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NGHIÊN CỨU THỰC NGHIỆM VỀ TÁC ĐỘNG CỦA AI TẠO SINH ĐẾN HIỆU QUẢ ÔN THI CỦA SINH VIÊN TẠI THÀNH PHỐ HÀ NỘI: VAI TRÒ TRUNG GIAN CỦA TỰ TIN VÀ TỐI ƯU HÓA THỜI GIAN HỌC TẬP

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Tóm tắt

Trí tuệ nhân tạo tạo sinh (GenAI) đã trở nên phổ biến trong đa số các lĩnh vực, bao gồm ngành giáo dục. Nghiên cứu này nhằm mục đích tìm hiểu về tác động của GenAI đến một khía

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cạnh cụ thể của ngành giáo dục, đó là hiệu quả ôn thi của sinh viên. Bên cạnh đó, nghiên cứu này cũng nhấn mạnh vai trò điều tiết của tần suất sử dụng GenAI và tìm hiểu vai trò trung gian của sự tự tin cũng như tối ưu hóa thời gian trong sự tương quan giữa trải nghiệm học tập và hiệu quả ôn thi. Mô hình cấu trúc bình phương nhỏ nhất từng phần (PLS-SEM). Dữ liệu được lấy từ khảo sát thực tế trên 412 sinh viên trên địa bàn thành phố Hà Nội. Trí tuệ nhân tạo tạo sinh (GenAI) đã có tác động trực tiếp theo hướng tích cực đến hiệu quả ôn thi của sinh viên tại Hà Nội. Ngoài ra, tác động này cũng được đo lường gián tiếp thông qua gia tăng sự tự tin và thời gian học tập được tối ưu hóa. Các nghiên cứu trong tương lai có thể thực hiện khảo sát các biến số khác (ví dụ: sự tập trung) và vai trò điều tiết của các yếu tố khác (ví dụ: năm học đại học).

Từ khóa: Hiệu quả ôn thi, tần suất sử dụng, trí tuệ nhân tạo tạo sinh, trải nghiệm học tập, tối ưu hóa thời gian, sự tự tin.

AN EMPIRICAL STUDY ON THE IMPACT OF GENERATIVE AI ON EXAM PREPARATION EFFICIENCY OF STUDENTS IN HANOI CITY: THE MEDIATING ROLES OF SELF-CONFIDENCE AND LEARNING TIME OPTIMIZATION

Abstract

Generative Artificial Intelligence (GenAI) has widespread influence in most industries, including education. The purpose of this paper is to discuss the impact of GenAI on a particular aspect of education: exam preparation efficiency among students in Hanoi, Vietnam from the perspective of Task-Technology-Fit Theory. Besides, this paper highlights the moderating role of GenAI frequency usage. Additionally, this study also explores the intermediary role of confidence and time optimization in the relationship between learning experiences and exam preparation efficiency. A Partial Least Squares Structural Equation Modeling (PLS-SEM) approach with latent constructs is applied to a self-administered survey data of 412 students in Hanoi, representing various academic disciplines to test the hypotheses. Generative AI has had a direct positive impact on students' exam preparation efficiency in Hanoi. Additionally, this impact is also indirectly measured through increased student confidence and optimized study time. Future studies would benefit from investigating other variables (e.g. concentration) and the moderating role of other factors (e.g: college years).

Keywords: Exam Preparation Efficiency, Frequency, Generative Artificial Intelligence, Learning Experiences, Time Optimization.

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1. Introduction

The rise of Generative Artificial Intelligence (GenAI) has transformed many aspects of daily life, including education, particularly how students approach learning and exam preparation. With generative artificial intelligence tools like ChatGPT, students now have instant access to the necessary knowledge, practice questions, and personalized study plans—all of which could significantly impact their study efficiency. Existing research on GenAI in education presents mixed findings. On one hand, studies have shown that AI-assisted learning can improve comprehension, reduce anxiety, and create personalized learning paths. On the other hand, some studies suggest that frequent use of GenAI might lead to passive learning, where students rely too much on AI-generated answers instead of engaging deeply with the material (Wecks, 2024). Given these conflicting perspectives, it is necessary to explore whether GenAI usage directly improves study efficiency. This study explores the impact of GenAI on exam preparation efficiency among students in Hanoi, using the Task-Technology-Fit (TTF) Theory as a framework.

2. Literature review

2.1. International research

2.1.1. Application of GenAI in general education

According to McKinsey (2024), GenAI encompasses algorithms (such as ChatGPT) with the ability to generate new content, ranging from audio, code, images, text, simulations, and videos. In regard to education, those tools include AI-powered teaching systems, personalized learning platforms, and content creation for learning materials. Several current studies have emphasized the potential of GenAI. Specifically, GenAI can improve learning and assessment processes, provided that teachers are closely involved in the process (Z.Elmourabit et al. 2024). According to the research by Fauzi et al. (2023), ChatGPT, one of the most used GenAI, can make a major contribution in enhancing the quality of student productivity. The study also proves the ability of GenAI to help students in various ways, such as providing useful information and resources, increasing time efficiency and effectiveness, and strengthening support and motivation.

