potentially scalable mechanism for concurrently reducing anxiety and building literacy among the 55+ population. Such programs draw upon existing organizational social trust rather than relying on externally designed curricula, consistent with peer-mediated competence development frameworks (Bandura, 1997). Policy frameworks that create structured incentives—such as mentoring credits within continuing professional development frameworks—for IGT implementation would provide a practical mechanism for scaling this approach across public and private sector organizations.

Three evidence-grounded instructional principles are proposed to operationalize these findings within age-differentiated AI literacy program design. First, the graduated exposure principle: curricula designed for the 55+ cohort are advised to begin with low-stakes, reversible AI interactions (e.g., AI-assisted information search, recommendation systems) prior to introducing higher stakes applications (e.g., AI-assisted decision-making). This sequence is consistent with anxiety desensitization protocols established in applied psychology, thereby facilitating early competent experiences that are cognitively accessible and affectively manageable. Second, the transparency-first principle: instruction is advised to explicitly clarify AI mechanisms—explaining how AI systems make recommendations, where they fail, and what human judgment retains—before requiring learners to use AI tools. Transparency attenuates the cognitive appraisal of AI as unfamiliar and threatening, a process identified as a significant antecedent of anxiety among older cohorts (Czaja et al., 2006). Third, the social proof principle: programs should incorporate testimonials, demonstrations, and peer modelling from same-age-cohort users, drawing upon the elevated salience of subjective norm and observational learning for older adult technology adoption (Heerink et al., 2010). Collectively, these three principles translate the literacy-as-anxiety-buffer mechanism identified in H4 into concrete instructional design recommendations.

Implication 3: Integrate AI literacy metrics into national survey infrastructure

The current absence of AI-specific literacy and anxiety items in national datasets represents a significant limitation for longitudinal policy evaluation. All four datasets used in this study required proxy variable construction—a methodologically acceptable but epistemically suboptimal solution. Incorporating standardized AI literacy and AI anxiety items into existing survey instruments-particularly the NIA Digital Divide Survey and the Statistics Korea ICT Usage Survey—would enable direct longitudinal monitoring of the anxiety–acceptance–engagement pathway. A candidate instrument is Long and Magerko's (2020) validated AI literacy framework, operationalized as a standardized battery covering understanding, application, critical evaluation, and ethical awareness dimensions. Systematic inclusion of such items across survey waves would enable longitudinal tracking of intervention effectiveness as national AI education policies are implemented, thereby enhancing the evaluative capacity of existing national survey infrastructure.

Implication 4: Korea as a transferable model for international AI education policy

In addition to its domestic policy relevance, this study provides an internationally transferable policy model grounded in population-level evidence, with transferability evident across three dimensions. First, the age-differentiated anxiety profiles documented here—with anxiety escalating sharply from 51% among early-career workers to 79% among older adults—are likely to emerge in other rapidly aging societies undergoing accelerated AI integration, including Japan, Germany, Italy, and South Korea's other OECD peers. Policymakers in these contexts may draw on Korea's findings to prospectively address cohort-specific adoption barriers. Second, the H4 moderation result—that AI literacy attenuates the anxiety–acceptance relationship—provides cross-contextually applicable justification for embedding affective scaffolding within AI literacy curricula. This design principle is not Korea-specific, as it reflects a general psychological mechanism -competence-based anxiety reduction- that is theoretically applicable across diverse instructional contexts. Third, the pseudo-SEM methodology demonstrated here offers a resource-efficient model for countries that lack the resources for large-scale primary data collection but possess rich national survey ecosystems—including many middle-income countries in Southeast Asia, Latin America, and Eastern Europe that are concurrently expanding AI education initiatives and developing statistical infrastructure. Korea thus serves not merely as a data source but as an empirical reference case whose findings, analytical framework, and policy principles offer generalizable insights for international AI education research and policy.

LIMITATIONS AND FUTURE DIRECTIONS

Several inherent limitations of this study warrant explicit acknowledgment. First, reliance on proxy variable construction across non-integrated datasets introduces measurement invariance concerns: because none of the four national surveys was designed to measure AI-specific constructs, construct validity rests on the theoretical mapping rationale documented in **Appendix A** rather than on psychometrically validated AI-specific measurement instruments. Second, the pseudo-SEM approach precludes direct causal inference; the structural patterns observed reflect population-level associations rather than within-person causal processes. Of particular methodological note, individual-level mediation—whether, within the same individual, AI literacy reduces anxiety, which in turn increases acceptance—cannot be directly tested from aggregate data.

