

Enhancing Trust and Engagement Among Thai E-Learning Consumers Through AI Personalization, Chatbots, and E-Service Quality

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Abstract

Purpose: This study investigates the impact of artificial intelligence (AI) personalization, chatbots, and e-service quality on customer experience, flow state, and learning outcomes, as well as how these factors influence customer trust and engagement among Thai e-learning users. **Methodology:** Structural equation modeling (SEM) was employed to test the proposed conceptual framework based on data collected from 498 Thai e-learning platform users through a quantitative survey. **Findings:** AI personalization and chatbots significantly improved customer experience and learning outcomes. AI personalization also increased flow state, whereas the chatbot–flow path was not supported. E-service quality showed no unique effect once AI personalization and chatbots were modeled. Learning outcomes were the only significant proximal predictor of customer trust and customer engagement. Overall, personalization and chatbots primarily influenced trust and customer engagement indirectly by enhancing learning outcomes. **Applications of this study:** The findings provide actionable insights for regulators, platform operators, and educational institutions. Prioritizing adaptive AI personalization and responsive chatbot support can strategically improve learning outcomes to ultimately foster greater trust and sustained engagement in Thailand’s e-learning ecosystem.

Keywords: Artificial intelligence (AI), Chatbots, E-service quality, Customer experience, Customer trust, Customer engagement, Learning outcomes

Introduction

Following the COVID-19 pandemic, the rapid shift to online learning has continued to expose structural challenges, including disparities in technological resources and limited instructor readiness (Aroonsrimarakot et al., 2023; Chonraksuk & Boonlue, 2024). Despite substantial investment, many e-learning platforms struggle to sustain service quality, build credibility, and maintain engagement beyond initial enrollment (Kim et al., 2022). In response, platforms are increasingly deploying artificial intelligence (AI) personalization and chatbots to tailor content and provide real-time support, combining adaptive delivery with conversational assistance (Bae & Bozkurt, 2024; Baskara et al., 2023; Kaiss et al., 2023).

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AI has become integral to e-learning platforms, representing a shift from technological novelty to pedagogical necessity. A growing body of empirical research documents the benefits of AI-enabled interventions for learner experience and engagement, including positive effects from educational chatbots (Baha et al., 2024). Nevertheless, significant gaps remain. First, most studies analyze a single AI tool against a single outcome for example, chatbots and satisfaction rather than estimating how multiple AI features jointly shape downstream relational outcomes. Second, the mediating processes are underspecified. Constructs such as customer experience, flow state, and learning outcomes are often modeled in isolation, leaving it unclear which mechanisms transmit effects to long-term consequences, such as trust and engagement. As a result, managers receive limited guidance on where to allocate resources when funds are constrained.

From a service and marketing perspective, AI personalization is associated with a stronger customer experience and improved evaluations in digital settings, which also suggests potential gains in educational markets (Ameen et al., 2021). Existing work often emphasizes pedagogy or engineering, while underplaying the management implications. This omission is consequential in competitive and emerging markets such as Thailand, where trust and engagement are central to retention and platform sustainability (Brodie et al., 2011; Kim et al., 2022).

Prior work typically isolates a single AI feature and a single outcome. Chatbot studies mainly examine satisfaction or help-seeking, while personalization studies focus on performance and learning gains, and e-service quality research reviews service factors but rarely integrates AI-specific features. Recent syntheses of AI in higher education and educational chatbots document this fragmentation and call for integrative, theory-driven models (Bond et al., 2024). However, there is no empirical study that jointly models AI personalization, chatbots, and e-service quality as antecedents of trust and engagement in Thailand. Since the COVID-19 pandemic, Thai universities have expanded their online delivery, but they still face uneven access and readiness. Learning is often mobile and routed through chat apps such as LINE, and many learners judge value by measurable gains and certification (Aroonsrimarakot et al., 2023).

This research proposes and tests an integrated framework linking AI personalization, chatbots, and e-service quality to trust and engagement through customer experience, flow, and perceived learning outcomes. Using structural equation modeling (SEM) on survey data from Thai e-learning users, we estimate the relative contributions of each AI lever and the indirect pathways through which AI experiences translate into strong platform relationships.

Research Objectives

1. Investigate how AI personalization, chatbots, and e-service quality affect customer experience, flow state, and learning outcomes, and how these factors in turn influence customer trust and engagement in e-learning services for Thai consumers.
2. Examine the mediating roles of customer experience, flow state, and learning outcomes in the relationships between AI personalization, chatbots, and e-service quality, and customer trust and engagement.

Literature Review and Hypotheses Development

This research introduces the integrative theoretical foundation that combines flow theory, service-quality theory, customer-engagement theory, and trust theory to explain how AI personalization, chatbots, and e-service quality shape learner experience on Thai e-learning platforms. Accordingly, the literature review defines the focal constructs and clarifies boundary conditions relevant to AI-mediated learning. Subsequently, it synthesizes evidence on how AI personalization, chatbots, and e-service quality influence learner experience, flow, and perceived learning outcomes.

AI Personalization

AI personalization refers to the algorithmic adaptation of content, sequencing, difficulty, and feedback to match individual learner profiles. Unlike static features, these systems continuously update their recommendations based on ongoing interaction data (Huang & Rust, 2018). Research in higher education has shown that adaptive tutoring and recommender systems enhance engagement, satisfaction, and test performance by tailoring practice, pacing, and feedback to individual learners (Kulik & Fletcher, 2016; Ma et al., 2014; Zawacki-Richter et al., 2019). Recent reviews continue to report positive effects of adaptive personalization in university settings (Bond et al., 2024).

In terms of mechanisms, matching challenges to skill levels and delivering immediate, diagnostic feedback promote deep task absorption (flow) and strengthen perceived learning gains (Csikszentmihalyi, 1990; Hattie & Timperley, 2007; Hoffman & Novak, 2009). Recent e-learning studies confirm that adaptive or personalized delivery enhances flow experiences (D'Mello et al., 2024; Flores et al., 2019; Ha & Im, 2020; Oliveira et al., 2022).