As a result, GenAI is widely applied by students in different fields. In terms of open-ended queries and essay-writing tasks, GenAI appears to yield a better performance compared to students (Armin Alimardani, 2024). Approximately 60% of the students in the survey of N.T.Linh (2024) appreciated ChatGPT as "effective" or "very effective" in providing and solving questions, yet still has room for improvement.

2.1.2. GenAI and exam preparation efficiency

There have been empirical studies on the effectiveness of GenAI when being used to achieve exam scores. For instance, a survey on programming students by Tian et al. (2023) illustrated that ChatGPT not only enhanced the knowledge and retention of programming principles but also lifted students' confidence as they progressed through programming courses and finally did the test. Self-confidence is also a significant predictor of academic performance (Tavani, C. M., & Losh, S. C., 2003). De la Fuente et al. (2013) found that higher confidence was associated with strategy to study, yet not has direct relationship with GPA scores. In contrast, according to a survey conducted by Lee, H. P. H. et al. in 2025, the usage of GenAI reduces critical thinking, which means reducing self-confidence. However, the research only used critical thinking as a bridge to connect confidence and GenAI, removing other possible factors.

Furthermore, saving time in the process of learning is also an advantage when it comes to exam preparation. Research by Panda, S., & Kaur, D. N. (2024) unpacked a group of advantages brought forth by GenAI applications, including time-saving mechanisms. Khatib and Mattalo (2024) and Fauzi et al. (2023) showed that GenAI-based chatbots support students by providing answers to unclear questions, which is equivalent to saving time as they do not need to research too many different materials to answer. However both studies do not provide a tangible result on exam scores. Möller et al. (2024) witnessed a 27% increase in students’ learning speed when using GenAI as an assistant.

2.2. Domestic research

Despite the huge amount of research analyzing the correlation between GenAI utilization and education in general, there is still a deficiency of studies displaying the direct relationship between the application of GenAI and the preparation for examination among university students, especially in Vietnam. Although most students have known GenAI and ChatGPT, only a limited number of students have used it for learning purposes. However, participants expressed positive attitudes toward ChatGPT's potential to support learning, especially its ability to provide fast and accurate feedback and its potential to improve language skills (T.T.C.Trang, 2023). Besides, according to research on the current status of applying ChatGPT in learning and researching of students at Ho Chi Minh National University, most of the students have not fully exploited these tools.

There is also a fact that examination has remained one of the most popular methods to assess students in Vietnamese universities. One study by An Nguyen (2023) found that standardized test scores were the strongest predictor of academic performance in college, even after considering other factors such as high school grades and socioeconomic status. Students are required to take a series of high-stakes standardized tests at various stages of their education, including universities (Vietnam Journals Online, 2023). Yet we can acknowledge that an assistant like GenAI can fulfill the tasks included during the exam season with the aforementioned capabilities of personalizing learning experiences, managing time, developing suitable study plans, offering additional resources in subjects where students demonstrate less proficiency, and so on.

2.3. Research gaps and research questions

While there is existing literature on the relationship between GenAI and learning in Vietnam, this topic has many aspects that are yet to be explored. This is due to the fact that GenAI still has room for improvement, which means it will be optimized for future study. The purpose of this research is to concentrate more on the long-term impact of GenAI on exam preparation outcomes of university students within Hanoi, so there is a research gap in understanding the factors affecting the exam revision process of students. Besides, existing studies mentioned the impacts of GenAI on students' confidence, yet in this research paper, we will use confidence as an intermediary between learning experiences and exam preparation along with time optimization, which will provide a deeper understanding of this factor. Current research, moreover, only focuses on the correlation between GenAI utilization and overall learning process or exam performance, but not the revision process, so we will explore such relationships and provide some recommendations to fully exploit the potential of GenAI in achieving better academic performance. Overall, the study aims to present a comprehensive overview of the questions:

1. *How has GenAI influenced the overall effectiveness of exam preparation among students in Hanoi?*
2. *Does generative AI improve students' understanding of complex subjects compared to traditional study methods?*
3. *What are the main challenges faced by students in Hanoi when using generative AI for exam preparation and how to improve these challenges?*

3. Theoretical base

3.1. Theory of TFF (Task-Technology-Fit)

The integration of technology into various aspects of daily life requires a systematic evaluation of its effectiveness in meeting user needs. Goodhue and Thompson (1995) argue that the most significant determinant of a technology's effectiveness is its suitability for the specific tasks it is designed to support.

