Rethinking Perceived Usefulness in AI-based Learning for Cultural and Sustainability Education Using a Value-oriented Extended TAM

Sasiyanai Sanpang, Kemmanat Mingsiritham*, Apisit Thaoyabut, and Gan Chanyawudhiwan

Office of Educational Technology, Sukhothai Thammathirat Open University, Nonthaburi, Thailand
Email: sasiyanai.san@stou.ac.th (S.S.); kemmanat.min@stou.ac.th (K.M.); apisit.tha@stou.ac.th (A.T.); gan.cha@stou.ac.th (G.C.)
*Corresponding author

Manuscript received February 6, 2026; revised March 19, 2026; accepted April 14, 2026; published August 21, 2026

***Abstract*—Artificial Intelligence (AI) has become an influential force in contemporary education, particularly in cultural heritage and sustainability learning that require contextual and value-oriented understanding. This study investigates the factors influencing secondary school students' acceptance of an AI-based intelligent learning platform in Thailand using an extended Technology Acceptance Model (TAM). The model integrates core constructs—perceived ease of use, perceived usefulness, attitude toward use, intention to use, and actual platform acceptance—with additional variables, including self-efficacy, community support, learning engagement, and sustainability and cultural awareness. Data were collected from 400 learners using a five-point Likert scale questionnaire and analyzed through Structural Equation Modeling (SEM). The results indicate a good model fit. Perceived usefulness was the strongest predictor of attitude toward use. Self-efficacy, sustainability and cultural awareness, and community support significantly enhanced perceived usefulness. In contrast, learning engagement showed a small but significant negative effect, suggesting that engagement alone may not increase perceived usefulness without meaningful learning design. From a theoretical perspective, this study extends TAM by incorporating value-oriented constructs, thereby offering a more comprehensive explanation of technology acceptance in culturally and socially embedded learning contexts. From a practical standpoint, the findings highlight the importance of usability, learner confidence, and meaningful learning experiences in promoting sustained adoption of AI-based learning platforms. Overall, student acceptance is shaped by an interplay of technological, psychological, and socio-cultural factors.**

***Keywords*—Artificial Intelligence (AI)-based learning platforms, extended Technology Acceptance Model (TAM), value-oriented learning, perceived usefulness, cultural and sustainability education**

I. Introduction

Over the past decade, Artificial Intelligence (AI) has become increasingly embedded in educational systems, particularly through intelligent learning platforms that support the personalization of content, interaction, and learning pathways. Recent advances in these platforms have emphasized adaptive learning, real-time feedback, and data-driven personalization, enabling more context-responsive and learner-centered educational experiences. Such capabilities are especially pertinent to cultural heritage and sustainability education, where learning extends beyond conceptual understanding to include meaningful engagement with real-world contexts and value-oriented perspectives [1, 2].

Despite these advancements, the successful implementation of AI-based learning platforms depends not only on technological sophistication but also on learners' acceptance. A substantial body of research has consistently identified perceived usefulness, perceived ease of use, and learner attitudes as key determinants of technology adoption [3, 4]. However, existing studies have largely concentrated on higher education or general digital learning environments, with relatively limited attention given to secondary school learners and value-based learning domains such as cultural heritage and sustainability education. This gap is particularly important, as secondary education represents a critical stage in shaping learners' attitudes, values, and long-term patterns of technology use [5, 6].

Moreover, although Technology Acceptance Model (TAM) has been widely applied to explain technology adoption, its application in AI-based learning contexts has often focused predominantly on functional and cognitive dimensions. As a result, value-oriented constructs—such as cultural awareness and sustainability-related learning outcomes—remain insufficiently integrated. Consequently, existing models may not fully capture the complexity of AI adoption in educational contexts that are inherently social, cultural, and ethical in nature.

To address these limitations, this study extends TAM by incorporating psychological, social, and value-based factors, including self-efficacy, community support, learning engagement, and sustainability and cultural awareness, within the context of secondary education. Structural Equation Modeling (SEM) is employed to examine the causal relationships among these variables in a systematic manner. By linking AI adoption with value-oriented learning dimensions, this study offers a more comprehensive framework for understanding student acceptance of intelligent learning platforms in culturally and socially meaningful contexts.

Accordingly, this study contributes to both theory and practice by advancing current understandings of AI adoption in education and by providing insights for the design of AI-based learning platforms that support meaningful, contextually relevant, and sustainable learning experiences.

II. Literature Review

A. Core TAM in AI-based Learning Platforms

AI-based Intelligent Learning Platforms (ILPs), including AI tutoring systems, adaptive learning environments, and generative AI-supported tools, have increasingly been

doi: 10.18178/ijiet.2026.16.8.2686

recognized as high-impact educational technologies due to their capacity to personalize learning content, provide timely feedback, and promote learner autonomy. However, despite these technological advancements, recent research and policy discussions consistently emphasize that AI-driven learning environments are not value-neutral. Factors such as implementation quality, system transparency, and culturally responsive design significantly shape both learning outcomes and user trust, particularly among adolescent learners whose engagement with technology is mediated by teachers and institutional structures.

In parallel, cultural heritage and sustainability education emphasize place-based learning, value formation, and meaningful connections to real-world contexts. Consequently, research on technology adoption in such domains must extend beyond traditional considerations of usability and performance. While prior studies largely conceptualize technology adoption in functional terms, they often overlook the extent to which learning platforms align with learners' cultural values, sustainability perspectives, and the broader socio-educational ecosystem. This limitation suggests a critical need to reconceptualize technology acceptance in value-oriented learning contexts [7].