Personalization also boosts relevance and responsiveness, reducing friction during study sessions and improving the learner's moment-to-moment experience through customized materials and real-time support (Bhuiyan, 2024; Dwivedi et al., 2019; Maghsudi et al., 2021). Emerging research in AI-enabled higher education shows that adaptive support increases satisfaction, autonomy, and performance (Ellikkal & Rajamohan, 2024; Kaiss et al., 2023; Ngai et al., 2024). Accordingly, this research hypothesizes that AI personalization has a positive influence on customer experience, flow, and learning outcomes.

H1: AI personalization positively influences the customer experience of Thai e-learning users.

H2: AI personalization positively influences the flow state of Thai e-learning users.

H3: AI personalization positively influences the learning outcomes of Thai e-learning users.

Chatbots

Chatbots are increasingly utilized in digital learning to enhance interaction, facilitate real-time dialogue, and provide learner support (Okonkwo & Ade-Ibijola, 2021). Advances in natural language processing and machine learning have expanded chatbots' ability to interpret learners'

intentions accurately and provide instant, adaptive assistance, which can improve satisfaction and learning performance.

Chung et al. (2020) reported that interactive chatbots enhance users' perceptions of online learning environments by simplifying complex content and making it more understandable in the short term, thereby improving satisfaction and interaction. Reviews focused on generative-AI chatbots such as ChatGPT also identify positive effects alongside required safeguards for accuracy, privacy, and academic integrity (Ali et al., 2024; Bettayeb et al., 2024; Mai et al., 2024). Experimental and classroom studies in language learning and science, technology, engineering, and mathematics (STEM) further show gains in engagement and performance when chatbots provide timely feedback and explanations (Liu et al., 2024).

The flow state contributes to higher efficiency and focused attention, with learners becoming more immersed and positively engaged in learning activities as flow increases (Csikszentmihalyi, 1990; Pradeepa et al., 2024). Recent work suggests that interactive systems and conversational agents can enhance flow by tailoring interactions to users' skills and needs, thereby ensuring better adaptation (Oliveira et al., 2022). At the same time, micro-interactions that solve problems quickly might not always produce sustained immersion, which helps explain the mixed effects on flow in applied settings.

Baidoo-Anu and Owusu Ansah (2023) found that chatbots improve learning outcomes by delivering immediate instructional support matched to learners' needs, which enhances comprehension and performance. Similarly, Chung et al. (2020) demonstrated that providing quick feedback and simplifying tasks helps students improve their understanding and academic outcomes. Consistent with prior studies, the following hypotheses are proposed:

H4: Chatbots positively influence the customer experience of Thai e-learning users.

H5: Chatbots positively influence the flow state of Thai e-learning users.

H6: Chatbots positively influence the learning outcomes of Thai e-learning users.

E-Service Quality

E-service quality represents users' higher-order assessment of how effectively a digital service fulfills its promises, consistent with classic definitions of perceived quality as an overall judgment of excellence and with hierarchical models of service quality (Brady & Cronin, 2001; Zeithaml, 1988) and e-service definitions emphasizing effective online delivery (Zeithaml et al., 2002). Meta-analyses converge on the four core facets of usability or design, fulfillment, customer service, and security or privacy, and link stronger performance to improved downstream outcomes (Blut et al., 2015; Lionello et al., 2020). Within e-learning contexts, established measurement instruments emphasize efficiency or usability, system availability or reliability, fulfillment, and privacy, alongside recovery dimensions that become salient when service failures occur (Parasuraman et al., 2005).

These facets operate through two mechanisms. A capability pathway suggests that reliable access, accurate fulfillment, and responsive support reduce friction and stabilize feedback, which in turn improves the customer experience, increases the probability of flow, and strengthens perceived learning outcomes (Puriwat & Tripopsakul, 2021; Rodríguez-Ardura & Meseguer-Artola, 2017). Thus, the following hypotheses are proposed:

H7: E-service quality positively influences the customer experience of Thai e-learning users.

H8: E-service quality positively influences the flow state of Thai e-learning users.

H9: E-service quality positively influences the learning outcomes of Thai e-learning users.

Customer Trust and Customer Engagement

Customer experience reflects a cumulative evaluation built across touchpoints. When interactions are seamless, reliable, and helpful, they signal the provider's ability and integrity, which lowers perceived risk and increases the willingness to be vulnerable, thereby fostering trust (Lemon & Verhoef, 2016). In digital services, higher experience quality consistently leads to stronger trust and loyalty (Blut et al., 2015; Parasuraman et al., 2005). Studies in higher education similarly show that positive technology-mediated experiences and satisfaction predict continued usage and trust in providers (Puriwat & Tripopsakul, 2021; Zawacki-Richter et al., 2019).

Engagement represents a cognitive, emotional, and behavioral investment that intensifies when learners perceive high value and personal relevance, created by consistently positive experiences (Hollebeek, 2014). Research in higher education further links responsive, well-designed digital environments to stronger student engagement (Bond et al., 2024). Accordingly, the following hypotheses are proposed:

H10: Customer experience positively influences trust among Thai e-learning users.

H11: Customer experience positively influences engagement among Thai e-learning users.

Flow is an optimal state of deep absorption when challenges match skills and feedback is immediate (Csikszentmihalyi, 1990). In digital contexts, flow produces strong enjoyment, perceived control, and approach behaviors that shape relational evaluations (Hoffman & Novak, 2009; Novak et al., 2000). Learners who experience flow often attribute their positive cognitive and emotional states to the quality and reliability of the platform, which can elevate trust (Rodríguez-Ardura & Meseguer-Artola, 2017). Therefore, the following hypotheses are developed:

H12: Flow state positively influences trust among Thai e-learning users.

H13: Flow state positively influences engagement among Thai e-learning users.

