User Adoption of Generative AI for Government Information Services in Thailand

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Abstract

Recent advancements in generative AI have gained significant attention from both academic and industrial sectors. With the ability to generate new content like text, images, and audio from user inputs, generative AI has demonstrated considerable potential in enhancing organizational efficiency, improving service delivery, and automating complex tasks. In the government sector, generative AI offers opportunities to automate citizen inquiries, enhance administrative processes, and provide more personalized public services. This paper aimed to study the factors influencing user adoption of generative AI for government information services in Thailand. The sample included individuals, focusing on their intentions regarding the use of generative AI for accessing government information. Participants were selected using a convenience sampling method, and data was collected through 400 questionnaires. The data was then analyzed using descriptive statistics and a structural equation model (SEM) to test the hypotheses. The research results indicate that the factors influencing user adoption of generative AI for government information services in Thailand are social influence and user experience, which include perceived usefulness, perceived ease of use, and trust. The overall model explains 48.5% of the variance in the intention to use generative AI for government information services (R^2 = 0.485). The suggestions are proposed to increase adoption rates by developing strategies that involve engaging influencers and advocates, promoting community engagement and education, and improving the overall user experience. These findings provide valuable insights for government agencies and policymakers in Thailand on effectively promoting the adoption of generative AI, contributing to more efficient and accessible government services.

Keywords: generative AI; artificial intelligence; user adoption; government services

Introduction

Recently, AI has gained significant interest from both academia and industry, with generative AI emerging as one of the most attractive technologies in artificial intelligence. Representing a recent breakthrough, generative AI leverages multi-dimensional principles to enhance its capabilities (Wang & Zhang, 2023). This field encompasses AI models that can generate or modify new data based on given inputs (Oh & Shon, 2023). Generative AI technology has advanced to the point where it can produce images and text at a human-comparable level, demonstrating its impressive utility. For example, it can generate textual descriptions for videos and use semantic context to create images from training data without human intervention (Wang & Zhang, 2023).

Generative AI is being utilized across several industries, and its significance is steadily growing (Hwang & Oh, 2023), such as text, image, video, audio, and code generation (Oh & Shon, 2023). The business sector has shown specific interest in generative AI, and many more have expressed willingness to adopt it in the future. These systems are seen as tools to enhance organizational decision-making by providing employees with high-quality and timely information, addressing concerns related to human cognitive limitations, information access, and time constraints (Baabdullah, 2024).

In government sectors, generative AI is utilized to enhance citizen engagement and service delivery. AI-powered digital platforms automate routine inquiries, manage large volumes of communication, and provide personalized responses. This technology significantly improves access to government services and facilitates interactions, particularly in areas such as social services and local government administration (Lothery, 2024). Generative AI also enables automated policy analysis, data-driven decision-making, and increased citizen engagement. Governments use AI to rapidly process large amounts of data, supporting predictive analytics and policy modeling. The primary benefits include more informed, agile, and transparent governance, as well as the ability to deliver personalized public services and optimize resource allocation (Pandey, 2024).

The use of generative AI in Nigeria's e-government initiatives has been studied (Abdulkareem, 2024). Generative AI is applied to enhance citizen services by automating responses and improving access to services. The government benefits from AI by simplifying communication channels, processing large datasets, and promoting more transparent governance. However, challenges such as infrastructure gaps and digital literacy continue to be barriers to fully leveraging these advantages.

In Thailand, generative AI is being explored to improve the efficiency and accessibility of public information services. The successful deployment of these AI systems depends on user adoption, which is influenced by several factors. This research aims to examine the factors influencing user adoption of generative AI for government information services in Thailand. By understanding these factors, policymakers can enhance public engagement with AI-driven services. The results offer valuable guidance for integrating generative AI into government processes, which can improve service delivery and increase public satisfaction. Furthermore, this study addresses a gap in the literature by focusing on the specific context of Thailand and offering localized strategies that can enhance adoption rates and lead to more efficient and accessible government services.