The Task-Technology Fit (TTF) model is introduced by Goodhue and Thompson (1995), posits that the effectiveness of a technology is contingent upon its alignment with the tasks it is intended to facilitate. This model asserts that the value or efficacy of a technological system is determined by the extent to which its capabilities align with task requirements, thereby enabling users to perform their intended activities efficiently (Goodhue, 1998; Goodhue et al., 2000).

Accordingly, TTF serves as a measure of how well a given technology supports individuals in completing their tasks (Yang et al., 2013; Ammenwerth et al., 2006; Goodhue & Thompson, 1995). This alignment is influenced by the interaction between task characteristics, individual characteristics, and the functionalities of the technology (Spies et al., 2020). When a technology aligns well with task requirements, it is expected to enhance performance; conversely, a mismatch between task demands and technological capabilities can lead to reduced effectiveness (Goodhue et al., 2000). The TTF model has been applied alongside other technology adoption frameworks to explore the acceptance of various technologies.

In the context of Generative AI (GAI), the TTF framework can be understood as a measure of how effectively the technology assists users in performing their activities and to achieve goals.

3.2. AI (Artificial Intelligence)

Artificial Intelligence (AI) is a broad field within computer science that focuses on developing intelligent machines capable of thinking, learning, and acting similarly to humans (Dwivedi et al., 2021; Sarker, 2022). Since its inception in the 1950s, AI has evolved significantly due to scientific breakthroughs, increased computational power, and the emergence of new technologies (Kar et al., 2023).

AI models are typically categorized into Artificial Narrow, General, and Super Intelligence by the volutionary stage (Haenlein & Kaplan, 2019; Kar, 2016; Kar et al., 2023).

Artificial Narrow Intelligence (ANI), or Narrow AI, is designed to specialize in specific tasks, such as weather forecasting, data analysis, or playing strategic games like chess. ANI lacks self-awareness and the ability to demonstrate intelligence beyond its predefined functions. These systems are highly proficient within their designated domains but remain constrained in their adaptability and scope, making their capabilities significantly limited in comparison to human intelligence (V, Sowri & Krishna, 2024)

Artificial General Intelligence (AGI) refers to a system that is expected to comprehend, learn, and perform any intellectual task that a human is capable of (Legg et al., 2007). Unlike Narrow AI which is specialized for specific tasks, AGI exhibits general-purpose problem-solving skills. Key features of AGI include autonomy, adaptability, general-purpose learning, and goal orientation, enabling it to function independently, learn from experience, and plan strategically (Ehsan, 2023).

Artificial Superintelligence (ASI) represents an advanced level of AI that significantly surpasses human intelligence across all domains. It would possess exceptional cognitive abilities, capacity for continuous self-improvement and autonomous decision-making ability (Zohuri, 2023)

In summary, AI is often defined as a system's ability to extract information from external data and apply acquired knowledge to perform specific tasks and achieve particular objectives.

3.3. GAI (Generative Artificial Intelligence).

Generative Artificial Intelligence (GAI) is a branch of artificial intelligence that focuses on training generative models using existing datasets to produce new data that closely resemble the original (Kar et al., 2023). By leveraging generative modeling techniques and advancements in deep learning, GAI enables the creation of various types of content, including images, text, audio, and video (Dwivedi et al., 2023; Verma et al., 2021).

Research has identified two key models within generative AI: Generative Adversarial Networks (GANs) and Generative Pretrained Transformers (GPTs) (Dwivedi et al., 2023; Kar et al., 2023).

GANs, the first form of generative AI, function through the interplay of two competing neural networks: a generator and a discriminator (Senger et al., 2024). The generator aims to produce data that closely resembles authentic data, while the discriminator is designed to differentiate between real and fake data (Ding et al., 2022). This process, known as "adversarial competition," allows GANs to generate highly realistic and novel content, making them valuable for applications in image and video synthesis, as well as text generation (Kar et al., 2023; Shamsolmoali et al., 2021). GANs have been particularly influential in domains such as 3 D object generation (Yu Y.et al, 2020; Q Ma et al., 2020; Chen et al.,2018) image processing (Zhou et al., 2020; Go et al., 2020), face detection (Mokhayeri et al., 2020) or text transferring (Sixt et al., 2019).

GPTs, the second major category of generative AI models is Generative Pretrained Transformers, which are deep learning-based models trained on large-scale text datasets to understand and generate human-like language (Kar et al., 2023). These models are trained on extensive datasets containing text and code, equipping them with the ability to generate coherent and contextually relevant text (Lund & Wang, 2023). Unlike GANs, GPTs operate using a single transformer-based neural network rather than two competing models (Dwivedi et al., 2023; Kar et al., 2023). One of GPT's most significant strengths lies in its ability to perform a wide range of language-related tasks, such as text generation, language translation, and creative content production.