Perceived learning outcomes serve as credible performance indicators of provider competence, a primary basis for trust (Mayer et al., 1995). When learners experience mastery and

measurable progress, they perceive the provider as competent and reliable, which reduces perceived risk and strengthens trust (Deci & Ryan, 2000). Mastery experiences also boost self-efficacy, increasing autonomous motivation and persistence, both of which are core drivers of engagement. Therefore, the following hypotheses are proposed:

H14: Learning outcomes positively influence trust among Thai e-learning users.

H15: Learning outcomes positively influence engagement among Thai e-learning users.

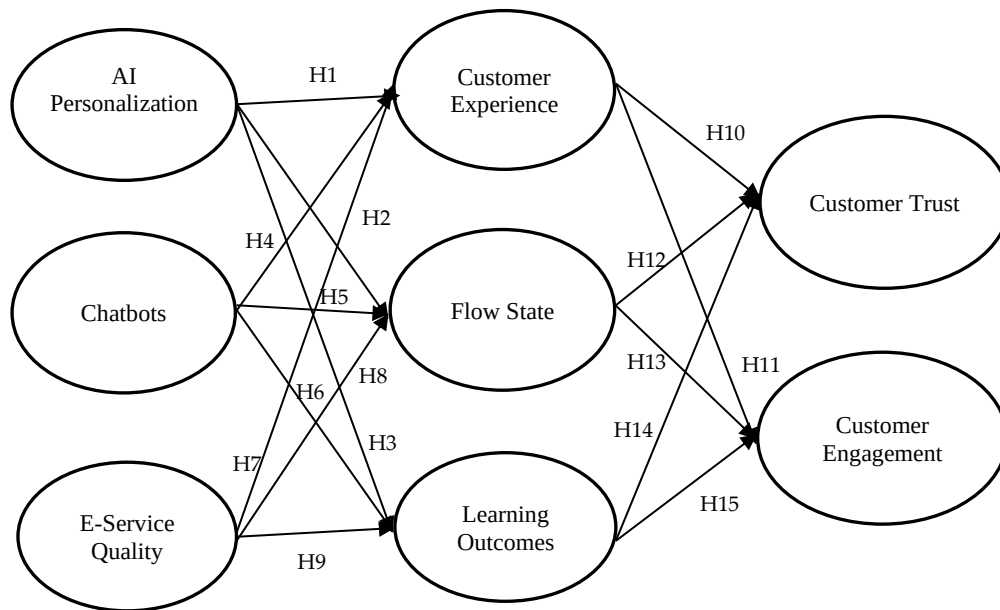


Figure 1 Conceptual Framework

Methodology

Sampling

The study was conducted in Bangkok, Thailand, using an online questionnaire. Convenience sampling was employed to recruit participants. The survey link was posted in Facebook groups and online communities related to e-learning for practicality and reach (Bhati et al., 2023). The study focused on general e-learning platforms in Thailand that deliver a variety of courses and learning experiences, including formal education, extracurricular activities, professional training, skill development, and personal enrichment. This approach efficiently reached a diverse pool of relevant respondents and increased the likelihood of capturing current platform users. While convenience sampling can limit generalizability (Hair et al., 2019), recruiting across multiple Facebook groups and online communities with varied audiences helped mitigate potential bias, as well as collecting responses at different times across an eight-week period. Recruitment aimed for broad coverage of Thai e-learning users by geography, demographics, and platform type. Groups included large, active communities that share online course opportunities,

platform reviews, and free or low-cost training resources, as well as broader education-related communities.

Target Population

The target population comprised Thai e-learning platform users aged 18 years or older, including university and college students, as well as working adults such as professionals, employees, and self-employed learners. Eligibility was verified at the start of the survey using mandatory screening items with automatic skip logic, allowing only eligible respondents to proceed to the main questionnaire.

Ethics

Ethical approval was obtained prior to data collection. The questionnaire was refined in line with reviewer feedback and then reviewed by two management and marketing academics to assess its content validity, clarity, and suitability. Participants were informed of their rights and provided informed consent. A pilot with 105 participants assessed item clarity and internal consistency. Cronbach's alpha for all scales exceeded 0.70 (Hair et al., 2019). Minor wording and item order adjustments followed.

Measures and Translation

The final survey comprised two sections. The first section captured demographics and usage, including age, gender, education, income, job category, motivation for e-learning, and frequency of use, while the second section measured the study constructs on a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. Chatbot dimensions were adapted from Borsci et al. (2021), AI personalization and customer experience items were adapted from Wolfinbarger and Gilly (2003), and e-service quality items followed Zhou et al. (2018). Learning outcomes and flow state items were adapted from Cai et al. (2022), customer trust from Bhattacharjee (2002), and customer engagement from Sungkorn and Thongmak (2023).

A bilingual expert translated the questionnaire from English to Thai, and an independent bilingual expert back-translated the Thai items into English. Two academics compared versions, resolved discrepancies, and standardized terminology for e-learning and e-service. Cognitive interviews with students and working adults assessed cultural relevance. The measurement items can be found in Appendix I.

Data Collection and Analysis

Data collection yielded 498 valid responses. Recommended SEM samples are 200 to 400 for acceptable power and stable estimation (Hair et al., 2019). A sample of 498 increases power and narrows confidence intervals relative to these targets. The typical completion time was approximately 15 minutes, based on observations of respondents during piloting and early data collection.

Descriptive statistics (including mean and standard deviation) were used to analyze the data, and SPSS was used to perform calculations. A confirmatory factor analysis (CFA) validated the reflective measurement model before hypothesis testing. Evidence of convergent validity was demonstrated by standardized loadings within the acceptable range and an average variance extracted (AVE) of ≥ 0.50 , along with composite reliability and Cronbach's alpha exceeding the recommended threshold of 0.70. After establishing measurement quality, the full structural model was estimated to test the hypothesized relations among latent constructs. The AMOS program was used for structural equation modeling (SEM) to verify measurement models and hypotheses, and effects were obtained with confidence intervals.

