

The Impact of AI Chatbot–Based Academic Support on Student Loyalty in Higher Education

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Abstract

Original Research Article

This study investigates the role of AI chatbots in fostering student loyalty toward educational institutions in the context of academic support and inquiry resolution. Integrating the Unified Theory of Acceptance and Use of Technology (UTAUT), Habit Theory, and Dual-Process Theory, we develop a comprehensive framework examining both the antecedents of AI chatbot engagement and the mechanisms through which engagement translates into institutional loyalty. The theoretical model proposes that habit strength moderates the engagement-satisfaction-loyalty chain, creating two distinct pathways: a deliberate, satisfaction-mediated route (System 2 processing) for low-habit users and an automatic, engagement-driven route (System 1 processing) for high-habit users. Survey data from 223 university students in Ho Chi Minh City, Vietnam, were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). Results reveal that conversational quality ($\beta = 0.391$), perceived technology capability ($\beta = 0.372$), and perceived usefulness ($\beta = 0.161$) significantly drive student engagement with AI chatbots, collectively explaining 69% of engagement variance. Engagement demonstrates substantial effects on both satisfaction ($\beta = 0.555$) and user loyalty ($\beta = 0.458$). Critically, all three moderation hypotheses were supported: habit strength negatively moderates the engagement-satisfaction relationship ($\beta = -0.135$) and the satisfaction-loyalty relationship ($\beta = -0.244$), while positively moderating the direct engagement-loyalty relationship ($\beta = 0.273$). These findings confirm a mechanism substitution model wherein, as habits strengthen, loyalty formation shifts from a satisfaction-mediated deliberate pathway to an engagement-driven automatic pathway. The study contributes to technology adoption literature by demonstrating that habit strength fundamentally alters how loyalty develops, reconciling inconsistent findings in the satisfaction-loyalty literature. Practical implications suggest differentiated retention strategies: satisfaction-focused interventions for novice users and habit reinforcement tactics for experienced users.

Keywords: AI chatbots, Student loyalty, Habit strength, Dual-process theory, UTAUT.

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1. INTRODUCTION

"New learning technologies like artificial intelligence (AI) chatbots" (Rahman et al., 2025), which give students instant feedback,

personalized learning support, and automated replies to their questions, are causing a rapid transformation in higher education (Chen et al., 2025). Additionally, many universities have



created chatbots to assist "students with administrative, academic, and real-time learning tasks" within their learning management systems (Chen et al., 2025; Hopkyns, 2022). Chatbots assist in LMS to answer administrative and academic questions and provide real-time learning support. Chatbots are considered "efficient and simple ways of exchanging information in digital environments" because they enhance interaction and provide effective support.

In higher education practice, the implementation of AI chatbots in student consulting and answering questions still faces many challenges. Firstly, the level of technology readiness of students is uneven, making access and use of chatbots ineffective, especially for those who lack digital skills or experience interacting with AI technology (Rahman et al., 2025). Secondly, the perceived usefulness is still limited as many students do not consider chatbots as a reliable learning consulting tool, leading to low usage and engagement. In addition, tech literacy and tech simplicity are still major barriers; the interface and response ability of some chatbots are not friendly, causing difficulties in the user experience.

Moreover, the quality of conversation is not high, especially in the ability to understand context and express empathy, reducing students' trust. Critically, the development of usage habits plays a pivotal role in determining whether students will continue to engage with and remain loyal to AI chatbot services. Without the formation of consistent usage patterns, even technically superior chatbots may fail to generate sustained engagement and institutional loyalty. These challenges hinder the effective use of AI chatbots, affecting student satisfaction and long-term loyalty.

In the current context of higher education, the use of AI chatbots has emerged as a potential solution to support academic advising and answering questions for students. Although this technology brings many promising opportunities in improving the accessibility and timeliness of student support services, there are still many concerns related to the effectiveness of use, especially in terms of technology readiness, perceived usefulness, tech literacy, tech

simplicity, and conversation quality (Rahman et al., 2025). Furthermore, understanding the mechanisms through which students develop habitual usage patterns and how these patterns influence their satisfaction and loyalty remains unclear. The discrepancy between these factors can reduce the level of student engagement and satisfaction, thereby limiting the possibility of them becoming loyal users of AI chatbots in advising activities.

The majority of earlier research has mostly concentrated on the technical features of AI chatbots, like real-time feedback, tailored learning, and user experience optimization. However, these studies have not adequately considered the behavioral and social aspects such as technology readiness, perceived usefulness, tech literacy, tech simplicity that play a significant role in determining student satisfaction and loyalty in the context of university advising and inquiry. This limited approach leaves much room for understanding the cognitive and social environment's impact on students' long-term interactions with AI chatbots.

While some studies have contributed to elucidating the general technology acceptance process, there remains a significant gap in understanding how perceptions of usefulness, simplicity of technology, and technology knowledge influence student satisfaction and loyalty with AI chatbots (Polyportis & Pahos, 2025). More critically, existing research has not explored the dual mechanisms through which AI chatbot engagement translates into institutional loyalty. Specifically, there is limited understanding of whether students develop loyalty through a deliberate, satisfaction-based cognitive route or through an automatic, habit-based behavioral route. This dual-process perspective is essential for understanding how different student segments may develop loyalty through fundamentally different psychological mechanisms. Moreover, the moderating role of habit strength in shaping these alternative pathways to loyalty remains unexplored. Therefore, further research on the behavioral and psychological factors influencing student satisfaction and loyalty, particularly the role of

habit formation in creating dual pathways to institutional commitment, is needed.

The objective of this study is to examine the role of AI chatbots in fostering student loyalty in the realm of academic assistance and inquiry resolution at universities. The study specifically assesses the influence of engagement and satisfaction on student loyalty, with particular attention to how habit strength moderates these relationships and creates alternative pathways to institutional loyalty. By investigating both the cognitive-evaluative route (through satisfaction) and the automatic-behavioral route (through habitual usage), this study aims to provide a more comprehensive theoretical understanding of AI chatbot adoption for academic advising and support in higher education. The study also seeks to offer practical recommendations for educational institutions on how to leverage both conscious satisfaction and automatic habit formation to enhance student loyalty. Finally, this study addresses critical gaps in prior research regarding the behavioral and psychological mechanisms, particularly habit formation and dual-process pathways, that influence students' continued engagement with and loyalty to AI chatbot-supported institutions.

2. LITERATURE REVIEW

2.1 Review of Key Constructs

User loyalty among university students is increasingly recognized as a crucial factor for organizational success, reflecting the connection between students and their educational institutions. Recent research highlights various contexts that influence this loyalty, such as student satisfaction, perceived service quality, and organizational fairness. For example, previous studies emphasize that student satisfaction, driven by factors such as university competence and image, has a significant impact on loyalty, while organizational justice has been identified as a predictor that increases academic cohesion and perceived legitimacy, thereby further promoting loyalty. Additionally, Gürbüz & Acuner (2025) also illustrate that high service quality and technological innovation are important factors in enhancing student satisfaction and loyalty, demonstrating a direct relationship between these elements.

Other research indicates that students appreciate the 24/7 availability and user-friendly interface of chatbots, which enhances their learning experience and engagement (Roca et al., 2024). These studies emphasize the importance of satisfaction as a mediating factor in forming loyalty, aligning with broader theories of user loyalty that highlight the role of service quality and perceived value in driving loyalty. Overall, these findings collectively inform strategies to help universities enhance student academic motivation and engagement.

