Adoption of Generative Artificial Intelligence: The Roles of Perceived Usefulness, Self-Efficacy, and Workload

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Abstract **– As generative artificial intelligence (Generative AI) continues to advance rapidly, its applications have become increasingly prevalent. However, uncertainties persist regarding users' attitudes and willingness to adopt Generative AI. This study integrates Task-Technology Fit and Self-Efficacy Theories to examine key factors influencing Generative AI adoption. The study conducted an empirical survey (n=336) and revealed that workload, AI self-efficacy, and perceived usefulness significantly impact adoption. These findings contribute to theoretical advancements and offer practical recommendations for facilitating Generative AI implementation in business contexts.**

Keywords **– Artificial Intelligence, Generative AI, self-efficacy, workload, perceived useful, task-technology fit theory.**

DOI: 10.18421/TEM144-03
https://doi.org/10.18421/TEM144-03

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Received: 21 January 2025.
Revised: 22 July 2025.
Accepted: 25 August 2025.
Published: 27 November 2025.

1. Introduction

The advancements in artificial intelligence (AI) and information technology have enabled the development of powerful generative AI tools that enhance efficiency across various industries. However, like other technological innovations, not everyone adopts generative AI. Understanding the factors influencing adoption or non-adoption is critical for developers to design user-friendly tools that gain widespread acceptance.

Diverse factors drive the adoption of generative AI. Some users are motivated by its utility in improving efficiency or reducing workload [1], while others refrain from adoption due to a lack of necessary skills or knowledge [2]. Individual perceptions and contextual factors thus shape the decision to adopt generative AI.

From the Task-Technology Fit Theory perspective, technology adoption depends on aligning technology features and task requirements [3]. The Task-Technology Fit Theory posits that even advanced technologies may not suit all tasks. For instance, when workloads are high, generative AI can serve as an effective tool to alleviate pressure. Conversely, individuals are unlikely to adopt generative AI if their tasks do not require AI intervention. Perceived usefulness of technology, which refers to the extent to improve task performance, is widely recognized as a critical factor influencing adoption behavior [4], [5]. The influence of perceived usefulness on technology adoption is supported by extensive empirical evidence, highlighting the importance of utility in predicting adoption. Thus, it is reasonable to consider perceived usefulness as a potential driver of generative AI adoption.

Generative AI, as an emerging technology, remains unfamiliar to many. Individuals may perceive themselves as lacking the knowledge or skills to utilize it effectively. Self-efficacy, which refers to people's belief about their capability to perform a specific task, plays a pivotal role in the adoption of new technology. Literature has confirmed that self-efficacy influences adoption intentions [5], [6], and it is logical to infer its impact on generative AI usage.

Numerous factors shape individuals' adoption of new technologies. This study focuses on three key determinants: perceived usefulness, self-efficacy, and workload. Most existing literature focuses on technology adoption intentions rather than actual adoption behavior. However, research indicates notable differences between behavioral intention and actual usage [7], [8], highlighting the necessary to explore the factors influencing real-world adoption. This study emphasizes actual adoption behavior, addressing the gap between intention and action identified in the literature.

The paper is structured as follows: The next section reviews relevant previous research and theoretical foundations; The third section outlines the research design and method; The fourth section summarizes the research findings; and the final section 5 provides discussions on contributions, limitations, and directions for future research.

2. Literature Review

As Generative AI continues to evolve and integrate into various domains, understanding the factors that influence its adoption becomes increasingly important. Building on foundational theories such as the Task-Technology Fit (TTF) Theory, the Technology Acceptance Model (TAM), and Self-Efficacy Theory, this section reviews the theoretical and empirical foundations that inform the study's hypotheses. Specifically, it explores how perceived usefulness, self-efficacy, and workload affect the adoption and actual use of Generative AI technologies in academic and work-related contexts.

2.1. Theory of Task-Technology Fit

The concept of Task-Technology Fit (TTF), first proposed by [9], suggests that when the functionalities of a technology align well with the requirements of a given task, both users' willingness to adopt the technology and their performance efficiency are likely to improve significantly [10]. The TTF theory emphasizes that the alignment between new technology and task characteristics influences individuals' acceptance and work performance [11], [12].