Results

The demographic data in Table 1 show that most e-learning users in Thailand are aged 25–35 (41.2%), followed by 35–44 (28.3%) and 18–24 (16.9%). By income, the largest groups earn between \$773 and \$1,080 (24.8%) and between \$1,081 and \$1,389 (22.4%) per month, while smaller shares earn between \$464 and \$772 (19.1%) and over \$1,699 (12.4%). The $\leq \$463$ group accounts for 11.2%, and those earning between \$1,390 and \$1,698 account for 10.0%. The gender distribution is 51.2% female, 46.0% male, and 2.8% non-binary or other. Most respondents are employees (47.6%), followed by self-employed (20.3%) and government officials (17.5%). Most respondents use e-learning less than once a month (30.5%) or two to three times per month (20.3%). Their length of use is mainly one to two years (38.4%) or six months to one year (22.4%). The main reasons for using e-learning are career improvement (34.7%) and personal interest (29.9%).

To address the research questions and test the hypotheses, data were analyzed using SPSS 26.0 and AMOS 14.0, employing exploratory factor analysis (EFA), CFA, and SEM.

Table 1 Respondents' Profiles

Age	Percent	E-Learning Usage Frequency	Percent	Engagement Duration	Percent
18–24	16.9	Everyday	5.7	< 6 months	10.0
25–34	41.2	2–3 times/week	14.4	6 months - 1 year	22.4
35–44	28.3	Once a week	17.3	1-2 years	38.4
45–60	10.6	2–3 times/month	20.3	2-3 years	13.4
Over 60	3.0	Once a month	30.5	> 3 years	15.8
*Monthly Income (USD)	Percent	Less than once/month	11.6	Course Type	Percent
\$463	11.2	Once/year	0.2	Self-improvement	21.7
\$464–\$772	19.1	Occupation	Percent	Career improvement	34.7
\$773–\$1,080	24.8	Employee	47.6	Personal interest	29.9

Table 1 Respondents' Profiles (Cont.)

Age	Percent	E-Learning Usage Frequency	Percent	Engagement Duration	Percent
\$1,081–\$1,389	22.4	Self-employed	20.3	Study-related	13.4
\$1,390–\$1,698	10.0	Government officer	17.5	General knowledge	0.4
Over \$1,699	12.4	Student	9.8		
Gender	Percent	Other	3.2		
Female	51.2				
Male	46.0				
LGBTQ+	2.8				

*Exchange rate: \$1 = 32.4 THB (Thai Baht; date: 4 September 2025).

Exploratory Factor Analysis (EFA)

EFA was conducted on eight variables to identify the underlying factor structure and interrelationships among scale items. Principal axis factoring with varimax rotation was applied, with items retained based on factor loadings ≥ 0.50 on a single factor and < 0.40 on other factors (Hair et al., 2006). Items with low or cross-loadings were removed sequentially. The final solution yielded 27 items across eight factors, consistent with prior literature. These factors accounted for 67% of the total variance, with eigenvalues ≥ 1.0 . Factor loadings ranged from 0.512 to 0.811, with the chatbot-related factor contributing the most variance (37%) and the customer trust factor the least (2.9%). Eigenvalues for each factor were ≥ 1.0 . All 27 items had factor loadings ≥ 0.50 , ranging from 0.512 to 0.811 (Table 2).

Table 2 Factor Analysis Results

	Factor 1 (CB)	Factor 2 (LO)	Factor 3 (FS)	Factor 4 (CN)	Factor 5 (SQ)	Factor 6 (CE)	Factor 7 (AI)	Factor 8 (CT)
CB2	.709							
CB8	.685							
CB5	.611							
LO1		.693						
LO2		.642						
LO4		.580						
FS3			.811					
FS6			.711					
FS2			.651					
FS5			.545					
FS4			.512					
CN2				.705				
CN5				.652				
CN4				.561				

Table 2 Factor Analysis Results (Cont.)

	Factor 1 (CB)	Factor 2 (LO)	Factor 3 (FS)	Factor 4 (CN)	Factor 5 (SQ)	Factor 6 (CE)	Factor 7 (AI)	Factor 8 (CT)
SQ2								
SQ4					.715			
SQ5					.595			
SQ7					.536			
SQ8					.540			
SQ9					.520			
CE1						.686		
CE3						.632		
CE4						.589		
AI1							.630	
AI3							.542	
CT2								.642
CT3								.595
Eigenvalues	9.628	7.15	6.532	2.454	1.854	1.535	1.328	1.201
% of variance	37.031	6.089	4.329	3.753	3.482	3.385	3.205	2.964
Cumulative % of variance	37.031	43.12	49.21	53.54	57.29	60.77	64.16	67.36

Confirmatory Factor Analysis (CFA)

To validate these findings, CFA was performed on all 27 items simultaneously. Table 3 presents a summary of the correlations among observed variables and constructs.

Table 3 Correlation Matrix of Constructs

	CB	LO	FS	CN	SQ	CE	AI	CT
CB	1.00							
LO	.711	1.0						
FS	.784	.779	1.0					
CN	.531	.660	.694	1.0				
SQ	.774	.635	.775	.554	1.0			
CE	.717	.595	.776	.681	.729	1.0		
AI	.632	.662	.652	.504	.780	.688	1.0	
CT	.666	.772	.761	.773	.661	.779	.728	1.0

Note: AI = AI personalization, CB = chatbots, SQ = e-service quality, LO = learning outcomes, FS = flow state, CE = customer experience, CT = customer trust, CN = customer engagement

Table 4 Summary of Goodness-of-Fit Statistics for the Measurement Model

Measure of Fit	Model
χ^2	666.839
df	290
χ^2 / df	2.299
GFI	.905
AGFI	.876
RMR	.017
RMSEA	.051
NFI	.976
CFI	.925
TLI	.909

