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THE STRATEGIC-BEHAVIORAL ANALYSIS: FACTORS INFLUENCING AI-POWERED LEARNING PLATFORM ADOPTION IN THAI HIGHER EDUCATION

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ABSTRACT

Aim/Purpose	This study investigates how users' behavioral intention to adopt AI-powered learning platforms in Thailand is influenced by both traditional acceptance factors and organizational strategic capabilities, addressing the limited understanding of adoption determinants in rapidly evolving educational AI ecosystems.
Background	While substantial research has examined behavioral factors affecting technology adoption, less attention has been given to how users' perceptions of organizational strategic capabilities and trust in AI affect their adoption decisions. This study addresses this gap by integrating the UTAUT2 framework, dynamic capabilities theory, and trust perspectives into a unified model specifically contextualized to Thai educational settings.
Methodology	Data were collected from 1,368 Thai users (63.9% students, 14.0% teachers/faculty) through online and offline questionnaires. PLS-SEM was employed to test the proposed structural model, with multi-group analysis examining differences across user experience levels, occupations, and usage frequencies.

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Contribution	This study extends existing adoption theories by demonstrating how strategic capabilities (sensing, seizing, reconfiguring) influence both direct adoption intention and traditional acceptance factors. It establishes a novel dual pathway of trust influence and develops a comprehensive framework that bridges individual-level behavior with organizational-level strategic readiness.
Findings	All hypothesized relationships were supported, with the integrated model explaining 63.4% of the variance in behavioral intention. Strategic capabilities significantly influenced both traditional adoption factors and direct adoption intention. Trust in AI demonstrated dual pathways of influence: direct effects and enhanced perceptions of platform adaptability.
Recommendations for Practitioners	Educational institutions should prioritize user-centered design (emphasizing ease of use and social integration) and demonstrate strategic adaptability through transparent roadmaps and responsive feature development. Building trust through ethical governance frameworks and clear data practices is essential for sustainable adoption.
Impact on Society	Understanding the complex interplay can help institutions implement AI technologies more effectively. This potentially addresses educational inequities, supports linguistic diversity, and scales quality learning experiences across diverse contexts.
Future Research	Future research should explore cultural and institutional moderators of strategic capability influence, examine longitudinal adoption patterns as AI technologies evolve, and investigate how strategic capability perceptions form across different user demographics and educational contexts. Cross-cultural validation of the integrated model across countries with varying philosophies would enhance generalizability.
Keywords	edtech adoption, artificial intelligence, strategic capabilities, trust in AI, UTAUT2, PLS-SEM, Thailand

INTRODUCTION

The Asia-Pacific region has experienced unprecedented transformation in higher education through the rapid evolution of online learning platforms, which have transitioned from supplementary tools to core instructional delivery systems. This shift, accelerated by the COVID-19 pandemic, has led to the widespread adoption of digital learning technologies across higher education institutions (Chen & Reyes, 2024). Platforms like Coursera, Duolingo, and Moodle have democratized access to education, offering flexible, personalized learning pathways that extend beyond traditional classroom boundaries (Supic, 2024; Zhao, 2024). Thailand exemplifies this transition with its 78.7% mobile internet penetration and rapidly developing digital economy, presenting a critical research context for understanding technology adoption patterns that reflect unique cultural, institutional, and infrastructural characteristics.

Within this digital transformation, artificial intelligence (AI) has emerged as a powerful force reshaping pedagogical approaches and learning experiences. AI-powered learning platforms – defined as digital educational technologies incorporating machine learning algorithms, natural language processing, and adaptive personalization features – fundamentally differ from traditional digital tools through their capacity for intelligent adaptation, automated feedback generation, and personalized content delivery. These platforms include generative AI chat-based systems like ChatGPT, Google Gemini, and Claude; adaptive self-paced learning systems like Duolingo and Khan Academy; AI-augmented learning management systems such as Moodle with AI plugins; and specialized AI learning applications for language learning and coding (Duraes et al., 2024; Sari et al., 2024). Despite this proliferation of AI-powered educational technologies, there is a limited understanding of the factors driving user adoption in Thai higher education. While the Unified Theory of Acceptance and Use of Technology (UTAUT2) provides valuable insights into behavioral factors influencing technology adoption – including performance expectancy, effort expectancy, social influence, facilitating conditions, and hedonic motivation (Hasan et al., 2023; Kumar et al., 2024; Suyanto et al., 2024) – recent research suggests that user adoption is not determined solely by these factors. It is increasingly shaped by trust in AI systems and perceptions of organizational and technological readiness (Almogren et al., 2024; Shweta & Panicker, 2025; Wicaksono et al., 2024).

Organizations that demonstrate dynamic capabilities – the ability to sense opportunities, seize them through resource mobilization, and reconfigure internal processes – are better positioned to succeed in digital transformation initiatives (Froehlich et al., 2024; Teece, 2007; Weritz et al., 2024). These capabilities enable institutions to continuously innovate and adapt to rapid technological changes, which may positively influence users' perceptions of platform credibility, utility, and pedagogical value (Fu et al., 2025). However, the interplay between behavioral factors, organizational strategic capabilities, and trust mechanisms in shaping AI adoption decisions remains unexplored, particularly in Southeast Asian educational contexts where collectivist cultural values and varying technological infrastructure create distinct adoption dynamics.

This study investigates the determinants of AI-powered learning platform adoption in Thai higher education by developing and testing an integrated model combining UTAUT2, dynamic capabilities theory, and trust in AI. By examining how these multi-level factors interact to shape adoption intentions among Thai university users, this research addresses three critical questions:

RQ1: How do traditional technology acceptance factors (performance expectancy, effort expectancy, social influence, facilitating conditions, and hedonic motivation) influence behavioral intention to adopt AI-powered learning platforms among Thai university users?

RQ2: To what extent do perceived organizational strategic capabilities (sensing, seizing, and reconfiguring) influence both traditional acceptance factors and direct adoption intention of AI-powered learning platforms?

RQ3: How do trust in AI and adoption patterns vary across different user segments (experience levels, occupations, and usage frequencies), operating through both direct and indirect pathways via strategic capability perceptions in the Thai educational context?

The integration of AI in educational settings introduces significant challenges, including ensuring data privacy, developing appropriate educator competencies, establishing ethical guidelines, and building trust in AI systems (Sheh, 2024; Shweta & Panicker, 2025; Sirnoorkar et al., 2024; Zhang, 2023).

The remainder of this paper is organized as follows. The next section reviews the literature on AI-powered learning platforms, the UTAUT2 framework, dynamic capabilities theory, and trust in AI, culminating in our integrated theoretical framework. The research methodology, including survey design, data collection procedures, and PLS-SEM analytical approach, is then presented, followed by the empirical findings from measurement and structural model testing. The theoretical and practical implications for educational AI adoption in Southeast Asia are then discussed. Finally, the contributions, limitations, and future research directions are presented.

LITERATURE REVIEW

ONLINE LEARNING PLATFORMS AND AI INTEGRATION

The educational landscape has been fundamentally transformed by online learning platforms, which evolved from supplementary tools to core instructional systems following the COVID-19 pandemic (Chen & Reyes, 2024; Tantiathimongkhon et al., 2025). Platforms like Coursera and Moodle have democratized education, offering flexible learning pathways beyond traditional classrooms (Supic, 2024; Zhao, 2024). Within this digital transformation, artificial intelligence (AI) has emerged as a catalyst for pedagogical innovation, revolutionizing how educational content is created, delivered, and personalized.

AI-powered learning platforms are fundamentally distinguished from traditional digital tools by their incorporation of machine learning algorithms, natural language processing capabilities, and adaptive personalization features that dynamically respond to individual learner behaviors and needs (Duraes et al., 2024; Sari et al., 2024). These core capabilities enable advanced functionalities such as automated feedback generation, predictive analytics for learner success, and intelligent content adaptation, which extend beyond traditional rule-based software (Gebremariam & Mulugeta, 2024; Herrmann & Weigert, 2024; Talebi et al., 2025). Such features allow platforms to identify learning patterns, anticipate student difficulties, provide timely interventions, and continuously optimize the learning experience based on accumulated data. Examples include generative AI chat-based systems like ChatGPT, adaptive self-paced learning systems, and AI-augmented learning management systems.

The implementation of AI in education has profound implications for pedagogical practices and learning outcomes. Studies demonstrate that combining AI platforms with project-based pedagogies enhances critical thinking, collaboration, and digital literacy – competencies directly linked to improved academic performance (Guerra-Macías & Tobón, 2025). As AI systems assume routine tasks such as grading and content curation, educators' roles evolve toward mentorship, facilitation, and higher-order instructional design, necessitating new digital literacies among both teachers and students (Bader & Kaiser, 2019; Duong, 2025). These technological capabilities are particularly relevant for addressing educational challenges common across the Asia-Pacific region, including bridging the urban-rural educational divide, supporting linguistic diversity, and scaling quality education to meet growing demand (Shi & Ma, 2025).

However, integrating AI into educational settings presents significant challenges that extend beyond technical implementation. Infrastructure limitations, training gaps, and varying levels of digital readiness create substantial adoption barriers, particularly in developing educational contexts (Gebremariam & Mulugeta, 2024). Furthermore, cultural factors and personality traits significantly influence adoption patterns, with effectiveness varying considerably across different regional and institutional contexts (Y. Joshi et al., 2023).