Objective

To investigate the factors influencing user adoption of generative AI for government information services in Thailand.

Literature reviews

Generative AI

Generative AI is used as an umbrella term to describe machine learning solutions trained on massive amounts of data to produce output based on user prompts (input in the form of commands). It is a large language model (LLM) that is specialized for natural language processing (Sætra, 2023).

Generative AI's maturity and free availability have made it accessible and beneficial for a wide range of users. Its significant impact is evident in the rapid integration into everyday tasks by individuals without technical backgrounds. For instance, students have leveraged ChatGPT for academic purposes, while higher education institutions address its implications for assignments and exams. The utility of generative AI extends beyond education, benefiting professionals in various fields, such as consultants, who use it for preparing presentations, writing reports, and drafting carefully worded communications (Sætra, 2023).

Generative AI is being utilized to create custom content based on user inputs. Text models generate text for document summarization, chatbots, automatic sentence generation, and creative writing support. Image models create or transform images for artistic works, style transfer, and restoration. Video models generate or alter videos for art, special effects, and virtual reality content. Audio models produce music, speech, and audio content for composition assistance, speech synthesis, and voice transformation. Code models generate and modify code for autocompletion, bug fixing, and educational purposes (Oh & Shon, 2023; Sætra, 2023). Furthermore, the recent articles addressing the end of traditional programming further emphasize the significant impact of generative AI's coding capabilities (Sætra, 2023).

Technology Adoption Model

The Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) is widely used to forecast consumer behavior across various domains, including library and information science, education, sports, e-learning, internet banking, cloud computing, operations management, and IT adoption (Rajak & Shaw, 2021). Originally developed by Fred Davis, TAM suggests that perceived usefulness and perceived ease of use influence a person's attitude toward using technology, thereby affecting their intention to use it. Perceived usefulness refers to the belief that technology will enhance productivity, while perceived ease of use indicates the effortlessness of using the technology.

Studies have demonstrated that the Technology Acceptance Model (TAM) can be adapted by integrating variables specific to research contexts. Some researchers have simplified TAM by excluding certain variables, such as perceived ease of use. These modifications have occasionally resulted in more accurate predictions of consumer behavior. For instance, some recent studies, like the study by Cudjoe et al. (2023), focus exclusively on perceived usefulness.

The Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a technology acceptance model designed to study user acceptance of information technology. UTAUT aims to explain users' intentions to use information systems and their subsequent usage behavior. It focuses on four main constructs: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. Additionally, four key moderators—gender, age, experience, and voluntariness of use—affect the relationships between these constructs and behavioral intention (Puspitasari et al., 2019).

The UTAUT2 model, an extension of the original UTAUT framework, is highly influential in understanding consumer technology adoption and usage. It identifies several key variables, including effort expectation, that affect user adoption of technology. Researchers have used UTAUT2 to study adoption intentions for various technologies, such as Internet banking and AI-based smart speakers. For instance, the study found that all UTAUT2 variables, along with safety and security, are crucial in explaining user intentions for AI products in the home, mobility, and health sectors (Gansser & Reich, 2021). Many other studies have similarly applied UTAUT2 to understand user intentions toward AI-based technologies (Wang & Zhang, 2023).

Factors influencing User Adoption

Perceived Usefulness (PU)

Perceived usefulness (PU) refers to an individual's belief that a technology will enhance their efficiency or productivity. Within the Technology Acceptance Model (TAM), PU is a crucial factor influencing technology adoption. When people perceive technology as valuable, they are more likely to develop a positive attitude towards its use. In the case of ChatGPT, users are likely to adopt and continue using it if they believe it helps them complete tasks effectively (Saif et al., 2024).

