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Gender differences in technology acceptance: Exploring UTAUT2 constructs for AI chatbot adoption

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Abstract This study examines the factors influencing the adoption of LanGTa, an AI-powered chatbot developed to support historical tourism, through the lens of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework. Data were collected from 427 participants (51% male, 49% female) via structured surveys, focusing on core constructs including Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), Price Value (PV), and Habit (HT). Structural equation modeling (SEM) was employed to analyze the relationships between these constructs and Behavioral Intention (BI) to adopt LanGTa. The model demonstrated an excellent fit, with indices such as CFI = 1.00, GFI = 1.00, RMSEA = 0.00, and SRMR = 0.02. PE and EE emerged as the strongest predictors of BI, indicating that perceived usefulness and ease of use significantly influence adoption. HM was also a significant factor, particularly among male respondents, suggesting that enjoyment enhances the intention to use the chatbot. SI had a weaker yet statistically significant effect, especially among females, highlighting the influence of peer recommendations. Notable gender differences were observed: females prioritized PE, EE, and SI, whereas males emphasized EE, FC, HM, and PV. These findings underscore the importance of gender-sensitive strategies for promoting AI chatbot adoption. The study contributes to technology acceptance research by extending the UTAUT2 framework to AI chatbots in the tourism sector and offers practical recommendations for developers focused on usability, engagement, and contextual relevance.

Keywords: user behavior, digital tourism, chatbot usability, smart tourism, intention to use

1. Introduction

Thailand recognizes the vital role of the tourism industry in generating substantial revenue and ensuring the equitable distribution of income across various regions. Local economies benefit significantly as tourists spend directly in the areas they visit. Consequently, promoting tourism diversity has been integrated into Thailand's national strategic plan (2018–2037) to increase competitiveness. A key focus is the development of creative and cultural tourism, leveraging Thailand's rich history, art, culture, traditions, and lifestyle to add value to products and services in response to tourist demands (Muangasame & Amnuay-Ngerntra, 2020). Cultural and historical tourism, in particular, has been identified as a strategic priority, reflecting the global trend toward more meaningful travel experiences that emphasize heritage, identity, and authenticity (Timothy, 2020). By promoting cultural assets and preserving historical sites, Thailand aims to create sustainable tourism products that appeal to both domestic and international visitors. Additionally, strategic initiatives aim to strengthen regional connectivity by capitalizing on Thailand's geographic position in Southeast Asia and establishing cross-border tourism routes. The plan also emphasizes the development of a robust tourism ecosystem, incorporating technological advancements such as centralized databases to support policy-making and improve tourist convenience (Suvannadabha et al., 2022). Using digital storytelling, virtual exhibitions, and AI-driven heritage interpretation can increase visitor engagement and help preserve intangible cultural heritage (Chung et al., 2015).

Ranong and Chumphon provinces have been designated secondary tourism destinations in Thailand with significant historical potential. Kra Isthmus has been a significant trans-peninsular trade route, with archaeological findings showing overseas trade dating back to the Suvarnabhumi era (Bellina et al., 2019; Krachaichan, 2023). These provinces offer a unique opportunity to develop heritage tourism experiences centered on ancient maritime trade and cultural exchanges that once connected East China and West China. Plans are underway to develop a land bridge route to facilitate transportation between the two peninsulas, making historical tourism development in this region especially promising. However, progress is hindered by a lack of critical infrastructure, including comprehensive historical data collection, management, and technology integration for information dissemination and promotion. In this case, establishing travel routes within the historical Suvarnabhumi region

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remains a persistent challenge, emphasizing the need for collaborative efforts between government agencies, local communities, and technology providers to unlock the region's full historical tourism potential.

1.1. AI-Driven solutions for historical tourism

Digital technology and artificial intelligence advancements present new opportunities to enhance tourism initiatives. To address existing limitations, the development of the AI-powered chatbot 'LanGTa' (Land of Gold Talk) was introduced to promote historical tourism in Ranong and Chumphon Provinces (Laosen et al, 2024). As a virtual travel assistant, LanGTa provided tourists with relevant historical insights, enriching their travel experiences. Such technological interventions could effectively bridge existing gaps and support sustainable tourism development in historically significant areas such as the Kra Isthmus. The integration of AI chatbots in the tourism industry has become a transformative tool for improving access to historical information. These chatbots enhance tourist experiences and contribute to the sustainable development of cultural heritage sites such as Suvarnabhumi. Effective chatbot design requires adherence to key principles, primarily ensuring information accuracy and cultural relevance, and leveraging advanced technologies for seamless information processing and delivery.

A fundamental component of chatbot development is the sourcing of reliable and authoritative information. Data accuracy is essential in historical tourism, as it guarantees that users receive authentic insights into cultural heritage. Reliable sources, such as research articles related to study routes across the southern upper peninsula (Bellina et al., 2019), provide valuable data on historical trade routes. Moreover, initiatives such as the cultural information online encyclopedia project offer extensive knowledge of historical landmarks (Pentzold et al., 2017). By integrating these sources, developers can build a robust knowledge base that enables LanGTa to deliver contextually relevant and accurate responses to users. Through the strategic implementation of AI chatbots such as LanGTa, Thailand can enhance the accessibility of historical tourism, address existing infrastructural challenges, and promote the sustainable development of culturally significant destinations.

For seamless interaction and efficient information retrieval, LanGTa must integrate advanced technologies. A fundamental component is the knowledge graph, which structures data on restaurants, accommodations, and tourist attractions, allowing the chatbot to provide personalized recommendations (Wust & Bremser, 2025). NLP also enables LanGTa to interpret user queries and generate coherent responses. Techniques such as text vectorization further enhance the chatbot's ability to retrieve historical data, including details on ancient trade routes between the Ranong and Chumphon archaeological sites (Mark, 2025). Moreover, generative AI allows LanGTa to answer complex questions efficiently, whereas genetic algorithms assist in planning travel routes that align with users' preferences and time constraints (Laosen et al., 2024). Figure 1 illustrates the operational workflow of LanGTa, an AI-powered travel assistant designed to enhance historical tourism experiences.

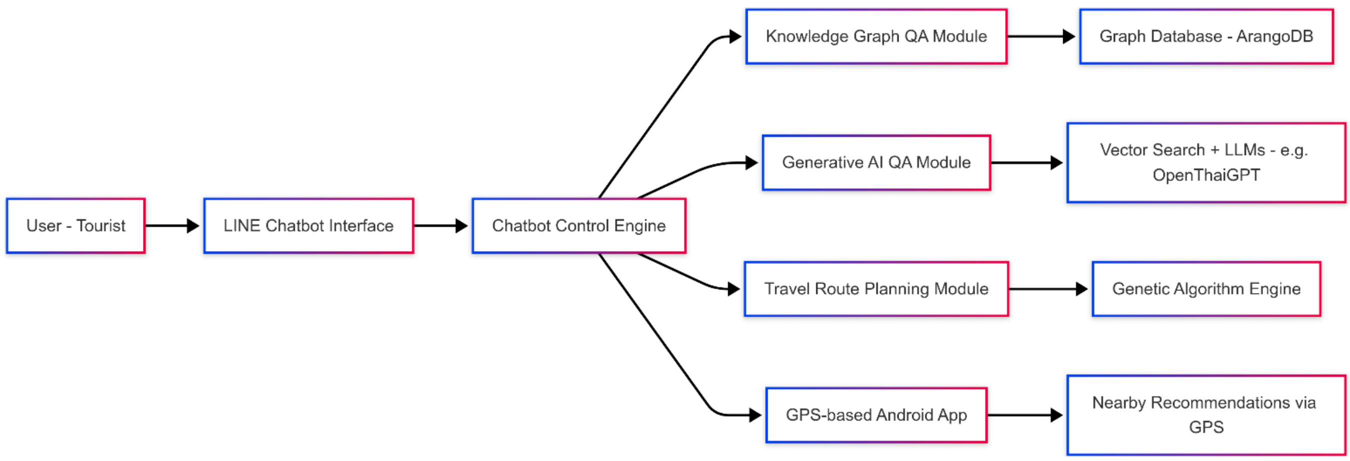

Figure 1 The system architecture of LanGTa.

