Secondary Teachers' Acceptance of Generative Artificial Intelligence in Teaching Based on the TAM

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***Abstract*—Artificial Intelligence (AI) is transforming global education by enhancing teaching effectiveness and supporting personalized learning. Among its applications, generative AI has gained increasing attention for its ability to create instructional content, assist assessment, and streamline lesson preparation. This study aimed to examine secondary school teachers' acceptance of generative AI in teaching using the Technology Acceptance Model (TAM). A quantitative survey design was employed, involving 367 teachers from secondary schools in Negeri Sembilan, Malaysia, who were selected through simple random sampling. Data were collected via a structured questionnaire and analyzed using descriptive statistics, Pearson correlation, and multiple regression. Results indicated high acceptance levels for perceived usefulness, perceived ease of use, and behavioral intention. The correlation analysis revealed strong and positive relationships among the three constructs, while regression results showed that both perceived usefulness and perceived ease of use significantly predicted behavioral intention, explaining 72.1% of its variance. Notably, perceived ease of use emerged as the stronger predictor. These findings confirm the applicability of the TAM framework in educational contexts and highlight the importance of training, user-friendly AI systems, and supportive policies to enhance teachers' readiness. Future studies are recommended to explore qualitative insights and extended models to better understand sustainable AI integration in education.**

***Keywords*—Artificial Intelligence (AI), generative AI, technology acceptance model, teacher acceptance, perceived usefulness, perceived ease of use, behavioural intention, secondary education**

I. Introduction

Artificial Intelligence (AI) has become a major driver of global educational transformation, particularly in enhancing teaching and learning processes [1–4]. According to UNESCO, AI is recognized as a key enabler for achieving Sustainable Development Goal 4 (SDG 4) by promoting inclusive and equitable quality education through innovative digital tools. One prominent branch of AI in education is generative AI, which can automatically create new content such as text, images, and videos from existing data [5]. In classroom contexts, generative AI is increasingly applied to develop teaching materials, design lesson plans, assess student work, and personalise learning experiences [6, 7].

For the purposes of this study, generative AI refers to artificial intelligence systems capable of creating new content—including text, images, lesson plans, assessment questions, and educational materials—based on user prompts and existing data. This includes but is not limited to widely accessible tools such as ChatGPT (OpenAI), Google Gemini (formerly Bard), Microsoft Copilot, and AI-powered educational platforms. In the questionnaire, teachers were asked to consider their experiences with and perceptions of "generative AI tools for teaching" broadly, recognizing that their familiarity and usage patterns may span multiple tools and applications.

This broad framing was intentional: the study aimed to measure teachers' general acceptance and readiness toward the category of generative AI technologies in education, rather than acceptance of a specific branded tool, in order to inform policy and professional development planning at a systemic level. However, we acknowledge that this approach sacrifices specificity regarding particular use cases (e.g., lesson planning vs. assessment creation vs. image generation) and tool-specific concerns (e.g., ChatGPT's conversational interface vs. DALL-E's image generation capabilities), which are important considerations for practical implementation.

In Malaysia, the Ministry of Education (MOE) has launched the Digital Education Policy to promote the integration of advanced technologies, including AI, in schools to strengthen the digital education ecosystem [8]. However, despite these initiatives, the level of teachers' acceptance and adoption of generative AI remains underexplored in the local context. Previous studies suggest that teachers' perceptions of usefulness and ease of use are critical determinants influencing their acceptance of technology [9–11]. As AI continues to evolve, understanding educators' readiness becomes essential to ensuring equitable technology-driven education, especially in line with Malaysia's national aspirations and UNESCO's AI ethics framework for education [12].

Therefore, this study aims to examine secondary school teachers' acceptance of generative AI in teaching using the Technology Acceptance Model (TAM) [9]. Specifically, it seeks to:

(1) Assess teachers' level of acceptance based on Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Behavioural Intention (BI).
(2) Determine the relationships between the constructs PU–BI, PEOU–PU, and PEOU–BI.
(3) Evaluate the extent to which PU and PEOU influence BI among teachers in Negeri Sembilan, Malaysia.

Guided by these objectives, the study addresses three core research questions:

(1) What is the level of teachers' acceptance toward generative AI in teaching?
(2) Are there significant relationships between PU and BI, PEOU and PU, and PEOU and BI?
(3) To what extent do PU and PEOU influence teachers' BI to

use generative AI

Based on the TAM framework, the following hypotheses were formulated:

H1: PU is positively and significantly related to BI.

H2: PEOU is positively and significantly related to PU.

H3: PEOU is positively and significantly related to BI.

H4: PU has a significant positive influence on BI.

H5: PEOU has a significant positive influence on BI.

By addressing these questions and hypotheses, this study contributes new empirical evidence on teachers' acceptance of generative AI in Malaysian schools. The findings are expected to inform policy formulation, teacher training, and digital education strategies aimed at enhancing effective and equitable technology integration.

II. LITERATURE REVIEW

Fig. 1 shows the Technology Acceptance Model (TAM), introduced by Davis [9], provides a robust theoretical framework for explaining and predicting user acceptance of new technologies. Built upon the Theory of Reasoned Action, TAM identifies two core constructs: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), both of which shape users' Behavioural Intention (BI) to adopt technology [9]. PU refers to the degree to which individuals believe that using a system enhances their performance, while PEOU reflects the degree of effort required to use it effectively. Both constructs interact to influence BI, where PEOU indirectly affects BI through PU [10, 13]. The model has been widely used in education to analyse teachers' and students' acceptance of emerging technologies [14, 15].

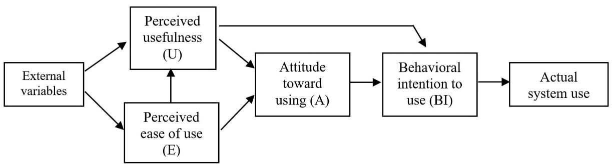

Fig. 1. Technology acceptance model (TAM) [9].

A. Extended Technology Acceptance Models

While the original TAM provides a robust and parsimonious foundation for understanding technology acceptance, several extended models have been proposed to enhance its explanatory power and address its acknowledged limitations. TAM2 [10] incorporates social influence processes (subjective norm, voluntariness, image) and cognitive instrumental processes (job relevance, output quality, result demonstrability), recognizing that users' perceptions are shaped not only by system characteristics but also by social context and task-technology alignment. TAM3 [16] further extends the model by including determinants of perceived ease of use, such as computer self-efficacy, computer anxiety, perceived external control, and perceptions of external support, acknowledging the role of individual differences and organizational context in shaping ease-of-use perceptions.

The Unified Theory of Acceptance and Use of Technology (UTAUT) [17] represents a comprehensive integration of constructs from eight competing technology acceptance models, including TAM, Theory of Reasoned Action, Theory of Planned Behavior, and the Innovation Diffusion Theory. UTAUT identifies performance expectancy (conceptually similar to PU), effort expectancy (similar to PEOU), social influence, and facilitating conditions as key determinants of intention and use behavior, with gender, age, experience, and voluntariness serving as moderating variables. UTAUT has been widely applied in educational technology research and has demonstrated superior explanatory power compared to individual models, typically explaining 60–70% of variance in behavioral intention [17]. The consumer-focused extension, UTAUT2 [18], further incorporates hedonic motivation, price value, and habit.

B. Generative AI Acceptance in Education: Emerging Research

In the specific context of generative AI adoption in education, recent studies have emphasized the importance of additional factors beyond the core TAM constructs, reflecting the unique characteristics and concerns associated with AI technologies. Al-Abdullatif [19] found that AI literacy (understanding of AI capabilities, limitations, and appropriate applications) and intelligent TPACK (integration of AI knowledge with pedagogical and content knowledge) significantly influenced higher education teachers' acceptance of generative AI, while perceived trust in AI systems mediated the relationship between these competencies and acceptance. Trust emerged as a critical factor, as teachers' willingness to adopt AI depends on their confidence in the technology's reliability, accuracy, and alignment with educational values.

Kong *et al.* [6] applied an extended TAM to examine secondary school teachers' behavioral intention to use generative AI tools for teaching and learning in Hong Kong, confirming the central roles of perceived usefulness and perceived ease of use while also highlighting the significant influence of attitudes toward AI and subjective norms (peer and institutional expectations). Their findings suggest that social context and normative pressures play important roles in shaping teachers' AI adoption decisions. Setälä *et al.* [13] explored upper secondary mathematics teachers' acceptance of generative AI in Finland through the TAM lens, noting that contextual factors such as institutional support, clear pedagogical guidelines, professional development opportunities, and alignment with curriculum standards play crucial roles in shaping acceptance and sustained use.