TAM remains one of the most widely used theoretical frameworks for explaining technology adoption. The model identifies Perceived Usefulness (PU) and Perceived Ease of Use (PEU) as the primary determinants of users' attitudes and intentions to use a system [8, 9]. Meta-analytic evidence in AI-in-education contexts confirms the continued robustness of these relationships, while also indicating that their strength may vary depending on cultural contexts and the nature of AI applications [10]. This suggests that, although TAM provides a solid theoretical foundation, it requires extension to account for AI-specific factors such as trust, privacy, system accuracy, institutional support, and learner competencies.

In secondary education, TAM becomes more complex due to the influence of school regulations, teacher mediation, and developmental characteristics of learners. Empirical evidence indicates that students' use of AI tools is often shaped by institutional policies and concerns regarding reliability and trustworthiness. For example, large-scale surveys have shown that, despite widespread access to AI tools, students' perceptions of teacher disapproval and system limitations may reduce both perceived usefulness and intention to use [11]. These findings underscore the importance of extending TAM to incorporate contextual and social influences in school-based settings.

Perceived Ease of Use (PEU), defined as the extent to which a system is perceived as requiring minimal effort, has consistently been shown to influence perceived usefulness. Learning platforms that are intuitive and user-friendly are more likely to be perceived as beneficial [12]. However, in AI-based environments, PEU assumes a more foundational role. The complexity of AI systems may increase cognitive load, thereby limiting learners' ability to recognize the system's potential value. Empirical evidence from studies involving secondary school learners using AI tutoring systems supports a strong positive relationship between PEU and PU. At the same time, this relationship suggests that usability is not merely a supporting factor but a necessary condition for value realization in AI-enhanced learning [13].

Perceived Usefulness (PU) remains a central construct in TAM, representing users' beliefs that a system enhances their learning effectiveness or academic performance. Extensive research has consistently identified PU as a primary predictor of intention to use across online learning environments and emerging educational technologies [14]. In the context of AI-based learning platforms, PU extends beyond functional efficiency to encompass meaningful support for domain-specific learning, such as cultural heritage and sustainability education. When learners perceive that an intelligent platform contributes to deeper understanding and value-relevant learning outcomes, they are more likely to develop favorable attitudes and stronger intentions to use the system [15].

Moreover, PU exerts both direct and indirect effects on behavioral intention, particularly through its influence on attitudes toward technology use [16]. Recent studies in AI adoption reinforce the dominant role of PU, with empirical evidence—such as PLS-SEM analyses—demonstrating that PU is the strongest predictor of both attitudes and intentions toward AI-based tools [17]. This perspective is especially relevant in value-oriented learning contexts, where the perceived usefulness of technology is evaluated not merely in terms of efficiency or convenience, but in terms of its capacity to support meaningful, contextually grounded, and value-driven learning experiences. Building on the core TAM framework, this study adopts PU and PEU as foundational constructs while recognizing the need to reinterpret their roles within AI-enhanced and value-oriented learning environments.

B. Extended Psychological and Social Factors

Learning Engagement (LE) refers to learners' levels of interest, involvement, and active participation in platform-mediated learning activities. Prior research generally assumes a positive relationship between engagement and perceived usefulness, suggesting that interactive and immersive learning environments enhance the perceived value of educational technologies. Empirical studies in technology-enhanced learning support this view, indicating that increased engagement is associated with improved learning outcomes and higher acceptance of digital platforms [18–20].

However, the relationship between engagement and perceived usefulness is not uniformly positive. Emerging research highlights important boundary conditions, suggesting that highly immersive or cognitively demanding technologies may increase cognitive load and operational complexity, potentially reducing perceived usefulness even when engagement is high [21]. This mixed evidence underscores the need to treat the relationship between learning engagement and perceived usefulness as an empirical issue rather than assuming a universally positive effect. This consideration is particularly important for adolescent learners, who may exhibit high levels of engagement driven by novelty without corresponding perceptions of meaningful academic benefit.

Community Support (CS), encompassing encouragement and guidance from teachers, parents, and peers, represents another critical factor influencing technology acceptance. Social support has been widely recognized as a determinant of both perceived usefulness and intention to use educational technologies [22]. In addition, social norms and expectations can shape learners' perceptions of whether technology is valuable and worth adopting. Within AI-enhanced learning environments, community support also includes institutional policies, classroom norms, guidance on responsible AI use, and structured onboarding processes. In secondary education, where learners' technology use is often mediated by teacher authority and school regulations, such support can significantly influence both perceived value and willingness to use AI tools for learning [11].

Moreover, recent models of AI adoption in educational contexts highlight that institutional and environmental support not only facilitate initial access to technology but also play a crucial role in shaping learners' perceptions of usefulness and ease of use. These findings suggest that supportive conditions enable learners to translate exposure to AI technologies into meaningful and sustained learning benefits.

C. Cultural and Sustainability-Oriented Learning Dimensions

Sustainability and Cultural Awareness (SCA) represent an important dimension of learning that can function both as an outcome of technology-enhanced learning and as a factor shaping learners' perceptions of technology use. Digital platforms designed to connect learning content with authentic community contexts have been shown to enhance learners' awareness of cultural heritage and promote positive orientations toward sustainable development [23, 24]. Recent empirical studies further indicate that technology-supported heritage learning can simultaneously foster learner engagement and deepen value-based understanding. Moreover, AI-driven personalized learning environments have been applied in lower secondary education to operationalize sustainability perspectives as measurable learning outcomes influenced by pedagogical design, system usability, and learner motivation [25].

This perspective suggests that PU is not solely determined by functional efficiency but is partially constructed through value alignment. In other words, technology is perceived as useful when it supports learners' personal and societal values. This reconceptualization extends the traditional TAM framework by introducing a value-oriented dimension of usefulness.