The process starts when a user (tourist) interacts with the system via the LINE Chatbot Interface, a popular and user-friendly communication platform in Thailand. This interface captures user queries, whether textual or voice-based, and sends them to the chatbot control engine, which functions as the central processing hub. After that, the chatbot control engine evaluates the user's input to determine the appropriate module for response generation. Each module feeds its response back to the chatbot control engine, which formats and sends the final answer to the user via the LINE interface. This modular, intelligent, and responsive architecture allows LanGTa to serve as an intelligent, location-aware travel companion for historical tourism in Thailand. On the basis of the nature of the query, it may delegate the task to one of the following four specialized modules:

1. Knowledge Graph QA Module: If the query involves information, such as nearby tourist spots, opening hours, or cultural site details, this module is triggered. It interacts directly with the graph database (ArangoDB), which stores structured

data as a knowledge graph. The chatbot uses natural language processing techniques to interpret the question, extract relevant entities, and convert the input into graph-based queries. The response is then sent back to the user through the LINE interface.

2. Generative AI QA Module: For more open-ended, abstract, or narrative-driven queries, the system uses this module, which employs large language models (LLMs) such as OpenThaiGPT. This module performs a vector search to find relevant textual content from a historical corpus. The selected content and user questions are then passed to the LLM, which generates a natural language response.

3. Travel Route Planning Module: This module is activated when users request personalized itineraries on the basis of specific interests and time constraints. It calls upon the genetic algorithm engine, which optimizes travel plans by evaluating various permutations of destinations and selecting the best route according to user-defined preferences. The result is a well-balanced travel schedule tailored to the user's interests.

4. GPS-based Android App: The chatbot interacts with the mobile application module if the user's query or context involves real-time geolocation, such as finding places nearby. This module collects the user's current GPS coordinates and sends them to the control engine. The system then uses these data to recommend nearby attractions within a 10-kilometer radius, enhancing contextual relevance and situational awareness.

1.2. Overall user interface of LanGTa

The initial interface of the LanGTa application is the primary navigation hub for users seeking cultural and historical tourism information in Ranong and Chumphon Provinces. This main screen is designed with six buttons, each offering access to a distinct category of information. The first button directs users to comprehensive listings of dining and accommodation options, enabling travelers to locate places to eat and stay within the region. The second button provides access to curated tourist routes, guiding users through cultural pathways and scenic trails. The third and fourth buttons focus on archaeological sites and antiquities, leading to ancient structures, excavation locations, and notable historical artifacts. The fifth button offers an overview of general tourist attractions, including natural landmarks, temples, and community-based cultural experiences. Finally, the sixth button connects users to information regarding the historical trade route of the Suvarnabhumi era, which traverses the Kra Isthmus and highlights the region's ancient role as a pivotal maritime and overland trade corridor.

Moreover, the location-aware feature of the LanGTa system provides real-time suggestions for nearby activities and dining options as tourists move closer to points of interest, such as natural hot springs or historical temples. This functionality is powered by GPS tracking embedded within the mobile application, allowing the system to detect the tourist's proximity to landmarks. Once within a specified radius (approximately 10 kilometers), the system automatically generates recommendations without the need for user prompts. For example, the chatbot might suggest wellness activities or nearby restaurants known to local people when they are approaching a popular hot spring. Similarly, the system may offer information on guided tours, cultural events, or places to enjoy traditional cuisine when near a cultural site such as a historic temple. This feature not only enhances user convenience but also promotes a richer and more immersive travel experience by connecting tourists with contextually relevant experiences as they explore Ranong and Chumphon.

Furthermore, the LanGTa capabilities cover a series of user queries related to a specific tourist destination. For example, when a user requests information about popular tourist attractions at Khao Matree (Matree Mountain), the chatbot provides comprehensive site details, including descriptions and notable features. If the user follows up with a more specific question, such as the recommended route to reach the summit of Khao Matree, the system responds with clear, navigable directions on the basis of geographical data. Additionally, when asked for images associated with Khao Matree, the chatbot delivers visual content sourced from its integrated media database, enhancing user engagement through multimodal interaction. This level of responsiveness reflects the system's underlying integration of natural language processing, knowledge graph querying, and media retrieval functionalities.

1.3. Theoretical framework for ai chatbot adoption

While technological innovation provides the backbone for advanced systems such as LanGTa, user adoption remains critical for success. The adoption of AI chatbots can be understood through various well-established theoretical frameworks that explain user behavior and technology acceptance. One of the earliest models is the theory of reasoned action (TRA), which posits that an individual's behavior is driven by their behavioral intentions, which are influenced by their attitudes toward the behavior and subjective norms (social pressures). The TRA provides a foundational understanding of how beliefs and social influences shape decision-making, making it relevant to the study of chatbot adoption. The theory of planned behavior (TPB) extends the TRA model by introducing the concept of perceived behavioral control, which reflects an individual's self-efficacy and perception of the ease or difficulty of performing a behavior. The TPB suggests that technology adoption is influenced by attitudes and social norms and users' confidence in their ability to use the technology effectively. This theory is beneficial for understanding how users' perceptions of control over chatbot interactions impact their adoption decisions.

The diffusion of innovations theory (DOI) offers another perspective by focusing on the characteristics of the technology itself that influence its adoption. According to DOI, five key factors, including relative advantage (the perceived benefits over existing solutions), compatibility (alignment with user needs and values), complexity (ease of use), trialability (ability to test before adoption), and observability (visibility of results), determine the rate and extent of technology adoption. These factors provide perspectives for analyzing how the design and functionality of AI chatbots influence their acceptance among users. The technology acceptance model (TAM) is one of the most widely used frameworks in technology adoption research (Davis, 1993; Demsash et al., 2024). TAM simplifies the adoption process by focusing on two core constructs: perceived usefulness (the degree to which a user believes the technology will enhance their performance) and perceived ease of use (the extent to which the technology is user friendly). The TAM also considers the role of attitudes toward technology in shaping users' intentions to adopt it. This model is particularly relevant for understanding how users evaluate AI chatbots' practical benefits and usability.

Finally, the unified theory of acceptance and use of technology (UTAUT) and its extension, UTAUT2, integrate elements from TRA, TPB, DOI, and TAM to provide a more comprehensive framework (Venkatesh et al., 2003; Williams et al., 2015). The UTAUT outlines four main factors in technology adoption: performance expectancy, effort expectancy, social influence, and facilitating conditions. UTAUT2 expands this model by adding three consumer-specific constructs: hedonic motivation (enjoyment), price value (cost–benefit analysis), and habit (automaticity of use) (Huang & Chuang, 2021; Kulak et al., 2019; Tamilmani et al., 2017). Together, these theories offer a robust foundation for examining the factors that drive the adoption and sustained use of AI chatbots, such as LanGTa, in the tourism industry. As such, this research utilizes UTAUT2, a psychological framework rooted in well-established technology adoption theories, to investigate the factors driving tourists' adoption and continued use of AI chatbots. The model integrates key constructs from multiple adoption theories to provide a holistic understanding of technology acceptance. UTAUT2 identifies several critical determinants of technology adoption and usage behavior:

- Effort Expectancy (EE): Users who find LanGTa easy to use are more likely to intend to adopt it.
- Performance Expectancy (PE): Users who perceive LanGTa as useful for accessing historical information or planning itineraries are more likely to intend to use it.
- Social Influence (SI): Users who perceive that others (e.g., peers, influencers) recommend LanGTa are more likely to intend to use it.
- Facilitating Conditions (FC): Users who perceive that the necessary resources and infrastructure are available to support LanGTa usage are more likely to intend to use it.
- Hedonic Motivation (HM): Users who have developed a habit of using LanGTa may rely less on conscious intention, as their behavior becomes more automatic.
- Price Value (PV): Users who perceive LanGTa as providing good value for the cost are more likely to intend to use it.
- Habit (HT): Users who have developed a habit of using LanGTa may rely less on conscious intention, as their behavior becomes more automatic.