2.2 Underpinning Theories

2.2.1 UTAUT as the Foundation

This study builds upon the Unified Theory of Acceptance and Use of Technology (UTAUT), which extends from the Technology Acceptance Model (TAM) (Cheng & Jiang, 2020; Venkatesh et al., 2012) to evaluate students' adoption of AI chatbot applications in higher education. According to Venkatesh et al. (2012) and Cheng & Jiang (2020), there are four key determinants that influence behavioral intention and technology use: performance expectancy, effort expectancy, social influence, and facilitating conditions. Performance expectancy can be described as the level to which students are convinced that the application of AI chatbots will enhance their performance (Camilleri, 2024). When learners perceive that chatbots can improve their comprehension, help them to get feedback in time, or organize learning resources, they will be more willing to incorporate such tools into their learning processes (Annamalai et al., 2023; Huang et al., 2022). Effort expectancy describes how easy AI chatbots are to use (Camilleri, 2024). When students feel that the tools are easy to use, they adopt them more readily (Mustofa et al., 2025). The ease of the chatbot interface and easy communication design create less cognitive load, which makes students more confident and willing to use the technology (Albayati, 2024). Facilitating conditions indicate the technological infrastructure and digital preparedness necessary to ensure that students can effectively use AI chatbots (Rahman et al., 2025). Students with higher digital abilities or greater technological preparedness are more likely to adopt and utilize

AI chatbots (Rahman et al., 2025; Stöhr et al., 2024). To conclude, according to the UTAUT model, the level of adoption of AI chatbots by students in higher education relies on their views of usefulness, ease of use, and technological preparedness. Favorable experiences and positive digital support may greatly boost the behavioral intentions of students to embrace AI-powered learning tools.

2.2.2 Habit Theory and Automatic Behavior

While UTAUT provides a robust framework for understanding initial technology acceptance, it primarily focuses on deliberate, reasoned decision-making processes. However, as Verplanken & Orbell (2003) argue, much of human behavior that particularly frequent, repetitive actions, becomes habitual over time, operating outside conscious deliberation. Habit is defined as "learned sequences of acts that become automatic responses to specific situations, which may be functional in obtaining certain goals or end states" (Verplanken & Aarts, 1999). In the context of technology use, habits develop through context-dependent repetition; when a behavior is performed repeatedly in stable contexts, cognitive associations between contextual cues and behavioral responses strengthen, eventually leading to automaticity (Verplanken, 2006; Wood & Neal, 2007).

Research on technology habits has demonstrated that habitual usage patterns can override conscious intentions in predicting actual behavior (Limayem et al., 2007). LaRose (2010) introduced the concept of "media habits," showing that continued use of digital technologies often transitions from intentional to automatic processing. Once formed, technology habits make usage behavior relatively insensitive to changes in attitudes or conscious evaluations (Oulasvirta et al., 2011). This automaticity has important implications for understanding student loyalty: students who have developed strong habits of using AI chatbots may maintain their engagement and loyalty even in the absence of continuous satisfaction evaluation. As Verplanken & Orbell (2003) note, habits are characterized by their "stickiness" once established, they persist independently of the original motivations that initiated the behavior.

2.2.3 Dual-Process Theory: Two Routes to Behavior

Dual-process theories propose that human cognition and behavior arise from two qualitatively distinct processing systems (Evans & Stanovich, 2013; Krämer, 2014). System 1 (Type 1 processing) is characterized as fast, automatic, effortless, associative, and unconscious, while System 2 (Type 2 processing) is slow, controlled, effortful, rule-based, and conscious (Krämer, 2014). These two systems often operate in parallel, but their relative influence on behavior varies depending on contextual factors and individual characteristics. As Krämer (2014) explains, System 1 operates automatically and cannot be easily turned off, whereas System 2 requires deliberate activation and is limited by cognitive capacity.

In the context of technology adoption and loyalty, dual-process theory suggests two distinct pathways through which users develop commitment. The deliberate, evaluative pathway (System 2) involves conscious assessment of service quality, satisfaction formation, and reasoned loyalty decisions. In contrast, the automatic, habitual pathway (System 1) bypasses extensive cognitive evaluation, with loyalty emerging directly from repeated behavioral patterns (Verplanken & Aarts, 1999). Importantly, the relative dominance of these pathways can shift over time and across individuals, with habit strength serving as a moderating factor that determines which route predominates (Ouellette et al., 1998). This perspective aligns with findings from Limayem et al. (2007), who demonstrated that as habits strengthen, the predictive power of intentions on technology use behavior diminishes.

2.2.4 Integrated Framework: UTAUT, Habit, and Dual-Process Pathways

This study integrates UTAUT, habit theory, and dual-process theory to develop a comprehensive framework for understanding how AI chatbot engagement translates into institutional loyalty. We propose that habit strength moderates the mechanisms through which engagement influences loyalty, creating two distinct pathways. When habit strength is low (novice

users or infrequent usage), behavior follows the deliberate pathway consistent with traditional UTAUT logic: technology acceptance factors (perceived usefulness, perceived technology, conversational quality) drive engagement, which then generates satisfaction through conscious evaluation, ultimately leading to loyalty. However, when habit strength is high (experienced users with established routines), the automatic pathway becomes dominant: engagement directly produces loyalty without requiring satisfaction as a mediating mechanism, as the behavior has become habitualized and operates outside conscious evaluation.

This integrated framework offers several theoretical advantages. First, it reconciles apparent inconsistencies in technology adoption literature regarding the role of satisfaction in loyalty formation. Second, it provides a temporal perspective, recognizing that the psychological mechanisms underlying technology-related loyalty may evolve as users transition from deliberate to automatic processing. Third, it suggests that interventions to enhance student loyalty must be tailored to users' habit strength, with novice users requiring satisfaction-enhancing strategies and experienced users benefiting more from habit reinforcement tactics. As Venkatesh et al. (2012) note in their extension of UTAUT, habit represents a critical factor in understanding continued technology use, yet its moderating role in shaping alternative pathways to loyalty has received limited attention in educational technology contexts.

2.3 Perceived Usefulness

"Perceived usefulness is the extent to which consumers believe that applying technology to a task will increase their productivity" (Guo & Erdenebold, 2025). The perceived usefulness has been extensively analyzed in the field of technology acceptance (Rahman et al., 2025). Some studies on the adoption of AI-powered chatbots in fields such as tourism (Pillai & Sivathanu, 2020) and customer service (Bilquise & Shaalan, 2023; Rachão et al., 2021) have shown that perceived usefulness has a direct and positive impact on the intention to use service-oriented chatbots. Students tend to find AI chatbots to be helpful "assistants" because they

can provide immediate feedback for personalized advice and support (T.-Q. Dang, Nguyen, & Duc, 2025; T.-Q. Dang, Nguyen, Tran, et al., 2025). This helps save time compared to having to go all the way to school to ask when encountering problems. Therefore, usefulness is considered an important factor contributing to increased student engagement with AI chatbots. We hypothesize that:

H1: Perceived usefulness has a significant positive impact on student engagement with AI chatbots.

2.4 Perceived Technology Capability

The relationship between technological literacy, readiness, and simplicity is critical to promoting student engagement within the university setting. Technological literacy involves the capacity to recognize, comprehend, and effectively utilize digital tools platforms that empower students to navigate online learning environments with confidence (Moore, 2011). Students who possess strong digital skills tend to engage more in learning activities, such as online discussions, group projects, and interactive assignments, which enriches their overall learning experience (Awdziej et al., 2023; Kim et al., 2019). On the other hand, technological readiness shows how students feel and are mentally prepared to embrace new technologies, shaped by their optimism and personal creativity (Blut & Wang, 2019). Numerous studies indicate that students who are well-prepared for technology tend to view the digital learning environment more favorably, resulting in greater satisfaction and involvement in their educational journey (Awdziej et al., 2023; Kim et al., 2019). Moreover, technology simplicity that showcased through an easy-to-navigate and accessible interface, significantly contributes to enhancing students' confidence and enthusiasm to engage (Nguyen et al., 2025). Universities that adopt learning platforms designed for ease of use frequently experience a significant boost in student engagement, as the accessibility and usability of technology become more straightforward (Pandita & Kiran, 2023). When these three elements come together, they enhance student interaction: the

ability to use tools effectively encourages engagement, a willingness to embrace new platforms increases motivation, and ease of use eliminates obstacles, ultimately fostering greater participation in digital learning activities. Nonetheless, the gap in technological skills among different student groups continues to be a notable challenge, prompting universities to adopt suitable support strategies to guarantee fair access to technology-driven learning systems. Therefore, we hypothesize that:

H2: Perceived technology capability has a significant positive impact on student engagement with AI chatbots.