Unlike traditional AI systems that focus on optimizing existing processes, Generative AI (GenAI) actively collaborates with human users to create novel ideas and explore innovative solutions beyond the capabilities of previous technologies. By facilitating rapid idea iteration and minimizing the costs of failure and experimentation, GenAI significantly accelerates the innovation process.

4. Research hypothesis

4.1. Relationship between learning experiences with GenAI, students' confidence and exam preparation efficiency

Bandura's self-efficacy theory (1997) points out that an individual's belief in their ability to succeed in specific situations or accomplish a task significantly impacts their motivation, behavior, and achievement. Based on this theory, Chakraborty, A. (2023) states that individuals who have low confidence in their abilities are more susceptible to experiencing stress and anxiety. In contrast, those who possess high self-efficacy tend to be more assured and less anxious leading to higher exam preparation effectiveness as well as overall academic performance.

Karimi and Saadatmand (2014) conducted a study to examine the relationship between self-confidence and academic achievement, considering the role of academic motivation. Their findings indicated a significant association between self-confidence, academic achievement, and educational motivation. The study concluded that students with higher self-confidence were more likely to succeed in learning. Furthermore, the researchers emphasized that factors such as positive feedback, motivation, and institutional support in addressing students' challenges contributed to increased self-confidence. Similarly, Afzal et al., (2010) also highlighted the connection between learning and motivation, asserting that both intrinsic and extrinsic motivation positively influence students' academic performance.

Additionally, a study by Lee and Kim (2019) found that besides self-evaluation and note-taking skills, confidence was a significant factor in students’ performance in the Korean Licensure Examination for Teachers.

Based on Bandura's theory and previous research, this study proposed a hypothesis;

- ***H1.1: As students' confidence grows, their exam preparation becomes more effective.***

The integration of Generative AI (GenAI) in education has been shown to enhance students’ confidence and engagement, thereby improving their overall learning experience (Hashmi et al., 2024). Specifically, GenAI tools such as ChatGPT-TM have demonstrated a significant impact on students’ confidence compared to conventional training approaches (Chang & Hwang, 2024). A key advantage of GenAI lies in its ability to provide personalized learning pathways, which prevent students from falling behind, maintain their engagement, and foster confidence in their academic abilities (Hashmi et al., 2024).

Empirical evidence further suggests that perceiving GenAI as a learning and problem-solving tool enhances students' confidence in their academic performance (Yinqi & Ouyang, 2024). By offering immediate assistance, GenAI allows students to address study-related challenges more efficiently, reducing the time spent waiting for teacher or friend support. This efficiency in accessing relevant information not only optimizes the learning process but also enhances exam preparation effectiveness. Therefore, GenAI positively influences students' confidence, motivation, engagement, and self-efficacy, all of which contribute to better academic outcomes (Hashmi et al., 2024).

- ***H1.2: Learning experiences with GenAI have a positive relationship with students' confidence.***

4.2. Relationship between learning experiences with GenAI, time optimization, and exam preparation effectiveness

During the pre-examination phase at the end of the semester, students typically develop individualized study plans based on the complexity and demands of each subject. These plans are structured according to their preferred learning strategies, allocated study time, optimal study periods, and the number of days available for preparation (Zerdani & Lotfi, 2021).

To better understand the varying effects of Generative AI (GenAI) on students' exam performance, Cognitive Load Theory (Sweller, 1988; van Merriënboer & Sweller, 2005) provides a relevant theoretical foundation. This theory posits that learning can be enhanced by minimizing extraneous cognitive load, thereby improving information processing and retention. In this context, GenAI functions as a cognitive aid, facilitating comprehension by simplifying complex information and scaffolding the learning process (Janik, 2024). The incorporation of GenAI tools into educational settings has demonstrated significant potential in enhancing student learning experiences (Chamber & Owen, 2024). Empirical studies suggest that GenAI enhances learning efficiency by accelerating the pace at which students absorb information (Möller et al., 2024), thereby optimizing study time. From that, GenAI contributes to improved academic performance by enabling learners to allocate their time more effectively and focus on essential aspects of exam preparation (Shahzad et al., 2024).

- ***H2.1: Learning experiences with GenAI help students save time in exam preparation***

Research of Alamdar on study habits in Iran indicates that managing study preparation throughout the semester poses a significant challenge for students. Many tend to concentrate their study efforts during free periods immediately before exams or on the eve of the assessment (Alamdar, 2017; Torshizi, 2013). Additionally, test anxiety is often manifested through students' concerns about insufficient time to review course materials or adequately prepare for exams (Abouserie, 1994). Therefore, optimizing time for exam preparation helps the student to enhance exam performance. Support this perspective, Duraku (2016) figured out that learners at the bachelor's level mentioned lack of preparation, and weaknesses in time management as factors associated with test anxiety, leading to poor performance.