The findings inform the iterative design and optimization of LanGTa, ensuring that it aligns with user needs and enhances efficiency in historical tourism. A systematic approach to understanding technology adoption will contribute to developing user-centric AI solutions that provide historical insights and enrich the overall travel experience. In this case, UTAUT2 provides a framework for improving AI-driven tourism technologies, with the aim of increasing user engagement and satisfaction within the context of historical tourism. The UTAUT posits that BI is influenced by EE, PE, SI, FC, HM, PV, and HT. The equation can be written as equation (1).

$$BI = \beta_1 EE + \beta_2 PE + \beta_3 SI + \beta_4 FC + \beta_5 HM + \beta_6 PV + \beta_7 HT + \epsilon \qquad (1)$$

Where:

- BI: Behavioral Intention to use LanGTa.
- EE: Effort expectancy (perceived ease of use of LanGTa).
- PE: Performance expectancy (perceived usefulness of LanGTa).
- SI: Social influence (perceived social pressure or recommendations to use LanGTa).
- HM: Hedonic motivation (enjoyment or pleasure derived from using LanGTa).
- PV: Price value (perceived cost–benefit trade-off of using LanGTa).
- FC: Facilitating conditions (perceived availability of resources and infrastructure to support LanGTa usage).
- HT: Habit (automaticity of using LanGTa due to past experience).
- $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7$: Regression coefficients representing the strength of the relationships.
- $\epsilon\epsilon$: Error term accounting for unexplained variance.

1.4. Gender effect on IT adoption

Gender plays a critical role in shaping user perceptions, technology adoption, and continued usage across various domains of digital engagement (Morris et al., 2005). As a socially constructed attribute, gender encompasses roles, behaviors, and expectations that influence how individuals interact with technology. Societal norms associated with masculinity and femininity can shape comfort levels and the perceived appropriateness of engaging with certain technologies. For example, gender differences have been observed in the adoption of e-learning platforms (Kanwal et al., 2020) and mobile payment services (Humbani & Wiese, 2017), where women more frequently report concerns regarding privacy and security. These gendered patterns extend to e-commerce behaviors as well, affecting preferences for website aesthetics, levels of trust in online shopping, and user satisfaction (Shaouf & Altaqqi, 2018). Craiut & Iancu (2022) present a systematic review of 45 studies investigating how gender stereotypes manifest in human interactions with AI, especially in the form of virtual assistants and robots. The review highlights that AI technologies, although inherently gender-neutral, are frequently anthropomorphized with gendered traits owing to users' cognitive biases. Female virtual assistants are generally perceived as warmer and more trustworthy, whereas male-gendered AI is perceived as more competent and task-efficient.

Beyond preferences and behaviors, gender also moderates key constructs in technology acceptance models, offering a nuanced lens for interpreting adoption outcomes (Aguirre-Urreta & Marakas, 2010). Humans and women may prioritize different aspects of technology, such as functionality versus usability, which enables the development of more inclusive systems (Shaouf & Altaqqi, 2018). Practical applications of these insights include adapting user interfaces to accommodate diverse cognitive styles, strengthening security protocols that address gendered concerns, and implementing training that reflects varying levels of digital literacy. A gender-sensitive approach not only enhances user satisfaction and engagement but also supports broader goals of equity and inclusiveness in digital transformation.

Moreover, socially constructed gender roles influence perceptions of usefulness, ease of use, and perceived risks associated with technology, all of which are fundamental to adoption decisions (Castel et al., 2010). Technologies perceived as aligned with masculine traits (e.g., complexity or competitiveness) may deter female users, whereas those seen as nurturing or user friendly might discourage male engagement. These patterns also intersect with risk perceptions; for example, women may exhibit greater caution in adopting emerging technologies (Díaz-Arancibia et al., 2023). Gender moderates the relationship between perceived usefulness, ease of use, and behavioral intention (Bao et al., 2013), with men typically being more responsive to perceived utility and women being more influenced by usability. Understanding these dynamics allows developers and policymakers to design interventions that not only bridge gender gaps in technology use but also ensure that digital innovations serve the diverse needs of all users. As such, we introduce interaction terms between gender and each construct to understand how gender influences the relationships between the UTAUT2 constructs and BI. To incorporate gender effects into the behavioral intention (BI) equation, we extend the model by adding interaction terms between gender and each of the UTAUT2 constructs. This allows us to examine how the relationships between the constructs and BI differ between males and females. Equation 2 describes how gender moderates UTAUT2 constructs.

$$BI = \beta_8(EE \times Gender) + \beta_9(PE \times Gender) + \beta_{10}(SI \times Gender) + \beta_{11}(FC \times Gender) + \beta_{12}(HM \times Gender) + \beta_{13}(PV \times Gender) + \beta_{14}(HT \times Gender) + \epsilon \quad (2)$$

Where:

- β8 to β14: Moderating effects of gender on the relationships between the constructs and BI.

1.5. UTAUT2 applications

The adoption of LanGTa, an AI-powered chatbot for historical tourism, can be evaluated through the lens of the UTAUT2, which integrates cognitive, emotional, and contextual factors into the analysis. According to the UTAUT2 model, gender can impact various constructs, such as EE, PE, SI, HM, PV, and HT. This study's research objectives focus on understanding the factors influencing BI to adopt LanGTa. The research objectives of this study can be outlined as follows:

1) To investigate the behavioral factors influencing tourists' and tourism professionals' intention to adopt LanGTa within the context of historical tourism, the UTAUT2 framework was used.

2) To assess the impact of key predictors such as PE, EE, SI, HM, PV, and HT on users' behavioral intentions (BIs) to adopt LanGTa.

3) To explore the moderating effects of demographic variables, specifically gender, on the relationships between the UTAUT2 constructs (PE, EE, SI, HM, PV, HT, and FC) and the BI to adopt LanGTa.

The hypotheses can be established on the basis of the UTAUT2 framework in the context of LanGTa adoption. Below are the reformulated hypotheses, incorporating the moderating effect of gender.

- H1: Effort expectancy (EE) positively influences the behavioral intention (BI) to adopt LanGTa.
- H2: Performance expectancy (PE) positively affects the ability of BI to adopt LanGTa.
- H3: Social influence (SI) positively impacts the ability of BI to adopt LanGTa.
- H4: Facilitating conditions (FCs) positively affect BI with respect to LanGTa adoption.
- H5: Hedonic motivation (HM) positively affects the ability of BI to adopt LanGTa.
- H5: Price value (PV) positively influences the BI to adopt LanGTa.
- H7: Habit (HT) positively affects BI concerning LanGTa adoption.
- H8: Gender moderates the relationship between H1 (PE) and H8 (HT) and behavioral intention (BI).

1.6. Conceptual framework

Figure 2 presents the conceptual framework of this study. The framework is grounded in the UTAUT2 model, adapted to evaluate the adoption of LanGTa, an AI-powered chatbot for historical tourism. The framework illustrates how the independent variables, including effort expectancy (EE), performance expectancy (PE), social influence (SI), facilitating conditions (FC), hedonic motivation (HM), price value (PV), and habit (HT), directly influence tourists' and tourism professionals' behavioral intentions (BIs) to adopt LanGTa. In addition, the framework incorporates gender as a moderating variable, which influences the strength of the relationships between the independent variables and BI.