Most critically, the unprecedented volumes of learning data generated by AI systems raise substantial ethical concerns regarding data privacy, algorithmic transparency, potential bias, and educational equity (Sheh, 2024). These multifaceted challenges necessitate robust governance frameworks to ensure AI applications align with pedagogical values and ethical standards across diverse educational settings (Shweta & Panicker, 2025; Zhang, 2023). Understanding how complex, multi-level factors influence user adoption of AI-powered learning technologies is, therefore, essential for successful implementation and sustained engagement with these increasingly sophisticated learning ecosystems.

UTAUT2 FRAMEWORK

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), developed by Venkatesh et al. (2012), represents one of the most comprehensive frameworks for understanding technology adoption behaviors. Building upon the original UTAUT by incorporating hedonic motivation, price value, and habit as additional constructs, UTAUT2 provides a particularly robust lens for examining consumer technology adoption in educational contexts. The framework's widespread application in educational technology research has consistently demonstrated its explanatory power in understanding how users engage with AI-powered learning platforms across diverse higher education settings (Camilleri, 2024; Tamilmani et al., 2020; Wang et al., 2024).

Cross-cultural applications of UTAUT2 across the Asia-Pacific region have revealed important variations in how different constructs influence adoption intentions. Studies conducted in Thailand (Chopvitayakun et al., 2025; Tamilmani et al., 2020), Australia (Mirkovski et al., 2025; Wang et al., 2024), and Malaysia (Camilleri, 2024) demonstrate that cultural context significantly moderates the relationships between behavioral determinants and adoption intention. In collectivist cultures like Thailand and Malaysia, Social Influence emerges as a particularly strong predictor, reflecting the importance of peer opinions and social validation in decision-making processes. Conversely, in more individualistic contexts like Australia, Performance Expectancy typically dominates as users prioritize individual benefits and utility. These regional variations underscore the importance of contextualizing technology adoption models to account for cultural values and social dynamics when implementing AI-powered learning platforms.

Performance Expectancy (PE), defined as the degree to which users believe technology will enhance their learning performance, consistently emerges as a critical adoption predictor. Recent studies demonstrate that students are significantly more likely to adopt AI tools like ChatGPT when they perceive tangible learning benefits and improved academic outcomes (Wu et al., 2025; Zhang, 2023). PE not only directly influences adoption intention but also amplifies the effects of other constructs such as effort expectancy and social influence (Cao & Peng, 2024). Interestingly, while demographic variables such as gender and age show limited moderating effects, the perceived usefulness of AI remains a universal motivator across diverse learner populations (Huang et al., 2024; Ma, 2025).

H1: Performance Expectancy (PE) positively influences Behavioral Intention (BI) to use AI-powered learning platforms.

Effort Expectancy (EE) captures users' perceptions of ease of use and the cognitive effort required to utilize technology effectively. In educational contexts, the intuitive design and user-friendliness of AI platforms significantly influence adoption decisions (Duong et al., 2023). However, the impact of EE varies across platforms and contexts; while generally significant in higher education settings, certain AI tools, such as Ernie Bot, show weaker EE effects, suggesting that perceived value may sometimes override usability concerns (Zhang, 2023). In developing countries like Indonesia, where digital literacy levels vary considerably, EE assumes heightened importance as users with limited technological experience require more accessible interfaces (Ramadhina et al., 2025).

H2: Effort Expectancy (EE) positively influences Behavioral Intention (BI) to use AI-powered learning platforms.

Social Influence (SI) reflects the extent to which users perceive that significant others – peers, instructors, family members, or professional communities – expect them to adopt particular technologies. The power of social influence in educational AI adoption has been consistently documented across diverse cultural contexts, with studies in Bangladesh (Asag et al., 2024), Korea (Jang, 2024), and China (Ma, 2025) all reporting robust relationships between SI and adoption intention. In socially connected learning environments, the collective opinions of peer groups, instructor endorsements, and online community recommendations create powerful normative pressures that shape individual adoption decisions (Stewart et al., 2024; Yang et al., 2022).

H3: Social Influence (SI) positively influences Behavioral Intention (BI) to use AI-powered learning platforms.

Facilitating Conditions (FC) encompass users' perceptions of available resources, support infrastructure, and organizational readiness to support technology use. These include technical support services, device compatibility, internet connectivity, training resources, and institutional policies that enable or constrain technology adoption. Wei (2025) emphasizes that robust facilitating conditions are essential for smooth AI tool adoption in educational settings, particularly given the technical complexity and resource requirements of advanced AI platforms. Research consistently demonstrates that well-supported systems with comprehensive technical infrastructure and responsive support services significantly enhance both initial adoption and sustained usage behaviors (Maruszewska et al., 2024; Wut et al., 2022).

H4: Facilitating Conditions (FC) positively influence Behavioral Intention (BI) to use AI-powered learning platforms.

Hedonic Motivation (HM) represents the enjoyment, pleasure, and intrinsic satisfaction derived from technology use. In AI-powered learning contexts, hedonic motivation plays a crucial role in sustaining engagement beyond initial adoption. Gamification elements, personalized feedback mechanisms, interactive conversational interfaces, and adaptive content that responds to user preferences create enjoyable learning experiences that enhance both motivation and platform engagement (Aini et al., 2025; Meilani et al., 2024). Platforms that successfully integrate entertainment with educational value, such as ChatGPT's conversational interface or Duolingo's game-like progression systems, demonstrate significantly stronger user retention and continued usage intentions (Ahmed et al., 2023; Zhang, 2023).

H5: Hedonic Motivation (HM) positively influences Behavioral Intention (BI) to use AI-powered learning platforms.

Dynamic Capabilities Theory and Perceived Strategic Capabilities

While UTAUT2 provides a necessary lens for individual adoption, a focus purely on behavioral and individual factors often overlooks the critical influence of the strategic organizational context, particularly in the rapidly changing AI landscape. Dynamic capabilities theory, pioneered by Teece and colleagues (Bazarova et al., 2025; Teece, 2007; Teece et al., 1997), provides a strategic framework for understanding how organizations develop and maintain competitive advantages in rapidly evolving environments. This theory has gained renewed relevance in the digital transformation era, particularly as educational institutions navigate the complexities of AI integration. Recent empirical validations across multiple sectors demonstrate the framework's robust explanatory power: financial institutions in Palestine with well-developed dynamic capabilities achieved smoother digital transformation (Alrub & Sánchez-Cañizares, 2025), while SMEs in Oman leveraging sensing-seizing-reconfiguring cycles realized both cost efficiencies and sustainability improvements (Rahman et al., 2025). These capabilities, emerging from organizational tacit knowledge, absorptive capacity, and strategic leadership (Faiz et al., 2024; Tamirat & Amentie, 2023), must permeate all organizational levels to deliver measurable performance improvements (Shiferaw & Kero, 2024).

In educational technology contexts, users perceive organizational dynamic capabilities through observable platform behaviors – responsiveness to feedback, frequency of feature updates, adaptation to emerging learning needs, and proactive communication about future developments (Cheng et al., 2023; Froehlich et al., 2024). These external manifestations of internal capabilities significantly influence user perceptions of platform credibility and future viability, suggesting that dynamic capabilities extend beyond organizational performance to shape stakeholder behavior.

Sensing capability (SC) represents an organization's proficiency in scanning environments, identifying technological shifts, detecting changing user expectations, and anticipating regulatory developments (Martin, 2023; Teece, 2007; Teece et al., 1997). In AI-powered educational platforms, this manifests through early detection of emerging pedagogical needs – adaptive assessments, privacy-conscious analytics, culturally responsive content, or multilingual support capabilities.

H6: Sensing Capability (SC) positively influences Performance Expectancy (PE) in the context of AI-powered learning platforms.

H7: Sensing Capability (SC) positively influences Behavioral Intention (BI) to use AI-powered learning platforms.

Seizing capability (SZ) involves translating environmental insights into actionable initiatives through strategic resource mobilization, rapid prototyping, and timely implementation (Teece, 2007). For educational technology providers, this encompasses deploying adaptive learning algorithms, integrating generative AI support, developing mobile-first interfaces, or pivoting resources toward emerging engagement channels.

H8: Seizing Capability (SZ) positively influences Effort Expectancy (EE) in the context of AI-powered learning platforms.

H9: Seizing Capability (SZ) positively influences Behavioral Intention (BI) to use AI-powered learning platforms.

Reconfiguring capability (RC) encompasses systematic reorganization of processes, assets, and structures to accommodate innovation and maintain competitive alignment (Nnadi et al., 2024; Teece, 2007). In educational contexts, this involves architectural revisions to learning management systems, comprehensive staff development programs, adjustments to pedagogical frameworks, and redesigns of assessments to integrate AI capabilities. Users readily recognize organizational adaptability, with rapid platform evolution positively influencing trust formation and perceived institutional commitment (Allen & Kendeou, 2023).

H10: Reconfiguring Capability (RC) positively influences Behavioral Intention (BI) to use AI-powered learning platforms.