Perceived ease of use (PEOU)

According to the Technology Acceptance Model (TAM), perceived ease of use (PEOU) reflects a user's belief that interacting with a specific technology is straightforward and uncomplicated. Research suggests that PEOU can positively influence individuals' preferences towards utilizing ChatGPT for assignment completion (Saif et al., 2024). For ChatGPT, studies have indicated that users are likely to develop positive attitudes toward ChatGPT if they find it user-friendly (Vaishya et al., 2023). Empirical research has shown a positive correlation between PEOU and favorable attitudes toward using technology for academic purposes, suggesting that PEOU can indeed positively impact perceptions of using ChatGPT for assignment completion (Das et al., 2023).

Familiarity (FML)

Familiarity with technology plays a significant role in shaping users' attitudes and intentions toward adopting new technologies. Research has shown that familiarity provides users with unbiased information, helping to mitigate concerns and positively influence their attitudes toward the technology (Hőgye-Nagy et al., 2023). For example, in the context of autonomous vehicles (AVs), studies indicate that prior knowledge and exposure to AVs can alleviate worries and increase the willingness to give up driving control. Charness et al. (2018) found that drivers with prior knowledge of AVs were less concerned and more willing to trust the technology. Similarly, Nees (2016) concluded that individuals who were familiar with self-driving technology and had access to relevant information were more accepting of self-driving cars.

The same principle applies to generative AI technologies. A study on generative AI in first-year writing found that a lack of familiarity with these tools leads to reluctance among students. This reluctance is expected to decrease as students become more familiar with how the tools work and what they can achieve (Cummings et al., 2024).

Social Influence (SI)

Social influence significantly impacts the adoption of services by shaping users' perceptions based on others' opinions (Rajak & Shaw, 2021). Research indicates that family, friends, and colleagues affect decision-making and behavior, motivating individuals to follow social norms and suggestions from reference groups (Limayem et al., 2004). To adopt new technology, users often rely on others' experiences, making social influence a key motivator for adoption. Research by Bouwman et al. (2007) shows that many people adopt services after being influenced by their social networks, which impact their attitudes, perceptions, and behaviors.

Trust (TR)

The trust factor was used by several researchers to assess the technology adoption (Chen et al., 2014). Trust is fundamental to social relationships and human communication, and it is crucial for the smooth functioning of businesses. Trust develops over time through continuous interactions and is essential for the optimal functioning of individuals, organizations, groups, or cultures. Trust can be directed towards individuals, objects, or events and is necessary for the exchange of knowledge within organizations (Rajak & Shaw, 2021). Empirical studies have shown a positive correlation between trust and perceived usefulness (PU) and perceived ease of use (PEOU). Trust acts as a catalyst for adopting services (Pavlou, 2003), with its impact influenced by the availability of the internet and the efficiency of the software.

Conceptual Framework

A conceptual framework used to investigate the factors influencing the intention to use generative AI for government information services is illustrated in Figure 1. The framework identifies several independent variables and their hypothesized relationships (denoted by H1 to H5) with the dependent variable, "Intention to Use." The five hypotheses are as follows:

H1: Perceived Usefulness (PU) will positively influence the intention to use.

H2: Perceived ease of use (PEOU) will positively influence the intention to use.

H3: Familiarity (FML) will positively influence the intention to use.

H4: Social Influence (SI) will positively influence the intention to use.

H5: Trust (TR) will positively influence the intention to use.