Furthermore, concerns about ethical implications, data privacy, academic integrity, and AI-generated misinformation have been identified as critical inhibiting factors influencing educators' willingness to adopt generative AI. Mishra *et al.* [5] discussed how generative AI fundamentally challenges traditional conceptions of TPACK and raises profound questions about the evolving role of teachers in AI-augmented learning environments, including concerns about deskilling, authenticity of student work, and the potential for over-reliance on AI-generated content. Tian and Jiang [20] highlighted that Malaysian secondary school teachers face both social and psychological challenges in adapting to AI-assisted teaching, including role ambiguity, anxiety about job security, concerns about loss of pedagogical autonomy, and fears of student over-reliance on AI systems that may hinder critical thinking development.

These studies collectively suggest that while classical TAM constructs (PU and PEOU) remain foundational and relevant, a truly comprehensive understanding of generative

AI acceptance requires careful attention to AI-specific factors such as trust, AI literacy, ethical concerns, perceived risks, institutional support structures, and pedagogical appropriateness.

C. Rationale for Employing Basic TAM in the Current Study

Despite the richness and explanatory advantages of extended models, this study employs the original TAM framework for several methodological, contextual, and pragmatic reasons. First, the basic TAM has demonstrated robust predictive validity across diverse educational technology contexts spanning three decades of research and remains the most widely tested, validated, and replicated model in the technology acceptance literature [14, 21] providing a solid and well-understood foundation for exploratory research in novel contexts.

Second, given that this study represents one of the early empirical investigations examining generative AI acceptance specifically among secondary school teachers in the Malaysian context, establishing baseline findings using the foundational TAM framework provides a necessary reference point, benchmark, and theoretical anchor for subsequent research to build upon, extend, and refine. Beginning with the core model allows for direct comparisons with the extensive body of TAM literature while avoiding premature theoretical complexity that could obscure fundamental relationships.

Third, the scope, scale, and sample size of this study ($N = 367$ from a single state) are well-suited to testing and validating the core TAM constructs in a focused, rigorous manner, whereas the more complex structural equation models proposed in TAM2, TAM3, or UTAUT require substantially larger samples (often $N > 500$), greater sample diversity, longitudinal data collection, and additional theoretical and methodological considerations (e.g., measurement invariance testing, moderation analysis) that are beyond the current study's feasible scope and resources.

Finally, the parsimony and clarity of the original TAM makes it particularly suitable for communicating findings to educational practitioners and policymakers who may be unfamiliar with complex theoretical models but who need accessible, actionable insights to inform AI integration decisions.

Nonetheless, we explicitly acknowledge that future research would benefit substantially from incorporating extended constructs and alternative theoretical frameworks to capture the multifaceted nature of generative AI acceptance. Specifically, future studies should examine AI literacy (teachers' understanding of AI capabilities, limitations, and appropriate applications), trust in AI systems (reliability, transparency, explainability), ethical concerns (plagiarism detection, bias mitigation, misinformation risks), subjective norms (influence of peers, school leadership, and ministry policies), facilitating conditions (infrastructure quality, technical support availability, training adequacy, policy clarity), perceived risks (data privacy breaches, job displacement fears, pedagogical appropriateness concerns), and AI self-efficacy (confidence in using and managing AI tools effectively). Such theoretical extensions, potentially using UTAUT or integrated models, would provide a more comprehensive, nuanced, and contextually rich understanding of the complex factors influencing generative AI adoption in Malaysian educational settings and would align Malaysian research with the cutting edge of international scholarship on AI in education.

Globally, a substantial body of research supports TAM's relevance in the context of AI adoption. Al Darayseh [22] found that PU and PEOU were significant predictors of science teachers' intentions to integrate AI into teaching. Similarly, Kong *et al*. [6] reported that PU exerted a stronger influence than PEOU on teachers' intention to use generative AI in Hong Kong, while Guo *et al*. [23] validated the TAM constructs in AI education, emphasizing the role of training and infrastructure support. More recently, Bawaneh [4] reported that science and mathematics teachers' satisfaction and motivation to adopt AI are closely linked to PU and PEOU, echoing findings by Davis [3], who highlighted the need for adequate training programs to strengthen teachers' AI readiness.

In Malaysia, Ahad *et al*. [24] found PU to be the strongest predictor of AI adoption among polytechnic students, whereas Tekin [25] confirmed the TAM framework among Turkish teachers, identifying trust in AI as a mediating variable. Similar conclusions were drawn by Rabab'h [26], who found both PU and PEOU to significantly predict AI adoption among Jordanian teachers, and Fakhar [15], who emphasized that teachers' familiarity with AI enhances both constructs. These findings confirm TAM's robustness across diverse educational and cultural settings, reinforcing its theoretical and practical relevance in explaining AI integration behaviour.

Nonetheless, research gaps persist. Although international studies have examined teachers' acceptance of AI technologies, investigations within the Malaysian secondary school context remain limited. Factors such as school location, resource availability, and digital competence may influence adoption levels [14, 22, 27, 28]. Studies such as Ho [29] show that rural teachers face unique challenges in adopting AI-based learning due to limited digital infrastructure. In higher education, Al-Qora'n [30] identified similar disparities, noting that educators' perceptions of AI are shaped by institutional support and technological access.

Moreover, some teachers remain hesitant to adopt generative AI because of limited awareness, insufficient training, and doubts about its pedagogical relevance [19, 20]. This hesitancy underscores the need for more context-specific evidence to bridge the gap between national policy such as Malaysia's Digital Education Policy [8] and actual classroom practice. By addressing these issues, this study extends previous TAM-based research to the Malaysian secondary education context, contributing fresh insights into how PU and PEOU influence BI among teachers.

III. METHODOLOGY

A. Research Design

This study employed a quantitative survey approach to investigate secondary school teachers' acceptance of generative Artificial Intelligence (AI) in teaching, using the Technology Acceptance Model (TAM) as the guiding framework. The structured questionnaire was designed to measure three TAM constructs: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Behavioural Intention (BI).

Data analysis included descriptive statistics (means, standard deviations) to summarise acceptance levels, and inferential statistics to test hypotheses. Pearson's correlation was used to assess relationships among constructs, while multiple regression analysis evaluated the effects of PU and PEOU on BI.

Unlike earlier TAM-based studies that focused on general technology adoption [9, 10, 14], this study extends the application of TAM to the emerging context of generative AI integration in secondary education, offering a novel empirical contribution. Specifically, it provides quantitative evidence from a Malaysian setting, where empirical validation of TAM for generative AI adoption remains scarce. This approach therefore not only replicates methodological rigour but also advances contextual understanding of how teachers' perceptions shape behavioural intention in the era of AI-driven teaching and learning.

B. Sampling Method

The study population comprised 7883 full-time secondary school teachers serving in Negeri Sembilan, Malaysia, according to the latest records from the State Education Department. For clarity, the target population included teachers teaching across lower and upper secondary levels (Forms 1–5) in a range of subject areas such as science, mathematics, languages and social sciences. Inclusion criteria required respondents to be currently practising secondary school teachers in Negeri Sembilan and to provide informed consent to participate; teachers on long-term leave or those who had already left service were excluded. A simple random sampling technique was employed to ensure equal selection probability, to minimise selection bias and to enhance the reliability and generalisability of the findings [31].

The sampling frame consisted of the complete teacher list supplied by the State Education Department, from which respondents were selected at random using a number-generator function in statistical software. This procedure aligns with the assumptions of inferential analyses used in the study, such as Pearson's correlation and multiple regression, which rely on random sampling to support statistical validity [32].

Sample size determination followed Krejcie and Morgan's table [33], which recommends a minimum of 367 respondents for a population of 7883. To allow for non-response and to increase the robustness of the dataset, 400 teachers were randomly selected and invited to participate. The questionnaire was distributed online with logistical support from school administrators.