- ***H2.2: Optimizing exam preparation time leads to improved exam preparation effectiveness.***

4.3. The moderating role of frequency usage of GenAI

The **Technology Acceptance Model (TAM)** (Davis, 1989) posits that individuals' perceptions of a technology's ease of use and usefulness shape their willingness to adopt it. In the context of education, when students view GenAI as advantageous, they are more inclined to integrate it into their learning process, ultimately enhancing their academic performance. Additionally, **Self-Determination Theory (SDT)** (Deci & Ryan, 1985) emphasizes the role of intrinsic motivation, which is influenced by perceived competence and satisfaction, in driving students' engagement with learning technologies. These theoretical foundations underscore the importance of examining how different levels of GenAI usage frequency impact its effectiveness in supporting learning outcomes.

Prior research suggests that the frequency of AI usage serves as a key moderating factor in shaping its influence on learning outcomes. Regular interaction with GenAI can strengthen students' familiarity with the technology and boost their confidence in its capabilities, thereby amplifying its positive effects on learning efficiency (Stamate et al., 2021). However, overdependence on AI tools without meaningful engagement may hinder cognitive development and encourage passive learning habits (Zhou & Kankanhalli, 2021).

The highlight of this study is the focus on the exploring moderating effect of GenAI Frequency usage on exam preparation effectiveness, by proposing three following hypotheses:

- ***H3: The relationship between learning experience through GenAI and exam preparation effectiveness is positively moderated by the frequency of GenAI usage.***
- ***H4: The relationship between students' confidence and exam preparation effectiveness is positively moderated by the daily frequency of GenAI usage.***
- ***H5: The relationship between exam preparation time optimization and exam preparation effectiveness is positively moderated by the daily frequency of GenAI usage.***

5. Research methodology

5.1. Data collection and processing methods

According to Joshi et al. (2015), the Likert scale is commonly used as a fundamental psychometric tool and is frequently applied in social sciences and education research. Therefore, to align with the research objectives, data were collected through a questionnaire based on a 5-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

After the data collection process was conducted through direct surveys targeting students in Hanoi, the data were cleaned by removing invalid responses, such as incomplete or inconsistent answers.

5.2. Descriptive Statistics

The research sample consists of 412 students in Hanoi, representing various academic disciplines to ensure the study's representativeness. Specifically, 26% of the students belong to the Social Sciences & Humanities field, 34% to the Engineering & Technology field, 29% to the Economics & Management field, while the remaining students are from Education and other disciplines.

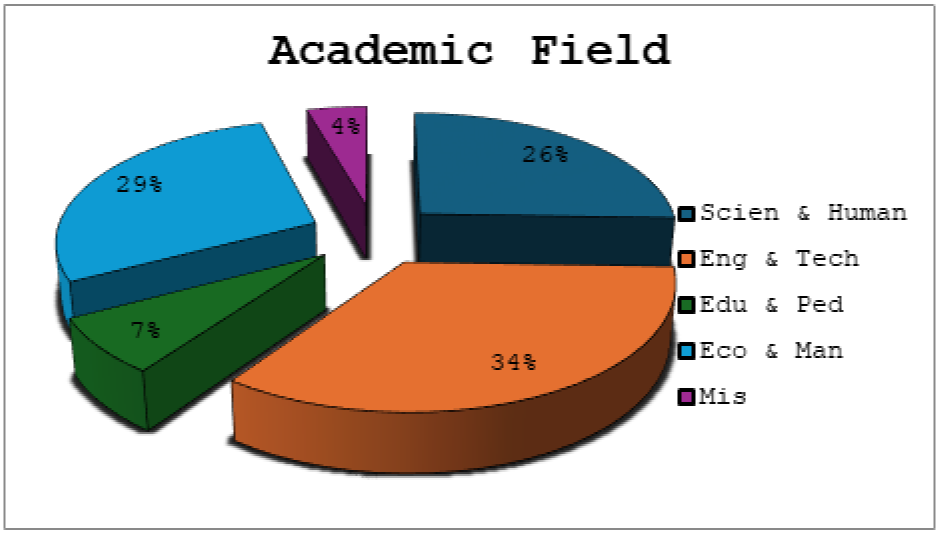

Figure 1. Distribution of Students by Academic Disciplines

Source: Compiled from the research survey results

Additionally, based on the daily usage frequency of generative AI (gen AI) during exam preparation, students were categorized into four main groups: less than 1 hour, 1–2 hours, 2–4 hours, and more than 4 hours. Descriptive statistics indicate that students who use gen AI for 2 to more than 4 hours per day tend to have higher average GPAs than the other groups. However, further analysis is required to determine whether the frequency of using this tool positively impacts students' exam preparation effectiveness.