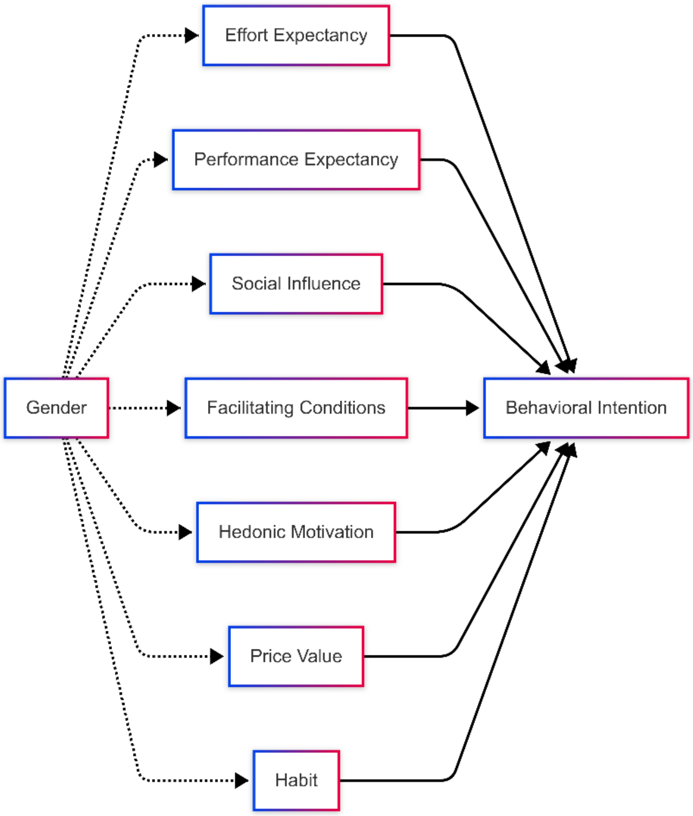

Figure 2 The proposed conceptual framework. *Note.* EE (effort expectancy), PE (performance expectancy), SI (social influence), FC (facilitated conditions), HM (hedonic motivation), PV (price value), HT (habit), and BI (behavioral intention).

2. Materials and Methods

This study employs UTAUT2 as a theoretical framework to evaluate the factors influencing the adoption and use of LanGTa, an AI-powered chatbot designed for historical tourism, specifically within the context of cultural heritage sites in Phuket. The methodology comprises several key steps, including population and sample, research instrument, data collection, data analysis, and ethical considerations, ensuring a rigorous and comprehensive examination of user behavior and technology acceptance.

2.1. Population and sample

This study employed a quantitative research methodology, utilizing online surveys to collect data from a target population. The participants included individuals likely to engage in historical tourism and use an AI chatbot, specifically LanGTa, to assist in exploring historical sites. A simple random sampling method was applied to ensure that every individual within the defined population had an equal chance of selection. The preliminary data analysis involved descriptive statistics, including means and standard deviations, to evaluate data reliability and quality. Additionally, advanced statistical techniques, such as structural equation modeling (SEM) and path analysis, have been employed to examine the relationships between variables (Fox, 2013). These methods provide an in-depth exploration of the factors influencing chatbot acceptance and usage in historical tourism. The analysis was grounded in UTAUT2, offering a comprehensive framework for identifying the key determinants of users' behavioral intentions and actual adoption of LanGTa.

The study population included Thai tourists aged 18 and above who had visited historical tourism sites in the Suvarnabhumi region, specifically in Ranong and Chumphon Provinces. No restrictions were placed on gender, occupation, or educational background, ensuring diverse representations. The sample size was determined via Yamane's (1973) formula, which initially targeted 400 participants. To account for potential data loss or errors, an additional 10% was included, resulting in a final sample size of 440 individuals. This adjustment maintained a tolerance level of 0.05, balancing precision and feasibility. Potential respondents received detailed information about the study to promote transparency and encourage participation, including its purpose, expected duration, and participation format (i.e., an online questionnaire). This approach fostered trust and informed consent, ensuring that participants met the necessary criteria while facilitating meaningful and representative data collection.

2.2. Research instrument

This study analyzed the factors influencing the adoption and use of LanGTa, an AI chatbot designed to promote historical tourism, using UTAUT2 as the guiding framework. To achieve this goal, the research began by collecting demographic information from participants, including age, gender, education level, occupation, and prior experience with technology. These data provided a contextual foundation for understanding the sample and enabled more nuanced interpretations of the findings. Following the collection of demographic data, a structured questionnaire was developed to measure key UTAUT2 constructs, including PE, EE, SI, FC, HM, PV, HT, and BI. To ensure thorough measurement, each construct was defined via three meticulously crafted question items. Table 1 illustrates the question items for measuring all UTAUT2 constructs.

Table 1 Examples of the question items used in this research.

Constructs	Question Items
Performance Expectancy (PE)	Using LanGTa enhances my ability to discover historical tourist attractions.
	LanGTa provides useful information that improves my travel planning.
	I believe LanGTa can help me learn about historical sites efficiently.
Effort Expectancy (EE)	I find it easy to interact with LanGTa for historical tourism purposes.
	LanGTa is user-friendly and does not require much effort to operate.
	I can quickly understand how to use LanGTa without assistance.
Social Influence (SI)	People whose opinions I value think I should use LanGTa for historical tourism.
	My friends or family have encouraged me to try using LanGTa.
	It seems important to others that I use LanGTa when exploring historical sites.
Facilitating Conditions (FC)	I can access the necessary resources (e.g., internet, smartphone) to use LanGTa effectively.
	I believe adequate support is available if I encounter issues with LanGTa.
	LanGTa works reliably on the devices I typically use.
Hedonic Motivation (HM)	I enjoy using LanGTa because it makes learning about historical sites engaging.
	The interactive features of LanGTa make exploring historical tourism more enjoyable.
	Using LanGTa enhances my travel experience by making historical content more immersive.
Price Value (PV)	The benefits I receive from using this chatbot are worth the cost (if any) associated with it.
	I find the price (if applicable) of this chatbot to be reasonable compared to the value it provides.
	Using this chatbot provides good value for the money I spend (or would spend) on it.
Habit (HT)	Using this chatbot has become a habit for me.
	I feel compelled to use this chatbot without thinking about it.
	Using this chatbot is something I do without much thought or effort.
Behavioral Intention to Use (BI)	I intend to use LanGTa in the future when planning visits to historical sites.
	I am likely to recommend LanGTa to others interested in historical tourism.
	I plan to incorporate LanGTa into my travel routine to discover historical attractions.

The questionnaire was reviewed by three experts specializing in educational technology, academic research, and tourism studies to ensure its validity and reliability. These experts assessed the content validity, ensuring alignment between each question item and its corresponding construct. The item-objective congruence (IOC) index was calculated for each item, with a threshold of 0.8 or higher set as the criterion for inclusion. This validation process ensured that the questionnaire accurately measured the intended constructs, enhancing the credibility of the collected data. The validated questionnaire was then administered to the target population, allowing researchers to gather empirical data on the factors influencing the adoption and use of AI chatbots in historical tourism. Since the questionnaire must be translated from English to Thai, three university lecturers proficient in both languages reviewed and validated both versions to maintain semantic and syntactic consistency. This validation process was completed before the Thai version was used in the research to ensure its accuracy and equivalence to the original English text.

2.4. Data collection

This study employed an online questionnaire as the primary data collection method. It was chosen for its efficiency in reaching a large and diverse sample while enabling the comprehensive collection of data on AI chatbot adoption in historical tourism. The questionnaire was carefully designed to ensure clarity, relevance, and alignment with the UTAUT2 framework (Huang & Chuang, 2021; Kulak et al., 2019; Tamilmani et al., 2017). It began with an introduction outlining the research purpose, instructions for participation, and an informed consent statement. To protect participant anonymity, no personally identifiable information was collected. The questionnaire assessed the psychological and behavioral factors influencing the adoption and use of LanGTa, an AI chatbot designed for historical tourism. Responses were measured via a 7-point Likert scale (Likert, 1932), ensuring precision and consistency in capturing participants' perceptions. The UTAUT2 framework guided the development of key constructs, including Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Behavioral Intention to Use (BI), Hedonic Motivation (HM), Price Value (PV), and Habit (HT). The UTAUT2 model tested these constructs to assess their impact on users' intentions to use LanGTa for historical tourism.