This study was conducted in Negeri Sembilan, a state in Peninsular Malaysia with a population of approximately 1.1 million. The state's educational infrastructure presents a mixed profile relevant to understanding generative AI acceptance. Negeri Sembilan has moderate digital connectivity, with urban schools (particularly in Seremban, the state capital) generally having reliable internet access and computer labs, while rural schools face more variable infrastructure quality. According to the Malaysian Communications and Multimedia Commission (MCMC) [34], approximately 87% of households in Negeri Sembilan have internet access, slightly below the national average of 90%, with significant urban-rural disparities.

The state's teaching force reflects Malaysia's broader demographic patterns, with the majority of secondary teachers holding Bachelor's degrees in education, teaching experience distributed across career stages, and variable exposure to technology integration depending on school location and subject specialization. Negeri Sembilan is neither the most technologically advanced state (like Selangor or Kuala Lumpur) nor the least (like more remote states such as Sabah or Sarawak), positioning it as reasonably representative of mid-tier states in Malaysia's educational system.

As part of Malaysia's national education system, schools in Negeri Sembilan implement centralized policies including the Digital Education Policy (2021–2030), which emphasizes technology integration, digital literacy, and 21st-century skills. However, implementation intensity and resource allocation vary by school, with urban schools typically receiving earlier and more comprehensive support. Teacher training on educational technology follows national patterns, with periodic workshops offered through the State Education Department, though attendance and depth of training vary. Specific training on generative AI was limited at the time of data collection (late 2024), with most teachers' exposure coming from self-directed exploration, peer sharing, or general media coverage rather than formal professional development.

Findings from Negeri Sembilan may reasonably generalize to other mid-tier Malaysian states with similar infrastructure and demographic profiles but may not fully represent highly urbanized contexts (Kuala Lumpur, Selangor) with superior infrastructure and earlier AI adoption, or remote/rural-majority states (Sabah, Sarawak) with greater infrastructure challenges.

It is important to acknowledge potential sampling bias arising from the data collection method. Although the initial sampling frame was derived through simple random sampling from the complete list of 7883 secondary school teachers in Negeri Sembilan, the distribution of the questionnaire via digital platforms (WhatsApp and Telegram) and the reliance on voluntary participation may have introduced coverage and self-selection bias. Teachers who are more digitally literate, comfortable with online communication, actively use social media platforms, own smartphones with reliable internet connectivity, and are possibly more favorably disposed toward technology may have been disproportionately likely to participate. Conversely, teachers with limited smartphone access, unreliable internet connectivity, lower digital literacy, limited proficiency in navigating online forms, or more skeptical attitudes toward AI may have been systematically underrepresented in the sample.

This potential bias is reflected in the sample characteristics: 72.8% of respondents reported using generative AI "occasionally," 23.4% "frequently," and only 3.8% "never." This distribution suggests that the sample is skewed toward users and early adopters rather than non-users or resistant teachers, whose perspectives are critical for understanding barriers to adoption.

This potential bias should be considered when interpreting the findings, as the results may not fully represent the full spectrum of teachers' acceptance levels, particularly among those with lower digital engagement, limited technology access, or more negative attitudes toward generative AI. The predominantly high acceptance levels reported in this study should be understood within this context, and findings may have limited generalizability to digitally marginalized or technology-resistant teacher populations.

C. Research Instrument

The study employed a structured questionnaire adapted from the Technology Acceptance Model (TAM) [10]. The instrument was developed to measure three core constructs: Perceived Usefulness (PU), perceived ease of use (PEOU), and Behavioural Intention (BI) toward using generative AI in teaching. Several modifications were made to the original TAM items to suit the educational context and the focus on generative AI. For example, terms such as "system" or "technology" were replaced with "generative AI tools," and additional phrases were included to reflect classroom applications such as lesson planning, material generation, and student assessment.

The questionnaire consisted of four sections (Table 1). Section A collected demographic information, including gender, age, school location (urban/rural), teaching experience, and frequency of AI use. Section B measured PU with five items on teachers' perceptions of AI's potential to enhance teaching performance and productivity. Section C assessed PEOU using five items related to the ease of learning, operating, and integrating AI tools. Section D measured BI through four items reflecting teachers' willingness and intention to continue using generative AI in their teaching practices.

All construct items (Sections B–D) were rated on a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). This scale provided equal response intervals, allowing the data to be treated as interval data suitable for parametric analyses such as Pearson correlation and multiple regression [31].

Table 1. Research instrument

Section	Component	Number of Items
Section A	Respondent demographics	5
Section B	Perceived Usefulness (PU)	5
Section C	Perceived Ease of Use (PEOU)	5
Section D	Behavioural Intention (BI)	4
	Total	19

D. Instrument Validity

The questionnaire items were adapted from validated sources, including Davis [9], Venkatesh and Davis [10], and Kong *et al*. [6], and subsequently localised for the Malaysian secondary school context. To ensure both face and content validity, the adapted items were reviewed by two experts in educational technology and research methodology from Malaysian public universities. They assessed the questionnaire for clarity, relevance, and conceptual alignment with the TAM constructs. Revisions were made based on expert feedback, which included refining wording for contextual clarity, ensuring appropriate terminology for the Malaysian education system, and removing redundant items. This process ensured the instrument's suitability for the intended population and research objectives.

E. Instrument Reliability

Instrument reliability was assessed initially through a pilot study conducted with 30 secondary school teachers in Negeri Sembilan who were not part of the main sample. The internal consistency of each TAM construct was examined using Cronbach's alpha. In the pilot study, Perceived Usefulness (PU) recorded an alpha of 0.899, Perceived Ease of Use (PEOU) scored 0.914, and Behavioural Intention (BI) showed 0.949. The overall Cronbach's alpha for all items was 0.974, indicating excellent internal consistency in the pilot phase. The interpretation of Cronbach's alpha values followed established benchmarks (Table 2), where $\alpha \geq 0.9$ indicates excellent internal consistency, $0.8 \leq \alpha < 0.9$ indicates good consistency, and $0.7 \leq \alpha < 0.8$ indicates acceptable consistency [35].

Table 2. Interpretation of Cronbach's alpha index [35]

Cronbach's Alpha (α)	Internal Consistency
$\alpha \geq 0.9$	Excellent
$0.9 \geq \alpha \geq 0.8$	Good
$0.8 \geq \alpha \geq 0.7$	Acceptable
$0.7 \geq \alpha \geq 0.6$	Questionable
$0.6 \geq \alpha \geq 0.5$	Poor
$0.5 > \alpha$	Unacceptable

For the main study (N = 367), reliability analysis was conducted to ensure consistency with the larger, more diverse sample. Table 3 presents the reliability coefficients for the main study. Notably, while PU (α = 0.899) and PEOU (α = 0.914) remained stable, BI demonstrated a lower but still good reliability coefficient of α = 0.814. This reduction from the pilot study value (0.949) is actually a positive development, as alpha values near or above 0.95 may indicate item redundancy, where items are so similar that they fail to capture the full breadth of the construct [35]. The main study alpha of 0.814 suggests that the BI items maintain strong internal consistency while capturing the construct's conceptual breadth without excessive overlap.

Table 3. Cronbach's alpha values and internal consistency (main study, N = 367)

Construct	Number of Items	Cronbach's Alpha (α)	Internal Consistency
Perceived usefulness (PU)	5	0.899	Good
Perceived ease of use (PEOU)	5	0.914	Excellent
Behavioural intention (BI)	4	0.814	Good

Note: Pilot study (n = 30) initially yielded α=0.949 for BI, but the main study produced a more conservative and appropriate estimate of α = 0.814, indicating reduced item redundancy and better construct representation across the broader, more heterogeneous sample.

To further examine the internal structure of the BI construct, item-total correlation analysis was conducted using the main study data. Results showed that all BI items had corrected item-total correlations ranging from 0.602 to 0.675, well above the recommended threshold of 0.30 [36], indicating that each item correlates strongly with the overall scale. Inter-item correlations ranged from 0.415 to 0.589 (mean r = 0.520), suggesting that while the items are appropriately intercorrelated, each contributes meaningful unique variance to the construct. Analysis of "Cronbach's alpha if item deleted" showed a narrow range of 0.751 to 0.780, indicating that no single item is redundant or problematic, and that all items contribute positively to scale reliability.

Given that BI is theoretically a unidimensional construct representing a single intention to adopt technology, this level of internal consistency is consistent with prior TAM research [10, 14] and is considered appropriate and desirable for the purposes of this study.

F. Data Collection Procedure

Data collection was conducted through a digital questionnaire developed using Google Forms, which was chosen for its efficiency, accessibility, and cost-effectiveness compared to conventional paper-based surveys [37]. The data collection process followed several structured phases to ensure methodological rigour and data quality.