Attitude toward Use (ATT) serves as a key mediating construct linking users' perceptions—particularly PU and PEU to INT. When learners perceive a system as both useful and easy to use, they are more likely to develop favorable attitudes, which subsequently influence their intention to adopt the technology. Empirical studies in AI-in-education contexts continue to confirm the central role of attitude and intention as proximal predictors of adoption. However, a recurring limitation in literature is the predominant reliance on intention rather than actual usage behavior, with relatively limited empirical evidence from secondary education compared to higher education settings [26].

Studies that examine both intention and actual usage provide strong support for the sequential pathway from Attitude toward Use (ATT) to Intention to Use (INT) to Actual Platform Acceptance (APA). This structure reflects the translation of cognitive evaluations into observable behavior under real-world conditions. Taken together, these findings highlight the importance of integrating value-based, psychological, and social dimensions into a comprehensive model of technology acceptance.

D. Hypothesis Development

Existing research on AI adoption has predominantly focused on higher education and function-oriented outcomes, with limited attention to secondary education and value-oriented learning contexts. This gap is particularly important, as technology use in secondary education is closely linked to identity formation, ethical reasoning, and long-term societal engagement.

To address this limitation, the present study extends the Technology Acceptance Model by incorporating sustainability and cultural awareness, community support, and self-efficacy as antecedents of perceived usefulness. This approach provides a more context-sensitive and theoretically enriched framework for understanding AI-based learning acceptance in secondary education.

Accordingly, the following research hypotheses are proposed:

H1: Perceived Ease of Use (PEU) positively influences Perceived Usefulness (PU).

H2: Learning Engagement (LE) influences Perceived Usefulness (PU).

H3: Sustainability and Cultural Awareness (SCA) positively influence Perceived Usefulness (PU).

H4: Self-Efficacy (SE) positively influences Perceived Usefulness (PU).

H5: Community and Learning Environment Support (CS) positively influence Perceived Usefulness (PU).

H6: Perceived Usefulness (PU) positively influences Attitude toward Use (ATT).

H7: Attitude toward Use (ATT) positively influences Intention to Use (INT).

H8: Intention to Use (INT) positively influences Actual Platform Acceptance (APA).

III. MATERIALS AND METHODS

A. Ethical Approval and Informed Consent

This study received ethical approval from Nakhonratchasima Rajabhat University (Approval No. HE-261-2568, dated October 9, 2025). Participation in the study was entirely voluntary, and informed consent was obtained from all participants through an online consent form prior to data collection. Participants were clearly informed about the study objectives, data collection procedures, and measures to ensure confidentiality and anonymity. No personally identifiable information was collected, and all data were analyzed and reported in aggregate form solely for research purposes. Participants were also informed of their right to withdraw from the study at any time or to decline answering any questions without any penalty or adverse consequences.

B. Research Design

This study employed a quantitative research approach using a survey design to examine the structural relationships among variables within an Extended TAM applied to an

AI-driven intelligent learning platform for cultural heritage and sustainability education. The primary objective was to investigate the interrelationships among multiple latent constructs within a theoretically grounded framework. SEM was adopted as the principal analytical technique, given its suitability for testing complex models involving multiple interrelated variables and mediating effects.

The study follows a theory-driven causal modeling approach in which hypotheses were specified as a priori based on the TAM and recent developments in AI-in-education research. Although directional relationships among variables are theoretically grounded and statistically modeled, the cross-sectional nature of the data limits causal inference to explanatory rather than confirmatory causality.

As shown in Fig. 1, the proposed research framework includes the core TAM constructs—PEU, PU, ATT, INT, and APA—alongside extended variables identified from contemporary literature, namely SE, CS, LE, and SCA. The hypothesized relationships among these constructs were systematically derived from a comprehensive review of relevant empirical and theoretical studies.

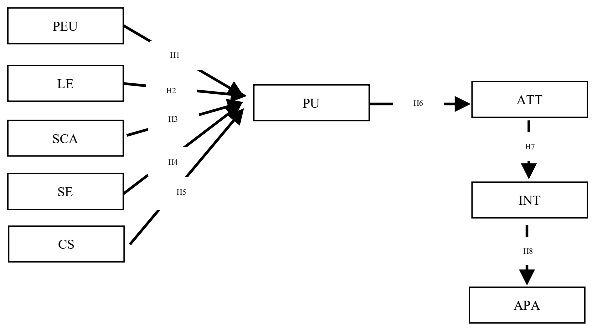

Fig. 1. Conceptual model of students' acceptance of an ai-based intelligent learning platform.

C. Implementation

The research implementation comprised three main phases: instrument development, content validity assessment, and data collection from the target population. The learning platform examined in this study was an AI-based intelligent learning platform specifically designed to support cultural heritage and sustainability education. The platform incorporates machine learning–based recommendation systems, adaptive learning pathways, and interactive AI-driven feedback mechanisms, enabling personalized, context-aware, and learner-centered learning experiences. This approach ensured that respondents' evaluations reflected actual learning experiences rather than hypothetical perceptions, thereby enhancing the validity of their reported perceptions, attitudes, and acceptance behaviors.

D. Participants

The study sample consisted of secondary school students in Thailand, selected using a convenience sampling approach due to practical constraints related to school access and platform implementation. A total of 400 learners were included in the analysis. The sample size was determined in accordance with methodological recommendations for Covariance-Based Structural Equation Modeling (CB-SEM), which require a sufficiently large sample to ensure stable Maximum Likelihood estimation, adequate statistical power, and reliable parameter estimates in models involving multiple latent constructs.

