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RESEARCH ARTICLE

Every Coin has Two Sides: Navigating Factors of Generative Pre-Trained Transformer Adoption Intentions Among Educators in Thailand

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ABSTRACT

Generative Pre-trained Transformer (GPT) has been widely adopted in education, due to its ability to enhance productivity and provide intelligent assistance. This study investigates the influence of attitude toward behavior, GPT usefulness, GPT ease of use, perceived fraudulent use of GPT, perceived learners' AI competency and GPT resistance on intention to use GPT among educators in Thailand. The research targets educators from fifteen public universities across Thailand with diverse faculty populations, aiming for a sample size of 465. A quantitative methodology was employed, involving the distribution of surveys to gather data. Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) were used for data analysis. The results indicate that attitudes toward behavior significantly enhance both the perceived usefulness and ease of use of GPT. Perceived fraudulent use increases resistance to GPT, which negatively affects the intention to use it. However, perceived usefulness does not significantly influence the intention to use GPT. These findings emphasize the importance of technological literacy, faculty training, institutional support, and peer influence in driving GPT adoption among educators in Thai higher education, highlighting the critical roles of behavioral attitudes and perceived fraudulent use.

INTRODUCTION

The advent of Generative Pre-trained Transformer (GPT) technology has significantly impacted the field of artificial intelligence (AI), particularly within education. GPT models, which generate human-like text based on input prompts, have seen widespread adoption for enhancing productivity and providing intelligent assistance in educational settings (Lv, 2023). These models help educators by automating routine tasks, delivering personalized feedback, and generating educational content (Abaddi, 2023). In Thailand, the integration of GPT technology in higher education is becoming increasingly prominent, driven by the country's efforts to innovate and modernize its educational practices (Wongwatkit et al., 2023).

Thailand's educational sector is actively embracing digital transformation, with AI technologies like GPT being integrated into academic environments to improve educational outcomes (Wongwatkit et al., 2023). The Ministry of Education Thailand has emphasized the role of AI in advancing educational quality and preparing students for future challenges (Shaengchart et al., 2023). Recent initiatives in Thai universities reflect a growing trend towards adopting AI tools to support educators in creating more dynamic and interactive learning experiences (Songsiengchai et al., 2023).

Despite the promising potential of GPT technology, there is a significant gap in understanding the factors that influence educators' intentions to use such technology in Thailand. Existing literature primarily focuses on the technical aspects and benefits of GPT, with limited research addressing the behavioral and perceptual factors that affect its adoption among educators. This lack of comprehensive understanding creates challenges for educational policymakers and institutions aiming to facilitate effective integration of GPT technology (Chaisuwan & Rasricha, 2024).

Current research largely overlooks the socio-psychological aspects influencing GPT adoption among educators. There is a notable gap in studies that examine how attitudes towards GPT, perceived ease of use, perceived usefulness, concerns about fraudulent use, and perceived AI competency impact educators' intentions to adopt this technology (Abaddi, 2023; Hidayat-ur-Rehman & Ibrahim, 2023;Kanval et al., 2024). Addressing this gap is crucial for developing targeted strategies to promote effective GPT adoption in educational contexts.

This study is significant for various stakeholders in the educational sector. For policymakers, understanding the factors that influence GPT adoption can help in formulating supportive policies and frameworks. Educational institutions can use these insights to design effective training programs and support systems for educators. Furthermore, educators will benefit from understanding how their perceptions and attitudes affect GPT use, leading to more informed and positive interactions with the technology.

The primary objective of this study is to investigate the factors influencing the adoption intentions of GPT technology among educators in Thailand. Specifically, the study aims to:

1. Examine the impact of attitudes toward behavior on the perceived usefulness and ease of use of GPT.
2. Assess the influence of perceived fraudulent use on GPT resistance and its subsequent effect on adoption intentions.
3. Determine the relationship between perceived learners' AI competency and educators' intention to use GPT.
4. Evaluate the overall influence of perceived usefulness, ease of use, and resistance on the intention to use GPT among educators.