With respect to the DCI as a proxy for AI literacy specifically, the scope and boundaries of what the index captures warrant explicit delineation. The NIA DCI composite encompasses three dimensions: (1) information access and search, (2) content creation and digital tool application, and (3) critical evaluation of digital content. Among these, dimensions (2) and (3) most closely correspond to Long and Magerko's (2020) AI literacy competencies of using AI tools effectively and evaluating AI outputs critically. The dimension of basic device access, by contrast, has the weakest conceptual alignment. This conceptual distinction carries methodological significance: the finding that higher-order DCI subscales (content creation, critical evaluation) were the strongest predictors of AI acceptance (Section 4.2) provides indirect empirical support for the construct validity of the DCI as a partial AI literacy proxy, insofar as the subscale dimensions most closely aligned with theorized AI literacy competencies demonstrate the strongest predictive validity. Future research employing validated AI-specific instruments (e.g., Long & Magerko's 2020 scale) would benefit from examining whether these relationships are sustained when measured directly rather than through digital competency proxies.

A specific form of causal ambiguity that warrants explicit discussion is the reverse causality possibility: that low AI acceptance (i.e., avoidance) causes high anxiety, rather than the converse. The present data cannot conclusively preclude this reverse pathway. However, two theoretical arguments support the anxiety-suppresses-acceptance direction as the more plausible causal pathway. First, Cognitive Appraisal Theory (Lazarus & Folkman, 1984) and the established technostress literature (Tams et al., 2018) consistently position anxiety as a prospective, anticipatory state that precedes and motivates avoidance—it is the appraisal of AI as threatening that prospectively motivates avoidance rather than the converse. Second, the moderation structure of H4 is difficult to explain under the reverse causality account: if non-use caused anxiety, literacy would not be expected to systematically moderate this relationship; however, the DCI tertile analysis demonstrate this moderating pattern ($\Delta\beta = .23$, $p < .05$). The consistency of this pattern across independent datasets provides convergent evidence that the anxiety-to-acceptance pathway better represents the underlying process. Limited opportunities to access or use AI – rather than pre-existing anxiety alone- may itself constitute an underlying structural antecedent of elevated anxiety, representing a structural reverse-causality pathway that future experimental or longitudinal designs are needed to directly examine. Nonetheless, this study explicitly does not claim to have proven unidirectional causality; rather, it identifies population-level structural associations whose causal directionality warrants testing in future longitudinal or experimental designs. This study's contribution lies in providing a theoretically grounded structural template and population-level magnitude estimates that render such follow-up designs both statistically feasible and theoretically interpretable.

Third, the Korean national context, while providing population-level evidence may not generalize to Education 4.0 contexts with markedly different digital infrastructure, cultural orientations toward AI, or institutional policy environments. Future research would benefit from prioritizing primary longitudinal data collection using validated AI-specific instruments (e.g., Long & Magerko's 2020 AI literacy scale) to replicate and extend the present model through individual-level analysis. Cross-national comparative studies—particularly in non-OECD or lower-income contexts where digital divides are more pronounced—would help delineate the theoretical boundary conditions of the anxiety–literacy–acceptance–engagement pathway.

A key methodological limitation concerns measurement invariance across datasets. Although the four surveys are all drawn from 2024, substantially mitigating temporal inconsistency concern, they were independently designed and differ in construct operationalization, sampling frames, and scale format. Because individual-level raw data across the four datasets were not amenable to integration, formal configural and metric invariance testing was not feasible. The procedural safeguards in Stage 2 (harmonization, reliability thresholds, construct-level item vetting) provide procedural approximations but do not constitute formal measurement invariance evidence. Future studies would benefit from incorporating invariance testing as a prerequisite for cross-source comparisons and from developing unified survey instruments designed to assess all four constructs within a single integrated measurement framework.

The absence of formal invariance testing is an acknowledged methodological limitation, but its practical implications for this study's conclusions are mitigated by two design features. First, the variance-weighted synthesis assigns influence proportional to dataset size, reducing the risk that idiosyncratic measurement properties of any single survey disproportionately influence the composite structural estimates. Second, and more critically from a validity standpoint, the convergent replication of directionally consistent findings across four independently designed surveys—each using different response formats, sampling frames, and administering agencies—constitutes indirect empirical evidence of practical measurement equivalence: constructs that yield consistent structural relationships across instruments with markedly different surface properties are more likely to reflect substantive underlying phenomena than measurement artefacts. This logic is analogous to the methodological heterogeneity principle in meta-analysis, whereby replication across methodologically diverse studies provides stronger cumulative evidence than replication across methodologically similar ones (Cheung, 2015). Future primary studies employing unified instruments are advised to treat these structural estimates as theoretically grounded hypotheses warranting direct empirical testing rather than as definitive conclusions.

CONCLUSION

This study proposes and empirically validates a four-hypothesis structural model linking AI anxiety, AI literacy, AI acceptance, and learning engagement in the context of South Korean Education 4.0. By synthesizing four nationally representative datasets using a pseudo-SEM approach, the study demonstrates that: (H1) AI anxiety is negatively associated with adoption; (H2) AI literacy enhances it; (H3) acceptance drives engagement; and most theoretically distinctive, (H4) AI literacy buffers the anxiety-acceptance relationship. The moderation finding represents the study's most theoretically distinctive contribution: it reconceptualizes AI literacy not merely as a skill competency but as a resilience mechanism that both facilitates engagement and attenuates the suppressive influence of anxiety on adoption.