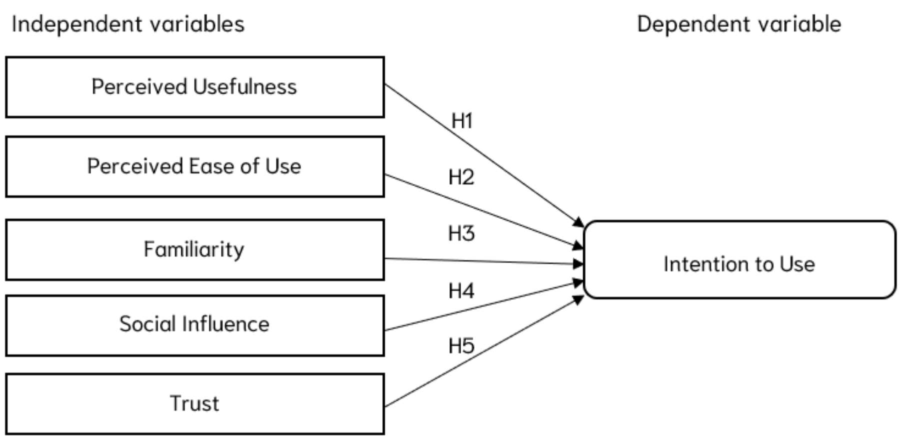

Figure 1. Conceptual Framework

Research Methodology

The respondents in this study were individuals (adults aged 18 and above), with the unit of analysis focusing on personal perceptions and intentions regarding the use of generative AI for accessing government information. The study targeted a diverse group of respondents to gather comprehensive insights across genders, age groups, educational backgrounds, and occupations, providing a thorough understanding of user behavior and preferences in the context of Thailand.

Participants were selected using a convenience sampling method. The sample group for this research study was determined based on the principles of structural equation modeling (SEM). A review of the literature and related research indicates that common guidelines suggest observation-to-free-parameter ratios of 10:1 or 20:1, or at least 200 observations (Hampton, 2015; Kline, 2011). However, there is no definitive rule for determining sufficient sample size, as it varies by case. For this study on the factors influencing the adoption of generative AI for government information services, 400 questionnaires were distributed.

The study utilized a five-point Likert scale, with response options ranging from 1 (strongly disagree) to 5 (strongly agree). This scale was chosen for its effectiveness in capturing the intensity of respondents' attitudes and perceptions. The initial draft of the measurement scale was validated by three experts in the field, ensuring its content validity and relevance. These experts included a professor specializing in information systems from Thammasat University, Thailand, a government employee experienced in AI applications from the Digital Economy Promotion Agency, Thailand; and a researcher with a background in technology adoption studies from Chulalongkorn University, Thailand. Based on their feedback, the questionnaire was revised to enhance clarity, comprehensiveness, and relevance.

A confirmatory factor analysis (CFA) is conducted to assess the validity of the instruments used. A structural equation model (SEM) is employed to test the hypotheses.

Research Results

This research aims to investigate the factors influencing user adoption of generative AI for government information services in Thailand. The results are divided into three parts: Descriptive Analysis, Measurement Model, and Hypothesis Testing.

Descriptive Analysis

The demographic characteristics of the 400 respondents are summarized in Table 1.

Table 1 Respondents' profile

Characteristic (n=400)	Categories	Number	Percentage
Gender	male	162	40.5
	female	208	52.0
	others	30	7.5
Age	18 – 25	31	7.8
	26 – 35	196	49.0
	36 – 45	135	33.8
	46 – 60	38	9.5
Education	Lower than a Bachelor's Degree	30	7.5
	Bachelor's Degree	325	81.3
	Master's Degree or Above	45	11.3
Occupation	Business owner	57	14.2
	Students	26	6.5
	State enterprise employee	45	11.3
	Private sector employee	143	35.8

Characteristic (n=400)	Categories	Number	Percentage
	Government employee/civil servant	76	19.0
	Freelancer	46	11.5
	Others	7	1.8

The gender distribution shows a higher proportion of females (52.0%) compared to males (40.5%), with a small percentage identifying as other genders (7.5%). For age, the majority of respondents fall within the 26–35 age group, accounting for 49.0% of the sample, followed by those aged 36–45 (33.8%), 18–25 (7.8%), and 46–60 (9.5%). In terms of educational background, a significant majority of respondents hold a bachelor's degree (81.3%), with 11.3% having a master's degree or higher, and a smaller group (7.5%) with education levels lower than a bachelor's degree. Regarding occupation, the largest group comprises private sector employees (35.8%), followed by government employees or civil servants (19.0%), and business owners (14.2%). Other notable occupational categories include freelancers (11.5%), state enterprise employees (11.3%), and students (6.5%), with a minor segment (1.8%) categorized as others.