LITERATURE REVIEW

Attitude Toward Behavior

Attitude toward behavior, derived from the Theory of Planned Behavior (TPB), refers to an individual's positive or negative evaluations of performing a particular behavior (Ajzen, 1991). This construct has been widely studied in the context of technology adoption, including AI technologies like GPT. Research has consistently shown that a positive attitude toward behavior enhances the likelihood of adopting new technologies by influencing perceived usefulness and ease of use (Venkatesh & Davis, 2000). Research has shown that individuals with a favorable attitude toward GPT are more likely to perceive it as useful. For example, a study by Abaddi (2023) explored the adoption of AI technologies and found that users' positive attitudes significantly predicted their perceptions of usefulness. This aligns with Ajzen's (1991) assertion that attitude toward behavior is a strong predictor of perceived usefulness. Iqbal et al. (2023) revealed that educators with a positive attitude toward GPT were more likely to view it as a valuable tool for enhancing teaching and learning. This finding underscores the importance of fostering positive attitudes to increase the perceived usefulness of GPT among potential users.

In the context of GPT and similar AI technologies, attitudes toward behavior can influence how educators perceive the ease of using these tools. For example, a study by Hartman et al. (2019) highlights that educators with positive attitudes toward technology integration are more likely to view educational technologies as user-friendly and less complex. This perception of ease of use can encourage more widespread adoption and integration of AI tools in educational practices. Further research by King and He (2006) supports this notion, demonstrating that attitudes toward technology are significantly related to perceived ease of use, which in turn affects technology acceptance. Positive attitudes can reduce perceived barriers and enhance the usability of educational technologies. Thus, below hypothesis are derived:

H1: Attitude toward behavior has a significant impact on GPT usefulness.

H2: Attitude toward behavior has a significant impact on GPT ease of use.

Perceived Fraudulent Use of GPT

GPT technologies, due to their advanced language generation capabilities, have been identified as prone to misuse in various fraudulent activities (Hidayat-ur-Rehman & Ibrahim, 2023). For instance, GPT can be exploited to create deepfake texts or generate misleading information (Reddy, 2023). Research indicates that users who perceive high risks of fraudulent use tend to exhibit higher resistance towards adopting these technologies (AlAfnan et al., 2023). According to Kasneci et al. (2023), perceived fraudulent uses of AI technologies often lead to heightened skepticism and reluctance to engage with these systems. This skepticism is not unfounded, as misuse cases can erode trust in the technology and diminish its perceived utility. One critical factor influencing resistance is the perception of misuse or fraudulent use (Sok & Heng, 2023). Therefore, this study proposes a hypothesis:

H3: Perceived fraudulent use of GPT has a significant impact on GPT Resistance.

GPT Usefulness

The Technology Acceptance Model (TAM), developed by Davis (1989), provides a foundational framework for understanding user acceptance of technology. AlAfnan et al. (2023) highlight that GPT's capabilities in automating routine tasks, generating high-quality text, and providing timely responses contribute to its perceived usefulness. Abaddi (2023) discuss how GPT's ability to assist in generating educational content, conducting literature reviews, and supporting research processes enhances its perceived usefulness. Yilmaz et al. (2023) found that perceived usefulness was a significant predictor of users' intention to adopt AI-based writing tools, including GPT. Chan and Hu (2023) highlighted that students and educators who recognized the potential benefits of GPT in enhancing learning outcomes were more inclined to adopt the technology. Therefore, this study suggests that:

H4: GPT usefulness has a significant impact on intention to use GPT.

GPT Ease of Use

Perceived ease of use refers to the extent to which a user believes that using a technology will be free from effort (Davis, 1989). For GPT, this involves how intuitively users can interact with the system, the simplicity of generating outputs, and the user-friendliness of the interface (Abaddi, 2023). Forman et al. (2023) emphasize that a well-designed interface that simplifies interaction and reduces cognitive load contributes to higher adoption rates. Users who find GPT easy to use are more likely to integrate it into their routines for tasks such as writing and communication (Menon & Shilpa, 2023). Yilmaz et al. (2023) discuss how a low learning curve and straightforward usability features of GPT contribute to its perceived ease of use. Users who can quickly understand and effectively use

GPT are more likely to exhibit a positive intention to continue using the technology (Jo, 2023). Consequently, a hypothesis is developed:

H5: GPT ease of use has a significant impact on intention to use GPT.