Given the complexity of the proposed model and the number of observed indicators, a sample size of 400 was considered sufficient to achieve robust estimation and model stability. This sample size also meets commonly recommended thresholds for SEM applications involving moderate to high factor loadings and multiple structural paths. However, the use of convenience sampling may limit the generalizability of the findings across different educational contexts, which should be considered when interpreting the results.

E. Data Collection

Data were collected using a structured questionnaire developed based on the Extended TAM framework and the study constructs, including PEU, PU, ATT, INT, APA, SE, CS, LE, and SCA. All items were measured using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). The questionnaire was reviewed by experts to ensure content validity. A pilot test with 30 participants yielded Cronbach's alpha values ranging from 0.82 to 0.90, indicating good reliability across all constructs.

Construct validity was assessed using factor loadings, Composite Reliability (CR), and Average Variance Extracted (AVE), all of which met the recommended thresholds. To address common method bias (CMB), both procedural and statistical controls were applied. Procedurally, anonymity and voluntary participation were emphasized. Statistically, Harman's single-factor test indicated that no single factor accounted for the majority of variance, suggesting that CMB was not a significant concern.

F. Data Analysis

Data analysis was conducted in several stages. First, preliminary data screening was performed to assess data completeness and suitability for analysis. Descriptive statistics were then used to summarize participants' demographic characteristics. Subsequently, Covariance-Based Structural Equation Modeling (CB-SEM) was employed to evaluate both measurement and structural models. Model fit was assessed using multiple indices, including Chi-square, Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), GFI, and SRMR. In addition, factor loadings, composite reliability, and discriminant validity were examined to confirm measurement adequacy. Path coefficients and their statistical significance were analyzed to test the hypothesized relationships. The model demonstrated an excellent fit to the empirical data (RMSEA = 0.022, CFI = 1.00), which may appear high for a sample size of $N = 400$. This result can be attributed to strong theoretical specification, high factor loadings, and low residual errors within the model. The Modification Indices (MI) were examined to ensure model validity, and the maximum MI value was relatively low, indicating that no substantial post-hoc modifications, such as correlated error terms, were required. Therefore, the final model retained its original theoretical structure, supporting both statistical validity and model transparency.

IV. Results

This section presents the results of SEM analysis conducted to examine factors influencing secondary school students' acceptance of an AI-based intelligent learning platform. The findings are reported sequentially, beginning with an assessment of model fit, followed by hypothesis testing of the structural relationships, and concluding with an evaluation of the explanatory power of the dependent variables. This structure ensures a clear and systematic interpretation of students' technology acceptance behavior.

A. Model Fit of the Structural Equation Model

The structural equation model demonstrated an excellent fit to the empirical data. Multiple goodness-of-fit indices were examined, including the chi-square to degrees of freedom ratio (χ^2/df), Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), and Tucker–Lewis Index (TLI). All indices met or exceeded commonly accepted SEM criteria, indicating that the model adequately represents the relationships among the constructions as shown in Table 1, the goodness-of-fit indices for the structural model.

Table 1. Goodness-of-fit indices of the structural model

Fit Index	Value	Criterion	Interpretation
χ^2/df	1.20	<3.00	Good fit
RMSEA	0.022	<0.05	Excellent fit
CFI	0.99	>0.95	Very good fit
TLI	0.98	>0.95	Good fit

The structural equation model demonstrated an excellent fit to the empirical data. The goodness-of-fit indices (χ^2/df = 1.20, RMSEA = 0.022, CFI = 0.99, and TLI = 0.98) all exceed recommended thresholds, indicating that the model adequately represents the observed data. Although the model fit indices, particularly CFI and RMSEA—are notably high for a sample size of N = 400, this can be attributed to strong theoretical specification, high factor loadings, and low residual covariance rather than model overfitting. No substantial post-hoc modifications were introduced based on Modification Indices (MI), confirming that the model retained its original theoretical structure and supporting statistical transparency and robustness.

B. Structural Model Analysis and Hypothesis Testing

Following confirmation of model fit, the structural model was analyzed to test the research hypotheses derived from the Extended TAM. Standardized path coefficients and their statistical significance were examined for each hypothesized relationship. The results indicate that most hypotheses were supported, demonstrating meaningful relationships among the constructions. The validated structural relationships and standardized path estimate as shown in Fig. 2, which illustrates the structural model of students' acceptance of the AI-based intelligent learning platform.

The structural analysis indicates that PEU has a positive effect on PU (β = 0.35), suggesting that students who perceive the AI-based learning platform as easy to use are more likely to recognize its usefulness for cultural heritage and sustainability learning. In contrast, LE exhibits a slightly negative effect on PU (β = −0.07), indicating that engagement alone does not necessarily translate into higher perceived usefulness without meaningful or contextually relevant learning outcomes.

SCA and SE both demonstrate positive effects on PU (β = 0.30 and β = 0.32, respectively), suggesting that value awareness and confidence in using technology contribute to stronger perceptions of usefulness. CS also shows a positive effect on PU (β = 0.19), underscoring the role of the learning environment in shaping students' perceptions.

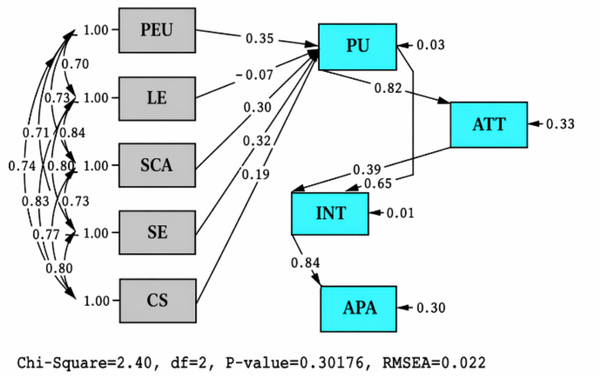

Fig. 2. Results of the structural model analysis.