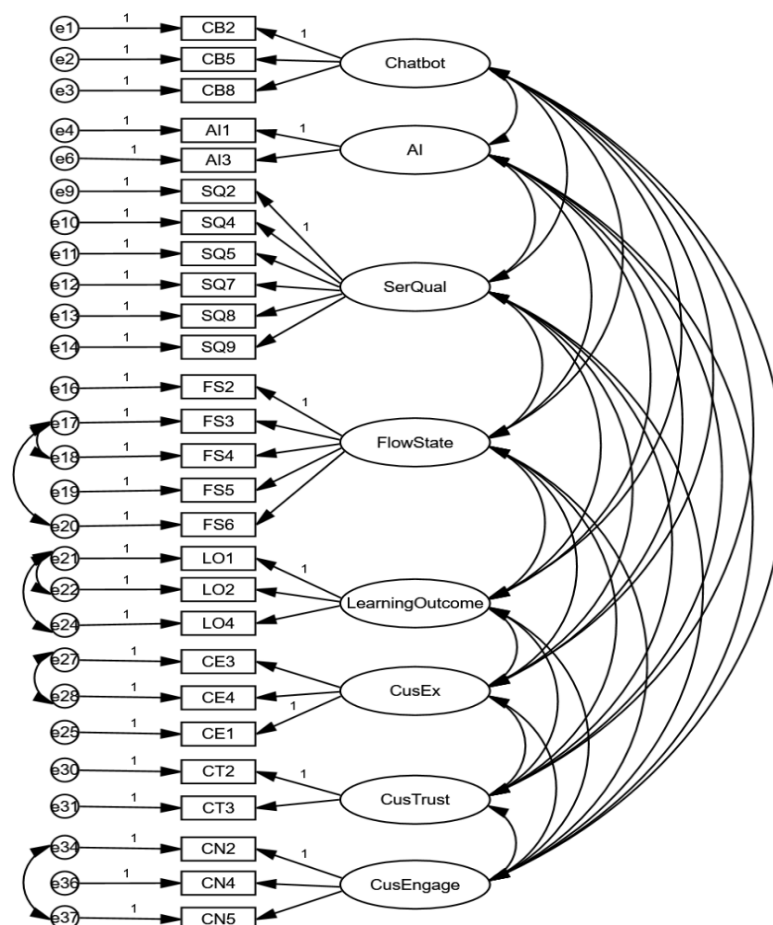


Figure 2 Measurement Model

Table 4 presents the results of the model fit, indicating an acceptable fit. Convergent validity was supported, with standardized factor loadings ranging from 0.473 to 0.742, AVE values from 0.525 to 0.687, and composite reliability (CR) values from 0.702 to 0.767.

Construct validity was then assessed through factor loadings, AVE, and CR (Table 5). Factor loadings ranged from 0.473 to 0.742, AVE values ranged from 0.525 to 0.687, exceeding the 0.50 threshold, while CR values ranged from 0.702 to 0.767, surpassing the recommended 0.70 benchmark (Cheung et al., 2024). These results provide strong evidence of convergent validity across all constructs.

Table 5 *Model Validity*

Measure	Factor Loading	AVE	Composite Reliability	Cronbach's Alpha Coefficient
Chatbot		.539	0.710	0.708
CB2	0.560			
CB8	0.694			
CB5	0.722			
Learning Outcome		.525	0.702	0.742
LO1	0.538			
LO2	0.473			
LO4	0.559			
Flow State		.617	0.710	0.708
FS3	0.507			
FS6	0.578			
FS2	0.587			
FS5	0.498			
FS4	0.634			
Customer Engagement		.565	0.729	0.730
CN2	0.524			
CN5	0.525			
CN4	0.517			
E-Service Quality		.655	0.767	0.766
SQ2	0.594			
SQ4	0.608			
SQ5	0.640			
SQ7	0.587			
SQ8	0.571			
SQ9	0.570			

Table 5 *Model Validity (Cont.)*

Measure	Factor Loading	AVE	Composite Reliability	Cronbach's Alpha Coefficient
Customer Experience		.687	0.739	0.735
CE1	0.706			
CE3	0.642			
CE4	0.742			
AI Personalization		.675	0.745	0.74
AI1	0.627			
AI3	0.597			
Customer Trust		.578	0.747	0.750
CT2	0.663			
CT3	0.562			

A structural model was specified based on the validated measurement model to test the relationships among the constructs. Model validity was assessed using the same fit indices applied earlier. Table 6 shows that the results indicated a satisfactory fit.