Perceived Learners' AI Competency

Perceived AI competency refers to learners' self-assessment of their ability to understand and utilize AI technologies effectively. This competency can significantly influence their intention to use GPT (Hidayat-ur-Rehman & Ibrahim, 2023). Delcker et al. (2024) found that perceived competency in using AI tools is a strong predictor of intention to use such tools. Mahapatra (2024) discusses how learners with greater AI skills are better able to exploit GPT's capabilities, such as generating content, performing complex tasks, and providing insightful feedback. According to Hatlevik (2017), learners who feel competent in their technology skills are less likely to experience technological anxiety and are more willing to engage with new tools like GPT. Subsequently, a hypothesis is indicated:

H6: Perceived learners' AI competency has a significant impact on intention to use GPT.

GPT Resistance

Resistance to GPT can be influenced by several factors, including concerns about reliability, ethical implications, and the perceived complexity of the technology. This resistance can, in turn, affect users' intention to adopt and use GPT (Hidayat-ur-Rehman & Ibrahim, 2023). Cheong (2024) highlight that users who are concerned about ethical issues and potential misuse of AI tools are more likely to resist adopting these technologies. Polites and Karahanna (2012) found that users who perceive GPT as complex or difficult to use are more likely to resist its adoption. Such resistance arises from the belief that the technology may not be user-friendly or may require significant effort to master (Oreg, 2003). This perception of complexity can negatively impact users' intention to use GPT. Talwar et al. (2020) discusses how skepticism regarding the capabilities of digital tools can lead to resistance and reluctance to use them. Hence, a below hypothesis is concluded:

H7: GPT resistance has a significant impact on intention to use GPT.

Intention to Use GPT

The TAM posits that perceived usefulness (PU) and perceived ease of use (PEOU) are primary determinants of technology acceptance (Davis, 1989). For GPT, users' intention to adopt the technology is influenced by their perceptions of its usefulness in enhancing productivity and its ease of integration into existing workflows (Abaddi, 2023). Unified Theory of Acceptance and Use of Technology (UTAUT) extends TAM by incorporating additional factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). These elements can be critical in understanding users' intention to use GPT, as they encompass not only individual perceptions but also social and organizational influences (Menon & Shilpa, 2023). Users' competence in handling AI tools affects their intention to use GPT. Those who perceive themselves as proficient in AI technology are more likely to adopt GPT (Delcker et al., 2024). Users' concerns about data privacy, potential misuse, and ethical implications can deter adoption (Cheong, 2024).

CONCEPTUAL FRAMEWORK

The research framework is informed by prior studies on GPT adoption. Abaddi (2023) identified key factors such as digital entrepreneurial intentions, technological innovation, and perceived benefits as crucial for the adoption of GPT technologies among entrepreneurs. Hidayat-ur-Rehman and Ibrahim (2023) proposed that factors including educators' technological readiness, perceived usefulness, and institutional support are significant for the adoption of ChatGPT in educational settings. These findings suggest that both individual and organizational factors are critical for GPT adoption, as illustrated in Figure 1.