Trust in AI and Its Role in Technology Adoption

Trust in AI represents a multidimensional construct encompassing competence trust (confidence in the AI's technical capabilities and accuracy), benevolence trust (belief that the AI acts in users' best interests), and integrity trust (confidence in the ethical and fair operation of the system) (Alamäki et al., 2024; An & Ngo, 2025; Ofosu-Ampong, 2023). In educational settings, this multifaceted trust extends beyond simple reliability assessments to include emotional and ethical dimensions that significantly influence adoption decisions, particularly as users grapple with algorithmic opacity, potential bias, and data governance issues.

The mechanisms through which trust influences AI adoption are complex and context-dependent. Trust operates as both a direct driver of adoption intention and an indirect influence through its effects on risk perception, perceived usefulness, and willingness to share personal data (Frank et al., 2023; Hsieh & Lee, 2024; H. Joshi, 2025). When AI systems exhibit human-like interactions, provide personalized feedback, or demonstrate learning from user behavior, trust formation accelerates through anthropomorphic attribution and social presence effects. Parallels with e-government adoption research further validate trust as a critical mediator of system success across technology-mediated service delivery (Hooda et al., 2023).

However, trust remains fragile and context-sensitive. Privacy concerns, algorithmic opacity, data breaches, or perceived bias can rapidly erode trust despite demonstrated utility (Almogren et al., 2024). Cultural factors further complicate trust formation, with collectivist societies showing greater institutional trust while individualistic cultures demand more transparent algorithmic accountability. Critically, high user trust signals a willingness to accept and engage with organizational change. Users who trust the benevolence and integrity of the AI platform provider are more likely to perceive the organization's attempts to reconfigure its systems and pedagogical structures (RC) as credible and beneficial adaptations rather than disruptive risks, thus making Trust a crucial antecedent to Reconfiguring Capability.

H11: Trust in AI positively influences Reconfiguring Capability (RC) in the context of AI-powered learning platforms.

H12: Trust in AI positively influences Behavioral Intention (BI) to use AI-powered learning platforms.

SUMMARY OF GAPS AND RESEARCH FRAMEWORK

While previous research has shed light on how users adopt educational technologies, much of it has centered on behavioral frameworks such as the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). This model has consistently identified key determinants of technology adoption – namely performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), and hedonic motivation (HM) – which are widely recognized as predictors of users' behavioral intention (BI) to engage with digital learning platforms.

In recent years, studies have also started exploring the role of trust in AI, particularly in the context of generative AI tools like ChatGPT. These studies highlight the importance of user confidence in the fairness, reliability, and ethical operation of AI systems. However, despite the progress, several gaps in the literature remain unaddressed.

First, most existing models focus on individual-level behavior and often overlook how users perceive the strategic readiness of the platforms or organizations behind these technologies. The theory of dynamic capabilities, especially its core constructs (sensing, seizing, and reconfiguring), offers a strategic lens for understanding how users evaluate the adaptability and innovation capacity of educational systems. Yet this perspective has been rarely applied in user-side adoption studies, especially in the domain of AI-based learning.

Second, although trust in AI has become an emerging theme, it is still often positioned as a peripheral factor rather than a core determinant of technology acceptance. Few studies directly link trust to users' behavioral intention or explore its influence on how users perceive the adaptability of AI-enabled platforms, including their ongoing innovation and ethical responsiveness.

Third, much of the prior research has examined a single type of learning technology, such as a language app or a learning management system, without addressing the increasingly diverse landscape of educational tools. These include AI chatbots, video-based learning, adaptive systems, and collaborative platforms. As such, many existing studies fail to capture the holistic adoption dynamics across this varied and complex ecosystem.

To address these gaps, the present study proposes an integrated conceptual framework that synthesizes three key perspectives: (1) behavioral motivations from UTAUT2 (PE, EE, SI, FC, HM), (2) perceived strategic capabilities drawn from dynamic capabilities theory (SC, SZ, RC), and (3) trust in AI as a psychological enabler of adoption.

This combined framework is designed to capture both the psychological factors and strategic perceptions that shape user adoption behavior in AI-powered learning environments. In total, the study formulates twelve hypotheses (H1–H12) to guide the research model, covering all major relational paths between constructs as derived from the literature.

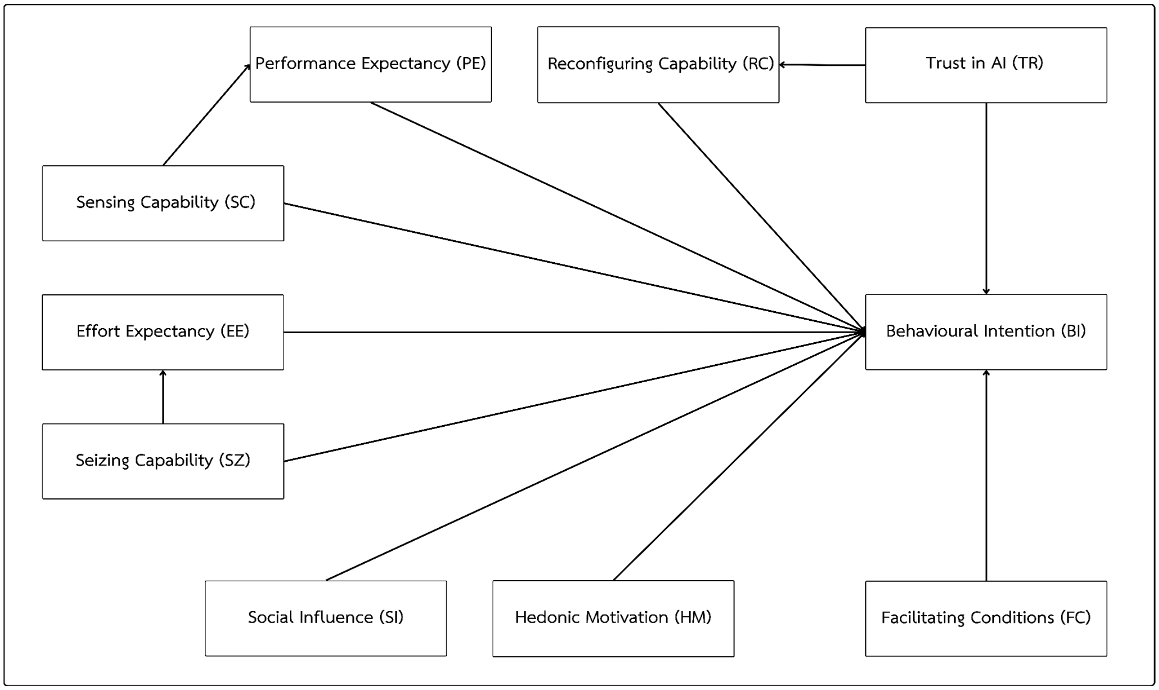

Figure 1. Research framework

RESEARCH METHODOLOGY

RESEARCH DESIGN AND PARTICIPANTS

This study adopted a quantitative research design utilizing a cross-sectional approach to examine factors influencing users' acceptance of AI-powered learning platforms. The target population comprised university students and adult learners in Thailand who had previously used digital learning technologies. Purposive sampling was employed to ensure the inclusion of participants with direct experience in AI-powered tools. A total of 1,368 valid responses were collected, exceeding the minimum sample size requirements for robust analysis (Hair et al., 2019).

INSTRUMENT DEVELOPMENT AND MEASUREMENT

The research instrument was a questionnaire developed based on validated measurement items drawn from the UTAUT2 framework, Dynamic Capabilities Theory, and the literature on Trust in AI. All constructs were measured using 5–6 items on a 5-point Likert scale. The study established Content Validity using the Item-Objective Congruence (IOC) method with domain experts. A pilot test further confirmed the reliability of all constructs, with Cronbach's alpha exceeding the threshold of 0.70. The full psychometric properties of the final measurement model, including Composite Reliability (CR), Average Variance Extracted (AVE), and the Heterotrait-Monotrait Ratio (HTMT), confirmed the reliability and validity of all constructs and are detailed in Table 2 of the Results section. Given the abstract nature of dynamic capabilities, these constructs were operationalized through observable platform behaviors as perceived by the user. For example, Sensing Capability was measured based on the platform's ability to identify learning needs, while Reconfiguring Capability focused on the platform's adaptability to new learning formats. The complete list of measurement items and their respective sources can be found in the Appendix.

DATA COLLECTION PROCEDURE

Data were collected over a six-week period, from February 16 to March 30, 2025, through both online surveys (approx. 70%) and offline printed questionnaires (approx. 30%) distributed at selected higher education institutions in Thailand to promote inclusivity. The study strictly adhered to ethical guidelines, obtaining informed consent and ensuring anonymity, and received ethical approval (ID: COA. No. SPUIRB-2024-0139). Quality control included screening responses for completeness and removing cases with excessive missing data or patterned responses before final analysis.