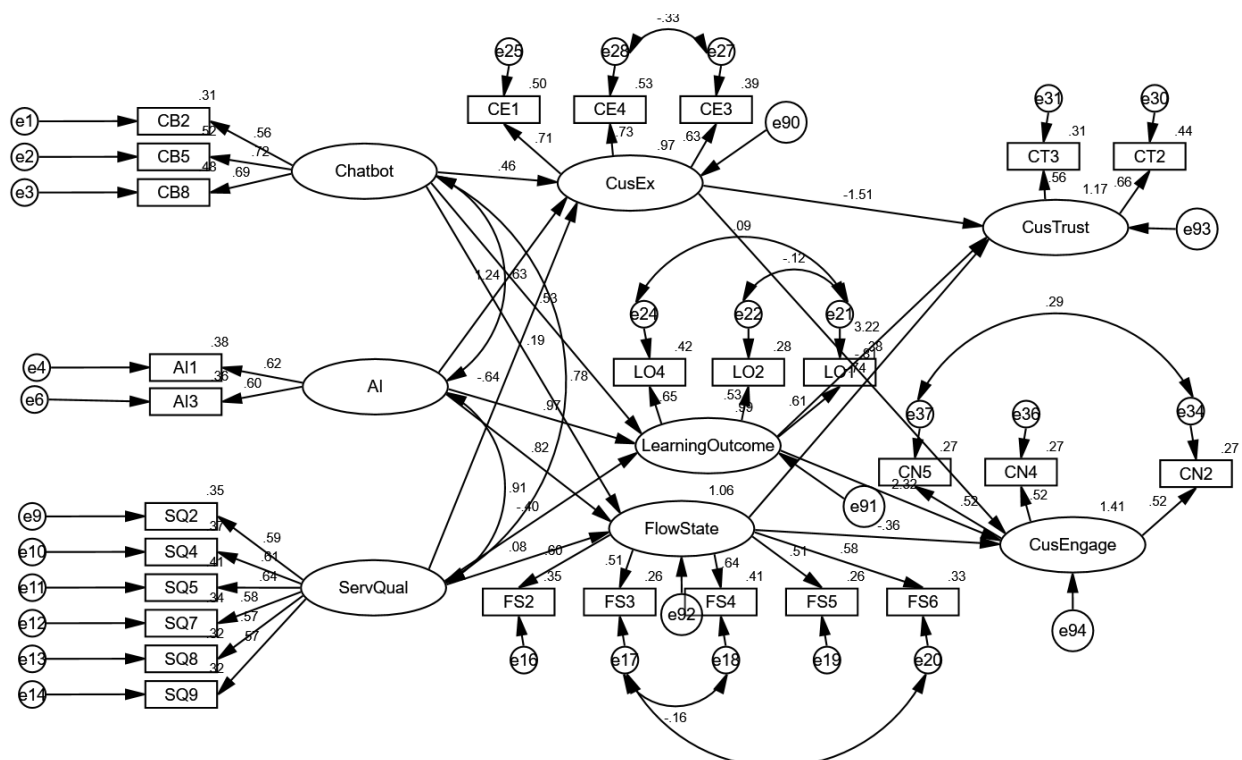


Figure 3 Structural Equation Model

The structural model in Figure 3 demonstrated acceptable fit on most indices, and no post-hoc respecification was undertaken. Although the chi-square statistic was likely due to sample size sensitivity (Hair et al., 2006), all other indices exceeded the recommended thresholds.

χ^2/df (2.382) was below the 3.0 guideline, while RMR (0.017) and RMSEA (0.051) indicated good fit. Additionally, GFI (0.902), CFI (0.925), NFI (0.902), and TLI (0.907) all exceeded the 0.90 benchmark, confirming the model's adequacy.

Following confirmation of overall fit, path coefficients were evaluated. Of 15 hypothesized relationships, seven were statistically significant ($p < .05$). AI personalization was positively associated with customer experience ($\beta = 0.736$), flow state ($\beta = 0.817$), and learning outcomes ($\beta = 0.967$). Chatbot use significantly influenced customer experience ($\beta = 0.460$) and learning outcomes ($\beta = 0.533$). Moreover, learning outcomes positively predicted customer trust ($\beta = 0.811$) and engagement ($\beta = 0.763$).

Table 6 Results of Structural Equation Model

Structural Path	Standardized Coefficient	t	Hypothesis Testing
AI Personalization ---> Customer Experience	0.736***	4.674	H1: Supported
AI Personalization---> Flow State	0.817***	4.423	H2: Supported
AI Personalization---> Learning Outcomes	0.967***	4.205	H3: Supported
Chatbot---> Customer Experience	0.460**	2.886	H4: Supported
Chatbot---> Flow State	0.192	1.636	H5: Not supported
Chatbot---> Learning Outcomes	0.533***	3.503	H6: Supported
E-Service Quality ---> Customer Experience	-0.640	-1.94	H7: Not supported
E-Service Quality ---> Flow State	0.085	0.365	H8: Not supported
E-Service Quality ---> Learning Outcomes	-0.402	-1.361	H9: Not supported
Customer Experience---> Customer Trust	-1.509	-1.665	H10: Not supported
Customer Experience---> Customer Engagement	-0.815	-1.311	H11: Not supported
Flow State---> Customer Trust	-0.743	-1.17	H12: Not supported
Flow State---> Customer Engagement	-0.36	-0.755	H13: Not supported
Learning Outcomes ---> Customer Trust	.811**	3.094	H14: Supported
Learning Outcomes ---> Customer Engagement	.763**	3.119	H15: Supported
Fit Indices:	$\chi^2=698.503$, $df=300$, $\chi^2/df=2.382$, $p<0.001$, GFI=0.902, AGFI=0.876, CFI=0.925, TLI=0.907, NFI=0.902, RMR=0.017, RMSEA=0.051.		

Discussion

The structural model fit supported theory testing ($\chi^2/df = 2.382$, CFI = .925, TLI = .907, RMSEA = .051). The findings suggest that AI personalization and chatbots enhance immediate user experiences, but their ultimate value is realized through learning outcomes, which are the sole direct driver of trust and engagement.

The results support H1, H2, and H3. AI personalization enhances relevance and responsiveness, improving journey evaluations in line with service quality and customer experience theory (Lemon & Verhoef, 2016; Parasuraman et al., 2005). In this research, AI personalization has a strong effect on customer experience, flow state, and learning outcomes in the Thai context, consistent with work that positions adaptive learning as transformative. As Murtaza et al. (2022) note, these systems deliver content matched to a learner's current level and preferred modes. The positive effect on customer experience (H1; $\beta = 0.736$, CR = 4.674, $p < .001$) confirms that moving beyond a one-size-fits-all model enhances satisfaction and perceived quality (Maghsudi et al., 2021). The significant influence on flow state (H2; $\beta = 0.817$, CR = 4.423, $p < .001$) aligns with the challenge–skill balance mechanism that underpins deep immersion (Dmello et al., 2024; Ha & Im, 2020). Most critically, the path to learning outcomes (H3; $\beta = 0.967$, CR = 4.205, $p < .001$) underscores the pedagogical value of personalization, with adaptive materials and feedback enhancing academic performance (Contrino et al., 2024).

Chatbot support positively influenced customer experience (H4; $\beta = 0.460$, CR = 2.886, $p = .004$) and learning outcomes (H6; $\beta = 0.533$, CR = 3.503, $p < .001$), consistent with the view that chatbots provide instant assistance that improves satisfaction (Chung et al., 2020) and timely feedback that enhances learning (Baidoo-Anu & Owusu Ansah, 2023). The non-significant relationship between chatbot and flow path (H5) is informative. While highly interactive systems can induce flow (Ha & Im, 2020), the transactional query–response format might provide helpful micro-interactions without sustaining the absorption required for flow. In practice, chatbots serve as functional support rather than as flow facilitators, highlighting the complexity of applying the flow concept in e-learning (Dmello et al., 2024). Put simply, chatbots are valuable for providing functional support, rather than creating an immersive experience.