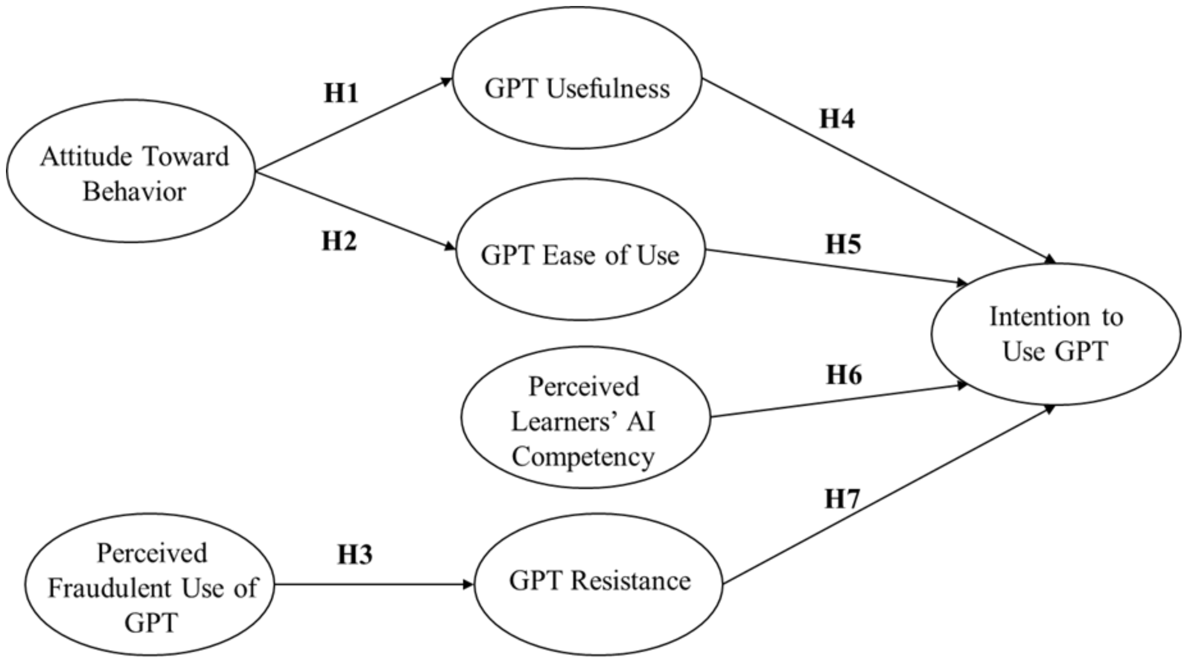

Figure 1. Conceptual Framework
Source: Created by Author.

METHODOLOGY

Research Design

The research methodology is quantitative, involving the distribution of a questionnaire to educators from fifteen public universities across Thailand, targeting a sample size of 465. The questionnaire is divided into four sections: screening questions, 35 items rated on a five-point Likert scale ranging from "strongly disagree" (1) to "strongly agree" (5), and demographic information including age, years of experience, and academic discipline. The content validity of the questionnaire was ensured through expert evaluations, with a panel of four Ph.D. experts assessing the relevance of each item. Reliability was measured using Cronbach's Alpha, achieving values of 0.70 or higher in a pilot test with 50 participants. Data analysis involved Confirmatory Factor Analysis (CFA) to assess the reliability, validity, and goodness-of-fit of the measurement model, and Structural Equation Modeling (SEM) to test the hypothesized relationships and overall model fit.

Population and Sample Size

The target population for this study consists of educators from fifteen public universities across Thailand. This selection ensures a diverse and representative sample from a broad range of educational institutions. The study aims to gather data from a sample size of 465 educators, which is considered adequate for the analysis of complex relationships in the study. According to Kline (2011), a complex model typically requires a minimum sample size of at least 200. The survey was distributed over a three-month period from February to April 2024, providing a robust dataset for analysis and enhancing the credibility and generalizability of the study findings.

Sampling Technique

The study utilizes a multi-faceted sampling approach to collect data from educators on their use of ChatGPT. Judgmental sampling is employed to select faculty members who are actively using ChatGPT for academic purposes, ensuring relevance to the research. Convenience sampling is used to gather responses from participants who are easily accessible and willing to participate, either through paper surveys or online questionnaires. Additionally, snowball sampling is applied, where initial participants refer other potential participants, helping to expand the sample size through their networks. This combined approach aims to ensure a diverse and representative dataset while addressing practical recruitment challenges.