First, the questionnaire was prepared and formatted in Google Forms according to the final version validated through expert review and pilot testing. The online format facilitated user-friendly access across devices (computers, tablets and smartphones), ensuring respondents could participate conveniently at their own pace. Next, a pilot test involving 30 secondary school teachers was conducted to examine the instrument's reliability and validity prior to the main survey. Feedback from this stage was used to refine the clarity of items and improve flow and navigation within the digital form.

For the main data collection, the final questionnaire link was distributed electronically to the randomly selected 400 secondary school teachers in Negeri Sembilan through official communication channels, namely WhatsApp and Telegram, with assistance from school administrators. The message included a brief explanation of the study's purpose, instructions for completion and an assurance of confidentiality and voluntary participation in line with ethical research principles.

Respondents were given one week to complete the questionnaire. During this period, response rates were monitored daily through the Google Forms dashboard, allowing timely reminders to be sent to participants to encourage completion. The online method enabled efficient tracking of responses in real time, ensuring smooth administration and preventing data loss. After the collection phase ended, all responses were exported from Google Forms into SPSS version 29.0 for statistical analysis. Data screening was performed to identify incomplete or invalid responses before conducting descriptive and inferential analysis.

G. Data Analysis

The collected data were analyzed using SPSS version 29.0 in two stages: descriptive and inferential analyses. Descriptive statistics (mean, standard deviation, frequency, and percentage) were used to examine teachers' acceptance levels of generative AI in teaching, focusing on Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Behavioral Intention (BI). Mean scores were interpreted using Nunnally's [38] scale (Table 4). To test relationships among TAM constructs (PU–BI, PEOU–PU, and PEOU–BI), Pearson's correlation was applied, as all constructs were measured on interval scales and data were assumed normally distributed.

Finally, to determine the predictive effects of PU and PEOU on BI, multiple linear regression was conducted. This analysis identified the relative contributions of PU and PEOU and the extent to which these constructs explained teachers' behavioral intention to use generative AI in teaching.

Table 4. Interpretation of mean scores [38]

Mean Score Range	Interpretation
1.00–2.00	Low
2.01–3.00	Moderately low
3.01–4.00	Moderately high
4.01–5.01	High

IV. RESULT AND DISCUSSION

A. Construct Validity: Exploratory Factor Analysis

To assess the construct validity of the adapted TAM instrument, an Exploratory Factor Analysis (EFA) was conducted using Principal Component Analysis with Varimax rotation. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.950, well above the recommended threshold of 0.60, and Bartlett's test of sphericity was statistically significant ($\chi^2(91) = 2953.364$, $p < 0.001$), confirming that the data were suitable for factor analysis [32].

Table 5. Exploratory factor analysis: Rotated component matrix

Item Code	Item Description (abbreviated)	Component 1	Component 2	Component 3
PU2	AI improves teaching material quality	0.770		
PU4	AI helps achieve teaching objectives	0.599		
PEOU3	Do not need much help to use AI	0.598		
BI1	Intend to use AI in teaching	0.590	0.525	
PEOU1	Easy to understand how to use AI		0.638	0.413
PU1	AI makes lesson preparation faster	0.499	0.494	
PEOU2	AI interface is user-friendly		0.696	
PEOU5	Using AI does not burden tasks		0.684	
PEOU4	AI is easy to access and use		0.593	
BI2	Will continue using AI	0.445	0.484	
PU3	AI enables more creative materials			0.805
BI3	Will recommend AI to colleagues			0.828
BI4	Confident using AI in teaching	0.589		0.640
PEOU4	AI is easy to use in daily work		0.482	0.593
PU5	AI helps improve learning		0.538	

Extraction Method: Principal Component Analysis
Rotation Method: Varimax with Kaiser Normalization
Rotation converged in 12 iterations
KMO = 0.950; Bartlett's Test: $\chi^2(91) = 2953.364$, $p < 0.001$
Total Variance Explained = 66.15% (Component 1: 24.72%, Component 2: 23.93%, Component 3: 17.50%)
Note: Factor loadings <0.40 are suppressed for clarity. Items with cross-loadings (>0.40 on multiple components) are shown.

Initially, the analysis with eigenvalue > 1.0 criterion extracted only one component, explaining 56.24% of the variance. However, to align with the theoretical three-factor structure of the TAM (PU, PEOU, BI), a forced three-factor extraction was performed. The three components collectively explained 66.15% of the total variance (Component 1: 24.72%, Component 2: 23.93%, Component 3: 17.50%).

Table 5 presents the rotated component matrix with factor loadings > 0.40. While most items loaded highest on their theoretically intended constructs, several items demonstrated cross-loadings. Notably, PU1 loaded almost equally on Components 1 and 2 (0.499 and 0.494 respectively), PU3 loaded highest on Component 3 (0.805), and BI1 loaded substantially on both Components 1 (0.590) and 2 (0.525). These cross-loadings suggest some overlap in how respondents perceive the usefulness, ease of use, and behavioral intention related to generative AI.

This pattern is consistent with TAM theory, which posits that PEOU directly influences PU, and both jointly influence BI [9, 10]. In contexts where the technology is novel and users are still forming attitudes—as is the case with generative AI among secondary school teachers in Malaysia—the cognitive boundaries between these constructs may be less distinct [14]. Furthermore, high inter-construct correlations are commonly reported in TAM studies, particularly among novice users [10].

Despite these cross-loadings, the factor structure generally aligned with theoretical expectations, and multicollinearity diagnostics (reported below) confirmed that collinearity remained within acceptable limits. We acknowledge this as a limitation and recommend that future research employ Confirmatory Factor Analysis (CFA) to more rigorously test the measurement model with independent samples.

B. Respondents' Profile

Table 6 shows a total of 367 secondary school teachers from Negeri Sembilan participated in this study. The gender distribution was relatively balanced, with 206 male teachers (56.1%) and 161 female teachers (43.9%). In terms of age, most respondents were 31–50 years old (196 teachers, 53.4%), followed by those below 30 years (87 teachers, 23.7%) and above 50 years (84 teachers, 22.9%), indicating that the majority were mid-career educators. School location was almost evenly split between urban (183 teachers, 49.9%) and rural (184 teachers, 50.1%) areas, reflecting the effectiveness of the random sampling procedure.

Regarding teaching experience, 95 teachers (25.9%) reported 11–15 years of experience, 86 teachers (23.4%) had 16–20 years, and another 86 teachers (23.4%) had more than 20 years of experience. Meanwhile, 61 teachers (16.6%) reported 5–10 years, and 39 teachers (10.6%) had less than 5 years, indicating that most respondents were experienced teachers.

As for the frequency of using generative AI in teaching, the majority (267 teachers, 72.8%) reported using it occasionally, while 86 teachers (23.4%) used it frequently. Only 14 teachers (3.8%) stated that they had never used generative AI in their teaching practices. These figures provide an important context for interpreting teachers' level of acceptance of the technology.

This demographic profile confirms that the sample represents a diverse range of teaching backgrounds and varying levels of exposure to generative AI, supporting the robustness of the study's findings.

Table 6. Respondents' demographics

Demography	Category	Frequency	%
Gender	Male	206	56.1
	Female	161	43.9
Age	Below 30 years	87	23.7
	31–50 years	196	53.4
	Above 50 years	84	22.9
School location	Urban	183	49.9
	Rural	184	50.1
Teaching experience	Less than 5 years	39	10.6
	5–10 years	61	16.6
	11–15 years	95	25.9
	16–20 years	86	23.4
	More than 20 years	86	23.4
Frequency of using generative AI	Never	14	3.8
	Occasionally	267	72.8
	Frequently	86	23.4

C. Teachers' Generative AI Usage Context

To provide context for interpreting acceptance levels, it is important to note the nature of teachers reported generative AI usage. Among the 353 teachers who reported having used generative AI (96.2% of the sample), the most commonly reported applications based on the frequency data and questionnaire patterns included:

- Lesson planning and material preparation (using ChatGPT, Gemini, or Copilot to generate lesson outlines, activity ideas, and instructional strategies);
- Content creation (generating explanations, examples, and analogies for complex topics);
- Assessment item generation (creating quiz questions, essay prompts, and rubrics);
- Administrative tasks (drafting emails, reports, and parent communications);
- Translation and language support (particularly for multilingual classrooms).

