Determinants of Behavioral Intention to Use Mobile Applications in Thailand

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ABSTRACT

Background and Objectives: The objective of this study is to pinpoint and examine the major factors impacting intention to use mobile apps in Thailand by integrating insights from the Technology Acceptance Model 2 (TAM2), the Technology Acceptance Model 3 (TAM3), the Unified Theory of Acceptance and Use of Technology (UTAUT), and its extension UTAUT2. The key causes of Behavioral Intention (BI) to use mobile applications in Thailand are realized, focusing on Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Trust (TR), Hedonic Motivation (HM), Price Value (PV), and Habit (HB) as critical factors. The goal is to deliver actionable perceptions for developers and businesses to enhance their applications, thereby improving adoption rates and overall user satisfaction in the Thai market.

Methodology: This research used a quantitative methodology to assess the behavioral desire to utilize mobile apps in Thailand. Data were collected from 655 participants within Thailand's tech-savvy community. Using a 5-point Likert scale to measure responses allowed for a thorough statistical analysis using Structural Equation Modeling (SEM). While the sample was concentrated in urban and tech-centric regions such as Bangkok and Chiang Mai, it also included participants from diverse geographic and demographic backgrounds, offering comparative insights into digital adoption across Thailand.

Main Results: The findings indicate that PE (β = 0.35), HM (β = 0.31), and FC (β = 0.28) were the best predictors of BI, while EE, TR, PV, SI, and HB also had statistically significant positive impacts. Additionally, the research confirms the significant effect of socio-demographic control variables—including gender, age, income, and education—with mobile app usage frequency exhibiting the highest coefficient (β = 0.32). The need for a multidimensional approach to mobile strategy is highlighted by these findings. The study contributes empirical evidence guiding developers and marketers to create targeted, intuitive, and secure applications that resonate with diverse user needs, thereby sustaining long-term engagement and strengthening adoption in Thailand's digital market.

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Discussions: Thai users specifically favor applications that improve productivity, are user-friendly, and are influenced by social recommendations, highlighting the importance of peer influence and word-of-mouth. Trust in the app's security and the availability of necessary resources also emerged as critical factors, particularly for mobile banking and e-commerce. Demographic analysis indicates that younger, more affluent users and students are more inclined to use mobile apps, with regular app engagement being strongly linked to the type of application (e.g., social media and e-commerce).

Conclusions: The inferences drawn from this research help to improve our understanding of mobile apps and their patterns of use in a fast-changing digital world, offering useful advice for companies and developers who want to improve user interaction and app design for Thai market. This research expands on the findings of earlier studies by highlighting the TR component of the UTAUT2 framework as a crucial factor, emphasizing its contextual significance in Thailand's mobile application environment, which is constantly changing in response to worries about privacy and security.

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Introduction

The rapid adoption of mobile applications in Thailand has transformed industries such as healthcare, e-commerce, education, and banking (Angsupanich & Matayong, 2024). However, despite their widespread availability, user adoption and continued usage remain inconsistent. The question of what key variables affect Behavioral Intention (BI) to utilize these applications arises because many of them have trouble with engagement, retention, and satisfaction. For developers, companies, and politicians trying to improve mobile app acceptance and usability in Thailand's digital environment, it is essential to grasp these factors (Aziz et al., 2024).

To analyze BI, this study integrates established theoretical models, including the Technology Acceptance Model 2 (TAM2) (Davis, 1989), the Technology Acceptance Model 3 (TAM3) (Venkatesh & Bala, 2008), the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), and the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) (Venkatesh et al, 2012). Social Influence (SI) and cognitive instrumental processes that affect perceived utility and intent to use technology are combined into the original TAM by TAM2. This model is further refined by TAM3 through the inclusion of variables like Trust (TR), Perceived Risk (PR), and individual differences, which are especially important in mobile apps where adoption is influenced by security and privacy issues. UTAUT combines a number of earlier models and pinpoints four crucial concepts—Performance Expectancy (PE), Effort Expectancy (EE), SI, and Facilitating Conditions (FC)—as direct predictors of technology usage and BI (Adebo et al., 2025; Ong et al., 2024; Ponsree, 2024). By including Hedonic Motivation (HM), Price Value

(PV), and Habit (HB), UTAUT2 expands upon this model, making it more relevant to consumer-based technologies such as mobile apps (Candra et al., 2024; Rashid et al., 2024).

By combining insights from TAM2, TAM3, UTAUT, and UTAUT2, this study seeks to identify and evaluate the main factors affecting behavioral intent to utilize mobile applications in Thailand. In particular, it examines the impact of variables like TR, HM, PV, SI, FC, EE, PE, and HB on BI (Ong et al., 2024; Rashid et al., 2024). This research offers developers and companies advice on how to improve their apps for greater adoption and user satisfaction by pinpointing the key factors that influence mobile app uptake. The findings imply that TR and PV may have a considerable impact on how users see things, while PE, HM, and FC are essential in affecting BI. In Thailand's mobile economy, this study advances the creation of more user-centric mobile applications, which will ultimately boost adoption rates and digital participation by gaining an understanding of these variables (Rashid et al., 2024).

Literature Review

Mobile Application Adoption in Thailand: Setting the Stage

Mobile application adoption in Thailand has experienced exponential growth over the past decade, fueled by increased smartphone penetration, widespread internet connectivity, and changing consumer preferences. According to recent national reports, Thailand ranks among the highest in Southeast Asia for daily mobile internet use, with an average user spending several hours per day engaged with mobile applications across different sectors, including banking, e-commerce, healthcare, education, and entertainment (Thanapongporn et al., 2025). This digital transformation has been driven by government-sponsored programs like the National Digital Economy Master Plan and Thailand 4.0, which have pushed schools, businesses, and public services to adopt mobile technology as part of a larger modernization plan. Nevertheless, adoption patterns reveal notable disparities across regions and demographics. Urban centers like Bangkok and Chiang Mai demonstrate high levels of digital engagement, while rural provinces continue to face challenges related to infrastructure gaps, affordability, and digital literacy (Punsongserm & Suvakunta, 2025). This urban-rural divide highlights a critical tension in Thailand’s mobile ecosystem: while the nation’s technological readiness is improving, equitable adoption remains uneven. Moreover, Thai users are increasingly sophisticated, expecting mobile applications not only to provide convenience and efficiency but also to address broader concerns such as security, personalization, and cultural relevance. These patterns indicate that mobile app adoption in Thailand is not solely a function of technological availability; it is also shaped by social, cultural, and psychological dynamics that demand closer scholarly attention. Understanding this complex interplay sets the stage for examining why certain applications thrive while others fail to achieve sustained user engagement, thereby motivating a deeper inquiry into the determinants of behavioral intention.