Literature used the TTF theory to explain the adoption of a variety of new technology products and information systems. For example [13] used the TTF theory to discuss the fit of mobile nursing information systems [13] on medical care. As [14] discussed online auction adoption by the TTF theory. The TTF theory is also used to explore the adoption of learning management systems [15], reverse logistics technology [16], Planning Support Systems [17], and many others.

Task-technology fit forecasts how people will perceive, intend, and behave, and how using technology will affect their performance [18]. However, empirical results have been inconsistent despite the expectation that task-technology fit will improve task performance and benefit technology adoption. According to the findings of a meta-analysis, [7] found that task-technology fit is more closely linked to individuals' perceptions and is contextualized to users and particular technology types.

2.2. Perceived Usefulness of Technology

The Task-Technology Fit idea posits that technology must align with tasks to facilitate adoption and enhance performance. Users adopt technology primarily due to its perceived utility. Perceived usefulness refers to people's perception that new technology can enhance their job performance [19]. The Technology Acceptance Model (TAM) posits that perceived usefulness of technology and ease of use of technology influence individuals' desire to adopt technology. Previous evidence validates the Technology Acceptance Model, asserting that perceived usefulness is essential for individuals to embrace new technology [20].

TAM is a fundamental idea for comprehending the determinants of human behavior regarding the acceptance or rejection of technology [21]. However, TAM is typically confirmed by behavioral intention rather than actual conduct [8]. Literature found in their meta-analysis that ease of use and perceived usefulness are less likely to correspond with actual usage than behavioral intention [8].

Generative AI is appropriate for some tasks rather than all tasks. For specific jobs, Generative AI remains inadequately proficient. Consequently, if individuals perceive that Generative AI can markedly enhance labor productivity, it is regarded as beneficial.

Accordingly, this study proposes the following hypothesis1:

H1: Perceived usefulness positively influences Generative AI usage.

2.3. Self-Efficacy

Self-efficacy denotes an individual's belief in their capability to accomplish a particular job [22]. Task-related self-efficacy is a factor affecting technology adoption [23], [24], [25]. Research indicates that individuals with strong confidence in task completion abilities are more inclined to adopt new technology [26]. Self-efficacy includes comprehending the technology's features, mastering operational techniques, and applying the technology to practical issues. As AI applications advance, it is important to comprehend the influence of perceived self-efficacy in utilizing AI technology [27]. AI self-efficacy denotes people's confidence to employ Generative AI to achieve tasks [28]. In the realm of Generative AI applications, users who can proficiently use Generative AI are more inclined to utilize Generative AI to improve productivity.

Thus, the study proposes the following hypothesis 2:

H2: AI self-efficacy positively influences AI usage.

2.4. Workload and Complexity

Workload and complexity are critical task characteristics. Some tasks require individuals to process large amounts of information and make quick decisions, which challenge users' cognitive resources and lead individuals to use Generative AI in tasks [29]. Generative AI can assist in simplifying task workflows, such as content generation and automated analysis, thereby reducing workload and improving task efficiency.

Time pressure refers to the time constraints faced when completing a task. In scenarios that require quick responses, users are more likely to rely on technological tools to shorten working time [30]. The study indicates that Generative AI, with its ability to generate content and provide real-time suggestions quickly, is particularly valuable in tasks with significant time constraints.

H3: Workload and complexity positively influence AI usage.

The interaction between Task-Technology Fit and self-efficacy is recognized as an important factor influencing technology adoption behavior. Task-Technology Fit emphasizes the fit between technology and tasks [9].

In contrast, the self-efficacy theory proposed by Bandura [22] focuses on individuals' confidence in their abilities. The integration of these theories provides a more comprehensive explanation of the process of technology usage.

3. Method

The study investigates the factors influencing the use of Generative AI. Figure 1 shows the research framework.