Data Analysis Method and Ethical

The proposed theoretical model was rigorously analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS. This variance-based approach was selected for its proven effectiveness in testing complex predictive models involving numerous latent constructs and is well-suited for the study's large sample size. The analysis followed a two-stage process: first, the measurement model's quality was assessed by establishing internal consistency through Composite Reliability (CR), confirming convergent validity using Average Variance Extracted (AVE), and verifying discriminant validity via the Heterotrait-Monotrait (HTMT) ratio. Subsequently, the structural model was tested to evaluate the hypothesized relationships using bootstrapping (5,000 subsamples), yielding the path coefficients (β), t-values, and p-values. Model fit was further evaluated using the SRMR index, while the model's explanatory and predictive power were confirmed through the coefficient of determination (R^2) and the Stone-Geisser's Q^2 statistic. Finally, a permutation-based Multi-Group Analysis (MGA) was conducted to examine potential differences across user segments.

Results

This section presents the empirical findings derived from the testing of the integrated structural model. We first detail the descriptive statistics and usage patterns of the sample. Subsequently, we evaluate the psychometric properties of the measurement model, followed by the presentation of the structural model results and hypothesis testing, including an analysis of direct, indirect, and total effects. Finally, the section concludes with the Multi-Group Analysis (MGA) results, which examine the role of user segments in the adoption process.

Descriptive Statistics

The survey collected 1,368 valid responses from Thai users between February 16 and March 30, 2025. The demographic profile is summarized in Table 1. In terms of gender, the sample reflected a diverse range, with 25.9% male and 25.2% female respondents. Notably, a combined 48.9% (22.4% "Other" and 26.5% "Prefer not to disclose") indicated a non-binary or undisclosed gender identity. This high percentage indicates the successful inclusion of a broad range of user identities in the data collection process, reflecting the study's effort to ensure inclusivity in the Thai context. The majority of the sample consisted of students (63.9%) and teachers/faculty (14.0%). To enhance the interpretability of generational adoption behavior, the age criteria were regrouped into socio-politically meaningful categories: Young Adults (20–35 years) (66.89%), Adults (36–59 years) (21.20%), and Senior Adults (more than 60 years) (11.92%). This distribution allows for a clearer analysis of behavioral differences across major user segments.

Table 1. Demographics

Measures	Criteria	N	%
Gender	Female	345	25.22%
	Male	354	25.88%
	Other	306	22.37%
	Prefer not to say	363	26.54%

Measures	Criteria	N	%
Age	20–24 years	461	33.70%
	25–29 years	454	33.19%
	30–39 years	290	21.20%
	More than 40 years	163	11.92%
Education	Below undergraduate	251	18.35%
	Bachelor's	661	48.32%
	Master's	342	25.00%
	Doctoral	113	8.26%
Occupation	Student	874	63.89%
	Teacher/Faculty	191	13.96%
	Entrepreneur	101	7.38%
	Company Employee	94	6.87%
	Government Officer	69	5.04%
	Other	39	2.85%
Usage Frequency	Daily	466	34.06%
	2–3 days/week	408	29.82%
	Once a week	303	22.15%
	Less than once	191	13.96%
User Experience	Fair	261	19.08%
	Moderate	553	40.42%
	Good	400	29.24%
	Excellent	154	11.26%
Platform Type		**F**	**%**
Self-paced learning platforms (e.g., Duolingo, Coursera)		412	15.42%
AI-powered chat-based platforms (e.g., ChatGPT, Gemini)		685	25.64%
Online learning systems (e.g., Moodle, Google Classroom)		391	14.63%
Communication tools for learning (e.g., Zoom, Google Meet)		372	13.92%
Video-based learning platforms (e.g., YouTube, MOOC)		405	15.16%
Language or skill apps (e.g., Memrise, Brilliant)		407	15.23%

Platform Usage Patterns and User Experiences

Our analysis revealed distinct usage patterns that provide insights into how participants actually experienced and engaged with AI-powered learning platforms across different user segments. Students, who comprised 63.9% of the sample, primarily utilized ChatGPT and Google Gemini for academic support, with common applications including assignment assistance and concept clarification. They reported using AI chatbots to explain complex theoretical concepts, generate study outlines, and provide feedback on draft assignments. Participants also described leveraging AI's ability to synthesize information from multiple sources for research and information gathering, while international students specifically used conversational AI for practice dialogues and grammar checking in language learning contexts.

Teachers and faculty members, representing 14.0% of the sample, demonstrated different engagement patterns focused on pedagogical and administrative applications. Faculty members reported using AI-enhanced LMS features to track student engagement patterns and identify at-risk learners through predictive analytics for student monitoring and assessment purposes. For content creation, teachers utilized AI tools to generate quiz questions, create explanatory materials, and adapt existing content for different learning styles, while also using AI for administrative efficiency through scheduling, communication management, and generating reports on student progress.

The study also revealed important cultural factors specific to the Thai educational context that influenced user experiences with AI-powered platforms. Many users demonstrated collective learning preferences by sharing AI platform recommendations within study groups and seeking consensus before adopting new tools, reflecting the collectivist values prevalent in Thai culture. Additionally, students frequently exhibited respect for authority by waiting for instructor endorsement before fully embracing AI tools, even when personally interested in the technology. Some participants initially experienced face-saving considerations and hesitated to use AI assistance due to concerns about academic integrity or appearing less capable than peers, though these concerns typically diminished with increased exposure and institutional support.

Measurement Model Evaluation

The measurement model was assessed for reliability, convergent validity, and discriminant validity. Reliability was confirmed as all constructs showed Composite Reliability (CR) and Cronbach's Alpha values above the recommended threshold of 0.70. Convergent validity was established as all Average Variance Extracted (AVE) values exceeded 0.50, indicating that the latent constructs explained more than half of the variance of their indicators. Discriminant validity was verified using the Heterotrait-Monotrait Ratio (HTMT) method, a robust criterion for assessing distinctiveness between constructs (Henseler et al., 2016). All HTMT values were below the conservative threshold of 0.85, confirming that the constructs were conceptually distinct.

Internal consistency reliability

To assess internal consistency reliability, two indicators were examined: Cronbach's alpha and Composite Reliability (CR). As shown in Table 2, all constructs demonstrated acceptable levels of reliability, with both Cronbach's alpha and CR values exceeding the recommended threshold of 0.70 (Hair et al., 2019). Specifically, CR values ranged from 0.841 to 0.937, confirming a high degree of internal consistency. Cronbach's alpha values were similarly strong, ranging from 0.802 to 0.922. These results suggest that the items within each construct consistently measure the intended latent variables.

Convergent validity

Convergent validity was assessed using two key indicators: the Average Variance Extracted (AVE) and the outer loadings of each indicator. According to Hair et al. (2010), AVE values should exceed 0.50, indicating that the construct explains more than half of the variance of its associated indicators. In addition, outer loadings should be greater than 0.708 to confirm that each item adequately reflects its underlying latent construct.

As presented in Table 2, all constructs met these criteria. The AVE values ranged from 0.570 to 0.755, exceeding the minimum threshold. Similarly, all outer loadings were above 0.708, demonstrating that the measurement items are highly correlated with their respective constructs. These results confirm the convergent validity of the measurement model.

Table 2. Construct reliability, validity, outer loadings, and collinearity (VIF)

Construct	Cronbach's alpha	CR	AVE	Item	Outer loadings	VIF
BI	0.808	0.867	0.566	BI1	0.752	1.563
				BI2	0.765	1.595
				BI3	0.748	1.552
				BI4	0.758	1.561
				BI5	0.738	1.491
EE	0.763	0.849	0.585	EE1	0.744	1.412
				EE2	0.743	1.429
				EE4	0.777	1.509
				EE5	0.794	1.54
FC	0.821	0.875	0.583	FC1	0.747	1.549
				FC2	0.76	1.617
				FC3	0.773	1.669
				FC4	0.804	1.788
				FC5	0.733	1.511
HM	0.738	0.836	0.561	HM1	0.718	1.355
				HM2	0.686	1.302
				HM4	0.791	1.537
				HM5	0.794	1.497
PE	0.722	0.844	0.643	PE1	0.813	1.433
				PE2	0.811	1.42
				PE3	0.78	1.401
RC	0.71	0.838	0.633	RC1	0.791	1.368
				RC4	0.796	1.405
				RC5	0.8	1.389
SC	0.792	0.865	0.616	SC1	0.775	1.544
				SC2	0.784	1.543
				SC3	0.782	1.576
				SC4	0.798	1.62
SI	0.787	0.862	0.61	SI1	0.77	1.571
				SI2	0.79	1.555

Construct	Cronbach's alpha	CR	AVE	Item	Outer loadings	VIF
				SI3	0.761	1.459
				SI4	0.802	1.631
SZ	0.801	0.87	0.626	SZ2	0.753	1.492
				SZ3	0.803	1.699
				SZ4	0.801	1.707
				SZ5	0.806	1.592
TRUST	0.721	0.843	0.642	TRUST3	0.802	1.43
				TRUST4	0.8	1.391
				TRUST5	0.801	1.426

Discriminant validity

Discriminant validity was evaluated using the Heterotrait–Monotrait Ratio (HTMT), with a suggested threshold of 0.90. As presented in Table 3, while most HTMT values fell within the acceptable range, it is important to note that some pairs of constructs exhibited high correlation values. For instance, the relationship between Reconfiguring Capability and Facilitating Conditions (0.866), as well as Sensing Capability and Behavioral Intention (0.850), approached the 0.90 threshold. This indicates a potential conceptual overlap, suggesting that while the constructs are largely distinct, the findings related to these specific variables should be interpreted with caution.