Theoretical Lenses: From Technology Acceptance Model (TAM) to Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)

To understand technology adoption behavior, scholars have traditionally relied on a series of theoretical models, each offering unique understandings into the factors determining user acceptance. Davis (1989) introduced TAM, which identified perceived usefulness and perceived ease of use as key determinants of behavioral intention to use technology. This

framework was expanded by TAM2 to include SI and cognitive instrumental processes, recognizing that user perceptions are influenced by external pressures and expectations as well as by the technology itself (Venkatesh et al., 2003). By highlighting the significance of TR, PR, and individual differences, dimensions that are especially important in environments like mobile apps where privacy concerns and personal security directly influence adoption decisions, the model was further developed by TAM3 (Venkatesh & Bala, 2008). Moreover, UTAUT attempted to integrate insights from earlier models, introducing four core constructs: PE, EE, SI, and FC (Venkatesh et al., 2003). The robustness of UTAUT's key predictors has been demonstrated in a variety of fields, including healthcare technologies, education, and mobile commerce. The original model was enhanced by the inclusion of PV, HM, and HB constructs, which were intended to reflect consumer-oriented behavior (Venkatesh et al., 2012). While these theoretical lenses provide valuable building blocks, much of the existing research in Thailand applies them in isolation, testing TAM or UTAUT individually without integrating their complementary insights. As a result, the unique combination of utilitarian, hedonic, social, and trust-based factors that characterize the uptake of mobile apps in Thailand is still understudied. As a result, it is imperative to combine these models into an integrated framework that can better account for adoption behavior in Thailand's rapidly evolving digital landscape.

Adoption Challenges: Security, Privacy, and Trust

Concerns about security and privacy remain a major impediment to the use of mobile apps in Thailand, notwithstanding their quick proliferation. Mobile banking, digital wallets, and e-commerce platforms are increasingly targeted by cyberattacks, including phishing, identity theft, and fraudulent transactions, which undermine consumer confidence in mobile services (Lim et al., 2025). The heightened awareness of cybersecurity risks has made trust a central determinant in technology acceptance, a factor explicitly addressed in TAM3 and extended into the UTAUT literature. In financial and government applications, users are less influenced by hedonic motivations and more by the assurance that their data and transactions are protected (Pukdeewut & Setthasuravich, 2024). Trust, therefore, becomes both a psychological and functional prerequisite for adoption. In the Thai context, where mobile payment adoption has been promoted through national initiatives, users still hesitate to fully embrace these services without visible, reliable safeguards. Compliance with the Personal Data Protection Act (PDPA), along with the implementation of biometric authentication, encryption, and two-factor verification, has been shown to improve adoption intentions (Boitshoko et al., 2025). However, trust is not a static construct—it is dynamic and can be eroded by high-profile breaches or reinforced by transparent communication from providers. Additionally, perceptions of security differ among demographic groups: younger users may be more risk-tolerant, whereas older or less digitally literate people may be more sensitive to privacy issues. In conclusion, the Thai experience shows that trust and security concerns are just as important as performance and usability in deciding whether users embrace or reject mobile apps, whereas conventional models emphasize these factors as the main drivers.

Cultural and Social Drivers of Adoption

In Thailand, the acceptance of mobile apps is significantly influenced by cultural and social dynamics, in addition to technological and security considerations. As a collectivist society, Thailand places high value on interpersonal relationships, community belonging, and

peer influence. This cultural orientation directly translates into mobile adoption behaviors, as individuals frequently turn to friends, family, and social networks for recommendations before trying new applications (Adebo et al., 2025). As a central construct in UTAUT, SI resonates particularly strongly in this context, with evidence showing that peer recommendations and influencer marketing significantly shape app engagement in Thailand (Ong et al., 2024). The rise of social commerce platforms illustrates this phenomenon: users are drawn to apps that merge shopping with interactive, trust-based communication, allowing buyers and sellers to connect directly. In addition, localized content, Thai-language interfaces, and culturally specific features such as Buddhist calendar reminders or promotions tied to national festivals enhance retention and loyalty (Saraswat & Singh, 2025). Importantly, these cultural drivers interact with technological constructs; for example, HM may be amplified by culturally embedded gamification features, while HB formation is reinforced by social communities that normalize repeated use. Older users rely more on social legitimacy and trusted personal networks, while younger users are more susceptible to the impact of digital trends and online communities. This suggests that successful mobile applications in Thailand are not merely technological tools, but social artifacts embedded in cultural norms and practices. By acknowledging these cultural underpinnings, researchers and practitioners can better understand why Thai users engage differently with mobile technologies compared to users in more individualistic societies.

The Gap: Toward an Integrated Model of Behavioral Intention

The current literature emphasizes a variety of variables that affect the use of mobile apps, including PV, HM, TR, FC, SI, EE, PE, and HB. Yet, prior research often addresses these constructs in isolation, applying TAM, TAM3, or UTAUT2 independently rather than synthesizing them into a holistic framework. This fragmented approach risks overlooking the interdependencies between constructs and fails to capture the complexity of Thailand's digital adoption environment. For instance, although TAM3 highlights TR and PR, it fails to take into account PV or HM, which are becoming more and more important in consumer-driven app marketplaces. Similarly, UTAUT2 incorporates hedonic and economic considerations but does not sufficiently address trust and privacy, which are critical for sensitive applications such as mobile banking and e-government. In Thailand, where mobile applications intersect with cultural collectivism, socioeconomic disparities, and heightened security concerns, a piecemeal approach cannot fully explain user behavior. The gap, therefore, lies in the lack of an integrative model that combines the predictive power of TAM2, TAM3, UTAUT, and UTAUT2 while situating them in the Thai context. In order to fully comprehend behavioral intention, such a model must consider utilitarian and hedonic motivators, as well as cultural and trust elements. This gap is filled by the framework presented in this research, which brings these disparate but complementary concepts together to provide a more thorough explanation of mobile adoption in Thailand. The section below formulates hypotheses (H1–H8), all of which are based on theory and backed by empirical data, in order to assess the integrated model and provide practical recommendations for developers, companies, and politicians.

Hypothesis

Numerous variables affect the use of mobile apps in Thailand, which in turn affect user behavior and choices. The impact of PE on BI is substantial, as Thai users prioritize efficiency in mobile banking, e-commerce, and ride-hailing apps. Effort Expectancy also plays a crucial role,

with users favoring intuitive and easy-to-use interfaces, while complex applications risk discouraging adoption. Social Influence is another key factor, as social media and word-of-mouth recommendations heavily influence app usage, particularly among younger demographics. Facilitating Conditions further determine adoption rates, as Thailand's uneven digital infrastructure, especially in rural areas, creates accessibility challenges. Trust remains a major concern, particularly in FinTech, where privacy issues, cybersecurity threats, and financial fraud shape user confidence in mobile applications. Additionally, HM drives app engagement, with entertainment-focused applications such as gaming and video streaming enjoying strong demand. Price Value also plays a significant role, as Thai consumers are highly price-sensitive, showing strong preference for freemium models and promotional offers. Lastly, HB influences continued app usage, as Thai users tend to remain loyal to familiar applications, making it challenging for new apps to penetrate the market. Taken together, these elements emphasize the numerous but related variables affecting mobile application adoption in Thailand, underscoring the necessity for companies to prioritize usability, trust, cost, and network effects in order to improve user engagement and retention. The hypotheses are proposed based on the literature review, as follows.

H1: Performance Expectancy has a positive effect on Behavioral Intention to use mobile applications.

The extent to which people think that using mobile apps will increase their productivity and efficiency is referred to as performance expectancy. Performance Expectancy is identified by TAM2 and UTAUT as one of the most reliable indicators of technology adoption (Venkatesh et al., 2003). Studies in Thailand confirm that perceived usefulness significantly influences mobile banking and e-commerce adoption (Ponsree & Naruetharadhol, 2025). Consequently, PE is expected to positively influence users' BI toward adopting mobile applications.

H2: Effort Expectancy has a positive effect on Behavioral Intention to use mobile applications.