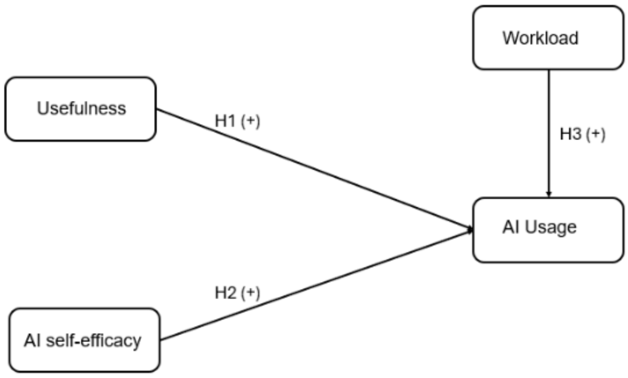

Figure 1. Research concept

3.1. Measurement

This study measures workload, perceived usefulness, AI self-efficacy, and actual Generative AI usage behavior. The workload was measured using a four-item scale, which was revised from [31] and [29]. Perceived usefulness was measured with a four-item scale based on [19] and [32]. The AI self-efficacy scale, consisting of four items, was modified from [33]. All measurement items were adjusted to align with the research objectives of this study, as shown in Table 1. Workload, perceived usefulness, and AI self-efficacy were assessed with a five-point Likert-type scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Actual Generative AI usage behavior was captured through a single-item measure of weekly time spent using AI tools.

Demographic information, including gender, age, education level, and employment status, was collected to provide insights into the sample's diversity.

Table 1. Measurement items

Variable	Measurement Items	Source
Workload	1. I feel overwhelmed by my academic or work burden. 2. Academic or work tasks make me feel overburdened. 3. I receive non-routine and particularly challenging tasks. 4. The tasks I need to complete are often highly complex.	[31], [29]
Perceived Usefulness	1. AI tools help improve my academic or work performance. 2. AI tools enhance the efficiency of my academic or work tasks. 3. AI tools increase productivity in academic or work activities. 4. AI tools are helpful for academic or work purposes.	[19], [32]
AI self-efficacy	1. I know how to use AI tools. 2. If someone teaches me how to use AI tools, I can apply them to my academic or work tasks. 3. If I have seen others use AI tools, I can imitate and apply them to my academic or work tasks. 4. If instructions are provided, I can apply AI tools to my academic or work tasks.	[33]
AI usage	How many hours per week do you spend using AI tools (e.g., ChatGPT, AI graphic generation) for academic or work purposes?	[34]

3.2. Procedure

The questionnaire included workload, perceived usefulness, AI self-efficacy, actual AI usage behavior, and demographic profiles (e.g., gender, age, education level). To ensure response accuracy, reverse-coded items were incorporated as attention checks to verify consistency.

As an incentive, participants were entered into a lottery offering ten NT$100 (US$3) cash prizes and ten mobile phone stands.

3.3. Sample

The call-for-volunteers post was distributed through online communities and supplemented with Facebook advertisements to broaden the survey's reach. Conducted from November 15 to November 25, 2024, the survey yielded 539 responses. After validity checks, including filtering questions, reverse-coded items, and excluding responses with excessively short completion times, 336 valid samples were retained.

Of the valid responses, 148 (44%) were from male respondents, 182 (54.2%) from female respondents, and 6 (1.8%) did not disclose their gender. The age distribution was concentrated in the 21–25 age group, which accounted for 34.2% of the sample. Other significant age groups included 26–30 years (12.5%), 36–40 years (10.1%), and 51 years and above (10.4%). The average age was 32.02 years.

Regarding educational background, 85.7% of respondents held a university degree or higher. Regarding occupation, the majority were employed individuals (56%), followed by students (36.3%).

3.4. Reliability and Validity Analysis

Table 2 reports the reliability and validity of the measurement scales. Cronbach's α was employed to assess the internal consistency of items within each construct. The α values were 0.797 for AI self-efficacy, 0.881 for perceived usefulness, and 0.835 for workload, all exceeding the commonly accepted threshold of 0.70. These results indicate satisfactory internal consistency and demonstrate that the reliability standards were met.