A notable finding is the lack of support for H7–H9, which propose direct effects from e-service quality to customer experience, flow state, and learning outcomes. E-service quality theory treats reliability, responsiveness, fulfillment, and privacy as foundational conditions rather than sources of value creation. Once personalization and chatbots are included, these general attributes function as hygiene factors, consistent with the non-significant e-service quality paths (Blut et al., 2015; Parasuraman et al., 2005). This finding contrasts with work identifying e-service quality as a consistent predictor of satisfaction (Al-Fraihat et al., 2020; Limbu & Pham, 2023). However, in integrated models, system or service quality often behaves as a hygiene factor: once baseline speed, stability, and help availability are in place, explanatory power shifts to content, feedback, and support. In modern e-learning platforms that combine personalization and conversational help, the unique direct effects of e-service quality can be attenuated due to overlap with these technology levers. This interpretation aligns with the current model and the Thai context. However, this result may be explained by the specific context of modern e-learning in Thailand. A study by Kim et al. (2022) on Thai university students found that factors such as system characteristics and learning content design were key determinants of perceived

usefulness. This research supports the evidence that Thai learners prioritize the pedagogical value and functionality of a platform over more generic service attributes.

In this research, learning outcomes serve as competence signals that translate AI support into trust, and subsequently into the cognitive, emotional, and behavioral investment described in engagement theory (Hattie & Timperley, 2007). Therefore, the results for H14 and H15 show that learning outcomes are the sole proximal driver of relationship outcomes, with positive effects on customer trust ($\beta=0.811$, $p=.002$) and customer engagement ($\beta=0.763$, $p=.002$). The pattern suggests that trust and engagement are rooted in performance, rather than experience alone. Online learning syntheses report that perceived effectiveness and satisfaction underpin continuance, as a behavioral indicator of sustained engagement (Meng & Jia, 2024). This outcomes-first mechanism explains why learning outcomes remain the only proximal predictor once experience and flow are included.

Customer engagement theory views engagement as a cognitive, emotional, and behavioral investment resulting from the value derived from use. (Hollebeek, 2014). Customers persist when the platform demonstrably advances competence and progress, not due to entertainment value. This notion aligns with customer engagement theory, which emphasizes cognitive, emotional, and behavioral investment in valued outcomes (Brodie et al., 2011), as well as evidence that progress cues sustain motivation in e-learning (Kaiss et al., 2023). For Thai e-learners, this translates into loyalty when pedagogical effectiveness is visible.

Customer experience and flow have rich literature connecting them to satisfaction and loyalty. Flow theory posits that deep absorption emerges when the task challenge aligns with the user's capability and feedback is immediate. Our findings suggest that AI personalization significantly enhances flow, whereas chatbots do not, implying that conversational agents primarily operate through friction reduction rather than immersion generation (Csikszentmihalyi, 1990; Hoffman & Novak, 2009). The non-significant direct paths here do not contradict those streams; instead, they suggest a mediated route in this context. Experience and flow might be necessary but not sufficient for relationship judgments unless they produce tangible gains. In other words, the model is consistent with an outcomes-first pathway, in which AI personalization and chatbots enhance experience and flow. These states facilitate learning, and learning carries the weight for trust and engagement. Previous studies in Thai higher education support this performance-driven framework. Perceived usefulness and satisfaction predict continuance intentions, learning delivery strongly relies on mobile and chat-based platforms, and evident progress and credential recognition maintain learner motivation (Jitpaisarnwattana, 2024; Puriwat & Tripopsakul, 2021; Van De Bogart & Wichadee, 2015). In Thailand's achievement-oriented context, demonstrable instructional effectiveness therefore represents a practical mechanism for building lasting engagement.

Study Implications

Theoretical Implications

Our results indicate that in AI-mediated e-learning, relationship outcomes are transmitted chiefly through perceived learning outcomes rather than experiential states. AI personalization emerges as the central design lever, showing the most significant upstream effects on learning and lifting flow and customer experience, consistent with evidence that adaptive systems outperform non-personalized instruction (Bond et al., 2024). Chatbots add value by improving experience and learning, but do not reliably increase flow, reflecting a consistent pattern of a friction-reduction mechanism rather than immersion (Chen et al., 2022; Okonkwo & Ade-Ibijola, 2021). Once AI features are modeled, e-service quality contributes no additional variance to experience, flow, or learning, suggesting that general service attributes operate as hygiene factors that enable value without directly generating it (Blut et al., 2015; Parasuraman et al., 2005). Together, these findings position perceived learning outcomes as the decisive mediator that converts AI design into trust and engagement in the Thai market, while flow primarily contributes through affective value.

Conceptually, the study extends customer-engagement theory to AI services by specifying a performance-led route to relational outcomes and comparing design levers within a single model rather than in isolation. It clarifies how personalization and chatbots influence downstream trust and engagement through learning in Thailand, helping to fill a regional gap in the literature on AI-enabled education (Labadze et al., 2023; Wang et al., 2024).

Practical Implications

The findings suggest a clear operational directive for e-learning providers in the Thai market, as relationship value is fundamentally predicated on demonstrable learner improvement. Learning outcomes emerge as the decisive antecedent to user trust and engagement. Consequently, factors such as customer experience and psychological flow primarily function as mediating variables, whose positive influence is contingent upon their capacity to enhance learning performance. Within this framework, AI-driven personalization represents the most significant strategic lever, exerting substantial positive effects on experience, flow, and—most critically—learning outcomes. Chatbots contribute value by mitigating transactional friction and clarifying instructional tasks, while general e-service quality operates as a foundational prerequisite, reflecting a hygiene factor rather than a primary driver of growth or differentiation.