Table 3. Discriminant validity (HTMT Ratio)

	BI	EE	FC	HM	PE	RC	SC	SI	SZ	Trust
BI										
EE	0.81									
FC	0.818	0.754								
HM	0.511	0.467	0.466							
PE	0.683	0.69	0.657	0.327						
RC	0.814	0.797	0.866	0.467	0.597					
SC	0.85	0.743	0.82	0.463	0.608	0.814				
SI	0.758	0.687	0.75	0.395	0.84	0.699	0.684			
SZ	0.605	0.54	0.552	0.382	0.479	0.544	0.581	0.504		
TRUST	0.451	0.412	0.376	0.553	0.281	0.412	0.408	0.325	0.378	

Model fit assessment

The assessment of model fit confirmed the model's overall validity. The Standardized Root Mean Square Residual (SRMR) value for the saturated model was 0.044 (Hu & Bentler, 1999), which falls below the recommended threshold of 0.08191919. The estimated model, however, yielded a higher SRMR value of 0.13020. This result, interpreted as a moderate fit21, is common in complex models combining multi-level theoretical frameworks (Hair et al., 2019) and suggests that future research could explore refinement by considering additional cultural or technological moderators not captured in the current framework. The coefficient of determination (R^2) for Behavioral Intention was 0.634, indicating strong explanatory power.

The coefficient of determination (R^2) for the primary endogenous construct, Behavioral Intention, was 0.634, indicating strong explanatory power according to the benchmarks proposed by Hair et al. (2019), who suggest that R^2 values above 0.26 represent meaningful explanatory capacity in behavioral science research. This demonstrates that the integrated model explains a substantial portion (63.4%) of the variance in users' intention to adopt AI-powered learning platforms.

The Stone-Geisser's Q^2 value for Behavioral Intention was 0.324, exceeding zero and approaching the threshold of 0.35 for high predictive relevance (Hair et al., 2022), as shown in Table 4. This confirms that the model has meaningful predictive ability for out-of-sample predictions. When contextualized within educational technology research in the Asia-Pacific region, these fit indices are comparable to recent studies on technology adoption in similar contexts (e.g., Jang, 2024; Wicaksono et al., 2024), suggesting the integrated model provides a robust framework for understanding AI adoption in educational settings across the region.

Table 4. Model fit and predictive relevance

Fit index	Value	Interpretation
SRMR (Saturated model)	0.044	Acceptable (< 0.08; Hu and Bentler, 1999)
SRMR (Estimated model)	0.130	Moderate fit
d_G (Saturated model)	0.489	Acceptable (< 0.95; Henseler et al., 2015)
d_G (Estimated model)	0.811	Acceptable (< 0.95; Henseler et al., 2015)
R^2 (Behavioral Intention)	0.634	Strong explanatory power (> 0.26; Hair et al., 2019)
Q^2 (Behavioral Intention)	0.324	Moderate predictive relevance (> 0.35; Hair et al., 2022)

The convergence of these fit indicators suggests that the proposed theoretical framework, combining UTAUT2 constructs, dynamic capabilities, and trust in AI, offers a valid representation of the psychological and strategic factors influencing the adoption of AI-powered learning platforms in the Thai educational context. This finding has particular relevance for understanding technology adoption patterns across the broader Asia-Pacific region, where similar educational transformation initiatives are underway.

Structural Model and Hypothesis Testing

Path coefficients and hypothesis testing

The structural model was evaluated to examine the hypothesized relationships among latent constructs. Bootstrapping with 5,000 subsamples was used to assess the path coefficients (β), t-values, and p-values for hypothesis testing Figure 2.

As summarized in Table 5, 11 out of 12 hypotheses (H1–H12) were supported at a significance level of $p < 0.05$. The results are further visualized in Figure 1, which presents the standardized path coefficients, significance levels, and explained variances (R^2) for all endogenous constructs. Among the UTAUT2 constructs, Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), and Hedonic Motivation (HM) all had statistically significant and positive effects on Behavioral Intention (BI), supporting hypotheses H1 through H5. PE and SI emerged as the strongest predictors within this group, while HM, though statistically significant, showed the weakest effect.

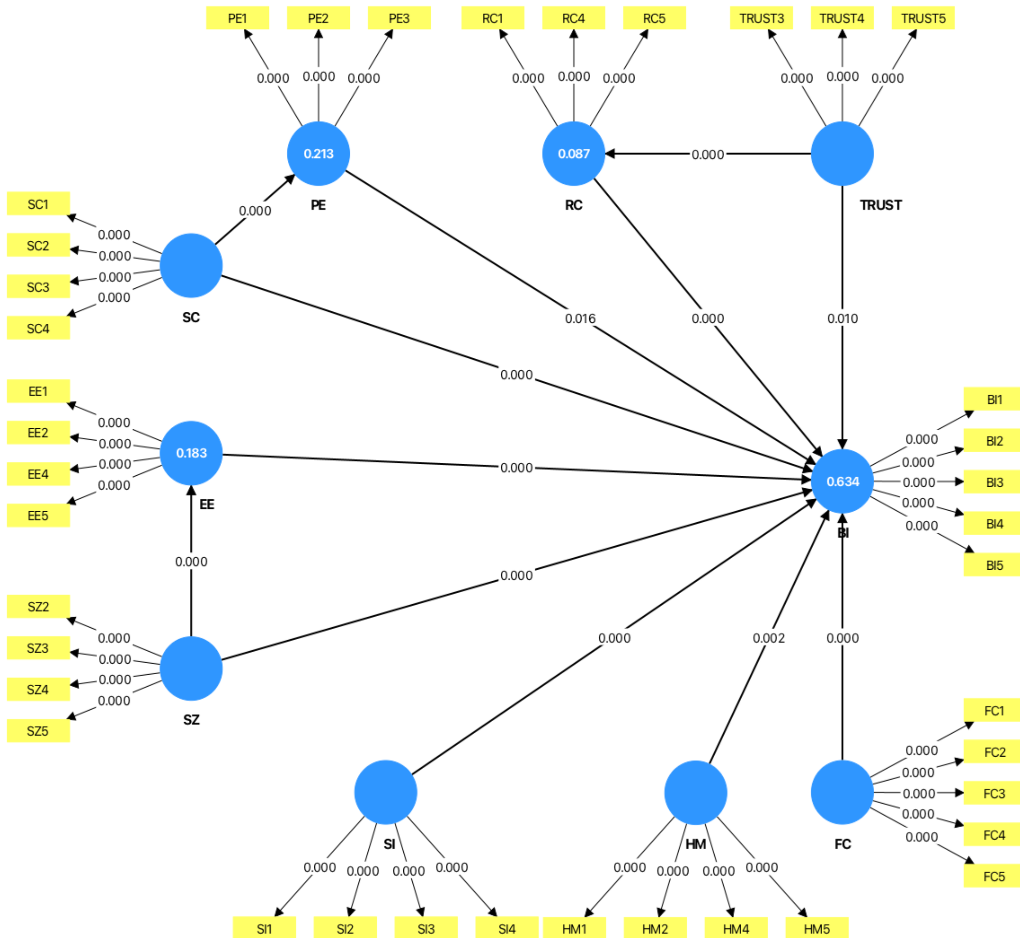

Figure 2. PLS-SEM with bootstrapping

Table 5. Hypothesis testing

Hypothesis		**Path coefficient**	**T-value**	**P-value**	**f²**	**Effect size**
H1	RG" "DK	0.062	2.402	0.016*	0.006	Small
H2	GG" "DK	0.17	6.783	0.000***	0.039	Small
H3	UK" "DK	0.137	4.944	0.000***	0.024	Small
H4	HE " "DK	0.149	5.149	0.000***	0.024	Small
H5	J O " "DK	0.06	3.08	0.002**	0.007	Small
H6	UE " "RG	0.461	18.577	0.000***	0.27	Large
H7	UE " "DK	0.243	9.341	0.000***	0.073	Medium
H8	U\ " "GG	0.427	18.415	0.000***	0.223	Large

Hypothesis		Path coefficient	T-value	P-value	f²	Effect size
H9	U\ " "DK	0.083	3.633	0.000***	0.013	Small
H10	TE " "DK	0.103	3.848	0.000***	0.014	Small
H11	VTWUV " "TE	0.295	12.229	0.000***	0.096	Medium
H12	VTWUV " "DK	0.049	2.568	0.010**	0.005	Small

Note: *p < 0.05, ** p < 0.01, *** p < 0.001

With respect to the Dynamic Capabilities Theory, Sensing Capability (SC) positively influenced both PE (H6) and BI (H7), while Seizing Capability (SZ) had significant effects on EE (H8) and BI (H9). Reconfiguring Capability (RC) also significantly predicted BI (H10), reinforcing the role of adaptive organizational capability.

Additionally, Trust in AI demonstrated positive and significant influences on both RC (H11) and BI (H12), emphasizing the importance of trust-related factors in the adoption of AI-powered learning technologies.

Overall, the results in Table 4 confirm the explanatory strength of the integrated model and support the theoretical synergy between behavioral (UTAUT2), strategic (Dynamic Capabilities), and trust-based perspectives in predicting user adoption within the AI-driven digital learning ecosystem.