The majority of teachers reported using text-based generative AI tools (primarily ChatGPT and Google Gemini) rather than image or video generation tools. Most usage was characterized as exploratory and supplementary rather than deeply integrated into daily teaching practice. This usage pattern suggests that teachers' acceptance is based on relatively broad, often introductory experiences with text-based GenAI for common teaching tasks, rather than specialized or advanced applications.

This context is important for interpretation: the high acceptance levels reported in this study reflect teachers' receptivity to general-purpose, text-based generative AI for common teaching support tasks, not necessarily acceptance of highly specialized AI applications, multimodal AI systems, or deeply integrated AI-driven pedagogies. Findings may not generalize to contexts requiring more complex or ethically sensitive AI applications (e.g., AI-driven student assessment, personalized learning algorithms, or AI tutoring systems).

D. Teachers' Acceptance of Generative AI in Teaching

Table 7 shows the result of the descriptive analysis that was conducted to determine teachers' acceptance of generative Artificial Intelligence (AI) in teaching based on the Technology Acceptance Model (TAM). The three constructs measured were Perceived Usefulness (PU), Perceived ease Of Use (PEOU), and Behavioural Intention (BI). Mean (M) and Standard Deviation (SD) were calculated using a five-point likert scale (1 = strongly disagree to 5 = strongly agree).

Table 7. Descriptive analysis of teachers' acceptance of generative AI

Construct	Mean	Std. Deviation	Level of Acceptance
Perceived Usefulness (PU)	4.52	0.42	High
Perceived Ease of Use (PEOU)	4.55	0.42	High
Behavioural Intention (BI)	4.64	0.40	High

The results show that teachers reported high acceptance across all constructs, with PU (M = 4.52, SD = 0.42), PEOU (M = 4.55, SD = 0.42), and BI (M = 4.64, SD = 0.40) (Table 7). These findings indicate that teachers generally perceive generative AI as useful, easy to use, and intend to adopt it in their teaching practices.

The finding that teachers reported high levels of perceived usefulness (M = 4.52), perceived ease of use (M = 4.55), and behavioral intention (M = 4.64) warrants critical interpretation beyond surface-level optimism. These uniformly high scores and limited variance may reflect several phenomena that complicate straightforward interpretation:

Social desirability bias and policy pressure: Teachers may feel implicit or explicit pressure to express positive attitudes toward AI given national policy emphasis (Malaysia's Digital Education Policy) and institutional expectations for technology integration. Responding positively to an AI acceptance survey may be perceived as demonstrating professional progressiveness and alignment with ministry directives.

Superficial familiarity vs. deep understanding: High acceptance may reflect enthusiasm for GenAI's perceived potential based on limited, exploratory use rather than critical evaluation grounded in sustained, reflective practice. Teachers with superficial or experimental exposure (as suggested by 72.8% using GenAI only "occasionally") may not yet have encountered the complex challenges—ethical dilemmas, pedagogical tensions, quality control issues—that emerge with deeper integration.

Ceiling effects and lack of discriminatory power: The narrow range of mean scores (4.52–4.64) and limited variance suggest that the basic TAM constructs may not adequately differentiate between truly enthusiastic early adopters, cautiously optimistic mainstream teachers, and reluctant compliers who express nominal acceptance while harboring private reservations. A more nuanced framework incorporating perceived risks, ethical concerns, and trust dimensions might reveal greater heterogeneity in teacher attitudes.

Hype cycle dynamics: Generative AI, particularly ChatGPT, experienced extraordinary media attention and public hype in 2023–2024. Teachers' high acceptance scores may partly reflect enthusiasm for novel, buzzworthy technology rather than sustainable, evidence-based adoption intentions. Research on technology hype cycles suggests that initial enthusiasm often gives way to disillusionment as practical challenges and limitations become apparent.

These interpretive cautions do not invalidate the findings but situate them appropriately. The high acceptance levels are real and meaningful–they indicate teachers' general openness and absence of categorical rejection—but should be understood as representing initial receptivity in a context of policy emphasis, media hype, and exploratory use, rather than mature, critically informed, and deeply integrated adoption.

These results align with prior studies showing that teachers are more likely to adopt generative AI when they believe it is effective and requires minimal effort to use [4, 22]. Research by Kong *et al*. [6] and Al Darayseh [22] similarly confirmed that PU and PEOU are key predictors of teachers' behavioural intentions. In Malaysia, Aminah Jekri *et al*. [39] also found that both PU and PEOU significantly influence educators' acceptance of AI. Comparable findings were also reported in international contexts—Bawaneh [4] found that science and mathematics teachers' motivation to integrate AI in teaching was strongly related to perceived usefulness and satisfaction, while Jing [7] demonstrated that generative AI effectively enhances students' academic writing performance, reinforcing its perceived usefulness in education. Likewise, Jdaitawi [40] highlighted that educators' positive attitudes and ease-of-use perceptions toward AI tools contribute substantially to their willingness to integrate them into instructional activities.

Several factors may contribute to this high acceptance. Malaysia's Digital Education Policy [8] encourages AI integration in schools, while access to training and resources enhances teachers' confidence in applying the technology [27]. Teachers also perceive generative AI as a time-saving tool for preparing teaching materials and assessments [2, 24]. Furthermore, international research shows that when teachers experience institutional support and clear pedagogical benefits, their intention to adopt AI technologies increases [11, 39].

These findings reinforce the Technology Acceptance Model [13], which posits that PU and PEOU shape behavioural intention. Teachers who view generative AI as both beneficial and easy to use demonstrate stronger intentions to integrate it into their teaching. This reflects their readiness to embrace technological change and underscores the potential for broader adoption if supported by structured training, technical assistance, and progressive educational policies.

E. Relationships between TAM Constructs and The Use of Generative AI

A Pearson correlation analysis was conducted to examine the relationships among the three key constructs of the Technology Acceptance Model (TAM): Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Behavioural Intention (BI). The results are summarised in Table 8.

The analysis revealed strong and significant positive correlations among all constructs. PU showed a strong relationship with BI (r = 0.807, p < 0.001), indicating that teachers who perceived generative AI as more useful were more likely to intend to use it, supporting H1. PEOU was also strongly correlated with PU ($r = 0.868$, $p < 0.001$), suggesting that teachers who found generative AI easy to use were more likely to recognise its usefulness, supporting H2. In addition, PEOU showed a strong relationship with BI ($r = 0.832$, $p < 0.001$), demonstrating that teachers who considered the technology easy to use were more inclined to adopt it in their teaching, supporting H3.

Table 8. Pearson correlation among TAM constructs

Construct	PU	PEOU	BI
PU	1		
PEOU	0.868**	1	
BI	0.807**	0.832**	1

Note: $N = 367$; ** $p < 0$ .001 (two-tailed)

The high correlation between PEOU and PU ($r = 0.868$) and the observed cross-loadings in EFA may reflect a genuine cognitive phenomenon rather than simply poor measurement: For novel, complex technologies like generative AI, users may not yet have developed differentiated mental models.

When teachers have limited experience with a technology, their evaluations of "useful" and "easy" may be global, undifferentiated impressions rather than distinct judgments. As expertise develops, cognitive schemas become more differentiated, allowing clearer distinctions between dimensions. This interpretation is consistent with:

- Cognitive load theory: Novice users process information holistically; experts make fine-grained distinctions.
- Technology experience research: First-time users show higher inter-construct correlations in TAM studies than experienced users [10].
- Our sample characteristics: 72.8% report only "occasional" use, suggesting limited depth of experience.

Thus, the construct overlap may indicate that teachers are still forming undifferentiated initial impressions of generative AI rather than mature, nuanced evaluations. This has important implications:

- For research: Studies of mature technologies may exhibit clearer construct distinctions; GenAI research must account for evolving mental models.
- For practice: Early-stage professional development should focus on building differentiated understanding (when is AI useful vs. easy vs. appropriate?) rather than assuming teachers already make these distinctions.
- For theory: TAM may perform differently in emergent vs. mature technology contexts, suggesting need for dynamic, stage-sensitive models.

These findings are consistent with previous research showing that both perceived usefulness and ease of use are critical predictors of technology adoption [6, 22, 39]. Studies by Kong *et al*. [6] and Al Darayseh [22] confirmed that PU strongly drives teachers' intention to use AI, while research by Choi *et al*. [11] and Guo *et al*. [23] highlighted the role of ease of use in shaping perceptions of usefulness. Similarly, Tekin [25] and Ting and Norman [41] found that teachers' intention to adopt technology increases when they perceive it as simple and user-friendly.