Measurement Model

In the study, various metrics were calculated to assess the measurement model's quality. The metrics, including standardized factor loadings, Cronbach's alpha coefficients, composite reliability (CR), and average variance extracted (AVE), are shown in Table 2. To improve the model's quality, the items TR3 and SI3 were removed. Furthermore, Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Trust (TR) were combined into a single construct named User Experience (UE).

Table 2 The validity and reliability of the instruments.

Construct	Loading	Alpha	CR	AVE
User Experience (UE)		0.943	0.944	0.678
Perceived Usefulness (PU)				
PU1: The government's generative AI services are useful for acquiring the information I need.	.860			
PU2: Utilizing the government's generative AI services helps me accomplish tasks more quickly.	.851			
PU3: The use of the government's generative AI services enhances my productivity.	.787			
Perceived ease of use (PEOU)				
PEOU1: Interacting with the government's generative AI services is simple for me.	.804			
PEOU2: I find the process of using the government's generative AI services easy to understand.	.866			
PEOU3: It is easy for me to learn how to use the government's generative AI services and become proficient at using them.	.854			
Trust (TR)				
TR1: The government's generative AI services provide clear services and reliable information.	.760			
TR2: The government's generative AI services are trustworthy.	.797			
TR3: I can rely on the benefits provided by the government's generative AI services.	removed			
Familiarity (FML)		0.912	0.913	0.777
FML1: I know a lot about various digital technologies.	.853			
FML2: I consider myself to be an experienced digital technologies user.	.927			
FML3: I have experience using Chatbot or generative AI (e.g. ChatGPT, Gemini, or Claude).	.862			
Social Influence (SI)		0.692	0.693	0.531
SI1: If the government's generative AI services are trendy and widely used, I will use them.	.743			
SI2: If socially influential individuals, celebrities, or people who are important to me use the government's generative AI services, I will use them.	.714			
SI3: Overall, the community will support my use of the government's generative AI services.	removed			

Construct	Loading	Alpha	CR	AVE
Intention (INT)		0.789	0.792	0.561
INT1: I will try to use the government's generative AI services for obtaining government information in the future.	.762			
INT2: I intend to utilize the government's generative AI services for accessing government information in the future.	.817			
INT3: I will use the government's generative AI services for my government-related inquiries in the future.	.660			

All items in the measurement model had standardized factor loadings above 0.50, ranging from 0.660 to 0.927. This indicates that the items effectively measured the latent constructs they were intended to represent.

The reliability of the research constructs was examined by assessing the composite reliability (CR) values. All constructs met the minimum CR threshold of 0.70, except for Social Influence (SI), which had a CR value of 0.693. Similarly, Cronbach's Alpha was used to measure internal consistency and reliability. Higher Cronbach's alpha values indicate greater reliability and consistency among the measurement model's elements. From the results, Cronbach's alpha coefficients for all constructs exceeded 0.70, except for Social Influence (SI), which had a value of 0.692. However, the CR and Cronbach's Alpha for Social Influence (SI) were close to 0.70. Therefore, the findings from the reliability measures confirmed that all the research constructs in the research framework were reliable.

The average variance extracted (AVE) values ranged from .531 to .777, all of which exceeded the threshold of 0.50, establishing convergent validity for all research variables (Hair. et al., 2022).

Furthermore, the AVE values for each construct were higher than the correlation coefficients with other constructs as shown in Table 3.

Table 3 Results of discriminate validity.

Model	User Experience	Familiarity	Social Influence	Intention
User Experience (UE)	**0.749**			
Familiarity (FML)	0.643	**0.729**		
Social Influence (SI)	0.381	0.490	**0.881**	
Intention (INT)	0.523	0.443	0.389	**0.823**

Considering the standards (Wang & Zhang, 2023), the measurement model demonstrated an acceptable fit (see Table 4). These values indicate that the measurement model fits the observed data well.

Table 4 Results of construct validity and reliability analysis.

