The Impact of Students' Using Generative AI for Learning on Self-learning Motivation: a Study Based on Self-determination Theory

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Abstract. This study was conducted to analyze the impact of Generative AI use on the self-learning motivation of university students in Ho Chi Minh City. The study explores how three factors from the Self-Determination Theory (perceived autonomy, perceived relatedness, and perceived competence) influence self-learning motivation through mediating factors like perceived usefulness and intrinsic motivation. Data was collected from an online survey of 294 students who used GenAI for learning. The data was tested for reliability by Cronbach's Alpha coefficient. Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), and Structural Equation Modeling (SEM) were used to test the research model. The results show that perceived autonomy and perceived relatedness positively affect both perceived usefulness and intrinsic motivation, which in turn, influence self-learning motivation. Perceived competence, however, only impacts intrinsic motivation. Based on these findings, recommendations are proposed to enhance student self-learning motivation by leveraging the benefits of Generative AI tools.

Keywords: Generative AI, Self-Determination Theory, Self-learning Motivation.

1 Introduction

1.1 Problem Statement

The emergence of generative artificial intelligence applications capable of generating content (GenAI) for users at the end of 2022 and the beginning of 2023 has caused a major disruption to teaching and learning methods at universities worldwide (Kelly et al., 2023). Since self-learning has also become the foundation of the learning process, GenAI plays a significant role in changing learning methods and supporting students in the self-learning process. With the advent of GenAI, students can be empowered with diverse resources, personalized learning, and optimal support. It helps students evolve into proactive learners, capable of self-identifying and organizing

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their learning. On the other hand, motivation helps students overcome difficulties and challenges in self-learning. Therefore, fostering self-learning motivation is an indispensable factor in individuals' lifelong learning process, which is not only contributes to students' progress and personal development but also enriches social education.

This research aims to evaluate how Generative AI (GenAI) impacts the self-learning motivation of Ho Chi Minh City students by examining the influence of three key psychological factors: perceived autonomy, perceived competence and relatedness, and perceived usefulness and intrinsic motivation. By identifying the factors influencing student motivation in this GenAI learning environment, the research seeks to develop recommendations for optimizing educational practices and maximizing the potential of GenAI to enhance self-directed learning.

1.2. Research Questions

Do perceived autonomy, perceived competence, perceived relatedness, perceived usefulness, and intrinsic motivation affect the university students' self-learning motivation in Ho Chi Minh City?

To what extent do these factors influence the self-learning motivation of Ho Chi Minh City university students in the context of GenAI for learning?

Based on the findings, what recommendations can be formulated to improve the integration of GenAI in learning environments to enhance self-learning motivation among Ho Chi Minh City university students?

2 Literature Review

2.1 Generative AI (GenAI)

Generative AI, or Generative Artificial Intelligence, represents a groundbreaking advancement within the field of artificial intelligence (AI) that is dedicated to the creation of new and unique content, encompassing a wide range of data types such as text, images, sound, voice, and video (Fui-Hoon Nah et al., 2023). Currently, notable Generative AI applications include GPT (Generative Pre-trained Transformer) for text, DALL-E for image creation,...

2.2 Self-Learning Motivation

Self-learning motivation is a key factor for success in learning and life. Studies suggested that motivated learners are engaging, showing high performance, undertaking challenging activities, and displaying resilience when facing troubles (Schunk, Pintrich, & Meece, 2008). Paris and Turner (1994) stated that motivation is the "engine" of learning. Meaning that it drives the students toward their goals. Motivation can influence what we learn, how we learn, and when we choose to learn (Schunk & Usher, 2012).

Therefore, self-learning motivation in this research study is understood as the factor that urges individuals to initiate and sustain the process of learning on their own, without the guidance of others.

2.3 Self-Determination Theory

Theory overview

Self-Determination Theory (SDT) emphasizes three basic psychological needs: autonomy (feeling in control), competence (feeling capable), and relatedness (feeling connected). These needs are crucial for motivation, learning, and development.

Developed by Deci and Ryan, SDT highlights the importance of autonomous motivation, driven by internal desires like curiosity and growth, rather than external pressures like rewards. Studies show that fulfilling the three psychological needs fosters autonomous motivation, which leads to better learning, creativity, and overall well-being.