Consistent with the TAM, PU exerts a strong positive effect on ATT (β = 0.82), confirming its role as the most influential predictor of students' attitudes toward the platform. The alternative direct path shows a negligible effect (β = 0.03), indicating that the influence of PU on ATT primarily operates through the main structural pathways.

Furthermore, ATT positively influences INT (β = 0.39), while INT exerts a strong positive effect on APA (β = 0.84), demonstrating that intention directly translates into actual usage behavior.

The total effects analysis confirms that PU remains the most influential construct, exerting both direct and indirect effects across the model. INT also shows a strong total effect on APA. Among external variables, SE and SCA exhibit comparable levels of influence on PU. The results of the hypothesis testing as shown in Table 2.

Table 2. Results of Hypotheses Testing

Hypothesis	Structural Path	Standardized Coefficient (β)	Significance Level	Result
H1	PEU → PU	0.35	$p < 0.01$	Supported
H2	LE → PU	−0.07	$p < 0.05$	Partially Supported
H3	SCA → PU	0.30	$p < 0.01$	Supported
H4	SE → PU	0.32	$p < 0.01$	Supported
H5	CS → PU	0.19	$p < 0.01$	Supported
H6	PU → ATT	0.82	$p < 0.01$	Supported
H7	ATT → INT	0.39	$p < 0.01$	Supported
H8	INT → APA	0.84	$p < 0.01$	Supported

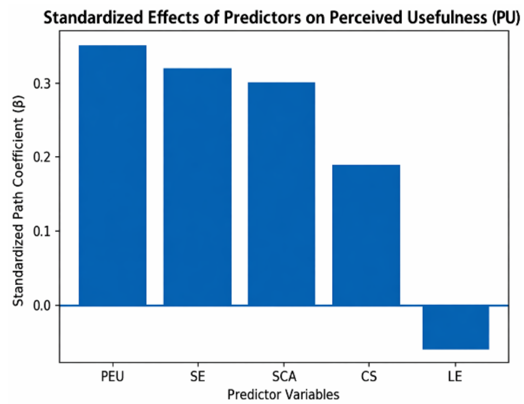

Fig. 3. Standardized effects of the predictors on Perceived Usefulness (PU).

To facilitate a clearer comparison of the relative influence of the independent variables on PU, the standardized path coefficients of the key predictors as shown in Fig. 3. The results indicate that PEU, SE, and SCA exert comparatively stronger effects on PU than the other variables included in the model. This pattern underscores the prominent roles of usability perceptions, learner confidence, and value-based awareness in shaping students' evaluations of the usefulness of AI-based intelligent learning platforms.

C. Explanatory Power of the Dependent Variables

Beyond assessing the statistical significance of the structural relationships, this study evaluated the model's explanatory power using the coefficient of determination (R^2) for each dependent variable. The results indicate that the model explains a substantial proportion of variance in PU, reflecting strong predictive capability regarding students' evaluations of the AI-based intelligent learning platform. In contrast, ATT, INT, and APA exhibit moderate but acceptable levels of explained variance.

Overall, these findings suggest that the proposed model demonstrates substantial explanatory power in accounting for secondary school students' acceptance of an AI-driven intelligent learning platform. The results further support the robustness of the extended TAM in explaining technology adoption behavior within the context of cultural and sustainability education, as shown in Table 3.

Table 3. Explanatory power of the dependent variables in the model

Dependent Variable	R^2	Interpretation
PU	0.65	High explanatory power
ATT	0.33	Moderate explanatory power
INT	0.39	Moderate explanatory power
APA	0.30	Acceptable explanatory power

The robustness of the structural model is further supported by the consistency among direct, indirect, and total effects, which align with the theoretical expectations of the Extended TAM. The absence of substantial discrepancies between direct and total effects indicates model stability and suggests that suppression effects are not present. Furthermore, the mediation structure demonstrates that external variables influence behavioral outcomes primarily through cognitive evaluations, specifically PU and ATT, rather than exerting direct effects on usage behavior. These findings provide additional statistical support for the model's adequacy, confirming that it is not only well-fitted but also theoretically coherent and robust, thereby strengthening its contribution to the literature on AI-based learning acceptance.

V. Discussion

The findings of this study support the applicability of the Extended TAM in explaining the acceptance of AI-based intelligent learning platforms among secondary school students. The structural equation modeling results indicate that the proposed model demonstrates satisfactory explanatory power in accounting for technology acceptance behavior. Beyond confirming the robustness of TAM, this study extends its applicability by incorporating value-based and context-sensitive constructs, particularly within the domains of cultural heritage and sustainability education, which remain underexplored in conventional technology acceptance research. These findings are consistent with recent studies in digital learning contexts [27], while advancing prior work through the integration of socio-cultural learning dimensions into the explanatory framework.

A key finding is the central role of PU as a primary determinant of ATT. While this aligns with classical TAM, the present study reconceptualizes usefulness as a multidimensional construct encompassing cognitive depth, cultural relevance, and sustainability awareness, rather than sole functional efficiency. When learners perceive that technology enhances deep understanding and supports connections with real-world contexts, they are more likely to attribute greater value to the platform. This perspective suggests a shift from utilitarian usefulness toward meaningful usefulness in AI-enhanced learning environments. PU thus operates as a core mechanism linking perceptions to attitudes and behavioral intentions [28]. Furthermore, research on youth engagement in cultural heritage contexts highlights inclusiveness and social value as key outcomes [29], reinforcing the view that perceived usefulness is socially and culturally constructed rather than purely instrumental.