Table 2. Test results of reliability and validity

	Cronbach's alpha	Composite Reliability	Average variance extracted (AVE)
AI Self-Efficacy	0.797	0.869	0.624
Usefulness	0.881	0.918	0.738
Workload	0.835	0.890	0.670

The Composite Reliability (CR) values were 0.869 for AI self-efficacy, 0.918 for perceived usefulness, and 0.890 for workload. The Average Variance Extracted (AVE) values were 0.624, 0.738, and 0.670, respectively, for AI self-efficacy, perceived usefulness, and workload. CR and AVE scores satisfy the established criteria, with CR exceeding 0.60 and AVE exceeding 0.50, demonstrating adequate reliability and convergent validity of the scales.

This study employed two primary methods to assess discriminant validity. The first method compares the correlations between constructs with the square root of their respective AVEs.

Table 3 shows the correlation matrix demonstrates that the square root of the AVE for AI self-efficacy (0.624) exceeds its correlation coefficients with workload complexity (0.196) and AI usage scenarios (0.468), satisfying the criteria for discriminant validity. Similarly, the square root of the AVE for perceived usefulness (0.738) and workload complexity (0.670) also surpasses the correlations with other constructs. Since AI usage is measured with a single item, its AVE can not be calculated. Nevertheless, the correlation matrix indicates relatively low correlations between AI usage and other constructs, supporting its independence as a distinct construct. Correlations among constructs were not higher than the square root of the corresponding AVEs, confirming favorable discriminant validity.

Table 3. Correlation matrix for discriminant validity

	AI Self-Efficacy	Usefulness	Workload	AI Usage
AI Self-Efficacy	0.624			
Usefulness	0.634	0.738		
Workload	0.196	0.259	0.670	
AI Usage	0.468	0.500	0.240	-

Note: The numbers are correlation coefficients. The number on the diagonal is the average variance extracted (AVE). No AVE for AI usage since there is only one item for measuring AI usage.

Table 4. Heterotrait-monotrait ratio (HTMT)

	Heterotrait-monotrait ratio (HTMT)
Usefulness ←→AI Self-Efficacy	0.634
Workload ←→AI Self-Efficacy	0.196
Workload ←→ Usefulness	0.259

The Heterotrait-Monotrait Ratio (HTMT) also evaluates discriminant validity by examining inter-construct correlations. The HTMT values below 0.85 indicate strong discriminant validity, while values between 0.85 and 0.90 warrant further examination of the model design.

The HTMT ratios were 0.634 between perceived usefulness and AI self-efficacy, 0.196 between workload and AI self-efficacy, and 0.259 between workload and perceived usefulness (Table 4). HTMT values were all below 0.85, confirming favorable discriminant validity.

4. Results

To explore the causal relationships among workload, perceived usefulness, generative AI self-efficacy, and generative AI usage, the study employed partial least squares structural equation modeling (PLS-SEM). SmartPLS 4 software was used.

Figure 2 displays the PLS-SEM results. The factor loadings ranged from 0.823 to 0.889 for perceived usefulness, 0.696 to 0.844 for AI self-efficacy, and 0.740 to 0.851 for workload. All loadings meet or are close to the recommended threshold of 0.70, supporting the convergent validity of the latent constructs.

The path analysis results of the PLS-SEM reveal that perceived usefulness, AI self-efficacy, and workload significantly influence AI usage. The standardized path coefficient for perceived usefulness on AI usage is 0.326, indicating a strong positive effect. For AI self-efficacy, the path coefficient is 0.223, demonstrating that users' confidence in their ability to operate AI effectively enhances its usage. Although weaker, the path coefficient for workload is 0.109, indicating a modest association between workload and AI usage.

The overall explanatory power (R^2) of the three antecedent constructs for AI usage is 26.9% (R^2 = 0.269), reflecting that the proposed model is in a moderate level of explanatory capability.

The findings mentioned above support the proposed model, confirming the significant effects of perceived usefulness, AI self-efficacy, and workload on AI usage. The results provide robust explanatory power and empirical evidence for the research hypotheses.