The theory is particularly relevant in education. By creating environments that satisfy students' autonomy, competence, and relatedness needs, educators can promote autonomous motivation, leading to improved learning and development.

Perceived Autonomy

Feeling in control (perceived autonomy) motivates us. Interesting and valuable experiences boost it, while rewards or punishments hurt it. This is linked to higher achievement and interest in learning.

Perceived Competence

In Self-Determination Theory, feeling competent (perceived competence) is key. It's the belief you can succeed and develop. Engaging in activities that let you use and grow your skills builds this feeling. When lacking, you might feel like a failure. Studies show students who feel competent set higher goals and try harder to reach them.

Perceived Relatedness

Self-Determination Theory sees feeling connected (relatedness) as a basic need. It's about love, support, and closeness from others. Lacking this can lead to loneliness. Studies show students with positive relationships with teachers and peers are happier and more motivated to learn.

Intrinsic Motivation

Self-Determination Theory emphasizes intrinsic motivation, the drive to do something for enjoyment and satisfaction itself, rather than external rewards. This type of motivation is crucial for lifelong learning because it fuels curiosity and a love for the subject, leading to deeper engagement and better development.

Perceived Usefulness

Self-Determination Theory (SDT) goes beyond just intrinsic motivation. It acknowledges external factors can influence us (extrinsic motivation) but also that we can take control of them. For instance, if a student sees the usefulness of a learning tool (e.g., online resources), even if assigned (external factor), they're more likely to find it interesting and valuable (internalized motivation). This leads to them being more engaged and performing better. Studies like Luo et al. (2021) support this, showing students who find online tools useful have better learning outcomes. So, creating helpful learning tools can boost student proactivity and achievement.

2.4 Previous research overview

The Impact of ChatGPT on Learning Motivation: A Study Based on Self-Determination Theory (Zhou, L. & Li, J. J., 2023)

This study investigated how using ChatGPT affects university students' motivation to learn. It found a positive impact on intrinsic motivation (feeling good about learning itself) through perceived competence (feeling capable). Although the study mentions Self-Determination Theory, it does not show the influence of autonomy and relatedness on students' intrinsic motivation, except for the perceived competence variable. - Nevertheless, the study still contributes both theoretically and in terms of results for the authors to refer to.

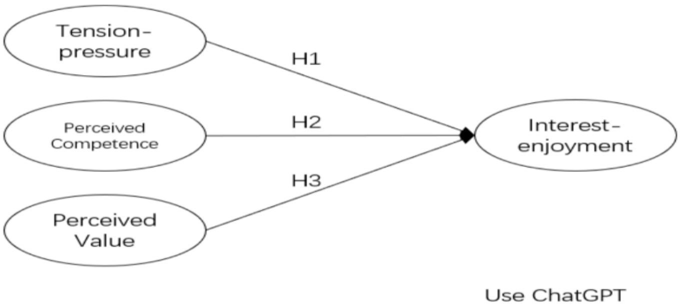

Fig. 1. Research Model by Zhou, L. & Li, J. J. (2023). Source: Zhou, L. & Li, J. J. (2023)

Exploring the role of intrinsic motivation in ChatGPT adoption to support active learning: An extension of the technology acceptance model (Lai, Chung Yee. & et al., 2023)

A study in Hong Kong found that wanting to learn for itself (intrinsic motivation) is the biggest reason why university students there would use ChatGPT for self-directed learning. Additionally, finding ChatGPT useful also plays a big role in their decision to use it. This research highlights the importance of both internal drive and practical value for students using AI tools to learn on their own.