RESULTS AND DISCUSSION

Demographic Profile

In Table 1, The demographic results of the study, which includes a sample size of 465 educators, show a diverse distribution across various characteristics. The gender breakdown reveals 46.4% male and 53.6% female participants. In terms of education, 15.1% hold an Associate Degree, 45.2% have a Bachelor's Degree, and 39.8% possess a Graduate Degree or above. The age distribution is as follows: 22.6% are under 30 years old, 30.1% are between 31 and 40 years, 26.9% are between 41 and 50 years, and 20.4% are between 51 and 60 years. Academic ranks include 37.6% Lecturers, 28.0% Assistant Professors, 22.6% Associate Professors, and 11.8% Professors. Regarding work experience, 17.2% have 5 years or less, 28.0% have 6–10 years, 24.7% have 11–15 years, 18.3% have 16–20 years, and 11.8% have more than 20 years.

Table 1: Demographical Results

Demographic Variable (n=465)	**Category**	**Frequency**	**Percentage**
Gender	Male	215	46.4%
	Female	250	53.6%
Education	Associate Degree	70	15.1%
	Bachelor's Degree	210	45.2%
	Graduate Degree or Above	185	39.8%
Age Group	Less than 30 years	105	22.6%
	31–40 years	140	30.1%
	41–50 years	125	26.9%
	51–60 years	95	20.4%
Academic Rank	Lecturer	175	37.6%
	Assistant Professor	130	28%
	Associate Professor	105	22.6%
	Professor	55	11.8%
Work Experience	5 years or below	80	17.2%
	6–10 years	130	28%
	11–15 years	115	24.7%

	16–20 years	85	18.3%
	More than 20 years	55	11.8%

Source: Created by Author.

Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) was utilized to assess and validate the measurement model in this study. The results, presented in Table 2, were evaluated using various metrics, including Cronbach's Alpha, factor loadings, composite reliability (CR), and average variance extracted (AVE). The analysis revealed that Cronbach's Alpha coefficients met the recommended validation threshold of 0.70 or higher, consistent with the standards set by Nunnally and Bernstein (1994). Factor loadings were deemed acceptable if they were 0.50 or above (Vongurai, 2024). Additionally, both composite reliability (CR) and average variance extracted (AVE) exceeded the suggested thresholds of 0.70 and 0.50, respectively, as proposed by Fornell and Larcker (1981). These results support the convergent and discriminant validity of the measurement model, underscoring the robustness of the CFA findings.

Table 2: Confirmatory Factor Analysis Result

Variables	Source of Questionnaire	No. of Items	Cronbach's (n=465)	Factors Loading	CR	AVE
Attitude Toward Behavior (ATB)	Abaddi (2023)	5	0.838	0.700-0.735	0.838	0.509
GPT Usefulness (USE)	Abaddi (2023)	6	0.877	0.630-0.828	0.878	0.548
GPT Ease of Use (EOU)	Abaddi (2023)	6	0.837	0.629-0.720	0.838	0.463
Perceived Fraudulent Use of GPT (PFU)	Hidayat-ur-Rehman and Ibrahim (2023)	4	0.821	0.697-0.770	0.822	0.537
Perceived Learners' AI Competency (PLA)	Hidayat-ur-Rehman and Ibrahim (2023)	5	0.826	0.624-0.767	0.829	0.493
GPT Resistance (RES)	Hidayat-ur-Rehman and Ibrahim (2023)	4	0.894	0.769-0.881	0.895	0.682
Intention to Use GPT (GPT)	Hidayat-ur-Rehman and Ibrahim (2023)	5	0.809	0.575-0.743	0.811	0.464

Note: Composite Reliability (CR) and Average Variance Extracted (AVE)

Table 3 presents the discriminant validity of the constructs used in the study. The diagonal values in the table represent the square root of the average variance extracted (AVE) for each construct, while the off-diagonal values indicate the correlations between constructs. The results reveal that the square root of AVE for each construct is higher than its correlations with other constructs, demonstrating adequate discriminant validity (Fornell & Larcker, 1981). For instance, the square root of AVE for RES (0.826) is greater than its correlations with other constructs such as ATB (0.557) and USE (0.278). Similarly, the construct GPT has a square root of AVE of 0.681, which is higher than its correlations with other constructs like PLA (0.637) and EOU (0.618). These findings confirm that each construct is distinct from the others, supporting the robustness of the measurement model.