Indices	Criteria	Results
CMIN/DF	1–3 Excellent, 3–5 Good	1.926
RMESA	< 0.05 Excellent, < 1 Good	0.0480
CFI	> 0.9 Excellent, > 0.8 Good	0.979
SRMR	< 0.1 acceptable	0.0335

Hypothesis Testing

The study findings revealed significant path coefficients for most variables, except for H3 ($p > 0.05$). According to Table 5, User Experience, which comprises Perceived Usefulness, Perceived Ease of Use, and Trust (estimate = 0.265, $p < 0.001$), exhibited a positive impact on the intention to use, supporting the H1, H2, and H5 hypotheses. Social Influence showed substantial positive effects on the intention to use (estimate = 0.513, $p < 0.001$), confirming the H4 hypothesis. However, Familiarity did not demonstrate a significant positive impact on the intention to use, failing to support the H3 hypothesis.

Therefore, according to the research objective, the results show that the factors influencing user adoption of generative AI for government information services in Thailand are social influence and user experience, which include perceived usefulness, perceived ease of use, and trust. Familiarity, although present, does not have a statistically significant impact.

Table 5 The results of the hypotheses test.

Hypothesis	Hypothesis Path	Estimate	S.E.	C.R.	P-Value	Result
H1, H2, H5	UE->INT	.265	.054	4.937	***	Supported
H3	FML->INT	.017	.047	.351	.726	Rejected
H4	SI->INT	.513	.085	6.039	***	Supported

*** $p < 0.001$

The revised model is shown in Figure 2 with standardized path coefficients for factors influencing the intention to use generative AI for government information services. The overall model explains 48.5% of the variance in the intention to use generative AI for government information services (R^2 = 0.485).

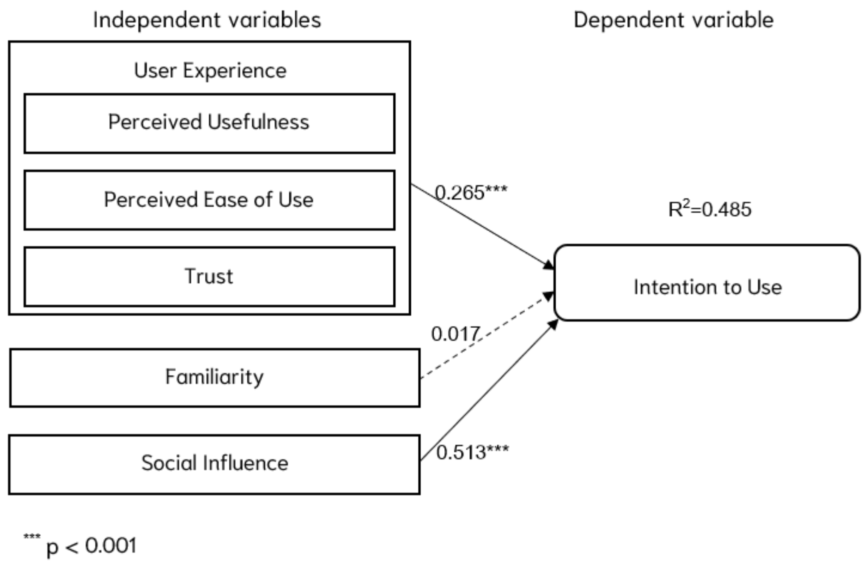

Figure 2. Revised model with standardized path coefficients

Discussions

This study investigates the factors influencing user adoption of generative AI for government information services in Thailand. According to the results, the factors influencing user adoption of generative AI for government information services in Thailand are social influence and user experience, which include perceived usefulness, perceived ease of use, and trust.

Social influence is crucial in shaping and altering individuals' perceptions and behaviors toward adopting new technology, suggesting that adoption can be effortless with positive social influence (Rajak & Shaw, 2021). Social influence plays a significant role in Thailand, where cultural and social norms strongly impact individual behaviors. The results of this research indicate that social influence has significant positive effects on the adoption of generative AI for government information services. These findings are consistent with previous research, which shows that family, friends, and colleagues affect decision-making and behavior, motivating individuals to follow social norms and the suggestions of their reference groups (Limayem et al., 2004).