The significant relationship between PEU and PU also provides important implications. Rather than functioning as a secondary factor, PEU appears to play a foundational role in enabling learners to access perceived value in AI-driven environments. Advanced AI features, such as personalization and automation, may reduce perceived usefulness if they increase cognitive load or limit transparency [30]. This finding contributes to ongoing discussions in AI education, emphasizing that usability and explainability are critical conditions for the perceived value of intelligent systems, particularly among younger learners.

The significant influence of SE on PU extends prior research by demonstrating that the perceived intelligence of AI systems does not inherently translate into value unless learners feel capable of interacting with and controlling them. While consistent with global findings on AI literacy and learner agency [31], this study further suggests that self-efficacy functions as a conversion mechanism through which technological potential is transformed into perceived educational value. This underscores the importance of explicitly integrating learner capability constructs into AI acceptance models.

The significant effect of SCA on PU highlights a key contribution of this study. In contrast to traditional TAM research that emphasizes cognitive and technological factors, the findings demonstrate that value-oriented awareness plays a critical role in shaping perceived usefulness. AI-based platforms are perceived as more beneficial when they support learners in understanding complex societal issues, including sustainability and cultural heritage. This result contributes to the literature on transformative and socially responsive learning, indicating that technology acceptance in education is increasingly influenced by value alignment rather than functionality alone [32].

Conversely, the negative relationship between LE and PU represents an unexpected yet theoretically meaningful finding. Although engagement is generally associated with increased perceived value, the results suggest that highly engaged learners may develop more critical expectations toward AI-based platforms. When such expectations are not fully met, perceived usefulness may decline. This finding challenges the assumption of a uniformly positive relationship between engagement and technology acceptance and suggests that engagement should be conceptualized as a more complex construct in AI-enhanced learning environments. This interpretation is consistent with recent research emphasizing the roles of trust, transparency, and user experience in AI adoption [33].

The sequential relationships from ATT to INT and from INT to APA confirm the staged nature of technology acceptance. However, the findings extend this perspective by showing that acceptance in AI-based educational contexts is not solely an individual cognitive process but is embedded within a broader socio-technical ecosystem. The significant influence of CS on PU further reinforces the importance of institutional and social structures in shaping learners' perceptions. This contributes to a systemic perspective of technology acceptance, suggesting that successful implementation of AI-based platforms requires alignment among technological design, learner readiness, and educational context. This view is consistent with research on digital cultural heritage learning, which emphasizes participatory and context-aware design [34].

Overall, this study advances technology acceptance research by integrating cognitive, psychological, and socio-cultural dimensions into a unified model of AI-based learning acceptance. In contrast to traditional TAM applications that emphasize efficiency and usability, this study foregrounds the roles of meaningful learning, value alignment, and learner agency. These findings offer theoretical insights into how AI technologies are evaluated by younger learners in complex educational contexts and suggest directions for future research to further refine acceptance models in the era of intelligent, value-driven learning systems.

VI. CONCLUSIONS AND IMPLICATIONS

This study provides evidence that secondary school students' acceptance of AI-based intelligent learning platforms emerges from the interaction of technological factors, learners' psychological characteristics, and value-laden socio-cultural contexts. Consistent with the TAM, PU remains the central mechanism driving technology acceptance, even within AI-driven environments. Importantly, this study advances the Extended TAM by reconceptualizing PU as a value-oriented construction that integrates cognitive, socio-cultural, and sustainability dimensions, rather than treating it as purely functional. By incorporating cultural and sustainability awareness, the model is better aligned with value-oriented learning contexts and extends its explanatory scope beyond technical considerations.

From a scientific perspective, this study contributes to the literature in three key ways: (1) it extends TAM by integrating value-based constructs into AI-supported learning contexts, (2) it provides empirical evidence from secondary education, which remains underrepresented in AI acceptance research, and (3) it identifies a non-linear and partially counterintuitive relationship between learning engagement and perceived usefulness, offering new theoretical insights into learner behavior in AI-enhanced environments.

From a policy perspective, the findings suggest that AI adoption in secondary education should extend beyond technological provision. Policies should emphasize meaningful, value-based learning experiences and embed AI within curricula that connect with local contexts, cultural heritage, and sustainability. This approach enables students to perceive AI as a tool for understanding real-world issues rather than merely a technical resource.

Furthermore, strengthening students' self-efficacy in using digital technologies should be prioritized. This can be supported through targeted teacher development, scaffolded learning activities, and supportive environments that encourage experimentation without fear of failure. Such measures can enhance learner confidence and support sustainable AI adoption in schools.

In terms of platform design, the findings provide clear implications. Perceived ease of use should be treated as a foundational design principle that enables learners to fully access the value of learning content. User experience design should minimize cognitive load and unnecessary complexity while leveraging AI capabilities to support meaningful learning, including contextualized content adaptation, culturally and ethically reflective prompts, and feedback mechanisms that reinforce value formation and sustainability connections. In addition, platforms should incorporate features that enhance students' self-efficacy, such as structured onboarding, visible progress indicators, and activity designs that promote frequent experiences of success. These elements facilitate the translation of AI functionality into perceived usefulness and sustained acceptance.

The finding that learning engagement does not directly enhance perceived usefulness underscores the need to prioritize the quality rather than the quantity of engagement. AI-based platforms for cultural and sustainability education should therefore foster deep engagement through reflective learning, value-oriented dialogue, and meaningful connections to learners' everyday experiences. Engagement is likely to strengthen perceived usefulness only when it is cognitively and socially meaningful.