Investment priorities should therefore start with the personalization stack. Providers need accurate learner models, mastery diagnostics, and adaptive sequencing that tailor content, pacing, and feedback to a learner's current skill level. Product roadmaps should treat learning outcomes as the primary success factor, with trust and engagement tracked as downstream outcomes. Resource allocation should logically follow, prioritizing data pipelines for granular, item-level analytics, immediate feedback mechanisms, and the creation of adaptive content variants, while de-prioritizing superficial user interface enhancements that do not yield pedagogical impact.

Chatbots are most effective when positioned as guided tutors and service-recovery agents. Their primary mandate is to scaffold learning and mitigate friction by resolving learner misconceptions, reducing help-seeking latency, and supporting task completion, rather than attempting to generate affective immersion. Effective implementation demands domain-specific knowledge bases, human-in-the-loop escalation protocols for ambiguous queries, and evaluation based on pedagogical effectiveness metrics rather than generic conversational fluency. Given the characteristics of the Thai language and code-switching, training data and evaluation should explicitly cover Thai tokenization, politeness particles, and mixed Thai-English usage to maintain precision and tone.

Because e-service quality operates as baseline infrastructure, managers should secure reliability, latency, and privacy to a clearly communicated standard and subsequently shift attention to learning-centric design. For Thailand's mobile-first usage and uneven connectivity, it is recommended to optimize for low-data consumption, asynchronous learning, and offline-capable modules (cached lessons and downloadable assessments). Consent, data minimization, and retention/deletion policies should be made visible at the point of use to convert learning gains into trust signals rather than allowing concerns about data practices to dilute perceived competence.

Given that execution depends on capabilities, teams should institutionalize rapid experimentation, A/B tests, and quasi-experiments that first verify objective learning gains before confirming mediated effects on trust and continued use. Instructor workflows must be redesigned to align with the adaptive system, including dashboards that surface mastery gaps, nudges triggered by stalled progress, and lightweight authoring tools to create remedial variants. Governance should couple pedagogical oversight with model monitoring to ensure that personalization remains aligned with curriculum goals and fairness expectations.

Finally, market strategy should reflect Thailand's heterogeneity. Where bandwidth and device quality are constrained, it is recommended to deploy "lite" clients and micro-learning sequences that still allow the adaptive engine to operate. Where outcome orientation is high, it is recommended to emphasize progress signals, such as mastery badges, course completion credentials, and readiness indicators, because these cues translate improvements into trust and encourage repeat participation. Put simply, it is recommended to build the organization around raising learning outcomes first, based on the notion that trust and engagement will follow.

Conclusions, Limitations, and Suggestions for Future Research

This study integrated AI personalization, chatbots, and e-service quality with customer experience, flow, learning outcomes, trust, and engagement on Thai e-learning platforms. The model fit supported theory testing, with the results showing that AI personalization had the largest positive paths to learning outcomes and enhanced experience and flow. Chatbots improved experience and learning outcomes, but did not enhance flow state. E-service quality added no incremental variance once AI features were included. Downstream, trust and engagement were

driven almost entirely by perceived learning outcomes. When learners perceived progress, they reported stronger trust and engagement. Affective states were not sufficient once learning was taken into account.

The findings advance an AI-mediated, performance-led view of relationship building, in which personalization and conversational support matter to the extent that they enhance learning, which in turn translates into durable trust and engagement in the Thai context. For practice, these findings suggest that managers should prioritize adaptive feedback, mastery diagnostics, and friction-reducing assistance over cosmetic service upgrades.

Limitations

The cross-sectional design and convenience sampling in one country limit the causal inference and generalizability of the findings. Self-report measures might introduce common-method variance. Given that platform timing was not logged, response-time screening and behavioral traces were not implemented.

Construct overlap might have introduced suppressor effects that attenuated the paths from experience and flow once learning outcomes were included. Multicollinearity among mediators and omitted covariates, such as prior ability, course difficulty, or instructor quality, might partly explain the pattern of coefficients. Measurement choices might also hold relevance. The e-service-quality scale used here might not fully capture education-specific facets such as instructional clarity or assessment transparency, which could contribute to the non-significant effects once AI features are modeled.

Moreover, the present analysis primarily relied on quantitative analysis. Accordingly, future research should utilize qualitative research methods including in-depth interviews and focus groups to elicit a richer understanding and context regarding user beliefs about AI personalization and chatbot interaction.

While this study fills a crucial gap by focusing on Thailand, the observed primacy of learning outcomes might reflect the preferences of goal-oriented learners in emerging economies. Therefore, cross-cultural comparative studies are necessary to increase the generalizability of the results. Future research should replicate the model across cultural and economic contexts, such as Western Europe and North America, and various educational settings, including K-12 and corporate training, to determine whether the mediating role of learning outcomes is a general principle of e-learning or a pattern specific to the pragmatic, career-focused user base common in Thailand and similar Southeast Asian markets.

Finally, while this research primarily examined customer engagement as an outcome influenced by trust, future research might consider the reverse relationship, in which increased customer engagement—for example—could potentially facilitate customer trust. Researching this relationship would be informative and instrumental in strengthening the theoretical basis of consumer engagement in digital environments.

Future Research

Future work should extend beyond cross-sectional perception surveys and trace how AI features change learning over time. Longitudinal or experimental designs could follow cohorts across modules and terms, estimate changes in learning outcomes, and link those changes to subsequent trust and engagement. Platform rollouts create natural opportunities for quasi-experiments, such as using staged releases, difference-in-differences comparisons, or randomized encouragement trials. Such designs would clarify whether personalization and chatbot assistance lead to improvements in outcomes or simply co-occur with them.

Self-reports should be triangulated with behavioral traces such as quiz scores, item-response patterns, time on task, and chatbot transcripts. Conversation quality, timing, and accuracy should be coded to evaluate which intervention styles improve learning and whether specific approaches can improve flow. Efforts should be undertaken to improve generalizability by conducting cross-cultural replications in Western Europe and North America and cross-setting replications in K-12 and corporate training. Finally, the potential reciprocal relationship between engagement and trust should be modeled to test whether sustained engagement subsequently strengthens trust.

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