2.5 AI Chatbot Conversational Quality

"To enable effective bidirectional interaction between consumers and AI chatbots, the chatbots must comprehend users' natural language input and respond in a manner similar to humans, either through voice or text" (Hao & Li, 2025). High-quality human-AI chatbot interactions have been shown to significantly increase customer satisfaction (Hsu & Lin, 2023). Three factors make up an AI chatbot's conversational quality: understanding anthropomorphism (input), perceiving contingency (process), and responding anthropomorphism (output). The ability of chatbots to comprehend user inputs effectively is known as understanding anthropomorphism. Good speech recognition (or text analysis) by chatbots is a major factor in encouraging customer loyalty (Hsu & Lin, 2023). On the other hand, chatbots could fail to satisfy users' needs by continuously giving them the same information if they are unable to effectively grasp their input intentions. Users are not just irritated by this, but they also believe that chatbot conversations are useless. Therefore, we hypothesize that:

H3: AI chatbot conversational quality has a significant positive impact on student engagement with AI chatbots.

2.6 Engagement with AI Chatbot

Engagement with AI chatbots for student consultation and support has become a significant aspect of higher education. These

chatbots promote smooth communication, boost student involvement, and offer prompt assistance, making the educational experience more enriching. AI chatbots enhance communication between students and institutions, providing swift answers to questions and tailored suggestions (Antony & Ramnath, 2023; Segovia-García, 2024). Chatbots have proven useful in addressing student questions, offering quick answers to frequent inquiries about enrollment, fee payments, and academic deadlines. This boosts student satisfaction by minimizing wait times and enhancing service efficiency (Mohamed, 2023; Tapia-Hoyos, 2024). They offer immediate assistance, tackling both educational and organizational requirements, which is essential for ensuring student contentment (Preetha & N. Alone, 2025). Building on the dual-process framework established earlier, we propose that engagement with AI chatbots can lead to institutional loyalty through two distinct mechanisms, depending on the strength of usage habits. For students with low habit strength, engagement operates through a deliberate, evaluative pathway where it first generates satisfaction with the school's consulting services, which then translates into loyalty. However, for students with high habit strength, engagement may produce loyalty directly through automatic processing, bypassing the need for conscious satisfaction evaluation. Therefore, we hypothesize that:

H4: Engagement with AI chatbot has a significant positive impact on satisfaction with school consulting service.

H5: Engagement with AI chatbot has a significant positive impact on user loyalty to the institution.

2.7 Habit Strength as a Moderator

Habit strength refers to the degree to which a behavior has become automatic through repeated performance in stable contexts (Verplanken & Orbell, 2003). In the context of AI chatbot usage, habit strength represents the extent to which students automatically turn to chatbots when needing academic support, without deliberate consideration of alternatives or conscious evaluation of the tool's utility. The Self-Report Habit Index (SRHI) developed by Verplanken &

Orbell (2003) conceptualizes habit through dimensions of automaticity ("I do it without thinking"), frequency ("I do it often"), and identity ("It is part of who I am"). As habits strengthen through repeated context-dependent performance, they increasingly guide behavior independently of conscious intentions or satisfaction evaluations (Wood & Neal, 2007).

Drawing on dual-process theory, we propose that habit strength fundamentally alters the psychological mechanisms through which AI chatbot engagement influences institutional loyalty. When habit strength is low, students engage in deliberate, System 2 processing: they consciously evaluate their chatbot interactions, form satisfaction judgments about the quality of school services, and make reasoned decisions about institutional loyalty. In this scenario, satisfaction serves as a critical mediator, translating positive chatbot experiences into institutional commitment. However, when habit strength is high, behavior shifts toward automatic, System 1 processing: engagement becomes routinized and operates outside conscious awareness, directly producing loyalty through repeated behavioral patterns rather than through satisfaction-based evaluation (Krämer, 2014; Limayem et al., 2007).

This theoretical perspective suggests that habit strength will negatively moderate the relationship between engagement and satisfaction, as well as between satisfaction and loyalty. Specifically, as habit strength increases, the positive effect of engagement on satisfaction weakens because students no longer engage in conscious evaluation of service quality, the behavior has become automatic and satisfaction judgments become less relevant. Similarly, the positive effect of satisfaction on loyalty weakens as habit strength increases because loyalty decisions are increasingly driven by automatic behavioral patterns rather than conscious satisfaction-based reasoning. This negative moderation reflects a substitution effect: as the automatic pathway (habit-driven) strengthens, it replaces the deliberate pathway (satisfaction-driven) as the primary mechanism linking engagement to loyalty (Tien et al., 2023).

Conversely, habit strength is expected to positively moderate the direct relationship

between engagement and loyalty. As LaRose (2010) notes, media habits create "behavioral lock-in" whereby repeated use becomes self-reinforcing and increasingly resistant to disruption. Students with strong chatbot habits develop automatic associations between academic support needs and chatbot use, creating direct loyalty to the institution that provides this habitualized service. This positive moderation reflects the automatic pathway becoming dominant: high habit strength enables engagement to produce loyalty directly, without requiring the intermediate step of satisfaction evaluation that characterizes the deliberate pathway (Verplanken & Aarts, 1999). Therefore, we hypothesize that:

H7: Habit strength negatively moderates the relationship between engagement with AI chatbot and satisfaction with school consulting service, such that the positive effect weakens as habit strength increases.

H8: Habit strength negatively moderates the relationship between satisfaction with school consulting service and user loyalty, such that the positive effect weakens as habit strength increases.

H9: Habit strength positively moderates the direct relationship between engagement with AI chatbot and user loyalty, such that the positive effect strengthens as habit strength increases.

2.8 Satisfaction with School Consulting Service

In organizational contexts, satisfaction is a common way to assess how effectively products and services satisfy consumers' needs (Ki et al., 2020). According to the expectation-confirmation paradigm, clients are more likely to be satisfied with a product or service if it performs better than they expected (Cheng & Jiang, 2020). Previous research has demonstrated that the benefits obtained, such as effective support and assistance, significantly influence users' satisfaction with service systems (Cheng & Jiang, 2020). In this study, satisfaction refers specifically to students' evaluation of the overall consulting service provided by their educational institution, of which AI chatbots are one component. When students engage

positively with AI chatbots and find them helpful in addressing academic inquiries, this experience contributes to their broader satisfaction with the institution's support services. However, as established in our dual-process framework, the strength of this relationship depends on habit strength, with more habitual users relying less on conscious satisfaction evaluation. Nonetheless, for students who engage in deliberate evaluation, satisfaction with school services remains a critical antecedent of institutional loyalty. Therefore, we hypothesize that:

H6: Satisfaction with school consulting service has a significant positive impact on user loyalty to the institution.

2.9 User Loyalty to Educational Institution

User loyalty in the educational context represents students' commitment to their institution, manifested through intentions to continue enrollment, recommend the institution to others, and maintain positive institutional identification. Unlike customer loyalty in

commercial settings, student loyalty encompasses both behavioral dimensions (continued enrollment, participation in institutional activities) and attitudinal dimensions (emotional attachment, advocacy) (Gürbüz & Acuner, 2025). This study's theoretical contribution lies in recognizing that institutional loyalty can emerge through two fundamentally different psychological mechanisms. Through the deliberate pathway, loyalty develops as students consciously evaluate service quality, form satisfaction judgments, and make reasoned commitments based on positive experiences. Through the automatic pathway, loyalty emerges from habitualized behavioral patterns that operate independently of conscious evaluation. Understanding these dual pathways has important implications for institutional strategy: fostering loyalty among novice users requires enhancing satisfaction through service quality improvements, while maintaining loyalty among experienced users requires reinforcing usage habits and preventing habit disruption.