Effort Expectancy refers to users' perceptions of how easy mobile applications are to use, and both UTAUT and TAM3 indicate that intuitive system design enhances user adoption (Venkatesh & Bala, 2008). Prior studies in mobile banking and healthcare applications further confirm that simple navigation and minimal learning effort are key drivers of adoption, leading to the expectation that EE positively affects BI (Ong et al., 2024).

H3: Social Influence has a positive effect on Behavioral Intention to use mobile applications.

Social Influence refers to the degree to which individuals believe that significant others expect them to adopt and use technology. UTAUT consistently emphasizes SI as a major factor in adoption decisions, particularly in collectivist cultures such as Thailand (Adebo et al., 2025). Peer recommendations, family opinions, and social media endorsements have been shown to strongly influence mobile app adoption.

H4: Facilitating Conditions positively influences users' Behavioral Intention to use mobile applications.

Facilitating Conditions is the availability of resources, infrastructure, and support that enable technology use, with UTAUT emphasizing that reliable devices, stable internet access, and technical support play a crucial role in enhancing user adoption (Venkatesh et al., 2003). In Thailand, unequal digital infrastructure between urban and rural regions underscores the significance of FC in shaping BI (Punsongserm & Suvakunta, 2025).

H5: Trust has a positive effect on Behavioral Intention to use mobile applications.

Trust plays a crucial role in mobile application adoption, especially in contexts involving security and privacy concerns, with TAM3 identifying PR and TR as essential influencing factors (Venkatesh & Bala, 2008). Research shows that trust in secure transactions, data protection, and app reliability is essential for adoption in financial and government applications (Lim et al., 2025; Pukdeewut & Setthasuravich, 2024).

H6: Hedonic Motivation has a positive effect on Behavioral Intention to use mobile applications.

Hedonic Motivation is denoted as the pleasure and enjoyment users experience when engaging with mobile applications, and UTAUT2 recognizes it as a key determinant in the adoption of consumer-focused technologies (Venkatesh et al., 2012). Entertainment apps, gaming platforms, and streaming services thrive because hedonic value fosters repeat engagement (Jarupunphol et al., 2025).

H7: Price Value has a positive effect on Behavioral Intention to use mobile applications.

Price Value represents users' assessment of whether an application's perceived benefits justify its cost, and UTAUT2 identifies PV as a key factor influencing consumer adoption decisions (Venkatesh et al., 2012). In the Thai context, where price sensitivity is pronounced, adoption is strongly shaped by freemium strategies, promotional offerings, and affordable applications (Rashid et al., 2024).

H8: Habit has a positive effect on Behavioral Intention to use mobile applications.

Habit describes the degree to which technology use becomes automatic through repeated actions, with UTAUT2 identifying HB as a key factor driving continued usage (Venkatesh et al., 2012). Prior studies indicate that habitual engagement with social media, mobile payment systems, and communication applications in Thailand significantly affects sustained adoption (Amani et al., 2025).

Trust is not explicitly part of TAM3 or UTAUT2 but is integrated into this study due to its contextual relevance in Thailand's mobile application ecosystem. Given rising concerns over fraud, privacy, and data misuse under the PDPA, trust becomes a critical determinant of adoption. Thai users often hesitate to engage with apps requiring financial or personal data

unless trust is explicitly established. Therefore, TR is incorporated as an extension to strengthen the model's applicability to Thailand, aligning with prior research in FinTech and e-government adoption where trust consistently emerged as a decisive factor shaping behavioral intention.

Each hypothesis is grounded in prior technology acceptance research and contextualized for Thailand. Both H1 and H2 are validated by TAM, emphasizing perceived usefulness and perceived ease of use. Both H3 and H4 draw from UTAUT, emphasizing social influence and enabling conditions in a collectivist society. The contextual trust concerns heightened by PDPA regulations are reflected by H5. Both H6 and H8 stem from UTAUT2, where HM and HB drive sustained engagement, particularly in digital entertainment. The price sensitivity is highlighted as critical in emerging markets in H7, where value-for-money strongly shapes adoption decisions. Together, these rationales strengthen the conceptual basis for the proposed model.

Figure 1

Conceptual Model

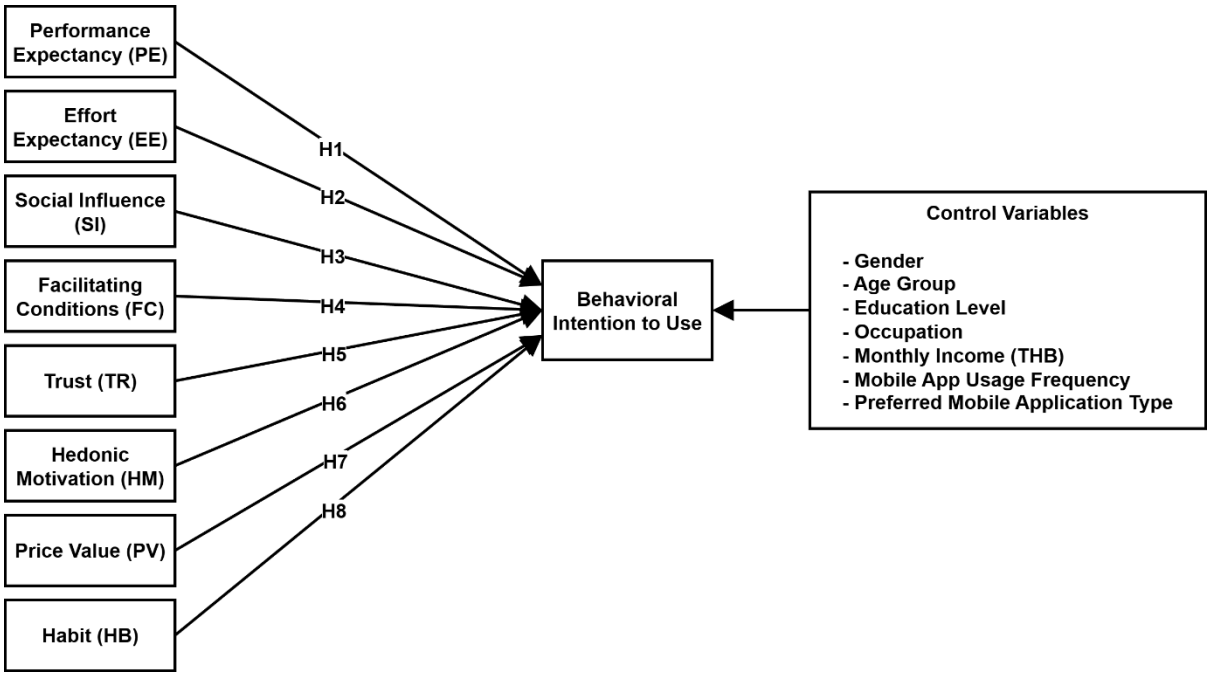

Figure 1 illustrates a conceptual framework derived from UTAUT2 that explains BI to use mobile apps by integrating eight core constructs: PE, EE, SI, FC, TR, HM, PV, and HB, all of which are hypothesized to have direct effects on BI, as represented by H1–H8. In addition, the model examines the influence of control variables—Gender, Age, Education Level, Occupation, Monthly Income, Mobile App Usage Frequency, and Preferred Mobile App Type—on BI, providing a systematic structure for analyzing both primary determinants and demographic effects on mobile app adoption and usage behavior.