2.5. Data analysis

The data analysis was conducted in two main stages: descriptive statistics and SEM. Descriptive statistics were used to analyze demographic information such as age, sex, education level, and prior experience with technology, providing an overview of the study participants. SEM was employed to assess the relationships between the factors influencing LanGTa adoption. On a 7-point Likert scale, the questionnaire items captured respondents' perceptions of the UTAUT2 constructs, including PE, EE, SI, FC, BI, HM, PV, and HT. To ensure the questionnaire's reliability, Cronbach's α values were calculated for each construct, measuring internal consistency. Moreover, model fit indices analysis is critical for evaluating how well the proposed model aligns with the collected data (Shi et al., 2019). A range of indicators was employed to evaluate model fit, comprising the Akaike information criterion (AIC), Bayesian information criterion (BIC), comparative fit index (CFI), goodness-of-fit index (GFI), relative noncentrality index (RNI), and Tucker–Lewis index (TLI). These metrics assess the appropriateness of models across different complexity levels, where lower values reflect superior model fit and enhanced parsimony. Additionally, other indices focus on measuring the alignment between the model and the actual data. For example, the standardized root mean square residual (SRMR) measures the discrepancy between the predicted and observed values, with values below 0.08 indicating a good fit. Similarly, the root mean square error of approximation (RMSEA) evaluates the model's error in estimating population parameters, with values less than 0.06 considered acceptable. These indicators collectively provide a comprehensive evaluation of model fit, ensuring both simplicity and accuracy in interpretation.

Descriptive statistics, including measures such as the mean and standard deviation, were employed to assess the reliability and quality of the data. Regression-based path analysis was used to examine the relationships among the UTAUT2 model constructs. Specifically, the study examined how EE and PE influence BI and the role of SI in shaping BI. Additionally, the study explored how BI and FC directly impact USE. The analysis also investigated the moderating effects of HM, PV, and HT on these relationships. Statistical significance tests were performed for each hypothesized relationship to validate or refute the research hypotheses. By integrating these analytical methods, the study ensured a rigorous and comprehensive evaluation of the proposed UTAUT2 model. The combination of descriptive statistics and structural equation modeling (SEM)-based path analysis provided a high level of confidence in the accuracy and precision of the findings. This dual approach not only enhanced the reliability of the results but also offered more profound insights into user behavior and decision-making trends related to the adoption of AI chatbots in the context of historical tourism.

2.5. Ethical considerations

The ethical approval process is crucial to research, ensuring that studies are conducted responsibly while safeguarding participants' rights. This is especially important in studies assessing potential risks and benefits, which require careful consideration of possible harm or discomfort and the implementation of mitigation strategies. This study was carried out in compliance with strict ethical guidelines approved by the Human Research Ethics Committee of Phuket Rajabhat University (PKRU2567/08) on April 29, 2024, with approval valid until April 28, 2025. Ethical considerations included obtaining informed consent, preserving participant anonymity, and securely managing data. The participants were informed of their right to withdraw without consequences, and all the data were securely stored, with plans for destruction six months after analysis to maintain confidentiality.

3. Results

This section presents the results, encompassing the sample description and descriptive findings, and highlights the key constructs influencing the adoption of LanGTa on the basis of the UTAUT2 model, including the moderating effects of gender.

3.1. Sample description

This study collected data from 427 participants, 51% male and 49% female, to examine the factors influencing the adoption of LanGTa, an AI-powered chatbot designed for historical tourism. The sample size was determined via Yamane's

(1973) formula, with an initial target of 400 participants. To account for potential data loss or errors, an additional 10% was included, resulting in a final sample size of 440 individuals. However, after data cleaning and removing incomplete responses, the final sample consisted of 427 participants, maintaining a tolerance level of 0.05 to balance precision and feasibility. This sample size is considered robust for structural equation modeling (SEM) and ensures reliable statistical analysis. The demographic distribution of the sample reflects a balanced representation of gender, with 218 males (51%) and 209 females (49%). This gender balance allows for a comprehensive analysis of gender differences in the adoption of LanGTa, ensuring that the findings are not skewed toward one gender. The participants were primarily Thai tourists aged 18 and above who had visited historical tourism sites in the Suvarnabhumi region, specifically in Ranong and Chumphon Provinces. No restrictions were placed on gender, occupation, or educational background, ensuring diverse representations and enhancing the generalizability of the findings.

The study also examined the operating systems used by participants to test AI platforms, such as LanGTa, for historical tourism. This analysis provides insights into the technological preferences and accessibility of users, which are critical for designing and optimizing AI chatbots. Android was the most commonly used operating system, with 244 participants (57.1%) reporting its use. This finding indicates that most users access AI platforms such as LanGTa through Android devices, which are widely available and often more affordable than iOS devices. In contrast, iOS was used by 183 participants (42.9%), representing a significant portion of the sample. While iOS users were fewer in number than Android users were, their presence highlights the importance of ensuring compatibility with Apple devices.

The study also explored participants' attitudes toward expanding the use of LanGTa for historical tourism to other areas in Thailand. This question aimed to gauge user interest in the broader application of AI technologies beyond the Suvarnabhumi region. Most participants (399 out of 427, or 93.4%) expressed a desire to expand AI platforms such as LanGTa to other areas in Thailand. This strong positive response indicates widespread enthusiasm for the potential of AI technologies to enhance historical tourism experiences across the country. Participants likely recognize the value of AI chatbots in providing accurate, engaging, and culturally relevant information, which can enrich their travel experiences and promote cultural heritage. Conversely, a small minority of participants (28 out of 427, or 6.6%) responded negatively to expanding AI platforms to other areas. This opposition may stem from concerns about overreliance on technology, potential loss of traditional tourism practices, or privacy and security issues associated with AI systems. While this group represents a small fraction of the sample, their perspectives highlight the need to address potential challenges and concerns when implementing AI technologies in tourism.

3.2. Descriptive findings

The study assessed the reliability of the measurement scales used to evaluate the UTAUT2 constructs (e.g., PE, EE, SI, FC, HM, PV, and HT) through two widely used reliability coefficients: Cronbach's α and McDonald's ω. These statistics provide insights into the internal consistency and reliability of the scales, ensuring that the items within each construct consistently measure the same underlying concept. The reliability analysis results are as follows: Cronbach's $\alpha = 0.979$ and McDonald's $\omega = 0.980$, which are well above the commonly accepted threshold of 0.70 for demonstrating good internal consistency. A Cronbach's α of 0.979 shows that the scale items are highly consistent and reliably measure the same construct. This high value suggests that participants responded consistently to the items, which means that the scale is robust and dependable for assessing the factors influencing LanGTa adoption. Similarly, the McDonald's ω value of 0.980 further reinforces the scale's reliability. McDonald's ω is considered a more robust measure of reliability than Cronbach's α is because it accounts for the scale's factor structure and is less sensitive to the number of items. Like Cronbach's α, values above 0.70 are considered acceptable, and values above 0.90 indicate excellent reliability. The high ω value of 0.980 confirms that the scale is internally consistent and that the items within each construct consistently measure the intended factors.

Figure 3 represents the goodness-of-fit of the proposed model. While the CFI measures the relative improvement in fit compared with a baseline model, with values closer to 1.00 indicating a better fit, the CFI value for the research framework was 1.00, which falls within the good fit range ($0.95 \leq \text{CFI} \leq 1.00$). The GFI value was also 1.00, within the good fit range ($0.95 \leq \text{GFI} \leq 1.00$). Moreover, the TLI value was 1.00, within the good fit range ($0.95 \leq \text{TLI} \leq 1.00$). The TLI compares the fit of the proposed model to that of a null model, with values closer to 1.00 indicating a better fit. The RNI value was 1.00, within the good fit range ($0.95 \leq \text{RNI} \leq 1.00$). The RNI measures the discrepancy between the proposed and perfect models, with values closer to 1.00 indicating a better fit. The RMSEA value was 0.00, which falls within the good fit range ($0 \leq \text{RMSEA} \leq .05$). This indicator measures the error of approximation in the population, with lower values indicating a better fit. The SRMR value was 0.02, which falls within the good fit range ($0 \leq \text{SRMR} \leq 0.05$). An SRMR of 0.02 suggests that the proposed model accurately predicts the observed data, further confirming the model's excellent fit. As such, the fit indices (CFI = 1.00, GFI = 1.00, TLI = 1.00, RNI = 1.00, RMSEA = 0.00, SRMR = 0.02) collectively indicate that the proposed model fits the data. This means that the relationships between the UTAUT2 constructs and BI are well supported by the data, providing confidence in the study's findings.