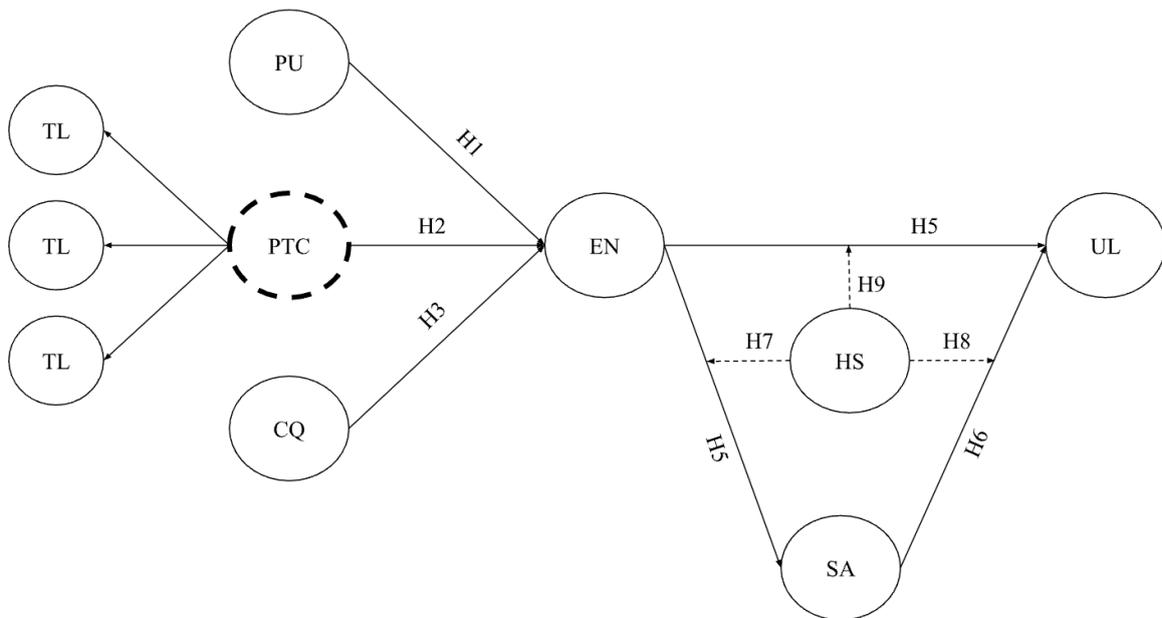


Figure 1. Conceptual Model

CHAPTER 3. RESEARCH METHODOLOGY

3.1 Research Design

This study employs a quantitative research approach with a cross-sectional survey design to investigate the factors influencing student loyalty toward educational institutions through AI chatbot engagement. The cross-sectional design is appropriate for this research as it allows for the examination of relationships among multiple variables at a single point in time, which is consistent with the study's objectives of understanding how perceived usefulness, perceived technology, and conversational quality influence engagement, satisfaction, and ultimately user loyalty, with habit strength serving as a moderating variable.

The research model integrates the Unified Theory of Acceptance and Use of Technology (UTAUT), Habit Theory, and Dual-Process Theory to examine both the deliberate (satisfaction-mediated) and automatic (habit-driven) pathways through which AI chatbot engagement translates into institutional loyalty. Partial Least Squares Structural Equation Modeling (PLS-SEM) is utilized as the primary analytical technique due to its suitability for exploratory research involving complex models with multiple constructs and moderation effects (Hair et al., 2019).

3.2 Data Collection Method

Data were collected through an online self-administered questionnaire distributed via Google Forms to university students in Ho Chi Minh City, Vietnam. The target population comprised undergraduate and graduate students who have experience using AI chatbots for academic purposes. A convenience sampling approach was employed, with the questionnaire distributed through university social media groups, student forums, and direct outreach to students across various institutions in the metropolitan area.

The questionnaire included a screening question to ensure that only respondents with AI chatbot usage experience for academic purposes were

included in the study. Respondents who answered "No" to the screening question were automatically excluded from the survey. The data collection process yielded 223 valid responses that met the screening criteria and were complete without missing values.

The sample size of 223 exceeds the minimum requirement for PLS-SEM analysis. According to (Hair et al., 2019), the minimum sample size should be ten times the largest number of structural paths directed at a particular construct in the structural model. In this study, with a maximum of four paths directed at any single construct, the minimum requirement would be 40 responses. Additionally, using G*Power analysis with a medium effect size ($f^2 = 0.15$), alpha of 0.05, and power of 0.80, the required sample size for detecting moderation effects is approximately 92. Thus, the sample size of 223 provides adequate statistical power for the planned analyses.

3.3 Measurement Scales

All constructs in this study were measured using multi-item scales adapted from previously validated instruments in the technology adoption and consumer behavior literature. Responses were recorded on a 7-point Likert scale ranging from 1 (Strongly Disagree) to 7 (Strongly Agree). The measurement items for each construct are presented in Table 1.

Perceived Usefulness (PU) was measured using three items adapted from Davis (1989) and Guo & Erdenebold (2025), capturing students' beliefs about how AI chatbots enhance their academic productivity and learning efficiency.

Perceived Technology Capability (PTC) is conceptualized as a second-order construct comprising three first-order dimensions: Tech Simplicity (TS, 4 items), Tech Literacy (TL, 3 items), and Tech Readiness (TR, 3 items). These dimensions collectively capture students' perceptions of the ease of use, their digital competencies, and their psychological readiness to adopt AI chatbot technology.

Conversational Quality (CQ) was measured using six items adapted from Hao & Li (2025)

and Hsu & Lin (2023), assessing the human-likeness and effectiveness of chatbot communication.

Engagement with AI Chatbots (EN) was measured using four items adapted from (Antony & Ramnath, 2023) and Segovia-García (2024) capturing the extent of students' active involvement with AI chatbots for academic purposes.

Habit Strength (HS) was measured using four items adapted from (Verplanken & Orbell, 2003) and the Self-Report Behavioral Automaticity Index (Gardner et al., 2012). These items capture the automaticity, frequency, and natural tendency of AI chatbot usage behavior.

Satisfaction with School Consulting Service (SA) was measured using three items adapted from Cheng & Jiang (2020) and Ki et al. (2020), assessing students' overall satisfaction with the academic support services provided through AI chatbots.

User Loyalty (UL) was measured using four items adapted from Gürbüzler & Acuner (2025), capturing students' intentions to recommend, continue using, and remain committed to the institution.

3.4 Sample Characteristics

Table 2 presents the demographic profile of the respondents based on their AI chatbot usage characteristics. All 223 respondents (100%) confirmed having experience using AI chatbots for academic purposes, which was a prerequisite for participation in the study.

Regarding the duration of AI chatbot usage, the majority of respondents (35.4%) have been using AI chatbots for more than one year, followed by those with 7-12 months of experience (25.6%) and 4-6 months (17.5%). A smaller proportion of respondents had less than 1 month (13.0%) or 1-3 months (8.5%) of experience. This distribution indicates that the sample predominantly consists of experienced AI chatbot users, which is favorable for examining habit strength as a moderating variable, as habits require sufficient time to develop through repeated behavior.

In terms of usage frequency, the largest group of respondents (46.2%) use AI chatbots several times per week, while 30.5% use them daily. Smaller proportions use AI chatbots once a week (15.2%), several times per month (6.3%), or rarely (1.8%). The high frequency of usage among the majority of respondents suggests that AI chatbot use has become integrated into their regular academic routines, providing a suitable context for investigating the role of habit strength in the engagement-satisfaction-loyalty pathway.