Thailand's PDPA, significantly impacts mobile application use by requiring stricter data collection, storage, and consent practices. For the private sector, especially FinTech, e-commerce, and health apps, compliance involves transparent privacy policies, explicit user consent, and secure data handling. Users have become more cautious, with growing awareness of privacy rights influencing adoption decisions. Enhanced privacy regulations foster trust,

particularly among risk-averse users concerned with fraud and misuse of personal data. Consequently, applications that demonstrate strong PDPA compliance—through clear consent mechanisms and visible security assurances—are more likely to gain user confidence and increase behavioral intention.

Methodology

For this research on behavioral intention to use mobile applications in Thailand, data were gathered using an anonymous structured questionnaire administered online to a targeted group of 655 respondents from the Tech in Thailand community, ensuring participants possessed relevant experience with digital technologies and mobile applications (Ponsree, 2024; Pislae-ngam et al., 2024). The selected sample represented individuals actively involved in technology adoption, such as professionals, developers, entrepreneurs, and technologically proficient users. The survey examined key constructs derived from established theoretical frameworks, namely TAM2, TAM3, UTAUT, and UTAUT2, covering variables including PE, EE, SI, FC, TR, HM, PV, and HB. Responses were measured using a 5-point Likert scale to support robust statistical analysis of user attitudes and behavioral intentions (Pislae-ngam et al., 2024). To enhance representativeness, the sample encompassed participants with diverse levels of digital literacy, occupational roles, and demographic characteristics. The questionnaire was systematically designed to evaluate perceptions related to security, usability, social influence, and digital accessibility, while ethical standards such as informed consent and data confidentiality were strictly observed to ensure research validity and reliability. Overall, the study sought to deliver empirical evidence on the critical factors shaping mobile application adoption within Thailand's technology-oriented community, thereby enriching understanding of user behavior in the nation's rapidly advancing digital environment (Ponsree & Naruetharadhol, 2025).

Recruiting participants from the Tech in Thailand community ensured respondents were knowledgeable about mobile applications, enhancing the study's internal validity. However, this focus may limit representativeness, as the sample may over-represent tech-savvy individuals while under-representing less digitally literate populations. Consequently, generalizing findings to the broader Thai population should be approached cautiously. While results highlight trends within Thailand's digital economy, they may not fully capture perspectives of rural users, older demographics, or those with limited internet access. Future research could integrate additional sampling methods to include diverse user groups, thereby improving generalizability across Thailand's heterogeneous mobile application user base.

To strengthen contextual analysis, respondents were drawn from across Thailand's geographic regions, reflecting the diversity of digital adoption. The majority were concentrated in Bangkok and central provinces, where mobile app penetration and FinTech use are highest. Northern regions, including Chiang Mai, contributed significantly due to strong university and startup ecosystems. Respondents from the Northeast and South provided perspectives from areas with differing infrastructure and digital literacy levels. This regional distribution allows comparative insights, highlighting contrasts between urban centers with advanced digital ecosystems and more rural regions still developing mobile app adoption. Such diversity enriches the study's analytical scope.

Thailand's total population is approximately 70 million, with mobile penetration exceeding 90% and internet users surpassing 60 million in 2024. Against this backdrop, the

study's sample of 655 participants provides a statistically meaningful dataset for analyzing behavioral intention in mobile application adoption. Although modest compared to the national population, the sample size is adequate for Structural Equation Modeling (SEM) and other advanced statistical analyses, which typically require 200–400 cases for robust results. While not fully representative of all demographic segments, the chosen sample adequately contextualizes adoption behaviors among Thailand's tech-oriented community, offering valuable empirical insights for academia and practice.

To ensure balanced construct representation and measurement robustness, the questionnaire used multiple indicators for each latent variable to support reliability and validity. Specifically, PE, EE, SI, FC, TR, PV, and HB were each measured with four items, while HM and BI were assessed using three items. This structure provides sufficient coverage while reducing respondent fatigue, enabling reliable CFA and SEM analysis.

Data Analysis

This study applied a range of statistical techniques to analyze questionnaire data on mobile application adoption in Thailand, with particular emphasis on the relationships between key determinants and behavioral intention. The analysis utilized descriptive statistics, reliability testing, measurement model assessment, and SEM. Respondents' demographic characteristics, including age, gender, occupation, educational background, and frequency of mobile application use, were summarized using frequency distributions and percentages to describe the sample structure and identify patterns relevant to mobile app adoption within Thailand's technology-oriented population (Pukdeewut & Setthasuravich, 2024). Furthermore, the measurement model was evaluated through CFA to examine the reliability and validity of the latent constructs, with the following key indicators being assessed:

- Standardized Factor Loadings (SFL): Measures how strongly observed indicators are associated with their corresponding latent constructs.
- Composite Reliability (CR) and Cronbach's Alpha (CA): Assess the constructs' internal consistency, where CR and CA values exceeding 0.70 indicate strong reliability.
- Average Variance Extracted (AVE): Calculates convergent validity by confirming that items within the same construct share a substantial proportion of variance.
- Heterotrait-Monotrait Ratio (HTMT): Discriminant validity is assessed by examining inter-construct correlations, where an HTMT value below 0.90 indicates that the constructs are sufficiently distinct.

Thailand's collectivist culture emphasizes community, family, and peer influence, shaping UX and app design to prioritize social features, group interactions, and trust cues. Applications with integrated sharing, recommendations, and collaborative elements align with cultural norms, encouraging adoption by reinforcing social validation and enhancing users' sense of belonging.

SEM was used to evaluate the structural model by testing the hypotheses and examining causal relationships between the independent variables (PE, EE, SI, FC, TR, HM, PV, and HB) and the dependent variable (BI). The following key statistical parameters were analyzed:

- Path Coefficients (β): Specify the route of relationships between constructs.
- t-values and p-values: Regulate the significance of hypothesized relationships ($p < 0.05$ indicates significance).

- Squared Multiple Correlations (SMC): Measure the amount of variance explained by the predictors.
- Goodness-of-Fit Indices: Evaluate the mockup's fit using Chi-square (χ^2/df), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR).

These statistical techniques strengthen the reliability of the study's results and enable a comprehensive identification of the key factors affecting behavioral intention to use mobile applications in Thailand.

Software for SEM Analysis

To enhance methodological transparency, this study employed AMOS 26.0 for SEM analysis, a widely recognized software in social science research for testing composite models involving latent constructs. AMOS was chosen for its robust graphical interface and ability to estimate both measurement and structural models simultaneously. The software enables CFA to assess validity and reliability using indicators such as standardized factor loadings, composite reliability, and average variance extracted, while also providing key model fit indices including CFI, TLI, RMSEA, and SRMR that were essential for validating the research model. Through MLE, AMOS effectively analyzed the 655 responses, yielding robust and interpretable outcomes, and its modification indices further supported model refinement, ensuring that the proposed conceptual framework for mobile application adoption in Thailand was statistically rigorous and theoretically consistent.