5.3. Research methodology

This study employs the PLS-SEM (Partial Least Squares Structural Equation Modeling) approach to test the proposed hypotheses. This method allows for examining both direct and indirect effects, facilitating the exploration of mediation and moderation mechanisms within the model. According to Đoàn Quốc Việt (2023), PLS-SEM effectively analyzes relationships between latent variables. Another significant advantage of this model is that it does not require data to follow a normal distribution, making it suitable for studies with small or unevenly distributed samples.

6. Research Findings

6.1. Measurement Scale Assessment

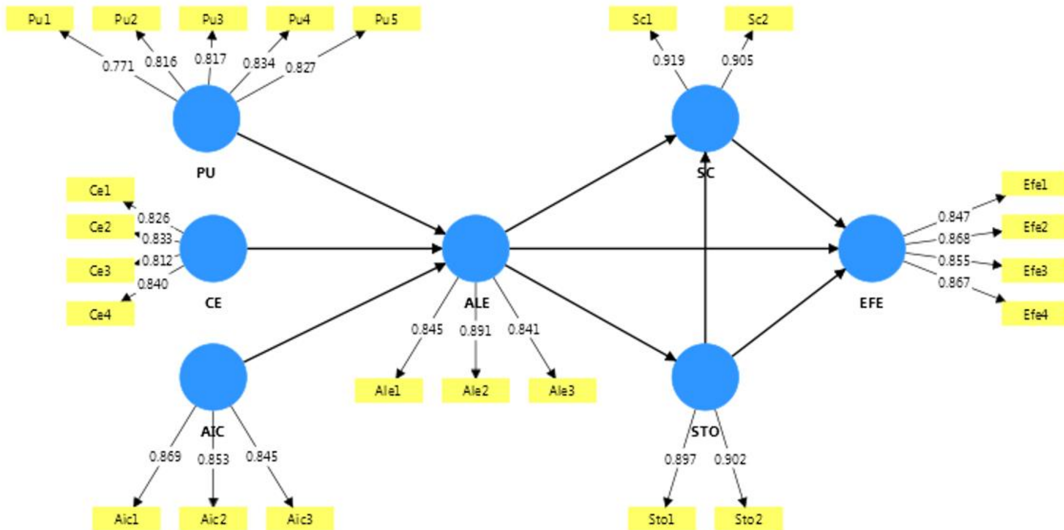

Figure 2. Measurement Model

Source: Research team's analysis results

Before estimating the PLS-SEM model to address the research questions, it is essential to validate the measurement scales by assessing the reliability, convergent validity, and discriminant validity of the indicators. According to Hair et al. (2016), an observed variable is considered of high quality if its outer loading is ≥ 0.708, meaning the observed variable explains at least 50% of the variance of its latent construct. As shown in Figure 2, all factor loadings exceed 0.708, confirming that the observed variables in this model meet quality standards.

In SMARTPLS software, both Composite Reliability (rho_c) and Composite Reliability (rho_a) are used to assess scale reliability alongside Cronbach's Alpha. Hair et al. (2022) argue that Cronbach's Alpha tends to underestimate reliability, whereas Composite Reliability (rho_c) tends to overestimate it. Therefore, the true reliability of a construct is generally considered to fall between these two values. In this study, the research team adopts Composite Reliability (rho_a) as the reliability criterion.

According to Table 1, all measurement scales pass this reliability test, as the CR values are ≥ 0.7 (Henseler & Sarstedt, 2013). Furthermore, in this model, the lowest Average Variance Extracted (AVE) is 0.661, while the highest reaches 0.832, indicating that all measurement scales demonstrate satisfactory convergent validity.

Table 1. Heterotrait-monatrait ratio (HTMT)

	CA	CR	rho_c	AVE	AIC	ALE	CE	EFE	PU	SC	STO
AIC	0.819	0.826	0.891	0.732							
ALE	0.823	0.825	0.894	0.739	0.739						
CE	0.847	0.851	0.897	0.685	0.654	0.781					
EPE	0.882	0.883	0.919	0.738	0.665	0.788	0.731				
PU	0.872	0.874	0.907	0.661	0.714	0.824	0.835	0.797			
SC	0.799	0.802	0.909	0.832	0.620	0.814	0.747	0.808	0.771		
STO	0.763	0.764	0.894	0.809	0.775	0.828	0.737	0.848	0.774	0.782	

Source: Research team's analysis results

According to the traditional approach, Fornell & Larcker (1981) suggest that discriminant validity of measurement scales can be assessed using the square root of AVE. Discriminant validity is considered satisfactory when the square root of AVE for each latent variable is greater than all correlations between that latent variable and others.