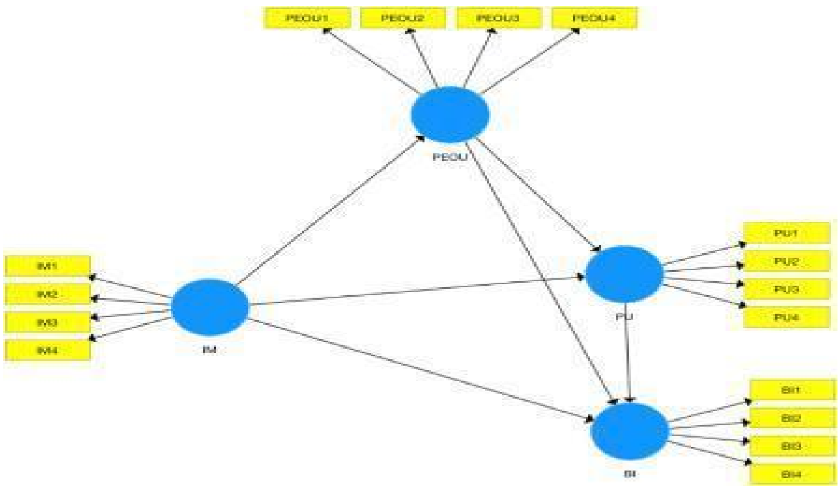

Fig. 2. Research Model by Chung Yee Lai, Kwok Yip Cheung, Chee Seng Chan (2023). *Source: Chung Yee Lai et al (2023)*

Examining the Impacts of ChatGPT on Student Motivation and Engagement (Muñoz. & et al., 2023)

This study found teachers and students both believe ChatGPT boosts motivation and engagement. They recommend including ChatGPT in education, but the research doesn't explore the specific reasons for increased motivation (like enjoyment of learning).

The mediating effects of needs satisfaction on the relationships between prior knowledge and self-regulated learning through artificial intelligence chatbot (Xia, Q. & et al., 2023)

This study investigated how AI tools and English skills affect students' self-directed learning (SRL) with Generative AI (GenAI). They found that prior English knowledge directly impacts SRL, while AI knowledge itself doesn't. Interestingly, feeling in control (autonomy) and competent mediated the link between both English and AI knowledge with SRL. This suggests that fulfilling these needs might be more important for young learners using GenAI to learn, especially when their English is weaker. It also highlights that current GenAI might not be ideal for students with lower English proficiency.

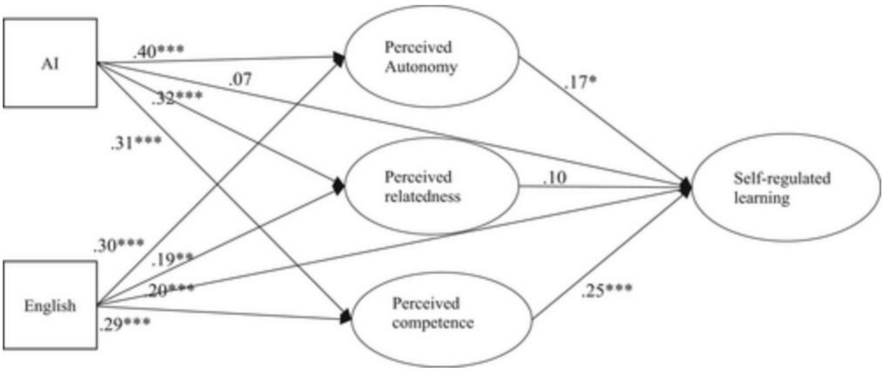

Fig. 3. Research Model by Qi Xia, Thomas K. F. Chiu, Ching Sing Chai, Kui Xie (2023). *Source: Xia, Q., & et al., 2023*

2.5 Hypotheses and Research model

Literature gap

Current research on how cool new learning tools like Generative AI (GenAI) motivate students doesn't dig deep enough. They just see a general boost in interest, but not why students are interested. Is it because they genuinely want to learn (intrinsic) or just for good grades (extrinsic)?

There's a theory (Self-Determination Theory) that suggests 3 things drive real motivation: feeling in control (autonomy), feeling capable (competence), and feeling connected (relatedness). GenAI could potentially address all three, making students want to learn for the sake of learning, not just grades. This would be much better for their self-directed learning. Basically, figuring out how GenAI fuels intrinsic motivation and autonomous motivation sources needs is key to making it a truly powerful learning tool.

Hypotheses

(1) Three basic psychological needs and Intrinsic Motivation

Self-Determination Theory (Ryan & Deci, 2000) proposes that supporting three basic psychological needs - autonomy, competence, and relatedness - strengthens intrinsic motivation. When these needs are fulfilled, individuals feel free to choose (autonomy), capable (competence), and connected (relatedness), leading to more motivated behavior.