Direct and indirect effects

To gain a comprehensive understanding of the relationships within the structural model, both direct and indirect effects were analyzed. This approach allows for the examination of mediating mechanisms through which exogenous variables influence endogenous variables, providing deeper insights into the complex relationships among behavioral factors, strategic capabilities, and trust in AI adoption.

Table 6 presents the total effects of all relationships in the model. The strongest total effects on Behavioral Intention (BI) were observed from Sensing Capability (SC) ($\beta = 0.272$, $p < 0.001$), followed by Effort Expectancy (EE) ($\beta = 0.170$, $p < 0.001$), and Seizing Capability (SZ) ($\beta = 0.156$, $p < 0.001$). The substantial total effect of SC on BI demonstrates the critical importance of organizational environmental scanning and trend detection in shaping user adoption decisions. This finding resonates with recent studies in the Asia-Pacific region, particularly in Singapore (Cheng et al., 2023) and Australia (Allen & Kendeou, 2023), where organizational responsiveness to technological trends was similarly identified as a key driver of educational technology adoption.

Table 6. Total effects

Hypothesis		Total effect	T-statistics	P-values
H1	PE -> BI	0.062	2.402	0.016
H2	EE -> BI	0.170	6.783	0.000
H3	SI -> BI	0.137	4.944	0.000
H4	FC -> BI	0.149	5.149	0.000
H5	HM -> BI	0.060	3.080	0.002
H6	SC -> PE	0.461	18.577	0.000
H7	SC -> BI	0.272	9.593	0.000
H8	SZ -> EE	0.427	18.415	0.000
H9	SZ -> BI	0.156	6.318	0.000

Hypothesis		Total effect	T-statistics	P-values
H10	RC -> BI	0.103	3.848	0.000
H11	TRUST -> RC	0.295	12.229	0.000
H12	TRUST -> BI	0.080	3.907	0.000

Of particular interest in Table 6 are the significant relationships between strategic capabilities and UTAUT2 constructs. SC exhibited a strong influence on Performance Expectancy (PE) ($\beta = 0.461$, $p < 0.001$), while SZ significantly affected Effort Expectancy (EE) ($\beta = 0.427$, $p < 0.001$). These substantial relationships suggest that users' perceptions of organizational strategic capabilities directly shape their expectations regarding platform performance and ease of use.

The specific indirect effects, presented in Table 7, reveal significant mediating mechanisms. SC indirectly influenced BI through PE ($\beta = 0.029$, $p = 0.017$), demonstrating that organizations that effectively sense learning trends and user needs enhance perceptions of platform usefulness, which in turn increases adoption intention. This finding extends prior research by establishing a clear pathway between organizational environmental scanning and user adoption behavior.

Table 7. Indirect effects

Specific indirect path	Indirect effect	T-statistics	P-values
SC -> PE -> BI	0.029	2.383	0.017
TRUST -> RC -> BI	0.030	3.689	0.000
SZ -> EE -> BI	0.073	6.237	0.000

As shown in Table 7, Trust in AI exerted a significant indirect effect on BI through RC ($\beta = 0.030$, $p < 0.001$), in addition to its direct effect ($\beta = 0.049$, $p = 0.010$). This dual-pathway influence of trust highlights its multifaceted role in technology adoption—both as a direct psychological driver and as a factor that shapes perceptions of platform adaptability. This finding is particularly relevant in the Asia-Pacific educational context, where studies in Malaysia (Rahman et al., 2025) and Japan (Suzuki et al., 2023) have similarly identified trust as a foundational element in educational technology acceptance.

SZ indirectly influenced BI through EE ($\beta = 0.073$, $p < 0.001$), as shown in Table 7, suggesting that the organization's ability to implement responsive features and capitalize on technological opportunities enhances user perceptions of ease of use, subsequently increasing adoption intention. When compared to similar studies in the region, this indirect effect appears stronger in the Thai context than reported in Indonesian studies ($\beta = 0.052$) (Wicaksono et al., 2024), potentially reflecting cultural or institutional differences in how implementation capabilities are perceived across Southeast Asian educational systems.

The magnitude of these indirect effects underscores the complex interplay between strategic organizational capabilities, user perceptions, and technology adoption in educational settings. The findings reveal that strategic capabilities not only directly influence adoption intentions but also operate through established behavioral pathways, enhancing the explanatory power of traditional technology acceptance models in the context of AI-powered learning platforms.

Coefficient of determination (R^2)

The coefficient of determination (R^2) was used to assess the explanatory power of the structural model. R^2 indicates the proportion of variance in the endogenous constructs that is explained by the exogenous constructs in the model. According to Chin (1998), R^2 values of 0.67, 0.33, and 0.19 are considered substantial, moderate, and weak, respectively.

As presented in Table 8, the R^2 value for Behavioral Intention (BI) was 0.634, indicating moderate to substantial explanatory power. The R^2 values for Effort Expectancy (EE) and Performance Expectancy (PE) were 0.183 and 0.213, respectively, which are interpreted as weak but acceptable in exploratory research. The R^2 value for Reconfiguring Capability (RC) was 0.087, suggesting a limited but relevant explanation from its predictor, Trust in AI.

Table 8. Coefficient of determination (R^2)

	R^2	Mean	Standard deviation	T-value	P-values	Interpretation
BI	0.634	0.637	0.016	39.913	0.000	Moderate
EE	0.183	0.184	0.02	9.192	0.000	Weak
PE	0.213	0.214	0.023	9.276	0.000	Weak
RC	0.087	0.089	0.014	6.083	0.000	Weak

These findings demonstrate that the integrated model has strong predictive capacity for user behavioral intention, while offering useful insights into intermediate constructs such as perceived usefulness, ease of use, and organizational adaptability.

Effect size (f^2)

Effect size (f^2) was calculated to determine the relative contribution of each exogenous construct to its respective endogenous variable. According to Cohen (1988), f^2 values of 0.02, 0.15, and 0.35 are interpreted as small, medium, and large effect sizes, respectively. As shown in Table 5, the most significant paths exhibited small to moderate effect sizes. For instance, the path from Performance Expectancy (PE) to Behavioral Intention (BI) produced an f^2 of 0.006, which is below the threshold for a small effect size. Sensing Capability (SC) had a medium effect on PE ($f^2 = 0.180$), while Seizing Capability (SZ) moderately influenced Effort Expectancy (EE) ($f^2 = 0.172$). The most substantial effect was observed from Social Influence (SI) to BI ($f^2 = 0.024$), approaching the threshold for a large effect.

These findings reinforce the theoretical framework by confirming that strategic capabilities and trust in AI exert meaningful, albeit varying, levels of influence on users' behavioral intention toward AI-powered learning platforms.

Predictive relevance (Q^2)

Predictive relevance was assessed using the Q^2 statistic through the blindfolding procedure, which evaluates the model's ability to predict data points for endogenous constructs. According to Hair et al. (2022), Q^2 values above zero indicate that the model possesses predictive capability.

As shown in Table 9, all Q^2 values for the key endogenous constructs – Behavioral Intention (BI), Performance Expectancy (PE), Effort Expectancy (EE), and Reconfiguring Capability (RC) – were greater than 0. This confirms the model's capacity to predict across multiple dependent variables. Notably, BI demonstrated the highest Q^2 value, supporting the model's strength in forecasting user intention toward AI-powered learning platforms.

Table 9. Predictive relevance (Q^2)

Latent variable	Indicators	Average Q^2 predict	Predictive power level
BI	BI1–BI5	0.324	Moderate
EE	EE1–EE5	0.105	Low
PE	PE1–PE3	0.135	Low
RC	RC1–RC5	0.054	Low

These results indicate that the proposed integrated model not only fits the observed data well but also demonstrates sufficient predictive relevance for generalizing to future observations.

MULTI-GROUP ANALYSIS

The multi-group analysis (MGA) revealed no statistically significant differences in path coefficients across user experience levels, occupations, or usage frequencies. This finding suggests that the integrated model's psychological and strategic mechanisms are robust and operate comparably across diverse user segments in the Thai educational context. However, consistent with best practices for exploratory analysis, several numerical patterns warrant cautious interpretation. For instance, high-experience users showed numerically stronger relationships for Performance Expectancy (PE → BI; β = 0.112 vs. 0.031) and Reconfiguring Capability (RC → BI; β = 0.137 vs. 0.081), suggesting a potential trend where advanced users may prioritize long-term performance benefits and adaptability. Conversely, moderate-experience users demonstrated numerically stronger Social Influence effects (SI → BI; β = 0.160 vs. 0.097), indicating a greater reliance on peer validation during initial adoption. These numerical differences must be treated as exploratory findings only and should not be generalized without further testing for moderation.

Analysis by user experience level

Users were categorized into two groups based on self-reported experience with digital learning technologies: moderate experience (Fair + Moderate; n = 814, 59.50%) and high experience (Good + Excellent; n = 554, 40.50%). Table 10 presents the detailed permutation multigroup analysis results for comparing path coefficients between these groups.