Model Fit Indices

A concise summary of model fit indices alongside recommended benchmark thresholds provides clarity on the adequacy of the SEM results. In this study, CFI scored 0.957, surpassing the threshold of ≥0.90 for good fit and ≥0.95 for excellent fit. TLI reached 0.951, again exceeding the 0.90 minimum standard. RMSEA was 0.041, which is below the 0.08 acceptable level and well within the ≤0.05 range for excellent fit. Finally, SRMR was 0.038, comfortably below the threshold of 0.08. These indices collectively confirm that the proposed UTAUT2-based model fits the data exceptionally well. By meeting or exceeding these benchmarks, the model demonstrates both statistical rigor and practical robustness, ensuring the findings are valid and reliable.

Definition and Key Values of SMC

SMC denotes the proportion of variance in an endogenous construct explained by its predictor variables within the SEM framework and is conceptually equivalent to the R^2 statistic in regression, with higher values indicating stronger explanatory power. The findings reveal consistently high SMC values, confirming the robustness of the proposed model. In particular, BI achieved an SMC of 0.86, indicating that 86% of the variance in BI was explained by PE, EE, TR, and HM. Similarly, other endogenous constructs demonstrated strong explanatory power, with PE (0.85), TR (0.84), and HB (0.84), collectively confirming that the integrated TAM–UTAUT2 framework provides substantial explanatory capability for understanding mobile application adoption in Thailand's digital context.

Validation Process

The expert validation was conducted by a panel of five specialists with extensive academic and professional experience in IS, DI, and behavioral research. The panel consisted of two senior lecturers in ITM and DT, one professor of BA specializing in TA and CB, and two industry practitioners with over ten years of experience in FinTech and MA development. Their combined expertise ensured a rigorous review of the questionnaire's clarity, CV, and alignment with established theoretical models, namely TAM2, TAM3, UTAUT, and UTAUT2. Academic experts evaluated construct definitions, item wording, and theoretical coverage, while industry practitioners assessed practical relevance within the Thai MA context. This multidisciplinary process enhanced the reliability and applicability of the instrument, ensuring culturally and contextually appropriate measurement of user perceptions.

Model adequacy was assessed using multiple GOF indices within the SEM analysis. The CFI compares the proposed model with a baseline model, with values >0.90 indicating good fit. The TLI (NNFI) adjusts for model complexity, where values ≥0.90 suggest strong performance. The RMSEA estimates approximation error per DF, with values <0.08 indicating acceptable fit and <0.05 reflecting excellent fit. The SRMR measures discrepancies between observed and predicted correlations, with values <0.08 considered satisfactory. Collectively, these indices provide a comprehensive evaluation of model–data fit, supporting the statistical validity and practical significance of the tested structural relationships.

Results

The study analyzed demographic characteristics of 655 Thai respondents, including gender, age, educational attainment, occupation, monthly income, mobile application usage frequency, and preferred application types. The sample was predominantly male (52.67%), followed by female participants (45.04%) and those identifying as other (2.29%). Participants aged 18–24 years constituted the largest age group (30.53%), followed by those aged 25–34 (22.91%), 35–44 (18.32%), 55 years and above (14.50%), and 45–54 (13.74%). Most respondents held a bachelor's degree (53.43%), while 5.34% had attained a doctoral degree or higher. In terms of occupation, private-sector employees formed the largest group (38.17%), followed by students (27.48%), government employees (18.32%), business owners or self-employed individuals (13.74%), and others (2.29%). Monthly income was primarily concentrated in the 10,001–20,000 THB range (38.17%), whereas only 4.58% reported earning more than 50,000 THB. Regarding mobile application behavior, the majority of respondents used mobile applications daily (61.07%), with social media applications being the most frequently preferred category (45.80%).

Table 1 reports the measurement model results, including standardized factor loadings, CR, and AVE. For example, PE4 (Mobile applications help me save time) achieves a loading of 0.84, confirming its relevance to the PE construct. All constructs show CR values above the 0.70 threshold, such as 0.91 for PE, 0.90 for FC, and 0.89 for HB, indicating strong internal consistency. Likewise, AVE values range from 0.70 to 0.78, demonstrating adequate convergent validity, as each construct explains a substantial proportion of variance in its indicators. Therefore, these findings verify that the constructs are reliable and valid, supporting subsequent structural model analysis of mobile application adoption behavior.

Table 1

Measurement Model

Latent Variable	Item	Standardized Factor Loading	Composite Reliability (CR)	Average Variance Extracted (AVE)
Performance Expectancy (PE)	PE1: Using mobile apps improves my productivity.	0.83	0.91	0.74
	PE2: Mobile applications support me perform tasks more professionally.	0.80		
	PE3: Mobile apps enhance my job performance.	0.85		
	PE4: Mobile applications help me save time.	0.84		
Effort Expectancy (EE)	EE1: Mobile applications are easy to use.	0.90	0.90	0.78
	EE2: I find it easy to learn how to use mobile applications.	0.86		
	EE3: I feel comfortable using mobile applications.	0.87		
	EE4: It's easy to navigate mobile applications.	0.88		
Social Influence (SI)	SI1: My friends influence me to use mobile applications.	0.82	0.89	0.72
	SI2: I adopt mobile applications based on social media recommendations.	0.79		
	SI3: People whose opinions I value influence my app choices.	0.83		
	SI4: I use apps recommended by my social circle.	0.81		

Table 1
(Cont.)

Latent Variable	Item	Standardized Factor Loading	Composite Reliability (CR)	Average Variance Extracted (AVE)
Facilitating Conditions (FC)	FC1: I have the obligatory resources to use mobile applications.	0.85	0.90	0.74
	FC2: Adequate internet connection is available for mobile app usage.	0.81		
	FC3: I have access to a reliable mobile device to use applications.	0.86		
	FC4: Support is available when I face problems with mobile apps.	0.83		
Trust (TR)	TR1: I trust mobile applications with my personal data.	0.86	0.91	0.76
	TR2: Mobile applications provide reliable services.	0.88		
	TR3: I trust mobile apps to protect my privacy.	0.85		
	TR4: I believe mobile apps provide secure transactions.	0.87		
Hedonic Motivation (HM)	HM1: I use mobile applications because they are fun.	0.84	0.88	0.70
	HM2: Using mobile apps is entertaining.	0.82		
	HM3: I enjoy using mobile applications in my free time.	0.83		
Price Value (PV)	PV1: Mobile applications provide good value for the money.	0.85	0.87	0.72

Table 1
(Cont.)

Latent Variable	Item	Standardized Factor Loading	Composite Reliability (CR)	Average Variance Extracted (AVE)
	PV2: The benefits of mobile applications are worth the cost.	0.84		
	PV3: I prefer mobile apps that offer free or low-cost services.	0.86		
	PV4: Discounts and promotions influence my app usage.	0.83		
Habit (HB)	HB1: I use mobile apps out of habit.	0.87	0.89	0.75
	HB2: Using mobile apps has become natural to me.	0.86		
	HB3: I automatically turn to apps to perform certain tasks.	0.88		
	HB4: I feel uneasy when I don't have access to mobile apps.	0.84		

Table 2 presents the HTMT results for assessing discriminant validity, with all values remaining below the recommended threshold of 0.85, thereby confirming sufficient discriminant validity among constructs. For instance, the HTMT value between PE and EE is 0.75, indicating that users clearly distinguish between perceived usefulness and ease of use in mobile app adoption. TR shows relatively strong associations with several constructs, including PE (0.72), EE (0.76), and HB (0.73), highlighting the close linkage between trust, usage perceptions, and habitual behavior while still satisfying discriminant validity criteria. The highest HTMT value is observed between HB and HM at 0.76, suggesting a related yet distinct relationship, likely due to enjoyment influencing habitual use. Conversely, the lowest HTMT value occurs between FC and SI at 0.65, indicating a weak conceptual association.