Despite these contributions, several limitations should be acknowledged. First, the cross-sectional design limits causal inference over time. Second, the use of convenience sampling within a single national context constrains generalizability. Third, reliance on self-reported data may introduce response bias and may not fully reflect actual usage behavior. Finally, although the model demonstrates strong explanatory power, additional variables—such as trust in AI, perceived risk, and system transparency—were not included and may further enhance predictive capability.

Future research should employ longitudinal or experimental designs to better capture causal dynamics and temporal changes in technology acceptance. It should also incorporate constructs such as AI trust, explainability, and ethical perceptions to reflect the evolving nature of AI-supported learning environments. Comparative studies across educational levels, cultural contexts, and platform types would further elucidate contextual variations in acceptance. Finally, mixed-method approaches integrating quantitative modeling with qualitative inquiry may provide deeper insights into how learners construct meaning and value in AI-mediated learning contexts.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

K.M. served as the principal investigator of the research project, responsible for drafting the manuscript, designing the research methodology, collecting data, and conducting data analysis; S.S. participated in conceptualized the study, conducted the literature review, and contributed to data collection; A.T. and G.C. served as data collection and organized expert validation procedures.; all authors had approved the final version.

FUNDING

This research was funded by Sukhothai Thammathirat Open University in 2024.

ACKNOWLEDGMENT

The authors wish to thank the Institute for Research and Development, Sukhothai Thammathirat Open University, Thailand in the completion of this research, recognition of sponsorship and financial support.

REFERENCES

[1] O. E. Hosayny, H. Razkane, and M. Yeou, "Extended TAM-based acceptance of AI for supporting critical thinking in academic research: An examination of perceived benefits and challenges," *Discover Artificial Intelligence*, vol. 5, 167, 2025. doi: 10.1007/s44163-025-00390-x

[2] A. Al-Momani and T. Ramayah, "Adoption of artificial intelligence in education: A systematic literature review," in *Current and Future Trends on Intelligent Technology Adoption*, M. A. Al-Sharafi *et al.*, Eds. Cham, Switzerland: Springer, vol. 1161, 2024, pp. 145–168. doi: 10.1007/978-3-031-61463-7_7

[3] A. Sultana, N. Abdul Latheef, N. Siby, and Z. Ahmad, "Exploring students' attitudes toward artificial intelligence: Psychometric validation of AI-attitude scale," *SAGE Open*, vol. 15, no. 4, 2025. doi: 10.1177/21582440251378375

[4] Ö. G. Tekin, "Factors affecting teachers' acceptance of artificial intelligence technologies: Analyzing teacher perspectives with structural equation modeling," *Instructional Technology and Lifelong Learning*, vol. 5, no. 2, pp. 399–420, 2024. doi: 10.52911/itall.1532218

[5] J. P. Aliño, A. J. Rebato, A. N. Abrenica, J. Baguio, M. Villanueva, D. M. Obenza, and K. Sumatra, "The relationship between AI self-efficacy and AI trust of college students," *International Journal of Multidisciplinary Studies in Higher Education*, vol. 1, no. 1, pp. 92–102, 2024. doi: 10.70847/587961

[6] H. Yang, N. Xu, X. Lin, and W. Zhang, "Integrating AI literacy into the TAM–TPB model to explain students' intention to use educational AI through a MASEM approach," *Computers in Human Behavior Reports*, vol. 20, 100833, 2025. doi: 10.1016/j.chbr.2025.100833

[7] F. Miao and W. Holmes. (2023). Guidance for Generative AI in Education and Research. Paris, France: UNESCO. [Online]. Available: https://www.unesco.org/en/articles/guidance-generative-ai-education-and-research

[8] A. Primartadi, S. Suyitno, F. Abdilla, Y. Kamin, S. Riyadi, and S. Nugroho, "Student acceptance of AI-driven deep learning tools: The influence of institutional support and teacher competency in vocational schools," *European Journal of Educational Research*, vol. 15, no. 2, pp. 481–495, 2024. doi: 10.12973/eu-jer.15.2.481

[9] Y. Lu, G. Mi, H. Lu, and Y. Wang, "Immersive technologies in built heritage spaces: Understanding tourists' continuance intention toward sustainable AR and VR applications at the Terracotta Warriors Museum," *Buildings*, vol. 15, no. 19, 2025. doi: 10.3390/buildings15193481

[10] L. Xue, J. Mahat, and N. Ghazali, "Technology acceptance model in artificial intelligence in education: A meta-analysis," *SAGE Open*, vol. 16, no. 1, 2026. doi: 10.1177/21582440251409441

[11] J. Schiel, B. L. Bobek, and J. Z. Schnieders. (2023). High School Students' Use and Impressions of AI Tools. *ACT Research*. [Online]. Available: https://www.luminafoundation.org/wp-content/uploads/2024/01/High-School-Students-Use-and-Impressions-of-AI-Tools.pdf

[12] R. Scherer, F. Siddiq, and J. Tondeur, "The Technology Acceptance Model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education," *Computers & Education*, vol. 128, pp. 13–35, 2019. doi: 10.1016/j.compedu.2018.09.009

[13] H. Huang, Y. Chen, and P. L. P. Rau, "Exploring acceptance of intelligent tutoring systems among high school students," *Universal Access in the Information Society*, vol. 21, pp. 381–393, 2022. doi: 10.1007/s10209-021-00835-x