Table 10. Permutation multi-group analysis by user experience level

Hypothesis		Path coef. (Exp_Moderate)	Path coef. (Exp_Good)	Original difference	p-value
H1	PE → BI	0.031	0.112	-0.081	0.130
H2	EE → BI	0.152	0.193	-0.041	0.423
H3	SI → BI	0.160	0.097	0.063	0.264
H4	FC → BI	0.167	0.124	0.042	0.484
H5	HM → BI	0.082	0.034	0.048	0.220
H6	SC → PE	0.479	0.434	0.044	0.391

Hypothesis		Path coef. (Exp_Moderate)	Path coef. (Exp_Good)	Original difference	p-value
H7	SC → BI	0.250	0.240	0.010	0.883
H8	SZ → EE	0.418	0.442	-0.024	0.607
H9	SZ → BI	0.100	0.056	0.044	0.346
H10	RC → BI	0.081	0.137	-0.056	0.301
H11	TRUST → RC	0.314	0.274	0.040	0.411
H12	TRUST → BI	0.041	0.056	-0.015	0.704

Note: Path coefficients represent standardized regression weights between constructs; p-values based on two-tailed permutation test (5,000 permutations)

The results reveal that there are no statistically significant differences in path coefficients between users with moderate and high experience levels. For all paths tested, the p-values exceed the conventional threshold of 0.05, indicating that any observed differences could be attributed to chance.

Despite the lack of statistical significance, some noteworthy numerical differences can be observed. Performance Expectancy appears stronger for users with high experience (PE → BI; $\beta = 0.112$ vs. 0.031), as does Reconfiguring Capability (RC → BI; $\beta = 0.137$ vs. 0.081). Conversely, Social Influence shows a stronger relationship among users with moderate experience (SI → BI; $\beta = 0.160$ vs. 0.097), as does Seizing Capability (SZ → BI; $\beta = 0.100$ vs. 0.056) and Hedonic Motivation (HM → BI; $\beta = 0.082$ vs. 0.034).

These findings suggest that the factors influencing behavioral intention to adopt AI-powered learning platforms operate similarly across different experience levels. The psychological and strategic mechanisms driving adoption intentions appear to be relatively consistent in the Thai educational context. This indicates that the theoretical model may be robust across varying levels of user experience, suggesting that platform developers and educational institutions might employ similar strategies when targeting users with different experience levels.

Analysis by occupation

To examine how perspectives differ between learners and educators, respondents were divided into student (n = 874, 63.89%) and teacher/faculty (n = 191, 13.96%) groups. Table 11. presents the permutation multigroup analysis results for comparing path coefficients between these occupational categories.

Table 11. Permutation multi-group analysis by occupation

Hypothesis		Path Coef. (Occ_Student)	Path Coef. (Occ_Teacher)	Original difference	p-value
H1	PE → BI	0.087	0.088	-0.001	0.988
H2	EE → BI	0.173	0.189	-0.015	0.850
H3	SI → BI	0.116	0.068	0.048	0.577

Hypothesis		Path Coef. (Occ_Student)	Path Coef. (Occ_Teacher)	Original difference	p-value
H4	FC → BI	0.128	0.180	-0.052	0.567
H5	HM → BI	0.061	0.120	-0.059	0.320
H6	SC -> PE	0.460	0.467	-0.007	0.919
H7	SC → BI	0.249	0.218	0.031	0.694
H8	SZ -> EE	0.446	0.406	0.040	0.537
H9	SZ → BI	0.069	0.079	-0.010	0.890
H10	RC → BI	0.116	0.111	0.005	0.953
H11	TRUST -> RC	0.299	0.293	0.006	0.939
H12	TRUST → BI	0.042	0.037	0.005	0.929

Note: Path coefficients represent standardized regression weights; p-values based on a permutation test.

The results show that there are no statistically significant differences in path coefficients between students and teachers/faculty members. For all paths tested, the p-values substantially exceed the conventional threshold of 0.05, indicating that any observed differences could be attributed to chance.

Despite the lack of statistical significance, several numerical differences are worth noting. Teachers appear to place somewhat greater emphasis on Facilitating Conditions (FC → BI; $\beta = 0.180$ vs. 0.128) and Hedonic Motivation (HM → BI; $\beta = 0.120$ vs. 0.061) compared to students. This could suggest that educators may be slightly more attentive to resource availability and the enjoyment of using AI-powered learning platforms, though these differences are not statistically significant.

Conversely, students showed slightly higher coefficients for Sensing Capability (SC → BI; $\beta = 0.249$ vs. 0.218) and Social Influence (SI → BI; $\beta = 0.116$ vs. 0.068), potentially indicating a marginally stronger sensitivity to platform adaptability and peer recommendations, though again these differences did not reach statistical significance.

The similarity in path coefficients across occupation groups suggests that the fundamental psychological and strategic factors driving AI platform adoption operate comparably for both students and educators in the Thai educational context. This finding has practical implications for platform developers and educational institutions, suggesting that similar design principles and implementation strategies may be effective across different occupational roles within the educational ecosystem.

Analysis by usage frequency

Respondents were categorized into frequent users (daily + 2-3 days/week; n = 874, 63.88%) and infrequent users (once a week + less than once; n = 494, 36.12%). Table 12 presents the permutation multigroup analysis results for comparing path coefficients between these usage frequency groups.

Table 12. Permutation multi-group analysis by usage frequency

Hypothesis		Path coef. (Freq_Once)	Path coef. (Freq_Day)	Original difference	p-value
H1	RG" "DK	0.028	0.080	-0.052	0.343
H2	GG" "DK	0.184	0.162	0.022	0.672
H3	UK" "DK	0.161	0.155	0.006	0.917
H4	HE " "DK	0.188	0.127	0.061	0.330
H5	J O " "DK	0.094	0.042	0.052	0.262
H6	SC -> PE	0.433	0.476	-0.043	0.419
H7	UE " "DK	0.232	0.248	-0.015	0.775
H8	SZ -> EE	0.393	0.447	-0.055	0.259
H9	U\ " "DK	0.034	0.108	-0.073	0.132
H10	T E " "DK	0.088	0.113	-0.026	0.650
H11	TRUST -> RC	0.295	0.292	0.003	0.947
H12	V T WUV " "DK	0.052	0.052	0.000	0.999

Note: Path coefficients represent standardized regression weights; p-values based on permutation test

The multi-group analysis by usage frequency revealed no statistically significant differences in path coefficients between frequent and infrequent users. All p-values are well above the conventional threshold of 0.05, indicating that any observed differences between the groups could be attributed to chance.

Despite the lack of statistical significance, several numerical differences are worth noting. Infrequent users (Freq_Once) showed somewhat higher coefficients for Facilitating Conditions (FC → BI; β = 0.188 vs. 0.127) and Hedonic Motivation (HM → BI; β = 0.094 vs. 0.042) compared to frequent users. This suggests that users who interact with the platforms less regularly may place slightly more emphasis on resource availability and enjoyment aspects, although these differences did not reach statistical significance.

Conversely, frequent users (Freq_Day) exhibited somewhat higher coefficients for Performance Expectancy (PE → BI; β = 0.080 vs. 0.028) and Seizing Capability (SZ → BI; β = 0.108 vs. 0.034). This might indicate that regular users develop a greater appreciation for the performance benefits and innovation implementation capabilities of the platforms, though again, these differences were not statistically significant. Interestingly, Trust in AI showed identical coefficients across both groups (TRUST → BI; β = 0.052 for both groups, p = 0.999), suggesting that trust considerations operate very similarly regardless of usage frequency.

These findings indicate that the psychological and strategic factors driving the adoption of AI-powered learning platforms function comparably across different usage frequency levels. The lack of significant moderating effects suggests that platform developers and educational institutions may not need to substantially differentiate their implementation approaches based solely on how frequently users engage with the technology.

DISCUSSION

This study investigated the factors influencing users' behavioral intention to adopt AI-powered learning platforms in Thailand through an integrated model combining UTAUT2, Dynamic Capabilities Theory, and Trust in AI. The findings provide comprehensive insights into the complex interplay between behavioral, strategic, and trust factors that shape technology adoption in educational contexts. This section addresses each research question systematically while exploring the broader implications for educational transformation across the Asia-Pacific region.

The unique contribution of this research lies in successfully bridging individual-level acceptance factors (UTAUT2) with organizational strategic readiness (Dynamic Capabilities) through the mechanism of Trust in AI. This expanded framework extends technology adoption theory by demonstrating that users evaluate AI platforms based on perceived strategic competence and long-term adaptability. Contextualizing these findings, it is important to note that the study's cross-sectional design limits the capture of how adoption intentions translate into sustained usage behavior over time. Furthermore, the measurement of strategic capabilities relied solely on user perceptions, which may introduce self-reporting biases.

THE DOMINANCE OF BEHAVIORAL AND CULTURAL FACTORS (RQ1)

In addressing the traditional acceptance factors (RQ1), the findings confirm that all UTAUT2 constructs significantly influence behavioral intention, yet with varying magnitudes reflecting the unique Thai context. The strongest predictor was Effort Expectancy (EE) ($\beta = 0.170$, $p < 0.001$), emphasizing that for Thai users, the ease of interaction and usability are prioritized when engaging with AI technologies. Closely following this, Social Influence (SI) demonstrated the second-strongest effect ($\beta = 0.137$, $p < 0.001$), which strongly reflects Thailand's collectivist culture where reliance on peer recommendations and instructor endorsements significantly shapes adoption decisions10. Interestingly, Performance Expectancy (PE) showed a notably weaker direct effect ($\beta = 0.062$, $p < 0.05$) than often observed in individualistic contexts, suggesting users may initially value accessibility and social acceptance over immediate performance benefits.