Table 3: Discriminant Validity

	RES	ATB	USE	EOU	PLA	PFU	GPT
RES	0.826						
ATB	0.557	0.714					
USE	0.278	0.198	0.740				
EOU	0.613	0.570	0.179	0.680			
PLA	0.514	0.565	0.189	0.667	0.702		
PFU	0.322	0.151	0.121	0.310	0.365	0.732	
GPT	0.654	0.521	0.256	0.618	0.637	0.432	0.681

Table 4 evaluates the goodness of fit for both the measurement and structural models. For the measurement model, the fit indices are as follows: CMIN/DF is 1.526, which is below the acceptable threshold of 3.00, indicating a good fit (Hair et al., 2006). The GFI (0.910), AGFI (0.894), NFI (0.896), CFI (0.961), and TLI (0.957) all exceed the acceptable values of 0.80, demonstrating a strong model fit (Al-Mamary & Shamsuddin, 2015; Bentler, 1990; Sharma et al., 2005; Sica & Ghisi, 2007; Wu & Wang, 2006). The RMSEA is 0.034, well below the recommended threshold of 0.08, further supporting model adequacy (Pedroso et al., 2016). For the structural model, while the CMIN/DF (2.353) remains within the acceptable range, the GFI (0.864), AGFI (0.845), NFI (0.835), CFI (0.897), and TLI (0.890) are slightly lower but still meet the acceptable criteria. The RMSEA value of 0.054 also indicates a good fit. Overall, both models demonstrate acceptable fit according to the recommended criteria.

Table 4: Goodness of Fit for Measurement and Structural Models

Index	Acceptable Values	Statistical Values	
		Measurement Model	Structural Model
CMIN/DF	< 3.00 (Hair et al., 2006)	822.780/539 = 1.526	1301.012/553 = 2.353
GFI	≥ 0.80 (Al-Mamary & Shamsuddin, 2015)	0.910	0.864
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.894	0.845

Index	Acceptable Values	Statistical Values	
		Measurement Model	Structural Model
NFI	≥ 0.80 (Wu & Wang, 2006)	0.896	0.835
CFI	≥ 0.80 (Bentler, 1990)	0.961	0.897
TLI	≥ 0.80 (Sharma et al., 2005)	0.957	0.890
RMSEA	< 0.08 (Pedroso et al., 2016)	0.034	0.054
Model summary		Acceptable Model Fit	Acceptable Model Fit

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker-Lewis index, and RMSEA = root mean square error of approximation

Research Hypothesis Testing Result

The study evaluated seven hypotheses with standardized path coefficients (β), standard errors (S.E.), and T-values.

Table 5: Hypothesis Result of the Structural Model

Hypotheses	Paths	Standardized Path Coefficients (β)	S.E.	T-Value	Tests Result
H1	USE<---ATB	0.206	0.065	3.832*	Supported
H2	EOU<---ATB	0.575	0.061	9.063*	Supported
H3	RES<---PFU	0.332	0.056	6.048*	Supported
H4	GPT<---USE	0.077	0.027	1.610	Not Supported
H5	GPT<---EOU	0.237	0.039	4.404*	Supported
H6	GPT<---PLA	0.351	0.041	5.931*	Supported
H7	GPT<---RES	0.507	0.043	7.646*	Supported