Table 2. Demographic Profile of Respondents (N = 223)

| Characteristics | Frequency | % |
|----------------------|-----------|-------|
| <i>Genders</i> | | |
| Male | 95 | 42.6% |
| Female | 128 | 57.4% |
| <i>Academic Year</i> | | |

| | | |
|---------------------------------------|-----|-------|
| Year 1 | 12 | 5.4% |
| Year 2 | 11 | 5% |
| Year 3 | 46 | 20.6% |
| Year 4 | 154 | 69% |
| <i>Level of using the AI chatbots</i> | | |
| High | 114 | 51.1% |
| Average | 109 | 48.9% |
| <i>AI Chatbot Usage Experience</i> | | |
| Yes (screened) | 223 | 100.0 |
| <i>Duration of AI Chatbot Usage</i> | | |
| Less than 1 month | 29 | 13% |
| 1 - 3 months | 19 | 8.5% |
| 4 - 6 months | 39 | 17.5% |
| 7 - 12 months | 57 | 25.6% |
| More than 1 year | 79 | 35.4% |
| <i>Frequency of AI Chatbot Usage</i> | | |
| Daily | 68 | 30.5% |
| Several times per week | 103 | 46.2% |
| Once a week | 34 | 15.2% |
| Several times per month | 14 | 6.3% |
| Rarely (once a month or less) | 4 | 1.8% |

4. DATA ANALYSIS

4.1 Common Method Bias Assessment

Since all data were collected through a single self-reported questionnaire at one point in time, common method bias (CMB) was assessed to ensure that the relationships observed were not artificially inflated due to the measurement method (Podsakoff et al., 2003). Two approaches were employed to evaluate CMB (T.-Q. Dang et al., 2023)

First, Harman's single-factor test was conducted by loading all measurement items into an exploratory factor analysis. The results revealed that no single factor accounted for the majority of the variance, with the first factor explaining only 38.2% of the total variance, well below the 50% threshold that would indicate CMB concerns (Podsakoff et al., 2003).

Second, the full collinearity assessment approach recommended by Kock (2015) was applied. All variance inflation factor (VIF) values from the full collinearity test were below 3.3, indicating that CMB is not a significant concern in this study. Based on these assessments, common method bias does not appear to pose a serious threat to the validity of the findings (T. Q. Dang et al., 2025).

4.2 Measurement Model Assessment

The measurement model was assessed for internal consistency reliability, convergent validity, and discriminant validity. Table 3 presents the results of the measurement model assessment.

4.2.1 Internal Consistency Reliability

Internal consistency reliability was evaluated using Cronbach's alpha and composite reliability (CR). As shown in Table 3, Cronbach's alpha values ranged from 0.637 (TL) to 0.844 (CQ), with most constructs exceeding the recommended threshold of 0.70 (Binh et al., 2024; T.-Q. Dang et al., 2026; T.-Q. Dang, Nguyen, Tran, et al., 2025; Hair et al., 2019). The Tech Literacy (TL) construct showed a slightly lower alpha of 0.637, which is acceptable for exploratory research and when the construct has few items (T.-Q. Dang et al., 2023; Tien et al., 2023; Wojujutari et al., 2024). Composite reliability values ranged from 0.804 to 0.889, all exceeding the minimum threshold of 0.70, indicating adequate internal consistency across all constructs.

Table 3: Measurement model assessment

| <i>Constructs</i> | <i>Items</i> | <i>Factor loadings</i> | <i>Cronbach's alpha</i> | <i>Composite reliability (rho_a)</i> | <i>Composite reliability (rho_c)</i> | <i>Average variance extracted (AVE)</i> | <i>VIF</i> |
|------------------------------|--------------|------------------------|-------------------------|--------------------------------------|--------------------------------------|---|------------|
| <i>First order construct</i> | | | | | | | |
| <i>CQ</i> | <i>CQ1</i> | 0.775 | 0.844 | 0.857 | 0.889 | 0.615 | 1.798 |
| | <i>CQ2</i> | 0.724 | | | | | 1.641 |
| | <i>CQ4</i> | 0.792 | | | | | 1.696 |
| | <i>CQ5</i> | 0.835 | | | | | 2.021 |
| | <i>CQ6</i> | 0.790 | | | | | 1.827 |
| | <i>EN</i> | <i>EN1</i> | | | | | 0.817 |
| | <i>EN2</i> | 0.798 | | | | | 1.741 |
| | <i>EN3</i> | 0.855 | | | | | 1.980 |
| | <i>EN4</i> | 0.704 | | | | | 1.355 |
| <i>HS</i> | <i>HS1</i> | 0.666 | 0.788 | 0.808 | 0.863 | 0.613 | 1.325 |
| | <i>HS2</i> | 0.782 | | | | | 1.658 |

| | | | | | | | |
|-----------------------|-------------------------------|-------|-------|-------|-------|-------|-------|
| <i>PU</i> | HS3 | 0.840 | | | | | 1.802 |
| | HS4 | 0.832 | | | | | 1.823 |
| | PU2 | 0.861 | 0.770 | 0.808 | 0.866 | 0.685 | 1.804 |
| | PU3 | 0.893 | | | | | 1.912 |
| <i>SA</i> | PU4 | 0.719 | | | | | 1.359 |
| | SA1 | 0.781 | 0.734 | 0.735 | 0.850 | 0.654 | 1.341 |
| | SA2 | 0.810 | | | | | 1.523 |
| <i>TL</i> | SA3 | 0.833 | | | | | 1.579 |
| | TL1 | 0.701 | 0.637 | 0.645 | 0.804 | 0.579 | 1.232 |
| | TL2 | 0.812 | | | | | 1.364 |
| <i>TR</i> | TL3 | 0.766 | | | | | 1.222 |
| | TR1 | 0.833 | 0.728 | 0.740 | 0.846 | 0.648 | 1.516 |
| | TR2 | 0.739 | | | | | 1.325 |
| <i>TS</i> | TR3 | 0.840 | | | | | 1.543 |
| | TS1 | 0.828 | 0.840 | 0.843 | 0.893 | 0.677 | 2.220 |
| | TS2 | 0.878 | | | | | 2.711 |
| <i>UL</i> | TS3 | 0.747 | | | | | 1.502 |
| | TS4 | 0.834 | | | | | 1.826 |
| | UL1 | 0.806 | 0.747 | 0.762 | 0.838 | 0.565 | 1.628 |
| | UL2 | 0.784 | | | | | 1.480 |
| <i>PTC</i> | UL3 | 0.713 | | | | | 1.495 |
| | <i>Second order construct</i> | | | | | | |
| | LV scores - TL | 0.909 | 0.861 | 0.861 | 0.915 | 0.783 | 2.663 |
| | LV scores - TR | 0.875 | | | | | 2.177 |
| LV scores - TS | 0.869 | | | | | 2.020 | |

4.2.2 Convergent Validity

Convergent validity was assessed through factor loadings and average variance extracted (AVE). All factor loadings, as in Table 3 exceeded 0.70, except for HS1 (0.666), which is close to the threshold and acceptable given the exploratory nature of the habit strength construct in this context (Hair et al., 2019). One item (CQ3) was removed during the analysis due to low loading. AVE values ranged from 0.579 (TL) to 0.685 (PU), all exceeding the minimum threshold of 0.50, confirming that each construct explains more than half of the variance in its indicators.

4.2.3 Discriminant Validity

Discriminant validity was evaluated using the Fornell-Larcker criterion (Table 4) and cross-loadings analysis (Table 5). The Fornell-Larcker criterion requires that the square root of each construct's AVE (shown on the diagonal) be greater than its correlations with other constructs. As presented in Table 4, all diagonal values exceeded the off-diagonal correlations, confirming discriminant validity.

It is worth noting that the correlation between Habit Strength (HS) and Perceived Usefulness

(PU) was relatively high ($r = 0.782$), approaching the square root of HS's AVE (0.783). This close relationship is theoretically expected, as students who find AI chatbots useful are more likely to develop habitual usage patterns (Limayem et al., 2007). Nevertheless, the Fornell-Larcker criterion was satisfied, and cross-loadings confirmed that each indicator loaded highest on

its intended construct, supporting discriminant validity.

Additionally, all variance inflation factor (VIF) values were below 3.3 (Table 3), indicating no multicollinearity issues that would threaten the validity of the structural model estimates (Kock, 2015).