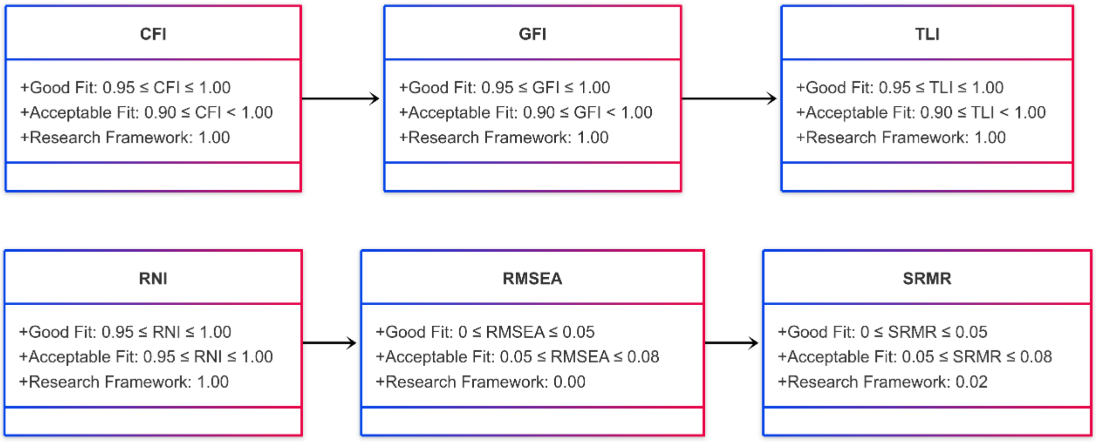

Figure 3 Examples of fit indices used in SEM. *Note.* CFI (comparative fit index), GFI (goodness-of-fit index), TLI (Tucker Lewis index), RNI (relative noncentrality index), RMSEA (root mean square error of approximation), SRMR (standardized root mean square residual).

3.3. Hypothesis testing results

Table 2 comprehensively analyzes the relationships between the UTAUT2 constructs and the BI to adopt LanGTa, an AI-powered chatbot designed for historical tourism. The table summarizes each predictor variable's path coefficients, standard errors, confidence intervals, standardized estimates (β), and significance levels (p values).

3.3.1. H1: Performance expectancy (PE) and behavioral intention (BI)

PE has the most substantial positive effect on BI, with an unstandardized estimate of 0.4715 ($\beta = 0.4740$, $p < 0.001$). This means that for every unit increase in users' perception that LanGTa enhances their ability to access historical information or plan itineraries, their intention to use the chatbot increases by 0.4715 units. The 95% confidence interval (0.4011--0.5420) does not include zero, confirming the significance of this relationship. This finding underscores the importance of LanGTa's perceived usefulness in driving adoption, as users are more likely to use the chatbot if they believe it will improve their experience.

3.3.2. H2: Effort expectancy (EE) and behavioral intention (BI)

EE also has a significant positive effect on BI, with an unstandardized estimate of 0.1778 ($\beta = 0.1788$, $p < 0.001$). This finding indicates that for every unit increase in users' perception of LanGTa's ease of use, their intention to adopt the chatbot increases by 0.1778 units. The 95% confidence interval (0.1195--0.2361) further supports the robustness of this relationship. This result highlights the critical role of a user-friendly design in encouraging LanGTa adoption, as users are more likely to engage with the chatbot if they find it easy to interact with it.

3.3.3. H3: Social influence (SI) and behavioral intention (BI)

SI has a weaker but still significant positive effect on behavioral intention (BI), with an unstandardized estimate of 0.0491 ($\beta = 0.0485$, $p < 0.01$). For each unit increase in users' perception that others (such as peers, family, or influencers) recommend LanGTa, there is a corresponding 0.0491 unit increase in their intention to use the chatbot. Although the effect size is small, the 95% confidence interval (-0.0031 to 0.1014) narrowly excludes zero, indicating a statistically significant relationship. This finding implies that social recommendations play a modest but meaningful role in shaping users' intentions to adopt LanGTa.

3.3.4. H4: Facilitating conditions (FC) and behavioral intention (BI)

FC has a significant positive effect on BI, with an unstandardized estimate of 0.1567 ($\beta = 0.1597$, $p < 0.001$). This means that for every unit increase in users' perception that the necessary resources and infrastructure are available to support LanGTa usage, their intention to adopt the chatbot increases by 0.1567 units. The 95% confidence interval (0.0712--0.2422) confirms the significance of this relationship. This result emphasizes the importance of ensuring that LanGTa is accessible, well supported, and compatible with users' devices and platforms.

3.3.5. H5: Hedonic motivation (HM) and behavioral intention (BI)

HM has a significant positive effect on BI, with an unstandardized estimate of 0.1862 ($\beta = 0.1964$, $p < 0.001$). This finding indicates that for every unit increase in users' enjoyment or pleasure derived from using LanGTa, their intention to adopt the chatbot increases by 0.1862 units. The 95% confidence interval (0.1170--0.2554) further supports the significance of this relationship. This finding suggests that making LanGTa engaging and enjoyable can significantly enhance users' willingness to adopt it.

3.3.6. H6: Price value (PV) and behavioral intention (BI)

PV has a week but significant positive effect on BI, with an unstandardized estimate of 0.0446 (β = 0.0455, p = 0.028). This means that for every unit increase in users' perception that LanGTa provides good value for the cost, their intention to use the chatbot increases by 0.0446 units. The 95% confidence interval (0.0049--0.0844) narrowly excludes zero, indicating a statistically significant but modest relationship. This result highlights the importance of ensuring that LanGTa is perceived as cost-effective, particularly for price-sensitive users.

3.3.7. H7: Habit (HT) and behavioral intention (BI)

HT has a significant negative effect on BI, with an unstandardized estimate of -0.1033 (β = -0.0979, p < 0.001). This suggests that for every unit increase in users' habitual use of LanGTa, their intention to use the chatbot decreases by 0.1033 units. The 95% confidence interval (-0.1569 to -0.0497) indicates that this relationship is statistically significant. This counterintuitive finding may indicate that users who have developed a habit of using LanGTa rely less on the conscious intention to engage with it, as their behavior becomes more automatic (Table 2).

Table 2 Parameter estimates from SEM analysis of the proposed model.

				95% Confidence Intervals			
Dep	Pred	Estimate	SE	Lower	Upper	β	p
BI	EE	0.1778	0.0297	0.11954	0.2361	0.1788	***<.001
BI	PE	0.4715	0.0359	0.40108	0.5420	0.4740	***<.001
BI	SI	0.0491	0.0266	-0.00310	0.1014	0.0485	***<0.01
BI	FC	0.1567	0.0436	0.07119	0.2422	0.1597	***<.001
BI	HM	0.1862	0.0353	0.11699	0.2554	0.1964	***<.001
BI	PV	0.0446	0.0203	0.00490	0.0844	0.0455	*0.028
BI	HT	-0.1033	0.0273	-0.15687	-0.0497	-0.0979	***<.001
BI	EE	0.1778	0.0297	0.11954	0.2361	0.1788	***<.001
BI	PE	0.4715	0.0359	0.40108	0.5420	0.4740	***<.001

Note: * p < .05. ** p < .01. *** p < .001

3.3.8. H8: Moderating effects of gender

Table 3 presents a multigroup analysis examining gender differences in the relationships between the UTAUT2 constructs and the behavioral intention (BI) to adopt LanGTa, an AI-powered chatbot for historical tourism. The table is divided into two groups: females (F) and males (M), and it provides the unstandardized estimates, standard errors, confidence intervals, standardized estimates (β), and significance levels (p values) for each predictor variable.

Table 3 Moderating influence of gender on the relationships within the UTAUT2 framework.