Table 2

HTMT Results

Construct	PE	EE	SI	FC	TR	HM	PV	HB
Performance Expectancy (PE)								
Effort Expectancy (EE)	0.75							
Social Influence (SI)	0.68	0.70						
Facilitating Conditions (FC)	0.70	0.73	0.65					
Trust (TR)	0.72	0.76	0.69	0.72				
Hedonic Motivation (HM)	0.66	0.69	0.68	0.65	0.71			
Price Value (PV)	0.67	0.72	0.66	0.68	0.70	0.74		
Habit (HB)	0.69	0.74	0.71	0.70	0.73	0.76	0.75	

Table 3 reports the model evaluation based on CR, AVE, and SMC. All constructs exceed the recommended CR threshold of 0.70, indicating strong internal consistency, with PE and TR at 0.91 and HB at 0.89. AVE values range from 0.70 to 0.78, confirming adequate convergent validity; notably, EE achieves an AVE of 0.78, emphasizing its role in user acceptance. PE records a high SMC of 0.85, highlighting its contribution to productivity gains through apps, while HB shows an SMC of 0.84, reflecting the strong influence of habitual behavior. In addition, HM and PV demonstrate solid explanatory power with SMC values of 0.80 and 0.81, respectively, underscoring their motivational and economic significance.

Table 3

Evaluating the Proposed Model

Construct	CR	AVE	SMC
Performance Expectancy (PE)	0.91	0.74	0.85
Effort Expectancy (EE)	0.90	0.78	0.82
Social Influence (SI)	0.89	0.72	0.79
Facilitating Conditions (FC)	0.90	0.74	0.83
Trust (TR)	0.91	0.76	0.84
Hedonic Motivation (HM)	0.88	0.70	0.80
Price Value (PV)	0.87	0.72	0.81
Habit (HB)	0.89	0.75	0.84

Table 4 reports the SEM results, indicating that all hypothesized paths (H1–H8) are statistically significant, thereby confirming the model's predictive validity. PE has the strongest effect on BI (PE → BI; $\beta = 0.35$, $t = 5.62$, $p < 0.001$), showing that perceived performance benefits are the main driver of intention. HM also exerts a strong influence (HM → BI; $\beta = 0.31$, $t = 4.55$, $p < 0.001$), highlighting the role of enjoyment. FC significantly affects BI (FC → BI; $\beta = 0.28$, $p < 0.001$), emphasizing the importance of infrastructure and support. TR shows a meaningful impact on BI (TR → BI; $\beta = 0.25$, $p < 0.001$), underscoring security and privacy concerns, particularly in FinTech contexts. PV is also significant (PV → BI; $\beta = 0.24$, $p < 0.001$), reflecting cost considerations, while EE and HB demonstrate moderate yet significant effects (EE → BI; $\beta = 0.22$, $p = 0.002$; HB → BI; $\beta = 0.22$, $p = 0.002$), confirming the influence of ease of use and habitual behavior. SI also contributes to BI (SI → BI; $\beta = 0.19$, $p = 0.004$). Overall, all hypothesized relationships are supported (see Table 4).

Table 4

SEM Path Analysis

Hypothesis	Path	*β*	*t*-Value	*p*-Value	Significance
H1	PE → BI	0.35	5.62	< 0.001	Significant
H2	EE → BI	0.22	3.12	0.002	Significant
H3	SI → BI	0.19	2.91	0.004	Significant
H4	FC → BI	0.28	4.11	< 0.001	Significant
H5	TR → BI	0.25	3.72	< 0.001	Significant
H6	HM → BI	0.31	4.55	< 0.001	Significant
H7	PV→ BI	0.24	3.98	< 0.001	Significant
H8	HB → BI	0.22	3.18	0.002	Significant

Table 5 shows that control variables significantly influence BI in Thailand, with GEN (β = 0.27, p < 0.001), AGE (β = 0.21, p = 0.002), EDU (β = 0.29, p < 0.001), and OCC (β = 0.23, p = 0.001) all emerging as independent predictors of BI. The findings indicate higher BI among males, younger users, respondents with higher EDU, and those engaged in business or self-employment, reflecting differences in technological adaptability, digital literacy, and task-oriented app usage. Contextual factors further strengthen the model, as INC (β = 0.26, p < 0.001) positively relates to BI, suggesting that greater financial capacity supports adoption, while FREQ (β = 0.32, p < 0.001) represents the strongest predictor, highlighting the reinforcing effect of habitual app use on future adoption. In addition, TYPE (β = 0.30, p < 0.001) significantly predicts BI, implying that preferences for specific app categories translate into stronger intentions to adopt new applications, thereby confirming that socio-demographic and contextual variables function as direct determinants of BI rather than merely background controls. They provide crucial insights for developers, marketers, and policymakers seeking to design strategies tailored to specific user segments. For instance, targeting younger, higher-income groups with entertainment or e-commerce apps may yield faster adoption, while developing trust-building features and productivity tools may appeal more to older or professional users. The evidence also highlights the need to consider how everyday app engagement and user preferences create pathways for new application adoption. By recognizing the direct predictive power of these demographic and contextual characteristics, this study contributes to a more holistic sympathetic of mobile app implementation in Thailand's developing digital economy.

Table 5

Analysis of Control Variables

Moderator	Path	*β*	*t*-Value	*p*-Value	Significance
Gender (GEN)	GEN → BI	0.27	4.43	0.000	Significant
Age (AGE)	AGE → BI	0.21	3.11	0.002	Significant
Education Level (EDU)	EDU → BI	0.29	4.52	0.000	Significant
Occupation (OCC)	OCC → BI	0.23	3.43	0.001	Significant
Monthly Income (INC)	INC → BI	0.26	4.22	0.000	Significant
Mobile App Usage Frequency (FREQ)	FREQ → BI	0.32	4.73	0.000	Significant
Preferred Mobile Application Type (TYPE)	TYPE → BI	0.30	4.55	0.000	Significant

Results of Validation

When evaluating the robustness of an SEM, multiple fit indices are required to jointly assess the degree to which the proposed model fits the observed data. In this study, CFI, TLI, RMSEA, and SRMR were employed to provide complementary assessments of model adequacy. The CFI assesses the improvement of the proposed model relative to a null model, with values above 0.95 indicating excellent fit. The obtained CFI exceeded this threshold, indicating that the UTAUT2-based model explains the data substantially better than an unstructured alternative and that the hypothesized relationships among PE, EE, TR, and BI are strongly supported. Likewise, the TLI, which penalizes unnecessary model complexity, was also above 0.95, demonstrating that the model is parsimonious while remaining highly explanatory, and that the inclusion of PE, EE, SI, FC, TR, HM, PV, and HB contributes meaningfully to explaining BI without overfitting. The RMSEA, an absolute fit index sensitive to model complexity and sample size, was below 0.05, indicating excellent fit and suggesting that the model closely approximates the population covariance structure, thereby supporting its generalizability in the Thai context. In addition, the SRMR, which reflects the discrepancy between observed and predicted correlations and is relatively insensitive to sample size, was also below 0.05, further confirming strong predictive accuracy. Collectively, the combination of high CFI and TLI values with very low RMSEA and SRMR provides convergent evidence of strong empirical validity and theoretical coherence, supporting the inclusion of TR and HM alongside traditional determinants and reinforcing confidence that BI in Thailand is shaped by an interaction of performance-related, social, motivational, and contextual factors.