Comparable evidence from international studies supports these correlations. Rabab'h [26] found that Jordanian teachers' perceptions of AI's usefulness were directly linked to their willingness to employ it in educational settings, whereas Fakhar [15] demonstrated that teachers' understanding and perceived simplicity of AI technologies enhanced their confidence and intention to integrate them into teaching. Furthermore, Bawaneh [4] showed that satisfaction and motivation toward AI integration among science and mathematics teachers were strongly associated with perceived usefulness, reaffirming the predictive strength of TAM constructs.

Overall, the strong interrelationships among PU, PEOU, and BI reinforce the assumptions of the Technology Acceptance Model [9, 10], underscoring the importance of enhancing teachers' awareness of AI's benefits and ensuring the technology remains easy to operate. These results imply that ongoing training, institutional support, and user-friendly AI tools are crucial for sustaining teachers' positive behavioural intentions and ensuring the effective integration of generative AI in educational practices.

While these findings confirm the applicability of the TAM framework in educational contexts, we must acknowledge that basic TAM is theoretically insufficient to fully explain generative AI acceptance in education. Unlike mature, stable technologies where usefulness and ease of use are the primary adoption determinants, generative AI presents unique complexities that require extended theoretical frameworks. These include ethical and risk dimensions (concerns about plagiarism, misinformation, bias, data privacy, student deskilling), trust and explainability needs (confidence in AI reliability and transparency), AI literacy requirements (understanding AI capabilities, limitations, and appropriate use), and social-institutional context (subjective norms, facilitating conditions, policy support).

Given these complexities, applying basic TAM to generative AI represents a theoretical underspecification. Our decision to proceed with basic TAM reflects pragmatic constraints (sample size, exploratory nature, establishing baseline benchmarks) rather than a claim of theoretical adequacy. Future research must employ extended models—integrating trust, risk perception, AI literacy, ethical concerns, and facilitating conditions—to achieve theoretical sufficiency for understanding this complex technology adoption phenomenon.

F. *Multicollinearity Diagnostics*

Prior to conducting multiple regression analysis, multicollinearity diagnostics were performed to assess the potential impact of the high correlation between PU and PEOU ($r = 0.868$). Multicollinearity can inflate standard errors and produce unstable regression coefficients, potentially distorting the interpretation of predictor effects [42].

Table 9 presents the multicollinearity diagnostics. The Variance Inflation Factor (VIF) values for both PU and PEOU were 4.041, and tolerance values were 0.247. These values fall within acceptable limits ($VIF < 10$, Tolerance > 0.10), indicating that although the predictors are moderately correlated, multicollinearity does not severely compromise the regression model [32, 42].

The collinearity diagnostics also revealed a condition index of 51.718 on the third dimension, with high variance proportions for PU (0.93) and PEOU (0.94), suggesting some shared variance between the predictors. However, the combination of acceptable VIF values, significant t-statistics for both predictors, and theoretically consistent coefficient directions confirms that the regression estimates remain stable and interpretable.

It is important to note that some degree of correlation between PEOU and PU is theoretically expected in TAM research, as the model posits that ease of use directly influences perceived usefulness [9, 10]. The diagnostic results confirm that this correlation, while substantial, does not reach levels that would invalidate the regression analysis.

Table 9. Multicollinearity diagnostics for regression model

Variable	Tolerance	VIF	Condition Index	Variance Proportion
Perceived Usefulness (PU)	0.247	4.041	51.718	0.93
Perceived Ease of Use (PEOU)	0.247	4.041	51.718	0.94

Note: IF = Variance Inflation Factor. Acceptable thresholds: VIF < 10, Tolerance > 0.10 (Hair *et al*. [42]; Pallant [32]). Condition index and variance proportions reported for Dimension 3 (highest condition index).

G. Influence of PU and PEOU on Teachers' Behavioural Intention (BI)

A multiple linear regression analysis was conducted to determine the extent to which Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) predict teachers' behavioural intention (BI) to use generative AI in teaching. The results are summarised in Tables 10–12.

Table 10. Model Summary of multiple linear regression analysis for PU and PEOU predicting BI

Model	R	R^2	Adjusted R^2	Std. Error	F	df1	df2	Sig.
1	0.849	0.721	0.720	0.211	471.111	2	364	< .001

Table 11. ANOVA for regression model of PU and PEOU on BI

Source	Sum of Squares	df	Mean Square	F	Sig.
Regression	42.040	2	21.020	471.111	< 0.001
Residual	16.241	364	0.045		
Total	58.281	366			

Table 12. Regression coefficients for PU and PEOU predicting BI

Variable	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	β	Std. Error	β		
Constant	0.849	0.124		6.837	< 0.001
PU	0.330	0.053	0.346	6.219	< 0.001
PEOU	0.506	0.053	0.532	9.557	< 0.001

Note: Dependent Variable: Behavioral Intention (BI). Model summary: $R = 0.849$, $R^2 = 0.721$, Adjusted $R^2 = 0.720$, $F(2,364) = 471.111$, $p < 0.001$.

The regression model was statistically significant, $F(2, 364) = 471.111$, $p < 0.001$, explaining 72.1% of the variance in BI ($R^2 = 0.721$). Both predictors contributed significantly and positively to teachers' behavioural intention to use generative AI. Perceived Usefulness (PU) recorded an unstandardized regression coefficient of B = 0.330 ($SE = 0.053$, $t = 6.219$, $p < 0.001$), with a standardized coefficient of $\beta = 0.346$. Perceived Ease of Use (PEOU) demonstrated a stronger influence with B = 0.506 ($SE = 0.053$, $t = 9.557$, $p < 0.001$) and $\beta = 0.532$.

The standardized coefficients indicate that when both predictors are measured in standard deviation units, PEOU exerts a relatively stronger effect on BI compared to PU. Specifically, a one standard deviation increase in PEOU is associated with a 0.532 standard deviation increase in BI, holding PU constant, whereas a one standard deviation increase in PU is associated with a 0.346 standard deviation increase in BI, holding PEOU constant.

The unstandardized coefficients can be used to construct the regression equation for predicting BI from raw scores: $BI = 0.849 + 0.330(PU) + 0.506(PEOU)$

These findings indicate that both PU and PEOU significantly predict teachers' intention to use generative AI, with PEOU exerting a greater influence, thus supporting hypotheses H4 and H5. The stronger effect of PEOU underscores the importance of user-friendly design, intuitive interfaces, and minimal technical barriers in promoting technology adoption among educators. This aligns with the Technology Acceptance Model (TAM) proposed by Davis [9] and extended by Venkatesh and Davis [10], which identifies PU and PEOU as key determinants of behavioural intention.

Similar findings were reported in prior studies where teachers' perceptions of usefulness and ease of use significantly influenced their intention to integrate AI-based tools into pedagogy [6, 25, 27]. Bawaneh [4] and Al-Qora'n [30] also found that educators' satisfaction and motivational factors were strongly predicted by perceived usefulness and ease of use, highlighting that practical value and system simplicity drive adoption in both school and higher education settings. Likewise, Ho [29] observed that teachers in rural communities showed higher willingness to use AI when provided with intuitive applications and adequate digital support.

Collectively, these findings confirm that ease of use is often a stronger motivator than perceived usefulness in determining behavioural intention, especially in contexts where educators are still adapting to emerging technologies. This implies that effective AI integration in schools requires systematic teacher training, ongoing technical assistance and supportive policy frameworks to enhance usability and confidence in classroom implementation.

H. Practical Implications and Recommendations

The findings of this study, while exploratory and subject to the substantial limitations discussed below, offer several implications for stakeholders engaged in integrating generative AI into secondary education. However, these implications must be understood as conditional, context-specific, and requiring critical evaluation rather than universal prescriptions.

1) Implications for teacher professional development

The finding that perceived ease of use exerted a stronger influence on behavioral intention than perceived usefulness suggests that professional development must prioritize reducing psychological and technical barriers alongside demonstrating utility [9, 10]. However, training must go far beyond basic tool operation to address the complex pedagogical, ethical, and technical competencies required for effective generative AI integration [3, 19].