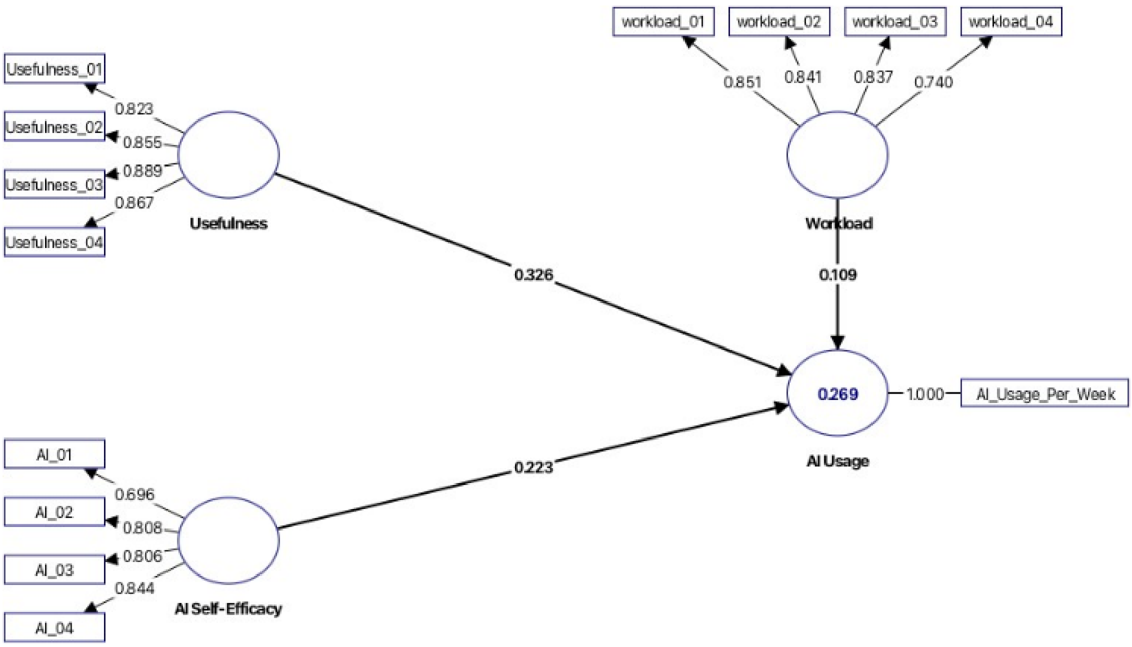

Figure 2. PLS-SEM results

5. Conclusion

This research examines the determinants affecting the utilization of Generative AI via PLS-SEM. The statistical analysis results revealed that perceived usefulness, AI self-efficacy, and workload significantly influence AI utilization, highlighting the significance of these factors in technology adoption. Among these characteristics, perceived usefulness exerts the most substantial influence, suggesting that when users acknowledge the efficacy of Generative AI tools in improving work or learning efficiency, their utilization of Generative AI correspondingly rises. This underscores the importance of technology's value and utility in fostering user acceptance of AI solutions.

AI self-efficacy significantly influences user behavior, demonstrating that confidence in one's ability to efficiently utilize AI technologies promotes adoption. Users with higher confidence in their capacity to employ AI for problem-solving or task completion are more likely to adopt these technologies. While the impact of workload is comparatively weaker, it still shows a positive correlation with AI usage. This indicates that during periods of high workload or pressure, users are more inclined to rely on Generative AI tools to reduce their burden and enhance productivity. Effectively managing workload and providing appropriate AI support can thus facilitate the broader adoption of AI technologies.

From the theoretical perspective, this study incorporates the Technology Acceptance Model, the Task-Technology Fit Theory, the Self-Efficacy Theory, and associated theoretical concepts within the Generative AI sector to explore the influence of perceived usefulness, AI self-efficacy, and workload on AI usage, consequently broadening the breadth and depth of current frameworks. The findings highlight the significance of usefulness perception as a fundamental component for AI adoption, illustrating its dual function in directly affecting usage intention and the practical value of technology in real-world scenarios. This improves the contextual relevance of the Task-Technology Fit Theory to Generative AI and opens new areas for academic study.