Future research is advised to replicate this model using primary longitudinal data amenable to individual-level mediation and causal directionality testing. Cross-cultural extensions—particularly to Education 4.0 contexts in lower-income or non-OECD settings where digital divides are more pronounced—would help delineate the theoretical boundary conditions and generalizability of these findings. The pseudo-SEM methodological template presented in this study, including systematic proxy mapping, harmonization protocols, and cross-dataset convergence validation, provides a replicable analytical framework for developing policy-relevant structural models in educational research from the expanding repository of national administrative and survey data.

The theoretical and policy significance of this study extends beyond its national context. Korea represents an instructive case—a society that has confronted the convergence of advanced AI integration, accelerated demographic aging, and intensifying lifelong learning demands earlier than most comparable economies. The anxiety–literacy–acceptance–engagement dynamics documented here are likely to emerge as salient policy challenges in other aging OECD societies as AI integration accelerates. By establishing a population-level structural model, identifying AI literacy as a psychological buffer against adoption resistance, and demonstrating a replicable methodology for developing educational theory from national administrative survey data, this study provides the international research community with both an empirical reference point and a methodological framework for examining the structural conditions that mediate AI adoption in learning contexts and for informing evidence-based policy responses to the affective and cognitive barriers that constrain such adoption.

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APPENDIX A

Data Source–Construct Mapping Table

Specific Survey Items / Variables Used for Each Theoretical Construct and Hypothesis

Agency / Source	Dataset Name	Specific Survey Item / Variable	Construct Mapped	Hyp.
KISTEP (2024)	Technology Impact Assessment Report on AI	Q: Perceived risk of cognitive dependency on AI (5-point Likert)	AI Anxiety	H1
KISTEP (2024)	Technology Impact Assessment Report on AI	Q: Concern about AI replacing human judgment in learning tasks (5-point Likert)	AI Anxiety	H1
KISTEP (2024)	Technology Impact Assessment Report on AI	Q: Perceived risk of AI over-reliance on decision-making (5-point Likert)	AI Anxiety	H1, H4
KISTEP (2024)	Technology Impact Assessment Report on AI	Q: Intention to use AI tools in occupational/educational contexts (5-point Likert)	AI Acceptance – Behavioral Intention	H1, H2
NIA (2024)	Digital Divide Survey	Digital Competency Index (DCI) – composite score (access + capacity + utilization)	AI Literacy (proxy)	H2, H4
NIA (2024)	Digital Divide Survey	Sub-scale: Information search and critical evaluation skills	AI Literacy – critical understanding	H2
NIA (2024)	Digital Divide Survey	Sub-scale: Content creation and digital tool usage skills	AI Literacy – application dimension	H2
NIA (2024)	Digital Divide Survey	Sub-scale: Online learning and e-learning participation frequency	Learning Engagement (proxy)	H3
NIA (2024)	Digital Divide Survey	Q: Perceived usefulness of digital/AI tools in daily activities (5-point Likert)	AI Acceptance – Perceived Usefulness (TAM)	H2, H3
KEIS (2024)	Korea Education and Employment Panel (KEEP)	Annual hours in voluntary training/continuing education programs	Learning Engagement – behavioral indicator	H3
KEIS (2024)	Korea Education and Employment Panel (KEEP)	Self-directed learning frequency (times per year)	Learning Engagement – SDL dimension	H3
KEIS (2024)	Korea Education and Employment Panel (KEEP)	AI/digital skill training participation (binary: yes/no)	AI Literacy – skill-building dimension	H2
KEIS (2024)	Korea Education and Employment Panel (KEEP)	Perceived usefulness of digital tools for career development (5-point Likert)	AI Acceptance – Perceived Usefulness (TAM)	H2, H3
Statistics Korea (2024)	Social Survey & ICT Usage Statistics	Internet/AI service usage frequency by age cohort	AI Acceptance – behavioral usage	H1, H3

Agency / Source	Dataset Name	Specific Survey Item / Variable	Construct Mapped	Hyp.
Statistics Korea (2024)	Social Survey & ICT Usage Statistics	Attitude toward AI in work and education (positive/negative 3-item scale)	AI Anxiety / AI Acceptance (combined proxy)	H1
Statistics Korea (2024)	Social Survey & ICT Usage Statistics	Participation in lifelong learning activities (binary + frequency)	Learning Engagement	H3

Note. DCI = Digital Competency Index (composite). TAM = Technology Acceptance Model. PU = Perceived Usefulness. SDL = Self-Directed Learning. Hyp. = Hypothesis number(s) the variable informs. Original instruments available at: KISTEP (www.kistep.re.kr); NIA (www.nia.or.kr); KEIS (survey.keis.or.kr); Statistics Korea (kosis.kr). All datasets are publicly accessible research datasets subject to each agency's data use agreement.