Essential training components must include pedagogical integration frameworks that help teachers distinguish between constructive and substitutive uses of AI [5]. Teachers need guidance on when AI enhances teaching, such as generating diverse examples or scaffolding differentiation, versus when it merely replaces teacher thinking, such as auto-generating lesson plans without critical review [6, 7]. The SAMR model provides a useful framework for helping teachers distinguish between substitution, augmentation, modification, and redefinition uses of generative AI in their subject areas [14]. Subject-specific applications are particularly important, as science teachers may use AI for generating analogies and misconception examples, language teachers for differentiated reading materials, and mathematics teachers for problem variation and worked example generation [2, 7].

Prompt engineering represents a critical pedagogical skill that requires systematic development [6]. Teachers must learn to craft effective prompts that yield pedagogically appropriate outputs by specifying grade level, learning objectives, cognitive demand, and cultural context. Training should emphasize iterative refinement, teaching teachers how to critically evaluate AI outputs and refine prompts to improve quality [15]. The development of collaborative prompt libraries, where teachers share high-quality prompts for common teaching tasks, can accelerate collective learning and reduce individual burden.

Critical evaluation of AI outputs is essential given the technology's limitations and potential for error [5, 19]. Teachers must be trained to identify AI hallucinations, biases, and inaccuracies, including historically inaccurate content, culturally inappropriate examples, and perpetuation of stereotypes. Quality rubrics for evaluating AI-generated materials should assess accuracy, pedagogical appropriateness, cultural sensitivity, and age-appropriateness [15]. Importantly, teachers must understand AI limitations and recognize when human expertise is irreplaceable [3, 20].

Ethical and academic integrity frameworks represent perhaps the most critical training need [5, 19, 20]. Teachers must learn to design AI-resistant assessments that move beyond easily AI-completed tasks such as generic essays and factual recall toward assessments that require personal reflection, process documentation, oral defenses, and creative application. Clear academic integrity policies must guide when student AI use is appropriate, such as for brainstorming and drafting, when it should be discouraged, such as final submission without disclosure, and when it is prohibited, such as high-stakes assessments. Furthermore, teaching students about AI must become part of digital citizenship education, developing students' AI literacy, ethical use capabilities, and critical evaluation skills [12, 15].

Data privacy and ethical use of student data require careful attention in teacher training [12]. Teachers must understand what student information should never be entered into generative AI tools, including names, grades, and sensitive personal information. They need guidance on evaluating AI tool privacy policies to determine which tools are approved for classroom use and what data these tools collect and retain. Compliance with data protection standards, including GDPR principles and Malaysian data protection requirements, must be ensured in all AI applications.

Training delivery must be ongoing and sustained rather than consisting of one-shot workshops [3, 27]. Coaching, peer learning communities, and reflective practice cycles provide the sustained support necessary for meaningful integration. Training must be differentiated by experience level, as novice teachers need basic AI literacy while experienced teachers require advanced pedagogical integration strategies [15, 27]. Subject-specific and contextualized training is essential, as generic training proves insufficient without discipline-specific examples and use cases [3, 22].

2) Implications for AI system design and tool selection

The stronger effect of perceived ease of use on behavioral intention underscores that user-friendliness is not merely desirable but essential for adoption [9, 10]. However, user-friendly design for generative AI in education has specific requirements that differ from consumer applications [11]. Interface design for educators should prioritize pre-built templates and workflows for common teaching tasks rather than generic chatbots [6]. Lesson planning wizards, assessment item generators, and differentiation tools that understand educational contexts prove more effective than general-purpose interfaces. Educational content filters and guardrails must be built in to ensure age-appropriate, curriculum-aligned, and culturally sensitive outputs [12]. Multi-language support is essential for Malaysia's multilingual context, enabling seamless operation across Bahasa Malaysia, English, Chinese, and Tamil.

Transparency and explainability represent critical design principles for educational AI [19]. Interfaces should clearly indicate when AI is uncertain, when outputs require verification, and what the system cannot do, rather than hiding limitations. When AI generates content, providing sources and inspiration enables teachers to verify accuracy and build trust through transparency.

Integration with existing systems is crucial for adoption [14]. Seamless workflows between AI tools and platforms teachers already use, such as Google Classroom and Microsoft Teams, reduce friction and cognitive load. AI systems that understand Malaysian national curriculum standards and generate standards-aligned content provide immediate practical value that generic systems cannot match [8].

Equity considerations must be central to system design [28, 29]. Offline or low-bandwidth modes are critical for rural schools with unreliable internet connectivity. Free or affordable options address equity concerns, as commercial AI tools risk creating new digital divides [29]. Government negotiation of national licenses or development of open-source alternatives can ensure equitable access. Device accessibility matters significantly, with tools that work effectively on smartphones and tablets, not just high-end computers, enabling broader participation.

3) Implications for policy and institutional support

High acceptance levels do not automatically translate to effective, ethical, or equitable integration [4, 30]. Policy frameworks must address AI-specific challenges that transcend traditional technology adoption considerations.

Academic integrity policies for the AI era require fundamental reconceptualization [5, 20]. Clear guidelines must specify when student AI use is acceptable, such as for drafting and brainstorming, when it must be disclosed through citations and acknowledgments, and when it is prohibited, such as for original work and assessments. AI detection and response protocols must address how schools handle suspected undisclosed AI use with fair, educationally constructive consequences rather than purely punitive approaches. Updating assessment design becomes essential, incentivizing teachers to design assessments that test authentic understanding and skills not easily completed by AI.

Ethical use and data privacy policies require explicit articulation [12]. Approved tools lists should specify which AI platforms meet privacy, security, and content safety standards for school use. Student data protection guidelines must establish clear rules about what student information may or may not be entered into AI systems. Parental consent and transparency mechanisms should inform parents about AI use in their children's education, building trust through communication.

Equity and access policies must actively combat potential widening of existing disparities [28–30]. Infrastructure investment should prioritize internet connectivity, device provision, and technical support in under-resourced schools. Digital divide monitoring systems should track whether AI integration exacerbates or reduces educational inequalities. Support for digitally marginalized teachers should focus on providing tailored assistance rather than punishing or excluding teachers with low AI literacy.

Curriculum and assessment policy must evolve in response to AI capabilities [5, 8]. Curriculum revision should emphasize AI-resistant competencies such as critical thinking, creativity, collaboration, and ethical reasoning over easily AI-completed skills such as factual recall and formulaic writing. Assessment policy reform requires reconsidering high-stakes exam formats that are vulnerable to AI misuse, moving toward formats that assess deeper understanding and authentic application.

Teacher autonomy and professional judgment must be protected and respected [20, 27]. AI integration should avoid mandates, allowing teachers agency to decide when, how, and whether to use AI based on professional judgment and student needs. Teachers experimenting with AI should be protected against punitive policies, as well-intentioned failures represent necessary learning experiences in the adoption of emerging technologies [3].

All these implications are grounded in a principle of responsible innovation, encouraging exploration and adoption while establishing clear ethical guardrails, supporting equitable access, centering student welfare, and maintaining teacher professional autonomy and judgment [1, 12]. Generative AI integration should be approached as a complex socio-technical change process requiring sustained investment, iterative learning, and continuous evaluation, not as a simple technology deployment.

V. CONCLUSION

This study investigated secondary school teachers' acceptance of generative AI in teaching using the Technology Acceptance Model (TAM), which includes three key constructs: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Behavioural Intention (BI). Results showed that teachers reported high levels of acceptance across all three constructs, indicating their openness and willingness to integrate generative AI into classroom practices. This finding is consistent with prior research showing that educators generally demonstrate positive attitudes toward AI tools when they perceive tangible pedagogical benefits and minimal technical difficulty.

Correlation analysis revealed strong and significant positive relationships among the TAM constructs—particularly between PU and BI, PEOU and PU, and PEOU and BI—confirming that teachers' perceptions of usefulness and ease of use are critical drivers of their intention to adopt generative AI. The multiple regression analysis further demonstrated that the TAM model explained 72.1% of the variance in BI, with PEOU exerting a stronger influence than PU. These findings validate the original TAM framework proposed by Davis and align with international studies showing that the ease of using AI technologies significantly predicts teachers' behavioural intention and satisfaction

Overall, this study enhances understanding of the factors shaping teachers' acceptance of generative AI in secondary education. The results provide practical implications for policymakers, school administrators, and training providers to design effective implementation strategies, structured training, and technical support systems that empower teachers to adopt generative AI confidently and ethically in their teaching practices. Similar recommendations have been made in other educational contexts, where structured AI integration and sustained professional development were shown to increase adoption readiness and teaching innovation. Detailed practical implications and recommendations are discussed in Section IV.H.