					95% Confidence Intervals			
	Dep	Pred	Estimate	SE	Lower	Upper	β	p
F	BI	EE	0.1703	0.0341	0.1034	0.2373	0.2088	***<.001
	BI	PE	0.5940	0.0374	0.5207	0.6673	0.7020	***<.001
	BI	SI	0.1359	0.0264	0.0843	0.1876	0.1736	***<.001
	BI	FC	0.0355	0.0514	-0.0652	0.1362	0.0409	0.190
	BI	HM	0.0757	0.0447	-0.0119	0.1634	0.0982	*0.045
	BI	PV	0.0274	0.0282	-0.0278	0.0827	0.0334	0.231
	BI	HT	-0.0294	0.0319	-0.0920	0.0333	-0.0315	0.258
M	BI	EE	0.1876	0.0330	0.1230	0.2522	0.2508	***<.001
	BI	PE	0.4359	0.0381	0.3612	0.5106	0.5150	***<.001
	BI	SI	0.0111	0.0255	-0.0389	0.0611	0.0134	0.363
	BI	FC	0.2027	0.0419	0.1205	0.2849	0.2365	***<.001
	BI	HM	0.2247	0.0333	0.1594	0.2900	0.3154	***<.001
	BI	PV	0.0614	0.0246	0.0133	0.1096	0.0850	***<.001
	BI	HT	-0.1458	0.0263	-0.1975	-0.0942	-0.1878	***<.001

Note: * p < .05. ** p < .01. *** p < .001

Table 4 provides an in-depth analysis of the results reported in Table 3, specifically addressing the moderating influence of gender on the UTAUT relationships.

Table 4 Detailed analysis of gender moderating effects on UTAUT2 relationships.

Constructs	Females	Males
Performance Expectancy	PE strongly affects BI (Estimate = 0.5940, β = 0.7020, p < 0.001). This indicates that females who perceive LanGTa as useful are significantly more likely to intend to use it.	PE has a strong positive effect on BI (Estimate = 0.4359, β = 0.5150, p < 0.001), but the effect is slightly weaker than females. This suggests that while both genders value the chatbot's usefulness, females place a higher emphasis on this factor.
Effort Expectancy	EE positively affects BI (Estimate = 0.1703, β = 0.2088, p < 0.001). Females who find LanGTa easy to use are more likely to intend to adopt it.	EE has a significant positive effect on BI (Estimate = 0.1876, β = 0.2508, p < 0.001), with a slightly more substantial effect compared to females. This suggests that males are more influenced by the chatbot's ease of use.
Social Influence	SI positively affects BI (Estimate = 0.1359, β = 0.1736, p < 0.001). Females are more likely to use LanGTa if they perceive others recommend it.	SI has no significant effect on BI (Estimate = 0.0111, β = 0.0134, p = 0.363). This indicates that males are less influenced by social recommendations when adopting LanGTa.
Facilitating Conditions	FC has no significant effect on BI (Estimate = 0.0355, β = 0.0409, p = 0.190). The availability of supportive infrastructure does not significantly influence females' intention to use LanGTa.	FC significantly affects BI (Estimate = 0.2027, β = 0.2365, p < 0.001). Males are more likely to intend to use LanGTa if they perceive that the necessary resources and infrastructure are available.
Hedonic Motivation	HM has a weak but significant positive effect on BI (Estimate = 0.0757, β = 0.0982, p = 0.045). Females who find LanGTa enjoyable are slightly more likely to intend to use it.	HM strongly affects BI (Estimate = 0.2247, β = 0.3154, p < 0.001). Males are significantly more influenced by the enjoyment derived from using LanGTa.
Price Value	PV has no significant effect on BI (Estimate = 0.0274, β = 0.0334, p = 0.231). Its perceived cost-value does not significantly influence females' intention to use LanGTa.	PV significantly affects BI (Estimate = 0.0614, β = 0.0850, p < 0.001). Males are more likely to use LanGTa if they perceive it as providing good value for the cost.
Habit	HT has no significant effect on BI (Estimate = -0.0294, β = -0.0315, p = 0.258). Females' intention to use LanGTa is not significantly influenced by habit.	HT has a significant negative effect on BI (Estimate = -0.1458, β = -0.1878, p < 0.001). Males who have developed a habit of using LanGTa are less likely to rely on conscious intention to use it, as their behavior becomes more automatic.

4. Discussion

This section discusses the key research findings, addresses the study's limitations, and explores the implications for advancing multidisciplinary disciplines.

4.1. Discussion of the main results

The study's findings offer critical insights into the factors shaping the adoption of LanGTa, an AI-powered chatbot for historical tourism, through the lens of the UTAUT2 model. Among the examined constructs, PE emerged as the most influential predictor of BI for both genders. Users who perceived LanGTa as beneficial for accessing historical information and planning itineraries were significantly more inclined to adopt it. This finding aligns with prior research asserting that perceived usefulness is a primary determinant of technology adoption, especially in tourism and education contexts where the delivery of actionable information enhances perceived value (Huang & Chuang, 2021; Venkatesh et al., 2003). The effect was more pronounced among female users, suggesting that women may place greater emphasis on informational utility when evaluating digital tools (Shaouf & Altaqqi, 2018).

EE was also a significant predictor, underscoring the importance of usability and intuitive design in chatbot adoption. Interestingly, EE had a slightly stronger effect among male respondents, indicating that ease of interaction may be particularly salient for this group. This observation resonates with prior findings that men often prioritize functionality and efficiency when engaging with digital platforms (Aguirre-Urreta & Marakas, 2010). As such, developers should focus on minimizing the cognitive load and simplifying user pathways to encourage broader adoption. The role of SI was found to be weaker than that of PE and EE but still statistically significant, particularly among females. This suggests that social norms and peer recommendations are important for women's adoption behavior, a trend echoing previous studies on e-learning and mobile payment adoption (Humbani & Wiese, 2017; Kanwal et al., 2020).

FC, or users' perceptions of the availability of necessary resources and infrastructure, significantly influenced BI for male users but not for females. This gender distinction may be rooted in varying degrees of confidence in navigating technical challenges. Prior studies have shown that women may be more likely to rely on social validation or perceived usefulness, whereas men tend to assess the technical environment more critically (Castel et al., 2010). HM, reflecting enjoyment derived from using the chatbot, had a strong positive effect for both genders, with a stronger impact among males. This aligns with research emphasizing that interactive and enjoyable features increase male users' engagement with virtual agents (Craiut & Iancu, 2022). The integration of gamified elements, virtual storytelling, or immersive design could therefore enhance the appeal and uptake of LanGTa.

PV, although relatively weak overall, demonstrated a statistically significant influence among male users, suggesting that cost–benefit analysis is a stronger determinant for men in evaluating AI tools. This aligns with earlier research showing that men tend to evaluate technology more from a utilitarian perspective (Bao et al., 2013). Emphasizing LanGTa's cost-effectiveness, whether through pricing transparency or free access to premium content, may be a key strategy for attracting male users. On the other hand, HT was found to have a significant negative effect on BI among males, indicating that habitual users may rely less on the conscious intention to use the chatbot. This finding, although counterintuitive, reflects a phenomenon observed in prior literature where habitual engagement reduces deliberate decision-making over time (Limayem et al., 2007). Among females, HT did not significantly influence BI, which may imply a more intention-driven engagement pattern.

The moderating role of gender revealed marked differences in technology adoption behaviors. Female users were influenced primarily by performance expectancy, effort expectancy, and social influence, indicating that informational value, usability, and peer recommendations play a central role in their decision-making. In contrast, male users were more strongly influenced by effort expectancy, facilitating conditions, hedonic motivation, and price value. These findings suggest that men are more drawn to ease of use, infrastructure support, enjoyment, and perceived value, whereas women are more responsive to usefulness and social validation. These gendered patterns of influence reflect broader societal and psychological constructs surrounding technology engagement (Díaz-Arancibia et al., 2023; Morris et al., 2005).