Table 4: Fornell and Larcker.

| | <i>CQ</i> | <i>EN</i> | <i>HS</i> | <i>PTC</i> | <i>PU</i> | <i>SA</i> | <i>UL</i> |
|------------|-----------|-----------|-----------|------------|-----------|-----------|-----------|
| <i>CQ</i> | 0.784 | | | | | | |
| <i>EN</i> | 0.772 | 0.795 | | | | | |
| <i>HS</i> | 0.591 | 0.596 | 0.783 | | | | |
| <i>PTC</i> | 0.768 | 0.774 | 0.658 | 0.885 | | | |
| <i>PU</i> | 0.591 | 0.627 | 0.782 | 0.632 | 0.828 | | |
| <i>SA</i> | 0.657 | 0.779 | 0.604 | 0.640 | 0.570 | 0.808 | |
| <i>UL</i> | 0.630 | 0.711 | 0.536 | 0.678 | 0.623 | 0.693 | 0.752 |

Table 5: Cross loadings.

| | <i>CQ</i> | <i>EN</i> | <i>HS</i> | <i>PTC</i> | <i>PU</i> | <i>SA</i> | <i>UL</i> |
|-----------------------|--------------|--------------|--------------|--------------|--------------|--------------|-----------|
| CQ1 | 0.775 | 0.537 | 0.553 | 0.630 | 0.475 | 0.514 | 0.491 |
| CQ2 | 0.724 | 0.468 | 0.401 | 0.517 | 0.371 | 0.481 | 0.482 |
| CQ4 | 0.792 | 0.708 | 0.463 | 0.674 | 0.531 | 0.563 | 0.614 |
| CQ5 | 0.835 | 0.681 | 0.456 | 0.529 | 0.454 | 0.541 | 0.467 |
| CQ6 | 0.790 | 0.579 | 0.452 | 0.660 | 0.467 | 0.468 | 0.404 |
| EN1 | 0.665 | 0.817 | 0.475 | 0.658 | 0.525 | 0.574 | 0.566 |
| EN2 | 0.523 | 0.798 | 0.483 | 0.509 | 0.392 | 0.694 | 0.528 |
| EN3 | 0.625 | 0.855 | 0.525 | 0.710 | 0.609 | 0.716 | 0.611 |
| EN4 | 0.644 | 0.705 | 0.405 | 0.570 | 0.452 | 0.482 | 0.556 |
| HS1 | 0.503 | 0.456 | 0.666 | 0.562 | 0.493 | 0.407 | 0.317 |
| HS2 | 0.462 | 0.454 | 0.782 | 0.405 | 0.572 | 0.429 | 0.348 |
| HS3 | 0.379 | 0.459 | 0.840 | 0.550 | 0.669 | 0.527 | 0.505 |
| HS4 | 0.534 | 0.504 | 0.832 | 0.544 | 0.689 | 0.513 | 0.475 |
| LV scores - TL | 0.666 | 0.676 | 0.616 | 0.909 | 0.610 | 0.522 | 0.622 |
| LV scores - TR | 0.628 | 0.680 | 0.556 | 0.875 | 0.476 | 0.553 | 0.594 |
| LV scores - TS | 0.743 | 0.696 | 0.573 | 0.869 | 0.589 | 0.620 | 0.582 |
| PU2 | 0.441 | 0.537 | 0.629 | 0.524 | 0.861 | 0.458 | 0.542 |
| PU3 | 0.561 | 0.601 | 0.685 | 0.614 | 0.893 | 0.477 | 0.538 |
| PU4 | 0.466 | 0.389 | 0.644 | 0.404 | 0.719 | 0.503 | 0.469 |
| SA1 | 0.481 | 0.593 | 0.510 | 0.493 | 0.476 | 0.781 | 0.600 |
| SA2 | 0.482 | 0.630 | 0.481 | 0.488 | 0.454 | 0.810 | 0.523 |

| | | | | | | | |
|------------|-------|-------|-------|-------|-------|--------------|--------------|
| SA3 | 0.628 | 0.667 | 0.474 | 0.569 | 0.451 | 0.833 | 0.556 |
| UL1 | 0.470 | 0.537 | 0.391 | 0.503 | 0.472 | 0.585 | 0.806 |
| UL2 | 0.590 | 0.684 | 0.529 | 0.594 | 0.571 | 0.564 | 0.784 |
| UL3 | 0.428 | 0.453 | 0.372 | 0.558 | 0.495 | 0.445 | 0.713 |
| UL4 | 0.368 | 0.413 | 0.279 | 0.358 | 0.299 | 0.469 | 0.699 |

4.2.4 Second-Order Construct Assessment

Perceived Technology Capability (PTC) was modeled as a second-order reflective construct comprising three first-order dimensions: Tech Simplicity (TS), Tech Literacy (TL), and Tech Readiness (TR). The latent variable scores of these first-order constructs served as indicators for PTC. As shown in Table 5, the loadings of TS (0.869), TL (0.909), and TR (0.875) on PTC were all substantial and exceeded 0.70, confirming the appropriateness of the second-order specification and indicating that all three dimensions contribute meaningfully to the overall technology capability perception (Dang Quan et al., 2024; Nguyen et al., 2025).

4.3 Structural model assessment

Following the confirmation of measurement model quality, the structural model was assessed to test the hypothesized relationships. The analysis employed bootstrapping with 5,000 resamples to obtain standard errors and t-statistics for significance testing (Hair et al., 2019; Phan et al., 2025).

4.3.1 Direct Effects

Table 6 presents the structural model results. All three antecedents significantly influenced Engagement with AI Chatbots. Conversational Quality exhibited the strongest effect on Engagement ($\beta = 0.391$, $t = 5.370$, $p < 0.001$), followed by Perceived Technology Capability ($\beta = 0.372$, $t = 3.610$, $p < 0.001$) and Perceived Usefulness ($\beta = 0.161$, $t = 2.102$, $p = 0.036$). Thus, H1, H2, and H3 were supported.

Engagement demonstrated significant positive effects on both Satisfaction ($\beta = 0.555$, $t = 7.175$, $p < 0.001$) and User Loyalty ($\beta = 0.458$, $t = 6.088$, $p < 0.001$), supporting H4 and H5. Satisfaction also significantly influenced User Loyalty ($\beta = 0.260$, $t = 3.237$, $p = 0.001$), supporting H6. Additionally, Habit Strength showed significant direct effects on both Satisfaction ($\beta = 0.212$, $t = 3.298$, $p = 0.001$) and User Loyalty ($\beta = 0.145$, $t = 2.754$, $p = 0.006$), indicating that habitual users tend to report higher satisfaction and loyalty levels.

Table 6: Structural model results

| | Original sample (O) | Sample mean (M) | Standard deviation (STDEV) | T statistics (O/STDEV) | P values |
|--------------------|----------------------------|------------------------|-----------------------------------|---------------------------------|-----------------|
| CQ -> EN | 0.391 | 0.387 | 0.073 | 5.370 | 0.000 |
| EN -> SA | 0.555 | 0.537 | 0.077 | 7.175 | 0.000 |
| EN -> UL | 0.458 | 0.460 | 0.075 | 6.088 | 0.000 |
| HS -> SA | 0.212 | 0.230 | 0.064 | 3.298 | 0.001 |
| HS -> UL | 0.145 | 0.148 | 0.053 | 2.754 | 0.006 |

| | | | | | |
|-------------------------|--------|--------|-------|-------|-------|
| HS x EN -> SA | -0.135 | -0.141 | 0.057 | 2.382 | 0.017 |
| HS x EN -> UL | 0.273 | 0.271 | 0.110 | 2.468 | 0.014 |
| HS x SA -> UL | -0.244 | -0.241 | 0.111 | 2.204 | 0.028 |
| PTC -> EN | 0.372 | 0.372 | 0.103 | 3.610 | 0.000 |
| PU -> EN | 0.161 | 0.167 | 0.076 | 2.102 | 0.036 |
| SA -> UL | 0.260 | 0.256 | 0.080 | 3.237 | 0.001 |

4.3.2 Moderation Effects of Habit Strength

The moderation analysis revealed that all three hypothesized moderation effects were significant, providing strong support for the dual-process mechanism proposed in the theoretical framework.

First, Habit Strength significantly moderated the relationship between Engagement and Satisfaction ($\beta = -0.135$, $t = 2.382$, $p = 0.017$), supporting H7. The negative coefficient indicates that as habit strength increases, the positive effect of engagement on satisfaction weakens. This finding aligns with Dual-Process Theory, suggesting that habitual users rely less on conscious evaluation of their engagement experience when forming satisfaction judgments.