[14] F. O. Santini, C. H. Sampaio, T. Rasul, W. J. Ladeira, A. K. Kar, M. G. Perin, and M. Azhar, "Understanding students' technology acceptance behaviour: A meta-analytic study," *Technology in Society*, vol. 81, 102798, 2025. doi: 10.1016/j.techsoc.2024.102798

[15] A. K. Khoso, W. Honggang, and M. A. Darazi, "Empowering creativity and engagement: The impact of generative artificial intelligence usage on Chinese EFL students' language learning experience," *Computers in Human Behavior Reports*, vol. 18, 100627, 2025. doi: 10.1016/j.chbr.2025.100627

[16] Z. Zhao, Q. An, and J. Liu, "Exploring AI tool adoption in higher education," *Frontiers in Psychology*, vol. 16, 1619391, 2025. doi: 10.3389/fpsyg.2025.1619391

[17] A. S. Al-Adwan, N. Li, A. Al-Adwan, G. A. Abbasi, N. A. Albelbisi, and A. Habibi, "Extending the technology acceptance model (TAM) to predict university students' intentions to use metaverse-based learning platforms," *Education and Information Technologies*, vol. 28, pp. 15381–15416, 2023. doi: 10.1007/s10639-023-11816-3

[18] J. Xu and Q. Deng, "Exploring Chinese secondary school students' acceptance of live video-streamed teaching platforms in EFL class: An application of the technology acceptance model," *Behavioral Sciences*, vol. 14, no. 7, 2024. doi: 10.3390/bs14070593

[19] H.-C. K. Lin, L.-W. Lu, and R.-S. Lu, "Integrating digital technologies for sustainable education," *Sustainability*, vol. 16, no. 21, 2024. doi: 10.3390/su16219451

[20] B. Koparan, "Augmented reality and students' attitudes toward sustainability," *Sustainability*, vol. 17, no. 13, 2025. doi: 10.3390/su17136172

[21] R. R. Saqr, S. A. Al-Somali, and M. Y. Sarhan, "Exploring the acceptance and user satisfaction of AI-driven e-learning platforms: An integrated technology model," *Sustainability*, vol. 16, no. 204, 2024. doi: 10.3390/su16010204

[22] M. Y. Doo, "An investigation of the social influence processes of flipped class students: An application of the extension of the technology acceptance model," *Education and Information Technologies*, vol. 28, pp. 16593–16613, 2023. doi: 10.1007/s10639-022-11030-7

[23] R. Bond, S. Bedenlier, O. Zawacki-Richter, and M. Kerres, "Mapping research in student engagement and educational technology in higher education: A systematic evidence map," *International Journal of Educational Technology in Higher Education*, vol. 17, no. 2, 2020. doi: 10.1186/s41239-019-0176-8

[24] A. Ni and A. Cheung, "Secondary students' continuance intention to adopt AI tutoring systems," *Education and Information Technologies*, vol. 28, no. 3, pp. 3191–3216, 2023. doi: 10.1007/s10639-022-11305-z

[25] F. Ouyang, W. Xu, and M. Cukurova, "An artificial intelligence-driven learning analytics method to examine the collaborative problem-solving process from the complex adaptive systems perspective," *International Journal of Computer-Supported Collaborative Learning*, vol. 18, pp. 39–66, 2023. doi: 10.1007/s11412-023-09387-z

[26] C. A. Ofozoba *et al.*, "AI-driven service-learning to enhance students' understanding of green nanomaterials in sustainability education," *Multidisciplinary Reviews*, vol. 8, no. 12, 2025. doi: 10.31893/multirev.2025429

[27] S. Wang, Z. Sun, H. Wang, D. Yang, and H. Zhang, "Enhancing student acceptance of artificial intelligence-driven hybrid learning in business education: Interaction between self-efficacy, playfulness, emotional engagement, and university support," *The International Journal of Management Education*, vol. 23, no. 2, 2025. doi: 10.1016/j.ijme.2025.101184

[28] E. C. Villaceran and C. M. Himang, "Data on behavioural intention to use AI copilot through TAM and AI ecological education policy lens," *Data in Brief*, vol. 61, 111686, 2025. doi: 10.1016/j.dib.2025.111686

[29] A. Towarak, L. Halicz, S. Matwin, and B. Wagner, "Machine learning in analytical chemistry for cultural heritage: A comprehensive review," *Journal of Cultural Heritage*, vol. 70, pp. 64–70, 2024. doi: 10.1016/j.culher.2024.08.014

[30] Y. Jiang, X. Liang, and C. Coscia, "Assessing digital tools in education process for cultural heritage: A literature review," *ISPRS Archives*, XLVIII-M-9, pp. 645–652, 2025.
[31] A. Jeilani and S. Abubakar, "Perceived institutional support and its effects on student perceptions of AI learning in higher education: The role of mediating perceived learning outcomes and moderating technology self-efficacy," *Frontiers in Education*, vol. 10, 1548900, 2025. doi: 10.3389/feduc.2025.1548900
[32] W. Leal Filho, E. Kim, J. M. L. S. Borsatto, and C. B. Marcolin, "Using artificial intelligence in sustainability teaching and learning," *Environmental Sciences Europe*, vol. 37, no. 124, 2025. doi: 10.1186/s12302-025-01159-w
[33] C. S. R. Saflor, "Modeling student acceptance of AI technologies in higher education: A hybrid SEM–ANN approach," *Future Internet*, vol. 17, no. 12, 581, 2025. doi: 10.3390/fi17120581
[34] M. Razzouki, S. B. Hammou, and M. Izenzal, "The adoption and effective use of artificial intelligence in Moroccan higher education: The moderating role of trust," *Cogent Education*, vol. 12, no. 1, 2025. doi: 10.1080/2331186X.2025.2553829