STRATEGIC CAPABILITIES AS CORE ANTECEDENTS (RQ2)

The results underscore that strategic organizational capabilities exert a substantial influence, extending adoption theory beyond individual behavior (RQ2). We establish clear mediating pathways:

> Sensing Capability (SC) strongly influences Performance Expectancy ($\beta = 0.461$, $p < 0.001$). This confirms that user perceptions of a platform's proactive environmental scanning (its ability to anticipate learning trends and future value) directly translate into higher expectations regarding platform usefulness.
>
> Seizing Capability (SZ) strongly influences Effort Expectancy ($\beta = 0.427$, $p < 0.001$). This demonstrates that organizational responsiveness, such as the rapid implementation of necessary features, significantly enhances user perceptions of ease of use. These strong relationships confirm that users evaluate AI platforms based on the organization's underlying strategic readiness and adaptive capacity.

The Dual Pathway of Trust (RQ3)

Addressing the role of Trust in AI (RQ3), the findings validate its operation through a dual pathway. Trust in AI exerts a direct psychological effect on intention, and an equally important indirect influence via Reconfiguring Capability (RC) ($\beta = 0.295$, $p < 0.001$). This mechanism is crucial: users who trust the AI system's integrity and benevolence are more willing to perceive necessary organizational or pedagogical changes (RC) as beneficial adaptations rather than disruptive risks19. Furthermore, the Multi-Group Analysis (MGA) confirmed the overall model's robustness across different user segments (experience, occupation, frequency), reinforcing that these psychological and strategic mechanisms are broadly consistent, although MGA numerical patterns suggest exploratory trends where users with less experience rely more heavily on Social Influence.

The findings yield significant and integrated implications for practitioners, policymakers, and theoretical advancement. Given the dominance of Effort Expectancy (EE) and Social Influence (SI), EdTech developers must prioritize intuitive design and actively foster a supportive social environment through instructor endorsement to align with the needs of collectivist cultures. Educational institutions must address Facilitating Conditions, as infrastructure and support resources are critical in developing contexts. Building sustainable adoption requires demonstrating strategic adaptability (Sensing, Seizing, Reconfiguring) through transparent roadmaps and responsive feature development, as user perceptions of organizational strategic readiness significantly influence their acceptance factors. Crucially, the dual pathway of Trust highlights the urgent need for ethical AI governance frameworks that address data privacy, algorithmic transparency, and bias to maintain user confidence. For policymakers, our findings emphasize the need for balanced regulatory frameworks that stress organizational readiness alongside technical infrastructure development, leveraging regional networks such as SEAMEO and APEC to align with Southeast Asian cultural values. Theoretically, this study makes a significant contribution by empirically validating a unified model and advancing the dual-pathway trust model. Future research should explore cultural and institutional moderators of strategic capability influence, examine longitudinal adoption patterns, and investigate how strategic capability perceptions form across different user demographics.

Conclusion

This study investigated the determinants of user adoption of AI-powered learning platforms by integrating the UTAUT2 framework, dynamic capabilities theory, and trust in AI into a unified behavioral-strategic model. This integrated approach – bridging individual-level behavior with organizational strategic readiness – represents the primary contribution to existing technology adoption theories. Based on data from 1,368 Thai respondents, the integrated model demonstrated strong explanatory power, explaining 63.4% of the variance in behavioral intention.

The empirical findings provided decisive support for all hypothesized relationships. The results underscore two core requirements for successful adoption in the Asia-Pacific context. Usability (Effort Expectancy) and Social Influence were the dominant predictors, reflecting the importance of intuitive design and the influence of collectivist culture. Furthermore, the findings confirm that strategic capabilities significantly influence user adoption by enhancing perceptions of platform performance and ease of use, thereby demonstrating that users evaluate platforms based on organizational responsiveness. Crucially, the dual pathway of trust influence highlights the multifaceted role of trust in enabling platform adaptability.

From a practical standpoint, EdTech developers and educational institutions should prioritize user-centered design (emphasizing ease of use) and social integration features to align with the needs of collectivist cultures. Building sustainable adoption requires demonstrating strategic adaptability through transparent roadmaps and responsive feature development, reinforced by ethical governance frameworks to maintain trust. For policymakers, our findings emphasize the need for balanced regulatory frameworks that address both technological infrastructure and ethical governance.

Limitations and Recommendations

Several limitations should be acknowledged. The study's cross-sectional nature (Source 396) and reliance on user perceptions of strategic capabilities limit causal inference and capture of long-term usage. Future research should examine cultural and institutional moderators of strategic capability influence, explore longitudinal adoption patterns as AI technologies evolve, and investigate how strategic capability perceptions form across different user demographics and educational contexts. Cross-cultural validation of the integrated model across diverse Asia-Pacific educational systems would also enhance generalizability.

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APPENDIX. MEASURE

Construct	Item	Question	Source
Performance expectancy	PE3	I believe that using AI-powered learning platforms increases my confidence in learning.	Venkatesh et al. (2012); Huang et al., 2024; Zhang, 2024; Wu et al., 2025
	PE4	AI-powered platforms help me improve my listening and comprehension skills effectively.	
	PE5	AI-assisted learning tools help me acquire new knowledge more quickly.	
Effort expectancy	EE1	AI-powered platforms are user-friendly and make it easy to access relevant lessons.	Venkatesh et al. (2012); Duong et al., 2023; Suyanto et al., 2024; Wen et al., 2024
	EE2	I can begin using AI learning platforms without needing detailed instructions.	
	EE3	AI learning systems offer accessible help when I encounter questions or problems.	
	EE5	It is easy to connect and use AI-powered platforms across different devices.	
Social influence	SI1	Experts in education recommend using AI-powered platforms for better learning outcomes.	Venkatesh et al. (2012); Asag et al., 2024; Jang, 2024; Ma, 2025
	SI2	My family supports the use of AI-assisted tools for improving my learning skills.	
	SI3	My educational institution encourages the use of AI-supported platforms for enhanced learning.	
	SI4	Friends and acquaintances influence my decision to use AI-enabled learning platforms.	
Facilitating conditions	FC1	AI-powered platforms are compatible with the devices I use regularly (e.g., computer, smartphone, tablet).	Venkatesh et al. (2012); Godwin-Jones, 2024; Hsu & Silalahi, 2024; Wei, 2025
	FC2	Having stable internet access allows me to use AI-powered learning tools smoothly.	
	FC3	AI platforms provide comprehensive and easy-to-follow user guides or manuals.	
	FC4	AI-based platforms have responsive technical support teams.	
	FC5	AI-powered learning platforms support self-directed learning across different devices and platforms.	
Hedonic motivation	HM1	I enjoy using AI-powered learning platforms.	Venkatesh et al. (2012); Ahmed et al., 2023; Aini et al., 2024; Zhang, 2025
	HM2	AI learning tools make the learning process more engaging and stimulating.	
	HM4	I enjoy spending time using AI-powered platforms	

Construct	Item	Question	Source
		to develop my skills.	
	HM5	Interacting with AI tools makes learning enjoyable.	
Behavioral intention	BI1	I intend to use AI-powered platforms as my main tool for learning and skill development.	Venkatesh et al. (2012); Asag et al., 2024; Wen et al., 2024; Zhang, 2024
	BI2	I intend to use AI tools to help me prepare for exams or assessments.	
	BI3	I plan to use AI-supported platforms alongside traditional learning methods.	
	BI4	I plan to continue using AI-powered learning platforms in the future.	
	BI5	I am confident that AI-powered platforms can meet my learning needs.	
Trust in AI	Trust3	I believe AI systems are reliable in teaching structured content such as grammar or logic.	Frank et al., 2023; Hsieh & Lee, 2024; Almogren et al., 2024
	Trust4	I consider AI-based learning platforms to be an important channel for acquiring knowledge.	
	Trust5	I trust the information and recommendations provided by AI learning systems.	
Sensing capability	SC1	The platform helps identify current learning needs through AI-based features.	Teece, 2007; Cheng et al., 2023; Kushwaha et al., 2024
	SC2	I feel that the platform is proactive in updating content to meet learner trends.	
	SC3	The system uses AI to anticipate learner difficulties or preferences.	
	SC4	The platform recognizes when to provide personalized support during learning.	
Seizing capability	SZ2	The system seizes opportunities to launch new AI-powered features.	Teece, 2007; Cheng et al., 2023; Froehlich et al., 2024
	SZ3	AI-enabled tools on the platform are timely and relevant to learners' goals.	
	SZ4	I perceive the platform effectively turns learning insights into actions.	
	SZ5	The platform is agile in launching features aligned with learner demand.	
Reconfiguring capability	RC1	The platform adapts its interface and content to stay relevant with new learning formats.	Teece, 2007; Cheng et al., 2023; Nnadi et al., 2024
	RC4	The platform reconfigures its structure in response to new AI capabilities.	
	RC5	I believe the platform can quickly adapt to changes in technology or learner needs.	

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