4.2. Limitations

While this study provides meaningful insights into the adoption of LanGTa, an AI-powered chatbot for historical tourism, several limitations must be acknowledged to contextualize the findings. First, the geographic and cultural scope of the research was limited to the Suvarnabhumi region in Thailand, specifically the Ranong and Chumphon provinces. Although this setting was appropriate for examining historical tourism in a local context, the results may not be generalizable to other regions with differing cultural, technological, or tourism dynamics. Cross-cultural variations in digital tourism behavior suggest that broader sampling would enhance external validity (Huang & Chuang, 2021). In addition, methodological constraints may affect interpretation. The reliance on self-reported data introduces the possibility of social desirability and recall biases, which may lead participants to overstate their behavioral intentions or perceptions of usefulness and ease of use (Jordan & Troth, 2020; Podsakoff et al., 2003). The study's cross-sectional design limits the ability to observe changes in user attitudes or behavior over time. Future research should consider longitudinal or mixed-method approaches, including usage log analysis, to provide more robust evidence (Venkatesh et al., 2012). The study explored gender as a moderating factor but did not incorporate other influential demographic or psychographic variables, such as age, digital literacy, cultural background, or personality traits, which are factors shown to influence technology adoption and interaction with AI interfaces (Tarhini et al., 2014).

Furthermore, the unexpected negative association between the Habit construct and Behavioral Intention among male respondents diverges from previous findings (Limayem et al., 2007), suggesting the need to refine how habit is operationalized in chatbot contexts and to explore such effects across user subgroups. Primarily, the study evaluated LanGTa in a theoretical and conceptual form, not through deployment in a real-world environment. Without live field testing, insights into usability, the user experience, and system performance remain limited. Practical adoption of AI in tourism requires rigorous empirical evaluation to understand real-world engagement and contextual challenges (Neuhofer et al., 2015). Addressing these limitations in future research would improve the generalizability, accuracy, and practical relevance of findings related to AI-powered tools in digital tourism.

4.3. Contributions to multidisciplinary research

This study offers substantial contributions to multidisciplinary research by intersecting the domains of technology adoption, tourism studies, cultural heritage, psychology, and information systems. By applying the UTAUT2 framework to evaluate the adoption of LanGTa, an AI-powered chatbot for historical tourism, the research enriches existing models of technology acceptance in nontraditional contexts, particularly in cultural tourism. The incorporation of consumer-oriented constructs (HM, PV, and HB) into the adoption framework provides a more comprehensive lens for understanding behavioral intention in digital tourism, extending prior applications of UTAUT2 (Tamilmani et al., 2017; Venkatesh et al., 2012). Notably, the inclusion of gender as a moderating variable deepens our understanding of differentiated adoption patterns between males and females, an area still underexplored in the technology acceptance literature (Aguirre-Urreta & Marakas, 2010; Bao et al., 2013). These insights contribute to ongoing debates around gendered technology use and support the need for more personalized AI design in tourism applications.

Furthermore, this research contributes to the cultural heritage and smart tourism literature by demonstrating how AI chatbots such as LanGTa can facilitate deeper cultural engagement and knowledge dissemination in heritage-rich areas such as Suvarnabhumi. As tourism evolves toward more meaningful and immersive experiences, intelligent systems offer scalable means to enhance visitor satisfaction while preserving cultural identity (Chung et al., 2015). The user-centered design of LanGTa reflects current best practices in smart tourism development, offering real-time, personalized, and location-aware content aligned with tourist expectations. These capabilities can support inclusive tourism and reinforce national objectives around sustainable and digitally enabled heritage promotion.

On an interdisciplinary level, the study also illuminates behavioral psychology by linking emotional and social factors, such as enjoyment and peer influence, to adoption behavior. The unexpected negative relationship between Habit and Behavioral Intention among males adds nuance to the traditional linear understanding of habitual technology use, suggesting that unconscious usage may decouple from intention over time (Limayem et al., 2007; Ouellette & Wood, 1998). This has implications for AI engagement strategies, where sustained use may not always equate to active intention. These insights contribute to interdisciplinary theory-building across psychology, communication, and human–computer interaction, particularly regarding the role of affect and cognition in digital behavior.

Finally, this study provides practical implications for developers and policymakers. Identifying gender-specific adoption patterns and motivational drivers lays a foundation for designing more inclusive and effective AI chatbots. This includes attention to user-friendly interfaces, emotional engagement features, and culturally relevant content. Moreover, the findings support AI's potential to democratize access heritage content, reduce reliance on physical infrastructure, and promote sustainable tourism models in emerging destinations (Neuhofer et al., 2015). This study contributes to theory and practice in multidisciplinary research and serves as a model for future work on AI, culture, and behavior.

5. Conclusions

This study explored the factors influencing the adoption of LanGTa, an AI-powered chatbot designed for historical tourism, via the UTAUT2 framework. The findings provide valuable insights into the drivers of BI adoption by LanGTa, highlighting the roles of PE, EE, SI, FC, HM, PV, and HT. In addition, the study revealed significant gender differences in how these factors influence adoption, offering a nuanced understanding of user behavior in the context of historical tourism. The study revealed that PE and EE strongly predicted BI, highlighting LanGTa's usefulness and ease of use as key factors for adoption. Users who find that a chatbot assists with accessing historical information and planning itineraries are more likely to use it, particularly when its interface is straightforward and easy to navigate. HM also played a significant role, particularly for males, indicating that users who find LanGTa enjoyable or fun are more likely to intend to use it. This highlights the importance of incorporating engaging and interactive features into chatbots to increase user satisfaction. SI had a weaker but still significant effect, particularly among females, suggesting that social recommendations and peer influence can encourage adoption, especially for female users. The study also revealed notable gender differences in the factors influencing LanGTa adoption. Females were influenced primarily by PE, EE, and SI, whereas males placed greater emphasis on EE, FC, HM, and PV. These findings suggest that females prioritize chatbots' usefulness, ease of use, and social recommendations, whereas males are more influenced by usability, enjoyment, cost value, and infrastructure support. This highlights the need for designed strategies to address gender-specific preferences and motivations in promoting LanGTa adoption.

The study offers actionable recommendations for developing and promoting LanGTa. To enhance adoption, LanGTa should provide accurate, relevant, and timely historical information to meet user expectations, particularly for female users. The chatbot should also feature intuitive interfaces and a user-friendly design to reduce cognitive effort, especially for male users. Marketing campaigns should leverage social proof and influencer endorsements to encourage adoption among female users while ensuring that adequate resources and infrastructure are available to support LanGTa usage, particularly for male users. Additionally, incorporating interactive and immersive features, such as gamification or storytelling, can make LanGTa more engaging, particularly for male users. Emphasizing chatbots' affordability and tangible benefits can also attract price-sensitive users, particularly males. The study also makes significant theoretical contributions by extending the UTAUT2 framework to the context of AI chatbots in historical tourism, demonstrating its applicability in diverse domains beyond traditional technology adoption settings. By incorporating constructs such as HM, PV, and HT, this research provides a more comprehensive understanding of the factors driving technology adoption in tourism. The findings also contribute to the literature on gender differences in technology adoption, offering insights into how males and females prioritize different factors when adopting AI-driven solutions.

In conclusion, this study highlights the potential of AI chatbots such as LanGTa to enhance historical tourism experiences by providing users with accurate, engaging, and culturally relevant information. By applying the UTAUT2 framework, this research offers valuable insights into the factors driving LanGTa adoption and provides actionable recommendations for developing user-centric and sustainable AI solutions. These findings advance academic knowledge and have practical implications for practitioners seeking to promote the adoption of AI technologies in tourism and cultural heritage contexts. LanGTa represents a promising tool for promoting historical tourism and supporting sustainable development in culturally significant regions. LanGTa has the potential to enrich travel experiences and play a significant role in preserving and promoting cultural heritage by effectively addressing user needs and preferences, with particular attention to gender-specific strategies. Future research and development efforts should build on these findings to refine AI-driven solutions and maximize their impact on the tourism industry.

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Ethical Considerations

I confirm that I have obtained all the consent required by the applicable law to publish any personal details or images of patients, research subjects, or other individuals used. I agree to provide the *Multidisciplinary Reviews Journal* with copies of the consent or evidence that such consent has been obtained if requested.

Conflict of Interest

The authors declare that they have no conflicts of interest.

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