However, Henseler et al. (2015) argue that discriminant validity is better assessed using the Heterotrait-Monotrait Ratio (HTMT), a metric they developed. Clark & Watson (2016) and Kline (2015) state that discriminant validity between two latent variables is ensured when the HTMT value is below 0.85. Regardless of whether the assessment is based on the HTMT method or the square root of AVE, a review of Tables 1 and 2 clearly shows that all variable pairs meet the criteria for discriminant validity.

Table 2. Discriminant validity-Fornell-Lacker criterion

	AIC	ALE	CE	EFE	PU	SC	STO
AIC	0.856						
ALE	0.614	0.859					
CE	0.553	0.655	0.828				
EFE	0.572	0.672	0.637	0.859			

PU	0.609	0.699	0.722	0.701	0.813		
SC	0.508	0.662	0.618	0.681	0.645	0.912	
STO	0.616	0.656	0.595	0.698	0.632	0.610	0.899

Note: PU = Perceived Usefulness, CE = Creativity, AIC = AI Interaction Capability, AIL = AI-Assisted Learning, SC = Self-Confidence, STO = Study Time Optimization, EFE = Exam Preparation Effectiveness

Source: Research team's analysis results

5.2. Model testing and hypothesis evaluation

When collinearity or multicollinearity occurs in a model, it can lead to biased regression coefficients and distorted p-values, potentially resulting in incorrect conclusions about relationships between variables. Hair et al. (2019) proposed threshold values for the Variance Inflation Factor (VIF) to assess multicollinearity issues.

Table 3. Collinearity statistics (VIF) - Inner model

	AIC	**ALE**	**CE**	**EFE**	**PU**	**SC**	**STO**
AIC		1.661					
ALE				2.170		1.756	1.000
CE		2.180					
EFE							
PU		2.404					
SC				1.969			
STO				1.945		1.756	

Source: Research team's analysis results

Based on Table 3, the independent variables ALE (AI Learning Experience), EFE (Exam Preparation Effectiveness), and SC (Self-Confidence) do not exhibit multicollinearity, as all VIF values are ≤ 3.

Bootstrapping analysis confirms that students' exam preparation effectiveness (EFE) improves when their self-confidence (SC) increases, their study time is optimized (STO), or their

AI learning experience (ALE) is enhanced. The corresponding regression coefficients are SC → EFE: 0.309 (p-value < 0.01), STO → EFE: 7.583 (p-value < 0.01) and ALE → EFE: 4.187 (p-value < 0.01)

These results indicate that hypotheses H1.2, H2.2, and H4 are supported. Additionally, the positive relationships between AI learning experience (ALE) and both self-confidence (SC) and study time optimization (STO) suggest that hypotheses H1.1 and H2.1 can also be accepted.

Table 4. Path coefficients

Hypothesis	Relationship	Estimated Value	T-values	P-values	Hypothesis ($p < 0.05$)
H1.1	ALE → SC	0.455	7.141	0.000	Accept
H1.2	SC → EFE	0.309	6.105	0.000	Accept
H2.1	ALE → STO	0.643	16.256	0.000	Accept
H2.2	STO → EFE	0.356	7.583	0.000	Accept
H6	ALE → EFE	0.235	4.187	0.000	Accept

Source: Research team's analysis results

Table 5. Specific indirect effects

Hypothesis	Relationship	Estimated Value	T-values	P-values	Hypothesis ($p < 0.05$)
H1	ALE → SC → EFE	0.140	4.830	0.000	Accept
H2	ALE → STO → EFE	0.229	7.594	0.000	Accept

Source: Research team's analysis results

Based on Table 5, it is evident that hypotheses H1 and H2 are supported. This means that self-confidence (SC) and study time optimization (STO) act as mediators, transmitting the impact of gen AI usage on students' exam preparation effectiveness (EFE).

According to James et al. (2006), diverse types of mediation exist in SEM models, including complementary mediation. A mediator is classified as complementary when both the indirect effect (a × b) and the direct effect (c) are statistically significant and share the same sign.

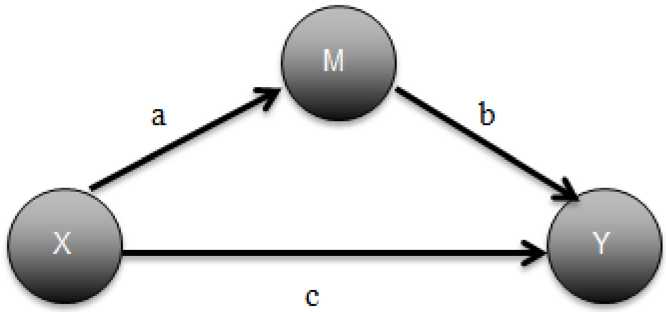

Figure 3. Mediation Mode

Thus, both self-confidence (SC) and study time optimization (STO) exhibit complementary mediation effects, meaning they do not fully explain all the mechanisms through which AI learning experience (ALE) influences exam preparation effectiveness (EFE). In other words, there are still many latent variables that could play a role in this relationship. This opens up potential directions for future research to explore additional mediators.