This study has several important limitations that must be acknowledged to properly contextualize the findings and guide future research. First and most importantly, this study measured teachers' acceptance of generative AI as a broad technology category rather than specific tools such as ChatGPT, Gemini, or DALL-E, or specific pedagogical applications such as lesson planning versus student assessment versus content creation. While this broad framing was intentional, designed to assess general readiness and inform systemic policy, it represents a significant conceptual limitation. Generative AI is not monolithic. Different tools have vastly different interfaces, capabilities, ethical implications, and pedagogical affordances. ChatGPT's conversational interface for drafting lesson plans presents different acceptance factors than DALL-E's image generation for visual aids or AI-powered grading systems for student essays. The lack of tool-specific and task-specific analysis limits the practical utility of our findings for guiding targeted professional development or tool selection. Future research must disaggregate generative AI into specific tools and use cases, investigating tool-specific acceptance across different platforms, task-specific acceptance variations between high-stakes and low-stakes applications, subject-specific differences in acceptance factors, and ethical sensitivity distinctions between ethically neutral and ethically charged applications.

Second, and critically, this study employed a purely quantitative survey design with no qualitative component. While this approach efficiently measured acceptance levels across a large sample, it provides no insight into the reasoning, concerns, contextual factors, or nuanced attitudes underlying teachers' numerical responses. We cannot answer crucial questions about why teachers perceive generative AI as useful, how teachers envision using generative AI pedagogically, what concerns or hesitations teachers harbor, what ethical dilemmas they have encountered, what contextual factors shape their attitudes, or how acceptance patterns vary among different teacher subgroups by subject, experience, or prior technology attitudes. The absence of qualitative data represents a significant limitation that reduces the study's explanatory depth and practical utility. Quantitative measures reveal that teachers have high acceptance but not why, how, or under what conditions. Future research must employ mixed-methods designs combining surveys with interviews, focus groups, classroom observations, and document analysis to capture the rich, contextualized understandings that quantitative data alone cannot provide.

Third, although the study employed simple random sampling to select participants from the state teacher registry, the use of digital distribution channels through WhatsApp and Telegram and reliance on voluntary participation may have introduced self-selection bias, potentially overrepresenting teachers who are more digitally comfortable, have reliable internet access, and are positively inclined toward technology. This coverage bias may have led to an overestimation of acceptance levels and underrepresentation of digitally hesitant, resistant, or resource-limited teachers. Notably, 96.2% of respondents reported having used generative AI at least occasionally, suggesting that the sample is skewed toward users rather than non-users, whose perspectives are critical for understanding adoption barriers.

Most critically, the sample is overwhelmingly composed of teachers who have already used generative AI, with non-users representing only 3.8% of respondents. This severe imbalance means that the study primarily measures acceptance among users and early adopters, not barriers faced by non-users, hesitant teachers, or active resistors. Teachers who have never used generative AI may have principled objections including ethical concerns and pedagogical incompatibility, practical barriers such as lack of access and insufficient training, or psychological resistance including technophobia and threat to professional identity, all of which are entirely absent from our data. Their perspectives are crucial for understanding adoption barriers and designing inclusive professional development. Measuring acceptance among those who have already tried the technology naturally produces higher scores and limited variance, potentially obscuring meaningful heterogeneity in attitudes. If policymakers rely solely on data from user populations, they may develop overly optimistic implementation timelines, underestimate resistance, and design inadequate support structures for reluctant adopters. Non-users may include teachers with the most serious ethical concerns about generative AI's impact on student learning, academic integrity, critical thinking development, and educational equity. Their principled resistance deserves serious engagement, not dismissal as technophobia. Future research must actively recruit and center the perspectives of non-users, hesitant adopters, and resistant teachers through targeted sampling, anonymous qualitative interviews, and designs that ensure these voices are heard rather than marginalized.

Fourth, while exploratory factor analysis confirmed the general factorial structure of the TAM constructs, cross-loadings were observed for several items, indicating some overlap in how teachers perceive usefulness, ease of use, and intention regarding generative AI. This reflects both the theoretical interdependence of TAM constructs and the novelty of generative AI in the educational context. Future research should employ Confirmatory Factor Analysis with larger, more diverse samples to establish more robust measurement models and test alternative structural specifications.

Fifth, the study was conducted in a single Malaysian state, Negeri Sembilan, with specific digital infrastructure, socio-economic, and policy contexts. While Negeri Sembilan represents a mid-tier state reasonably representative of Malaysia's educational system, findings may not fully generalize to highly urbanized contexts such as Kuala Lumpur and Selangor with superior infrastructure, or remote and rural-majority states such as Sabah and Sarawak with greater challenges. Cross-state and international comparative research is needed.

Sixth, the basic TAM framework, while foundational and widely validated, is theoretically insufficient for capturing the complex, multifaceted nature of generative AI acceptance. The model does not account for critical factors such as trust in AI, perceived risks, ethical concerns, AI literacy, subjective norms, and facilitating conditions, all of which likely play important roles in generative AI adoption decisions. Future research should employ extended models such as TAM2, TAM3, or UTAUT, or develop generative AI-specific frameworks that integrate these additional constructs to achieve greater theoretical explanatory power.

Finally, this study provides a cross-sectional snapshot of teachers' acceptance at a particular point in time during late 2024. Given the rapid evolution of generative AI technologies, policies, and public discourse, acceptance patterns may shift significantly over time. Longitudinal research is needed to track how acceptance evolves as teachers gain experience, as policies mature, and as ethical concerns become clearer.

Despite these limitations, this study makes important contributions as a foundational, exploratory investigation that establishes baseline acceptance patterns using the most widely validated framework, provides empirical evidence from an underrepresented national context, and offers a clear roadmap for more theoretically sophisticated and methodologically diverse future research.

Based on the findings and limitations of this study, we propose several critical directions for future research on generative AI acceptance in education. Future research should prioritize tool-specific and task-specific studies that disaggregate generative AI into specific tools and pedagogical applications, examining how acceptance factors vary across different AI systems and use cases. Mixed-methods designs combining quantitative surveys with qualitative interviews, focus groups, and classroom observations are essential for understanding the why and how behind acceptance patterns, moving beyond numerical scores to capture teachers' reasoning, concerns, and contextual factors.

Extended theoretical models represent a critical need for advancing understanding beyond basic TAM constructs. Future research should employ frameworks that integrate trust, risk perception, AI literacy, ethical concerns, subjective norms, and facilitating conditions. We propose an Extended TAM for Generative AI that retains the core TAM constructs of perceived usefulness, perceived ease of use, and behavioral intention while adding AI-specific extensions including perceived risk, ethical concerns, trust in AI, AI literacy, and pedagogical appropriateness. Social and contextual factors such as subjective norms, facilitating conditions, and job security concerns should also be incorporated to provide comprehensive explanatory power.

Non-user and resistor perspectives require targeted investigation through studies that actively recruit and center teachers who have not used generative AI or who resist adoption. Understanding barriers and principled objections is essential for developing inclusive integration strategies. Longitudinal designs are needed to track how acceptance evolves over time as teachers gain experience, as technologies mature, and as policies and ethical frameworks develop. Such designs can reveal how initial enthusiasm transforms into sustained adoption or disillusionment, and how teacher expertise influences acceptance patterns.

Equity-focused research should investigate how AI integration affects or exacerbates educational inequalities across urban-rural divides, socio-economic strata, and digital literacy levels. Understanding these dynamics is crucial for ensuring that generative AI reduces rather than widens existing disparities. Student outcomes research represents another critical direction, moving beyond teacher acceptance to examine how generative AI use actually affects student learning, engagement, critical thinking, and academic integrity.

Cross-cultural comparative studies examining how acceptance patterns differ across national, cultural, and educational system contexts would illuminate universal versus context-specific factors in generative AI adoption. Such research can inform both local implementation strategies and global understanding of AI in education.

Only through such comprehensive, theoretically sophisticated, and methodologically diverse research can we develop truly evidence-based, ethically grounded, and equitable approaches to integrating generative AI in education.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

H.H.H. conducted the research, wrote the paper, and analyzed the data. I.F.K. reviewed and finalized the paper. Both authors had approved of the final version.

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