Note: *p<0.05

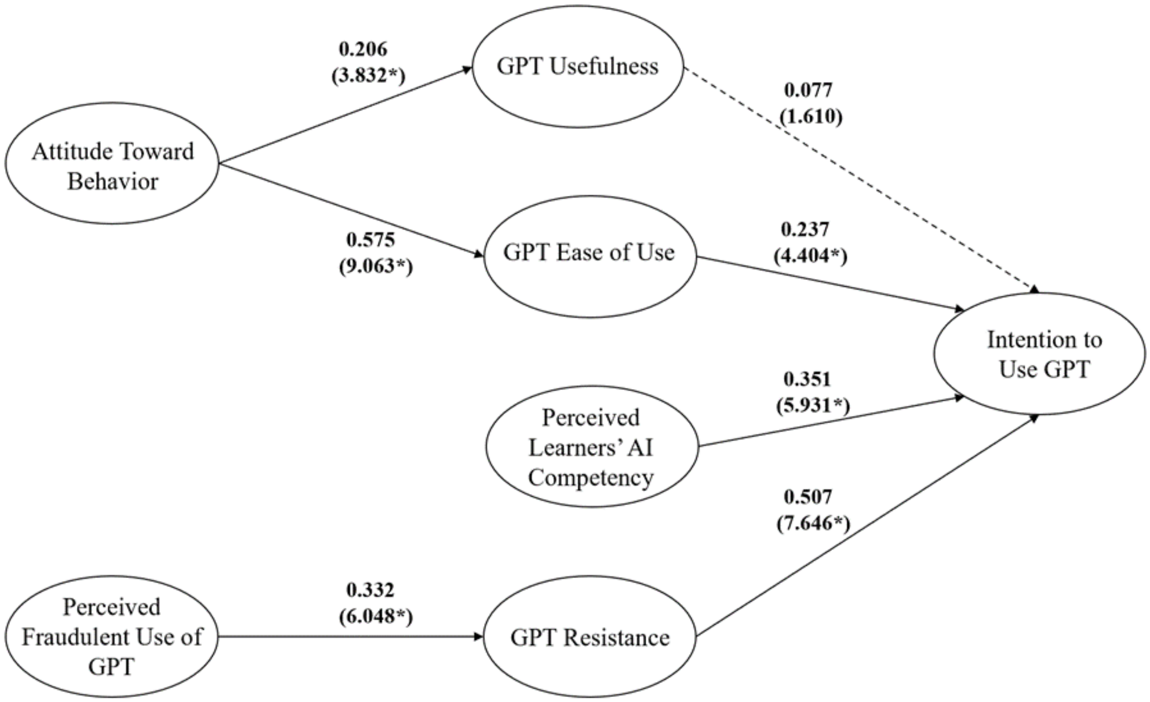

Figure 2. The Results of Structural Model

Remark: Dashed lines, not significant; solid lines, significant. *p<0.05

Source: Created by Author.

Table 5 and Figure 2 present the results of hypothesis testing for the structural model. The analysis shows that several hypotheses were supported at $p<0.05$.

H1 posited that attitude toward behavior (ATB) significantly influences GPT usefulness (USE). The hypothesis is supported with a standardized path coefficient of 0.206, a t-value of 3.832, and a p-value less than 0.05.

H2 proposed that ATB significantly affects GPT ease of use (EOU). This hypothesis is strongly supported, with a standardized path coefficient of 0.575, a t-value of 9.063, and a p-value less than 0.05.

H3 suggested that perceived fraudulent use (PFU) significantly impacts GPT resistance (RES). The hypothesis is supported, as indicated by a path coefficient of 0.332, a t-value of 6.048, and a p-value less than 0.05.

H4 hypothesized that USE has a significant effect on GPT intention (GPT). This hypothesis is not supported, with a path coefficient of 0.077, a t-value of 1.610, and a p-value greater than 0.05.

H5 proposed that EOU significantly influences GPT intention. This hypothesis is supported with a standardized path coefficient of 0.237, a t-value of 4.404, and a p-value less than 0.05.

H6 posited that perceived learners' AI competency (PLA) has a significant impact on GPT intention. This hypothesis is supported, with a path coefficient of 0.351, a t-value of 5.931, and a p-value less than 0.05.

H7 suggested that GPT resistance (RES) significantly impacts GPT intention. This hypothesis is supported with a path coefficient of 0.507, a t-value of 7.646, and a p-value less than 0.05.

The results show that attitudes toward behavior significantly influence both the perceived usefulness and ease of use of GPT, which aligns with the significant positive coefficients for H1 and H2. This suggests that positive attitudes towards GPT-related behaviors enhance perceptions of its usefulness and ease of use, contributing to its adoption.