Incorporating AI self-efficacy as a significant determinant emphasizes the fundamental significance of users' confidence in their capabilities during technology adoption. The findings emphasize that self-efficacy is essential not just in conventional job and educational contexts but also in the utilization of advanced technological tools, hence extending its significance to digital realms.

Integrating workload into the study demonstrates its beneficial impact on usage intention, suggesting that under significant job strain, Generative AI is perceived as a desirable supplementary tool for reducing stress. This discovery enhances the situational adaptability of the Task-Technology Fit Theory and offers empirical evidence for incorporating contextual elements into future models.

The study offers comprehensive theoretical contributions by extending the theories to the context of Generative AI. The findings enhance the understanding of emerging technologies across various application domains and provide a solid foundation for future academic research.

Practically, the findings highlight that Generative AI promotes adoption by augmenting its perceived usefulness, bolstering user confidence (AI self-efficacy), and reducing severe task pressures. The design and promotion of Generative AI must closely correspond with user requirements, prioritizing practical functionality and an intuitive user experience to optimize application results.

Traditional technological tools prioritize functionality while neglecting alignment with users' operational experiences and requirements. This study demonstrates that Generative AI can significantly boost user adoption by offering targeted functional support, such as solving complex problems or enhancing efficiency. Developers should prioritize understanding user needs across various scenarios to design intuitive and scenario-specific features. Generative AI is transitioning from an auxiliary tool to a primary solution for addressing challenging tasks.

The research highlights the critical role of user self-efficacy in adopting Generative AI. For people with minimal experience, offering explicit instructions and demonstrations helps bolster trust in utilizing AI solutions. Training programs and instructional modules function as successful techniques for corporations and educational institutions, facilitating users' advancement from novice to proficient. Enhanced user confidence directly correlates with elevated adoption rates.

The study also identified workload as a primary factor in pursuing efficient solutions, positioning Generative AI as a cost-effective high-performance alternative. In high-pressure work settings, Generative AI may manage repetitive or time-consuming tasks, reducing stress and enhancing productivity. Organizations ought to proactively implement Generative AI in certain contexts to assist staff in addressing workload difficulties and improving overall efficiency.

Advocating for Generative AI should emphasize its technological capabilities and the cultivation of significant user interactions. Excessive information or undue emphasis on features may provoke resistance among consumers.

User-centric marketing and educational initiatives could include multimedia and practical examples to illustrate how Generative AI tools improve productivity while fostering an emotional bond with users. Highlighting user-friendliness and practicality can enhance adoption rates.

Despite its contributions, this study has several limitations. The cross-sectional survey design restricts the ability to infer causality, and self-reported measures may be subject to biases. The absence of longitudinal data hinders examining evolving connections over time. Future research may implement a longitudinal design to monitor users' perceptions and behaviors about Generative AI over various time intervals.

Secondly, the study depends on self-reported questionnaire responses, which, although commonly utilized in technology adoption research, may be influenced by social desirability bias. Participants may respond under societal expectations instead of accurately representing their own behaviors or beliefs. Future research may explore integrating additional data collection methodologies, such as experimental designs or behavioral observations, to corroborate the findings. Furthermore, additional negatively phrased items in the questionnaire may evaluate internal consistency.

This study evaluates perceived usefulness, AI self-efficacy, and workload, although it abandons other potential determinants of Generative AI adoption, including technological innovativeness, use costs, privacy issues, and societal influence. Future research should incorporate other variables for a comprehensive framework that explores the interaction of various influence factors for the adoption of technology.

This study does not examine certain application situations for Generative AI. Generative AI possesses considerable potential in the entertainment, healthcare, and marketing sectors, where user requirements and usage habits might vary significantly. Subsequent research should encompass diverse application contexts to examine requirements and contributing variables, offering more focused empirical evidence.

This research provides significant insights into using Generative AI while allowing for additional investigation. Future research must address existing restrictions to explore Generative AI applications and effects more comprehensively, providing enhanced insights for both academic and practical purposes.

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