To further assess the role of mediating variables in the model, the research team proceeded with calculating the Variance Accounted For (VAF) index as a representative measure.

After performing the calculations, the VAF (Variance Accounted For) index was found to be 0.6455, indicating that both self-confidence (SC) and study time optimization (STO) contribute 64.55% to the total effect. This level of impact is statistically significant, confirming the important mediating role of these variables in the relationship between AI learning experience (ALE) and exam preparation effectiveness (EFE).

Table 6. Regression Analysis Results

	Model 1 (Base on Auf1)		Model 2 (Base on Auf2)		Model 3 (Base on Auf3)	
	Estimated Value	**P-values**	**Estimated Value**	**P-values**	**Estimated Value**	**P-values**
Aufa → EFE	0.056	0.186	-0.051	0.185	-0.089	0.025
Aufa × ALE → EFE	0.013	0.812	-0.012	0.812	0.030	0.509
Aufa × SC → EFE	0.010	0.864	-0.009	0.863	-0.097	0.076
Aufa × STO → EFE	0.008	0.873	-0.008	0.872	0.011	0.823
Aufb → EFE	0.086	0.026	0.036	0.303	-0.041	0.302
Aufb × ALE → EFE	-0.029	0.510	-0.040	0.400	0.045	0.400
Aufb × SC → EFE	0.094	0.076	0.085	0.136	-0.096	0.136
Aufb × STO → EFE	-0.010	0.823	-0.018	0.735	0.020	0.735
Aufc → EFE	0.062	0.097	0.014	0.669	-0.021	0.563
Aufc × ALE → EFE	-0.121	0.014	-0.132	0.013	-0.093	0.053
Aufc × SC → EFE	0.063	0.225	0.054	0.332	-0.028	0.622
Aufc × STO → EFE	0.075	0.167	0.068	0.248	0.085	0.148

Source: Research team's analysis results

Based on the regression analysis results, differences in exam preparation effectiveness (EFE) can be observed between Group 3 (gen AI usage of 2–4 hours per day) and Group 4 (gen AI usage of more than 4 hours per day) compared to Group 1 (gen AI usage of less than 1 hour per day). However, Group 2 (gen AI usage of 1–2 hours per day) does not show a significant difference from Group 1 in terms of exam preparation effectiveness. Additionally, a significant difference is also observed between Group 3 and Group 2 in students' exam performance in Hanoi.

Notably, the interaction term Auf4 × ALE → EFE = -0.132 (p-value < 0.05) indicates that exam effectiveness changes from Group 2 to Group 4. Furthermore, an increased frequency of gen AI usage appears to reduce the overall impact of AI on learning effectiveness. As a result, hypotheses H3, H4, and H5 are rejected.

6. Conclusion

According to the research findings of the authors, generative AI has indeed had a direct positive impact on students' exam preparation effectiveness in Hanoi. Additionally, this impact is also indirectly measured through increased student confidence and optimized study time. Therefore, overlooking the role of the mediating variable in assessing the impact of generative AI on exam preparation effectiveness may lead to inaccurate measurements.

Moreover, the study reveals differences in exam preparation effectiveness based on the frequency of generative AI usage per day. Excessive use of generative AI during exam preparation may have negative effects, potentially leading to lower scores. According to Nguyen (2023), overreliance on generative AI can make students dependent on the tool, discouraging them from actively seeking new knowledge and thereby reducing their critical thinking skills. Similarly, Tran (2022) pointed out that generative AI may provide inaccurate information due to its self-generated content or unverified sources.

Based on this study, we suggest applying generative AI as a virtual teaching assistant to provide study outlines and review methods. This approach allows students to leverage the positive aspects of the tool while maintaining logical thinking. Confidence also plays a crucial role in improving academic performance, as enhancing this trait can lead to better results even when the impact of generative AI is unclear. Additionally, students can utilize generative AI to schedule study plans, maximizing their preparation time for better outcomes. However, in this study, the two variables SC and STO account for only 64.55% of the total impact, meaning they may not fully capture the overall influence of generative AI on students' exam preparation effectiveness. This opens up an important research gap, suggesting that future studies could expand the model by considering additional mediating or moderating variables to further clarify the mechanism through which generative AI impacts academic performance.

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