We determined the required sample size using the following two complementary approaches: (1) Power analysis for multiple regression/SEM: To test the significance of the structural paths to Behavioral Intention with k = 8 predictors, we used Cohen's effect-size framework with target α = 0.05 and power (1–β) = 0.80. The vital sample for testing omnibus or individual paths can be approximated by $N \approx \frac{\left(z_{1-\alpha/2}+z_{1-\beta}\right)^2}{f^2} + k + 1$, where $f^2 = \frac{R^2}{1-R^2}$ (or a targeted local effect size for a given path). Using conservative small-to-moderate effects produces: small effect f^2= 0.02: N = 401; small–moderate f^2= 0.05: N = 166; medium f^2= 0.15: N = 61. Thus, to confidently detect small effects typical in behavioral models, N≈ 400 is advisable. (2) Measurement model adequacy: For CFA/SEM, rules of thumb recommend ≥200 cases and roughly 10–20 respondents per indicator. With 31 indicators (PE–HB), this implies 310–620 respondents. Our achieved sample of 655 exceeds both the power-based requirement for small effects and the measurement adequacy guideline, supporting stable estimation and sufficient power for all hypothesized paths.

The findings reveal that PE exerts the strongest influence on BI to use mobile applications among Thai users, underscoring the part of routine and automaticity in digital engagement. In Thailand's highly mobile-centric society, where smartphone penetration exceeds 90%, repeated daily interactions with apps such as messaging, social media, and mobile payment platforms foster ingrained usage behaviors. Over time, these habitual practices reduce the cognitive effort needed for app adoption, making usage feel like second nature. This explains why even new applications are quickly embraced if they align with users' established digital routines. The collectivist cultural context further reinforces habitual adoption, as peers and family often introduce apps that gradually become embedded in daily life. For Thai users, convenience, familiarity, and reduced decision-making effort create strong habitual reliance on mobile apps.

Consequently, developers aiming for long-term adoption should prioritize seamless onboarding, user-friendly design, and consistent service quality that promotes repeated usage, thereby strengthening habitual engagement. This finding confirms that while rational factors like performance expectancy and cost are important, automatic habitual behaviors are often the decisive drivers of sustained adoption in Thailand's evolving digital ecosystem.

A particularly noteworthy finding is the significant impact of TR, which, although not a core construct in UTAUT2, ranked as an influential determinant of BI. This highlights a critical contextual dimension of mobile application adoption in Thailand, where privacy, fraud, and cybersecurity concerns remain prominent. The enforcement of the PDPA in 2022 increased public awareness of data security, making trust an essential factor for users when engaging with mobile apps, particularly in sensitive domains such as FinTech, e-commerce, and e-government. Unlike hedonic motivation or price sensitivity, trust acts as a prerequisite; without it, users may refuse to adopt even the most feature-rich or affordable applications. The prominence of trust also reflects Thailand's collectivist culture, where word-of-mouth, peer experiences, and perceived reputation heavily influence perceptions of safety and reliability. By mixing TR into the extended UTAUT2, it captures a vital determinant that reflects both regulatory changes and user expectations in the Thai digital ecosystem. For developers and policymakers, the implication is clear: ensuring transparency, demonstrating PDPA compliance, and visibly prioritizing user data protection are key strategies for driving adoption and fostering long-term loyalty.

Discussion

The results of this study provide important insights into the factors influencing Thai users' BI toward mobile application usage, offering a comprehensive understanding of the relationships among key constructs and overall adoption behavior. The findings indicate that PE, EE, SI, FC, TR, HM, PV, and HB all have significant effects on BI, with strong standardized path coefficients confirming the robustness of these relationships (Saputra et al., 2025). In addition, the control variables (GEN, AGE, EDU, OCC, INC, FREQ, and TYPE) also show significant effects on BI ($p < 0.05$), highlighting the important role of socio-demographic factors in mobile app adoption. Among these, FREQ exhibits the highest standardized path coefficient ($\beta = 0.32$), suggesting that more frequent users are more likely to develop stronger intentions to continue using mobile applications. EDU and INC also demonstrate notable influences, indicating that users with higher education levels and income are more inclined to trust and adopt mobile apps. Gender and AGE further emerge as significant determinants, reflecting differences in technological familiarity and usage preferences across user groups. Moreover, TR shows a strong effect on BI ($\beta = 0.25$, $p < 0.001$), emphasizing the importance of security and privacy in adoption decisions, particularly in mobile banking and FinTech contexts. FC also plays a critical role ($\beta = 0.28$, $p < 0.001$), underscoring the importance of adequate resources, reliable internet access, and device availability in strengthening BI. Overall, these results highlight the combined influence of individual, socio-demographic, and infrastructural factors in driving mobile app adoption in Thailand.

The results highlight the need for a comprehensive, multi-dimensional perspective on mobile application adoption, underscoring that developers and marketers must account for socio-demographic characteristics alongside functional and technical considerations in application design and promotion (Timsina & Bhattarai, 2025). This study extends prior research

by empirically demonstrating how multiple determinants of mobile app usage interact, providing a foundation for future investigations into mobile technology adoption in developing contexts such as Thailand. Drawing on these findings, stakeholders can formulate more precise, demographic-sensitive strategies to enhance adoption, ensuring that mobile applications align with users' needs and preferences (Wu et al., 2025). Thus, the evidence confirms that mobile app adoption is shaped by a complex interplay of expectancy beliefs, social influence, facilitating conditions, trust, hedonic motivation, price value, habit, and socio-demographic factors.