Perceived usefulness and perceived ease of use positively impact the intention to use generative AI for government information services. These findings are consistent with previous research on AI technology acceptance. For instance, in the case of ChatGPT, users are likely to adopt and continue using it if they believe it helps them complete assignments effectively, demonstrating perceived usefulness (Saif et al., 2024). Additionally, studies have indicated that users develop positive attitudes toward ChatGPT if they find it user-friendly, reflecting perceived ease of use (Vaishya et al., 2023).

Trust is essential due to the advanced and often ambiguous nature of technology. Users need assurance that the technology will operate reliably and securely, especially when handling sensitive information. With the Personal Data Protection Act B.E. 2562 (2019) of Thailand (PDPA) coming into effect on 1 June 2022, there has been increased awareness of data privacy among Thai people. Consequently, trust has become a critical factor in the adoption of generative AI for Thai government information services. These findings align with previous research, which indicates that trust acts as a catalyst for adopting services (Pavlou, 2003).

For familiarity, research has indicated that familiarity can provide users with objective information, mitigating concerns and positively influencing their attitudes toward technology (Hőgye-Nagy et al., 2023). For instance, a study on generative AI in first-year writing found that unfamiliarity with these tools results in reluctance among students to use them (Cummings et al., 2024). However, the results of this research show that familiarity does not have a statistically significant impact. This might be because users may already have a baseline level of familiarity with generative AI due to its prevalence in various consumer applications. This general awareness might make additional familiarity less impactful.

The overall model demonstrates significant explanatory power, accounting for 48.5% of the variance in the intention to use generative AI for government information services ($R^2 = 0.485$). This indicates that nearly half of the variability in users' intentions can be explained by the factors included in the model. The relatively high R^2 value suggests that the model successfully captures the key determinants influencing user adoption of generative AI in the context of government services. Additional variables could be explored to further enhance the explanatory power and provide a more comprehensive understanding of what drives user intentions in this context.

Suggestions

According to the results, the suggestions for promoting the effective utilization of generative AI for government information services in Thailand are: 1) enhancing user experience, and 2) leveraging social influence.

Enhancing User Experience:

Increasing Perceived Usefulness: Government agencies should clearly emphasize the practical benefits of using generative AI for government services by emphasizing how AI can simplify processes, provide timely and accurate information, and solve common user problems. They should provide examples and case studies where generative AI has successfully improved service delivery.

Increasing Perceived Ease of Use: Developers should focus on creating intuitive and user-friendly interfaces for generative AI applications, ensuring that the services are easy to navigate and provide clear instructions to enhance perceived ease of use.

Building Trust: Service providers should implement robust security measures and transparent data privacy policies to build and maintain user trust and regularly update users about security practices and how their data is being protected.

Leveraging Social Influence:

Engaging Influencers and Advocates: Government agencies should utilize socially influential individuals, celebrities, and key opinion leaders to promote generative AI services, as their endorsement can significantly enhance the perception and adoption of these services.

Conducting Community Engagement and Education: Organizations should conduct workshops, seminars, and public awareness campaigns to educate citizens about the benefits and functionalities of generative AI in government services and highlight success stories and testimonials to demonstrate practical applications.

Conclusion

This research aimed to investigate the factors influencing user adoption of generative AI for government information services in Thailand. By focusing on personal perceptions and intentions, the study examined how several factors such as user experience (comprising perceived usefulness, perceived ease of use, and trust), familiarity, and social influence affect the intention to use these services.

The findings revealed that user experience and social influence significantly impact the intention to use generative AI for government information services. The study's model explained 48.5% of the variance in the intention to use generative AI. These insights emphasize the importance of enhancing user experience and leveraging social influence to promote the adoption of generative AI in the public sector.