Perceived fraudulent use is found to significantly increase resistance to GPT, as supported by H3. This highlights the role of concerns about misuse in affecting user resistance.

However, H4, which hypothesized that perceived usefulness directly impacts the intention to use GPT, was not supported. This indicates that while usefulness may enhance perceptions, it does not directly translate into higher usage intentions in this context.

On the other hand, EOU, PLA, and RES all significantly affect the intention to use GPT (H5, H6, and H7). This suggests that ease of use, perceived competency, and resistance factors play a crucial role in shaping the intention to use GPT. The significant impact of EOU and PLA underscores the importance of these factors in driving user engagement, while the substantial effect of RES indicates that overcoming resistance is critical for increasing usage intentions.

Overall, the findings underscore the importance of attitudes and perceived ease of use in influencing GPT adoption, while also highlighting the complex interplay of resistance and competency factors in shaping users' intentions.

DISCUSSION

The results from the hypothesis testing provide a nuanced understanding of the factors influencing the intention to use GPT among educators. The study reveals that attitude toward behavior significantly impacts both the perceived usefulness and ease of use of GPT, aligning with H1 and H2. This suggests that fostering positive attitudes toward GPT-related behaviors can enhance its perceived benefits and usability. The substantial positive effect of perceived ease of use on the intention to use GPT (H5) emphasizes the importance of designing user-friendly AI tools to encourage adoption.

Interestingly, perceived usefulness (H4) did not significantly affect the intention to use GPT, suggesting that other factors, such as ease of use or perceived competency, might be more critical in influencing adoption. This contrasts with traditional technology adoption models, where perceived usefulness often plays a pivotal role. The significant impact of perceived learners' AI competency (H6) on the intention to use GPT indicates that users' self-perceived competency with AI tools can drive their intention to use them, highlighting the need for improving AI literacy.

Resistance to GPT (H7) was found to have a significant negative impact on the intention to use GPT, underscoring that resistance factors must be addressed to promote adoption. The positive effect of perceived fraudulent use on resistance (H3) further suggests that concerns about misuse contribute to resistance, necessitating efforts to mitigate these concerns to improve acceptance.

IMPLICATIONS FOR THEORY

The findings extend existing theories on technology adoption by highlighting the nuanced role of perceived usefulness and the relative importance of ease of use and perceived competency. The study challenges the conventional emphasis on perceived usefulness, suggesting that ease of use and competency may have more immediate effects on technology adoption. This adds to the discourse on technology acceptance models by integrating factors like resistance and perceived competency, which can provide a more comprehensive understanding of technology adoption dynamics.

IMPLICATIONS FOR PRACTICE

For practitioners, the results underscore the importance of designing GPT tools that are user-friendly and enhance users' AI competency. Training programs and support systems should focus on improving educators' familiarity and comfort with GPT to reduce resistance and enhance the perceived ease of use. Additionally, addressing concerns related to fraudulent use through clear guidelines and safeguards can help mitigate resistance and foster a more positive attitude towards GPT adoption. Practitioners should consider these factors when implementing GPT tools to maximize their effectiveness and acceptance in educational settings.

LIMITATIONS AND FUTURE DIRECTIONS

The study's limitations include its focus on educators from only public universities in Thailand, which may limit the generalizability of the findings to other contexts or sectors. The reliance on self-reported data may also introduce bias, affecting the accuracy of the responses. Additionally, the cross-sectional nature of the study provides a snapshot in time and does not capture changes in attitudes or intentions over time. Future research could address these limitations by including diverse educational settings, using longitudinal designs, and incorporating objective measures of technology use.

CONCLUSION

In conclusion, the study provides valuable insights into the factors influencing the intention to use GPT among educators. While attitudes and ease of use significantly impact adoption, perceived usefulness does not have a direct effect on intention, suggesting that other factors may be more crucial in driving adoption. Addressing resistance and enhancing AI competency are essential for promoting GPT use. The findings contribute to the theoretical understanding of technology adoption and offer practical guidance for improving GPT implementation in educational contexts. Future research should build on these insights to explore broader contexts and longitudinal effects.

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