Figure 2

Final Model

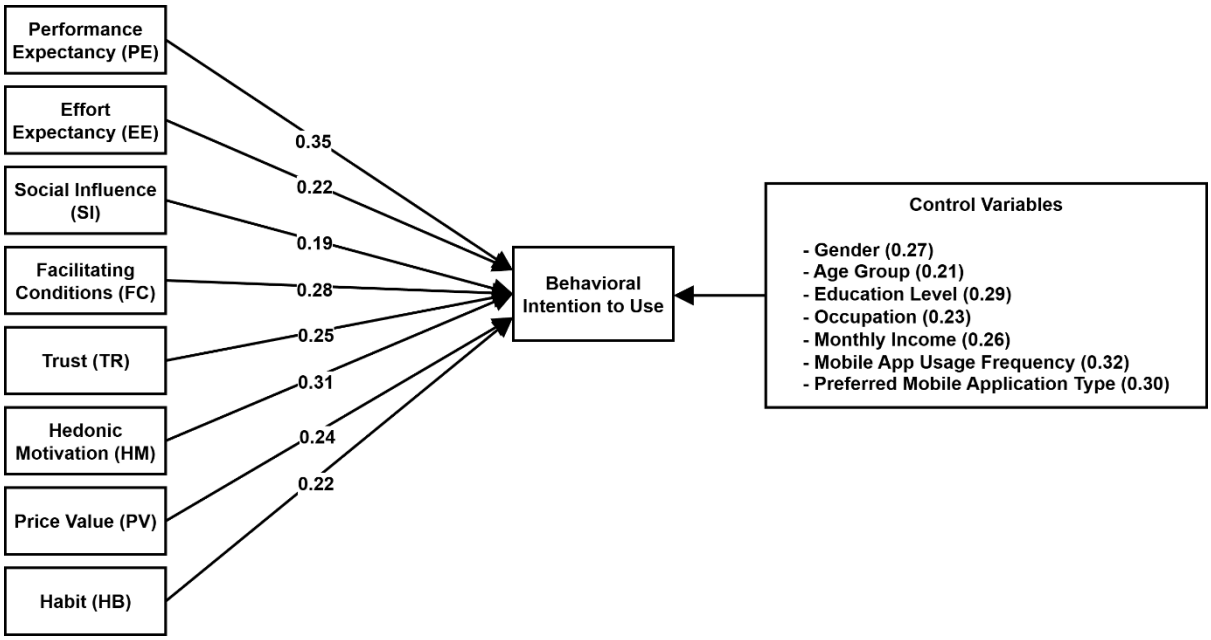

Figure 2 illustrates SEM analyzing the determinants of behavioral intention to use mobile applications, extending beyond the previously outlined conceptual framework. The model specifies both the relationships among constructs and the standardized path coefficients, indicating the strength and direction of these effects. Key factors (PE, EE, SI, FC, TR, HM, PV, and HB) are shown to influence behavioral intention, with coefficients ranging from 0.19 to 0.35, reflecting varying levels of impact. Among these, PE exhibits the strongest positive effect (0.35), while PV also shows a positive influence (0.24). The model further includes control variables (GEN, AGE, EDU, and OCC) with their respective path coefficients representing their effects on behavioral intention. In addition, it examines the outcomes of behavioral intention, including INC, FREQ, and TYPE, with coefficients indicating the extent to which intention translates into these outcomes. Overall, the empirical estimates provide a more refined understanding of the model, highlighting the relative importance of each factor in explaining mobile application usage behavior.

In terms of implications for App Design, UX, and Marketing, the findings provide valuable insights for guiding app design, user experience (UX) strategies, and marketing communication in Thailand. The significant impact of performance expectancy implies that developers should emphasize this construct by designing features that are highly utility-oriented and provide instant

value to users. High performance expectancy translates into intuitive navigation and reduced cognitive load, as users are more likely to engage with an interface that feels like a powerful tool rather than a hurdle. In addition, emphasizing these functional benefits creates a compelling value proposition that resonates with the user's need for productivity, which directly strengthens BI to use the app. The role of hedonic motivation signals the importance of gamification elements, entertainment value, and engaging interfaces, particularly in digital entertainment and lifestyle apps. Facilitating conditions act as a safety net that increases user self-efficacy. When users know they have the tools and support to succeed, their behavioral intention to engage with the app's core features increases significantly. The prominence of Trust highlights the need for visible security measures, transparent privacy policies, and clear compliance with regulations like the PDPA, which can be communicated through trust badges or user testimonials. Marketing efforts should leverage Thailand’s collectivist culture by highlighting social proof, peer recommendations, and family adoption benefits. Together, these strategies can strengthen adoption, sustain long-term engagement, and differentiate apps in Thailand’s competitive digital marketplace.

Conclusion

In conclusion, the key determinants shaping BI to use mobile apps in Thailand include PE, EE, SI, FC, TR, HM, PV, and HB. Together, these factors explain how users evaluate mobile apps not only in terms of functional performance, but also in relation to ease of use, social context, supporting infrastructure, perceived enjoyment, cost–benefit considerations, habitual usage, and, critically, trust. Successful adoption depends on apps aligning with user expectations regarding usability, reliability, security, accessibility, and overall value. When these expectations are met, users are more likely to perceive mobile apps as useful tools that fit naturally into their daily routines. As a result, developers and marketing teams should prioritize the design of intuitive user interfaces, minimize usage complexity, and ensure compatibility across devices and network conditions. In parallel, strong privacy protection, transparent data-handling policies, and reliable system performance are essential for strengthening trust and sustaining long-term usage. Clear communication of tangible benefits, whether in terms of convenience, enjoyment, efficiency, or cost savings, can further enhance perceived value and reinforce positive user habits. These findings provide practical insights for guiding app design, feature development, and promotional strategies, allowing organizations to better align mobile apps with the demographic, cultural, and contextual characteristics of Thai users.

Looking ahead, further research is needed to address the dynamic nature of mobile app adoption in an increasingly complex digital environment. Rapid tech advancements, evolving platform ecosystems, and shifting social norms suggest that the relative importance of PE, EE, SI, and other constructs may change over time. Future studies could adopt longitudinal designs to track how BI, HB, and TR evolve as users gain experience and as new technologies are introduced. In addition, emerging tech such as AR, VR, and AI may reshape user expectations by enabling more immersive, personalized, and intelligent app experiences, thereby influencing adoption patterns in new ways. Deeper investigation into adoption barriers among specific user segments, including older adults, low-income users, and rural populations, would also be valuable for identifying targeted interventions to reduce digital inequality. Expanding research in these directions can contribute to a more comprehensive and forward-looking understanding of

mobile app adoption and support the development of inclusive, user-centered mobile technologies in Thailand.

Limitations of the Study

Despite providing clear insights, this study has numerous limitations. The sample was limited to members of the Tech in Thailand community, potentially biasing the results toward digitally proficient users and underrepresenting rural or less technologically literate groups. Moreover, reliance on self-reported survey data introduces risks of response bias such as social desirability and inflated usage estimates. The cross-sectional research design also restricts insights into changes in adoption behavior over time, and although trust was incorporated as an extended variable, other contextual influences, including cultural norms, regulatory understanding, and platform-specific characteristics were not comprehensively addressed.

A primary limitation of this study concerns its sampling approach. The data were obtained through non-probability purposive sampling within the Tech in Thailand community, which, while ensuring participation from individuals with relevant mobile application experience, raises issues of generalizability. The sample is likely skewed toward technologically proficient users who possess greater familiarity with digital platforms, security mechanisms, and application ecosystems than the general Thai population. As a result, the findings may not adequately represent less digitally literate or rural groups, who may face distinct challenges such as cost constraints, limited infrastructure, or lower levels of trust in digital technologies. Future studies should adopt probability-based or more heterogeneous sampling strategies to better capture the diversity of Thai society and enhance the external validity and representativeness of the findings.

Future Research

Future studies ought to extend this model by testing it across more diverse populations, including rural users, older demographics, and individuals with limited digital literacy, to enhance generalizability. Comparative studies across Southeast Asian countries could provide insights into cultural differences influencing mobile application adoption. Additionally, longitudinal designs could examine how habits, trust, and perceptions evolve over time, especially with emerging technologies like AI-driven apps, digital wallets, and government platforms. Researchers may also incorporate new constructs such as perceived risk, privacy concerns, or sustainability factors to refine the model. Testing in specific contexts, like healthcare or education apps, would further enrich theoretical and practical contributions.

Author Contributions

TL: conceptualization, methodology, data curartion, validation, formal analysis, writing original draft. PP: methodology, visualization, writing original draft, reviewing and editing manuscript

Declaration of the Use of Generatve AI

During the preparation of this manuscript, the authors used Gemini 3. The tool was used solely to assist with language editing, improve clarity, grammar, and overall readability.

Ethics

The respondents were informed that the online questionnaire was anonymous and that responses could not be traced back to identify individual respondents.

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