To promote the effective utilization of generative AI for government information services in Thailand, it is suggested to enhance user experience and leverage social influence. Enhancing user experience involves clearly emphasizing the practical benefits of generative AI, creating intuitive and user-friendly interfaces, and building trust through robust security measures and transparent data privacy policies. Leveraging social influence includes engaging socially influential individuals and conducting community engagement and education to inform citizens about the benefits and functionalities of generative AI. By addressing the factors influencing user adoption of generative AI and the suggestion, government agencies can significantly improve the adoption rates and effectiveness of generative AI in delivering information services to the public.

Future studies could examine additional variables to enhance the model's explanatory power such as technological readiness, economic incentives, or broader social attitudes towards AI. Furthermore, qualitative research could be conducted to offer an in-depth understanding of users' personal experiences, motivations, and concerns regarding generative AI.

Knowledge from Research

The research investigates the factors influencing user adoption of generative AI for government information services in Thailand. The findings contribute to the understanding of how different variables impact the intention to use these services.

The study reveals that user experience, encompassing perceived usefulness, perceived ease of use, and trust, along with social influence, significantly affects the intention to use these AI services. As illustrated in Figure 3, the government should prioritize improving perceived usefulness, ease of use, and trust to enhance the overall user experience. Key actions include emphasizing the practical benefits of generative AI, designing intuitive and user-friendly interfaces, and implementing strong security measures and policies. Moreover, acknowledging the impact of social influence, strategies should involve engaging influencers and advocates, as well as promoting community engagement and education.

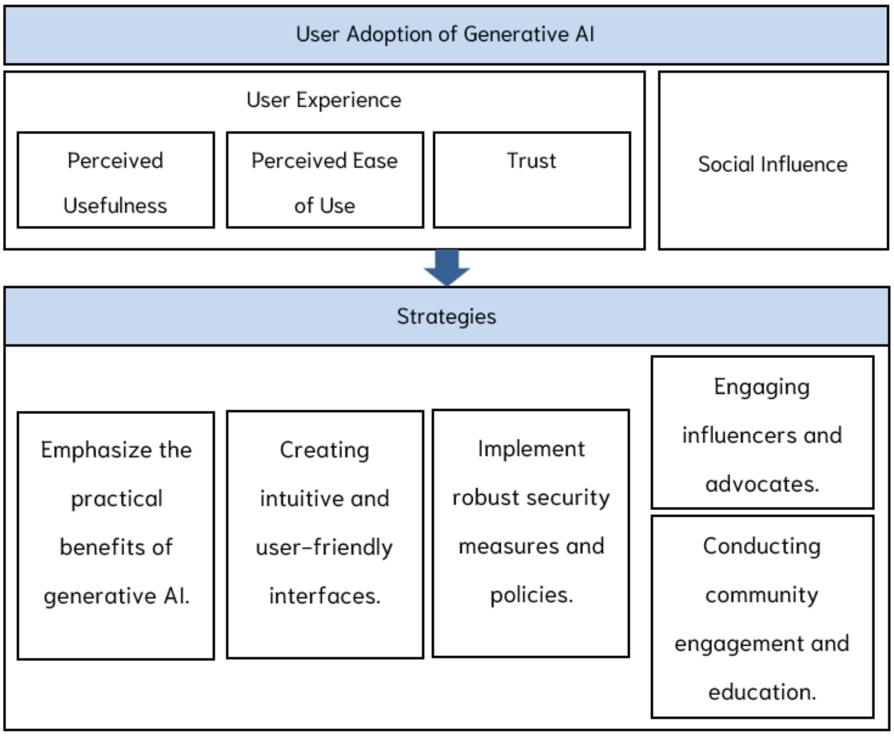

Figure 3. User Adoption and Strategies for Generative AI in Government Information Services

This study provides knowledge that can be directly applied to improve the implementation and adoption of generative AI in Thai government services. Other countries can extend this knowledge to develop tailored strategies that address their specific challenges, leading to efficient, transparent, and accessible government services.

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