Second, Habit Strength negatively moderated the relationship between Satisfaction and User Loyalty ($\beta = -0.244$, $t = 2.204$, $p = 0.028$), supporting H8. This suggests that the traditional satisfaction-loyalty link becomes less important as users develop stronger habits. For habitual users, loyalty formation increasingly bypasses the satisfaction evaluation pathway.

Third, Habit Strength positively moderated the direct relationship between Engagement and User Loyalty ($\beta = 0.273$, $t = 2.468$, $p = 0.014$), supporting H9. This positive moderation indicates that as habit strength increases, the direct path from engagement to loyalty strengthens, representing the automatic pathway in the dual-process framework. High-habit users develop loyalty directly through repeated

engagement behavior without necessarily requiring satisfaction as a mediating mechanism.

4.3.3 Mediation Analysis

The results indicate that Satisfaction partially mediates the relationship between Engagement and User Loyalty. The direct effect of Engagement on User Loyalty ($\beta = 0.458$) was significant, while the indirect effect through Satisfaction ($\beta = 0.555 \times 0.260 = 0.144$) was also substantial. This partial mediation pattern suggests that engagement influences loyalty through both direct and satisfaction-mediated pathways, with the relative importance of each pathway varying based on habit strength as demonstrated by the moderation results.

4.3.4 Model Explanatory and Predictive Power

The model demonstrated substantial explanatory power. The coefficient of determination (R^2) for Engagement was 0.69, indicating that 69% of the variance in engagement was explained by the three antecedents (PU, PTC, CQ). Satisfaction achieved an R^2 of 0.65, while User Loyalty showed an R^2 of 0.579. According to Cohen (1988), R^2 values of 0.26 are considered substantial in behavioral research, thus all endogenous variables exceeded this threshold considerably.

Table 7 presents the PLS-predict results for assessing out-of-sample predictive relevance. All Q^2 predict values were positive (EN = 0.668, SA = 0.465, UL = 0.379), indicating that the

model outperforms a naive mean-based prediction benchmark (Shmueli et al., 2019). The relatively high $Q^2_{predict}$ value for Engagement (0.668) suggests particularly strong predictive

power for this central construct. The RMSE and MAE values provide additional evidence of acceptable prediction error levels.

Table 7: PLS-predict

| | R-square | $Q^2_{predict}$ | RMSE | MAE |
|----|----------|-----------------|-------|-------|
| EN | 0.69 | 0.668 | 0.587 | 0.425 |
| SA | 0.65 | 0.465 | 0.742 | 0.527 |
| UL | 0.579 | 0.379 | 0.798 | 0.561 |

5. DISCUSSIONS AND IMPLICATIONS

5.1 Discussion of Findings

This study investigated the factors influencing student loyalty toward educational institutions through AI chatbot engagement, with particular attention to the moderating role of habit strength. The findings provide comprehensive support for the integrated theoretical framework combining UTAUT, Habit Theory, and Dual-Process Theory.

5.1.1 Antecedents of AI Chatbot Engagement

The results revealed that all three antecedents significantly influence student engagement with AI chatbots, collectively explaining 69% of the variance in engagement. Conversational Quality emerged as the strongest predictor ($\beta = 0.391$), followed by Perceived Technology Capability ($\beta = 0.372$) and Perceived Usefulness ($\beta = 0.161$). This hierarchy of effects offers important insights for understanding student interaction with AI chatbots in educational contexts.

The dominant role of Conversational Quality aligns with recent findings in AI chatbot research. Cheng & Jiang (2020) similarly emphasized that the quality of human-AI interaction significantly shapes user responses to chatbot services. In educational settings, students expect AI chatbots to understand their queries contextually and respond coherently, much like a human academic advisor would. The ability of chatbots to maintain conversation flow and demonstrate understanding of context appears

crucial for sustaining student engagement. This finding is consistent with Hsu & Lin (2023), who found that perceived human-likeness and dialogue coherence are key drivers of continued chatbot use.

The significant effect of Perceived Technology Capability, operationalized as a second-order construct comprising Tech Simplicity, Tech Literacy, and Tech Readiness, extends UTAUT's facilitating conditions to the AI chatbot context. This finding resonates with Venkatesh et al. (2012), who emphasized that technology adoption depends not only on the technology itself but also on users' capability to leverage it effectively. The strong and relatively equal loadings of all three dimensions on PTC (TS = 0.869, TL = 0.909, TR = 0.875) suggest that successful AI chatbot engagement requires a holistic approach addressing interface design, user competencies, and psychological readiness simultaneously.

While Perceived Usefulness showed the smallest effect among the three antecedents, its significance ($p = 0.036$) confirms the continued relevance of Davis (1989) Technology Acceptance Model in AI contexts. Students who perceive AI chatbots as useful for academic tasks are more likely to engage with them. However, the relatively weaker effect compared to conversational quality suggests that in the era of conversational AI, how technology communicates may matter as much as what it delivers. This represents a notable shift from

traditional technology acceptance research where usefulness typically dominates.

5.1.2 The Engagement-Satisfaction-Loyalty Chain

The findings strongly support the engagement-satisfaction-loyalty chain in the AI chatbot context. Engagement exhibited substantial effects on both Satisfaction ($\beta = 0.555$) and User Loyalty ($\beta = 0.458$), while Satisfaction significantly influenced Loyalty ($\beta = 0.260$). These results align with the service marketing literature, which consistently identifies engagement and satisfaction as key drivers of customer loyalty (Pansari & Kumar, 2016).

The strong direct effect of engagement on loyalty ($\beta = 0.458$) is particularly noteworthy, as it suggests that engagement creates loyalty beyond its effect through satisfaction. This finding supports Brodie et al. (2011), who argued that engaged customers develop emotional connections that translate directly into loyalty behaviors. In the educational context, students who actively engage with AI chatbots may develop a sense of connection with the institution's digital services that fosters loyalty independently of their satisfaction evaluations. The partial mediation pattern confirms that both pathways, direct and satisfaction-mediated, contribute to loyalty formation.

5.1.3 The Dual-Process Mechanism of Habit Strength

Perhaps the most theoretically significant contribution of this study lies in the confirmation of the dual-process mechanism through which habit strength shapes loyalty formation. All three moderation hypotheses were supported, providing empirical evidence for the proposed framework integrating Habit Theory and Dual-Process Theory.

The negative moderation of habit strength on the engagement-satisfaction relationship ($\beta = -0.135$) supports the theoretical proposition that habitual users shift from deliberate (System 2) to automatic (System 1) processing (Krämer, 2014). For low-habit users, each engagement experience is consciously evaluated to form satisfaction judgments. However, as habits strengthen, this deliberate evaluation diminishes,

and satisfaction becomes less dependent on individual engagement experiences. This finding aligns with Verplanken & Orbell (2003), who noted that habitual behaviors become automatic and require less conscious attention.

Similarly, the negative moderation of habit strength on the satisfaction-loyalty link ($\beta = -0.244$) indicates that the traditional satisfaction-loyalty paradigm weakens for habitual users. This finding extends Limayem et al. (2007), who demonstrated that habit can override intention in IS continuance. Our results suggest that habit similarly weakens the satisfaction-loyalty relationship, as habitual users continue their behavior regardless of satisfaction levels. This has profound implications for understanding customer retention in digital service contexts where habitual usage patterns are common.

The positive moderation of habit strength on the direct engagement-loyalty relationship ($\beta = 0.273$) completes the dual-process picture. As users develop stronger habits, the automatic pathway from engagement directly to loyalty strengthens. This aligns with Ouellette et al. (1998), who found that well-practiced behaviors in stable contexts become automatic and no longer require deliberate decision-making. For habitual AI chatbot users, loyalty emerges naturally from repeated engagement patterns rather than through conscious satisfaction evaluation.

Collectively, these findings support a mechanism substitution model: as habit strength increases, loyalty formation shifts from a satisfaction-mediated deliberate pathway to an engagement-driven automatic pathway. This theoretical contribution reconciles seemingly contradictory findings in the satisfaction-loyalty literature by demonstrating that the relationship varies systematically based on habit strength. The sample characteristics support the relevance of this mechanism, as 61% of respondents had used AI chatbots for more than six months and 76.7% used them at least several times weekly, conditions conducive to habit formation.

5.2 Theoretical Implications

This study makes several contributions to the theoretical understanding of AI chatbot adoption and user loyalty in educational contexts.

First, the study extends UTAUT to the educational AI chatbot context by demonstrating that technology capability perceptions, operationalized as a multidimensional second-order construct, significantly drive engagement. Unlike traditional UTAUT applications that focus on adoption intention, this study examines actual engagement behavior and its downstream consequences. The findings suggest that UTAUT's facilitating conditions concept should be expanded to include user-side capabilities (tech literacy, readiness) alongside technology-side features (simplicity), particularly in contexts involving sophisticated AI technologies.

Second, the study integrates Habit Theory into the engagement-satisfaction-loyalty framework, addressing a notable gap in the literature. While previous studies have examined habit as a direct predictor of continuance intention (Limayem et al., 2007; Venkatesh et al., 2012), this study demonstrates habit's moderating role in shaping how loyalty develops. The finding that habit strength alters the mechanism of loyalty formation rather than simply adding to it represents a theoretical advancement in understanding habitual technology use.

Third, the application of Dual-Process Theory (Evans & Stanovich, 2013; Krämer, 2014) to explain the moderating effects of habit strength provides a cognitive foundation for understanding user behavior evolution. The distinction between deliberate (satisfaction-mediated) and automatic (engagement-driven) pathways to loyalty offers a parsimonious explanation for why satisfaction-loyalty relationships vary across users and contexts. This theoretical lens can be applied to other technology adoption contexts where habitual use patterns emerge.

Fourth, the study highlights the primacy of conversational quality over perceived usefulness in driving AI chatbot engagement. This finding suggests that for conversational AI technologies, interaction quality may supersede functional utility as the primary engagement driver, challenging traditional TAM assumptions that emphasize usefulness as the dominant factor. This has implications for how researchers conceptualize and measure technology acceptance in the age of conversational AI.

5.3 Practical Implications

The findings offer actionable insights for educational institutions seeking to leverage AI chatbots for student engagement and loyalty.

Prioritize conversational quality in chatbot design. Given that conversational quality emerged as the strongest predictor of engagement ($\beta = 0.391$), institutions should invest in AI chatbots capable of contextual understanding, coherent dialogue maintenance, and human-like responsiveness. Natural language processing capabilities should be continuously refined to ensure chatbots can grasp student queries accurately and provide contextually appropriate responses. Training the chatbot on institution-specific academic content and frequently asked questions can enhance its ability to respond meaningfully to student needs.

Develop comprehensive technology capability support. The significant effect of Perceived Technology Capability ($\beta = 0.372$) suggests that institutions should address both technology design and user preparation. On the design side, AI chatbot interfaces should be intuitive and require minimal technical expertise. On the user side, institutions should offer digital literacy programs that enhance students' confidence and competence in using AI tools. Orientation sessions demonstrating chatbot capabilities can improve both tech readiness and awareness of the chatbot's potential usefulness.

Adopt differentiated strategies based on user habit levels. The dual-process findings have critical implications for retention strategies. For new or infrequent users (low habit strength), satisfaction is crucial for loyalty development, institutions should focus on ensuring positive experiences and addressing any dissatisfaction promptly. For regular users (high habit strength), maintaining consistent availability and ease of access is more important than constantly improving satisfaction. Disruptions to habitual patterns (e.g., interface changes, downtime) may be more detrimental to loyalty than minor dissatisfaction with individual interactions.

Foster habit formation through strategic engagement initiatives. Given that habit strength creates a direct pathway to loyalty (moderated $\beta = 0.273$), institutions should

implement strategies that encourage regular chatbot use. This might include integrating the chatbot into routine academic activities, sending periodic prompts about chatbot capabilities, creating seamless access points across institutional platforms, or gamifying chatbot interactions. The demographic profile showing that 76.7% of respondents use AI chatbots at least several times weekly suggests that habit formation is achievable in educational contexts.

Leverage AI chatbots as institutional loyalty drivers. The strong effect of engagement on user loyalty ($\beta = 0.458$) indicates that well-implemented AI chatbots can contribute meaningfully to institutional loyalty. Marketing and communication strategies should highlight the institution's AI-powered support services as a distinctive feature. The finding that engaged users develop loyalty both directly and through satisfaction suggests that AI chatbots represent a valuable touchpoint for strengthening student-institution relationships, potentially influencing retention, recommendations, and alumni engagement.

5.4 Limitations and Future Research

Several limitations should be acknowledged when interpreting these findings. First, the cross-sectional design precludes causal inference. While the theoretical framework proposes directional relationships and the model fit statistics are favorable, the data cannot definitively establish causality. Longitudinal studies tracking users over time as habits develop would provide stronger evidence for the proposed dual-process mechanism and enable examination of how the pathways evolve.

Second, the sample was drawn from university students in Ho Chi Minh City, Vietnam, limiting generalizability to other educational contexts, age groups, or cultural settings. Vietnamese students may have different technology adoption patterns or cultural orientations toward AI compared to students in other countries. Future research should replicate this study in different cultural and institutional contexts to assess the boundary conditions of the findings.

Third, habit strength was measured through self-report items capturing perceived automaticity

and frequency. While validated scales from Verplanken & Orbell (2003) and Gardner et al. (2012) were employed, objective behavioral measures such as actual usage logs would complement self-reported habit strength. The high correlation between habit strength and perceived usefulness ($r = 0.782$) also warrants attention in future studies, though discriminant validity was established. Future studies might combine survey data with behavioral tracking to strengthen the habit strength construct measurement.

Fourth, the study focused on AI chatbots generally rather than specific platforms or institutional chatbots. Different AI chatbot systems (e.g., ChatGPT, institutional chatbots, specialized academic assistants) may vary considerably in their conversational capabilities and usefulness for academic purposes. Future research could compare specific chatbot platforms or examine institution-developed versus commercial AI chatbots to understand how chatbot characteristics influence the proposed relationships.

Future research directions include: (1) longitudinal designs examining habit formation trajectories and their effects on loyalty pathways over time; (2) experimental studies manipulating conversational quality features to establish causal effects; (3) multi-group analyses comparing the model across different academic disciplines, year levels, or institutional types; (4) qualitative research exploring the lived experiences of habitual versus non-habitual AI chatbot users; and (5) extension of the framework to other AI-powered educational technologies beyond chatbots, such as AI tutoring systems or automated feedback tools.

5.5 Conclusion

This study examined the factors driving student loyalty toward educational institutions through AI chatbot engagement, with particular attention to the moderating role of habit strength. Integrating UTAUT, Habit Theory, and Dual-Process Theory, the research proposed and tested a comprehensive framework explaining both the antecedents of AI chatbot engagement and the

mechanisms through which engagement translates into institutional loyalty.

The findings reveal that conversational quality, perceived technology capability, and perceived usefulness all significantly drive student engagement with AI chatbots, with conversational quality exhibiting the strongest effect. This suggests that in the era of conversational AI, the quality of human-machine dialogue may be as important as functional utility. Engagement, in turn, influences user loyalty both directly and indirectly through satisfaction, with satisfaction serving as a partial mediator.

Most importantly, habit strength moderates these relationships in theoretically meaningful ways that support the dual-process conceptualization: as habits strengthen, the deliberate satisfaction-mediated pathway weakens (H7, H8 supported with negative coefficients) while the automatic engagement-driven pathway strengthens (H9 supported with positive coefficient). This mechanism substitution model reconciles inconsistent findings in the satisfaction-loyalty literature and provides a nuanced understanding of how user behavior evolves with experience.

For practitioners, the findings underscore the importance of conversational quality in AI chatbot design and suggest differentiated retention strategies based on user habit levels. Early-stage users require satisfaction-focused interventions, while established users benefit more from consistency and seamless access. As AI chatbots become increasingly prevalent in educational settings, understanding how students engage with these technologies and develop loyalty toward institutions deploying them becomes essential for educational administrators and technology developers alike.

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