The need for autonomy refers to controlling one's choices, competence refers to feeling effective, and relatedness refers to social connection. Studies by Zhou et al. (2023) and Luo et al. (2021) support this theory, showing that fostering a sense of competence and fulfilling all three needs in students increases their learning motivation. Additionally, Deci & Ryan (1985) found that meeting these needs leads to more voluntary participation and satisfaction in learning.

Therefore, the authors believe that when using generative AI, students with all three needs satisfied will experience a stronger drive to learn. Therefore, the authors propose the following hypotheses:

H1a: Perceived autonomy has a positive impact (+) on intrinsic motivation when using GenAI.

H1b: Perceived competence has a positive impact (+) on intrinsic motivation when using GenAI.

H1c: Perceived relatedness has a positive impact (+) on intrinsic motivation when using GenAI.

(2) Three basic psychological needs and Perceived Usefulness

Supporting students' autonomy, competence, and relatedness needs boosts intrinsic motivation (Ryan & Deci, 2020). This, in turn, helps students see value in external motivators (e.g., grades), leading to better academic achievement. Autonomy is linked to perceiving e-learning as useful (Roca & Gagné, 2008), with competence further strengthening this connection (Luo et al., 2021). Feeling connected to others (relatedness) also plays a positive role in seeing value in learning activities (Nikou & Economides, 2017).

However, there is currently a lack of scientific research on the impact of perceived usefulness of generative AI (GenAI) on learning motivation. Based on Self Determination Theory and perceived usefulness (related to internalization of extrinsic motivation), this researches propose the following three hypotheses:

H2a: Perceived Autonomy has a positive (+) impact on Perceived Usefulness with GenAI.

H2b: Perceived Competence has a positive (+) impact on Perceived Usefulness with GenAI.

H2c: Perceived Relatedness has a positive (+) impact on Perceived Usefulness with GenAI.

(3) Intrinsic Motivation, Perceived Usefulness and Self-learning motivation

Studies show that strong intrinsic motivation makes people see things as more valuable. In Self-Determination Theory, when people are truly interested in a task (high intrinsic motivation), they put more effort in, leading to better results and a stronger belief in the task's value (perceived usefulness) (Ryan & Deci, 2017).

For example, Deci and Ryan (1985) found people with high intrinsic motivation valued their work more than those driven by external factors. Similarly, Lai et al. (2023) showed that students with high intrinsic motivation found ChatGPT, a generative AI tool, to be more useful for learning.

Based on this, the researchers propose a hypothesis:

H3: Intrinsic Motivation has a positive (+) impact on Perceived Usefulness.

Self-Determination Theory separates motivation into two types: intrinsic (personal interest) and extrinsic (external rewards). Perceived usefulness aligns with internalized extrinsic motivation, where students see value in external factors. When students have both high autonomy (control) and internalized motivation, they tend to learn more effectively (Deci & Ryan, 2000).

Research supports this connection. Luo et al. (2021) found that both intrinsic motivation and perceived usefulness of online platforms increased students' intention to learn. Similarly, Lai et al. (2023) showed that intrinsic motivation and perceived usefulness influenced students' desire to use generative AI for learning.

Based on this, the researchers propose two hypotheses:

H4: Perceived Usefulness has a positive (+) impact on Self-learning motivation Motivation.

H5: Intrinsic Motivation has a positive (+) impact on Self-learning motivation Motivation.

Research Model

All the above-mentioned hypotheses are summarized into the research model in Figure 2.4.

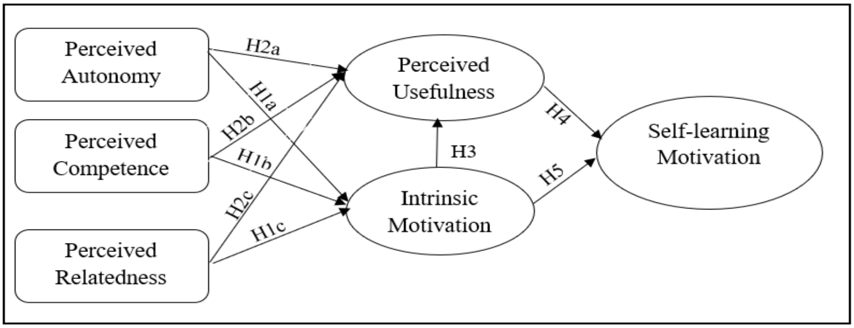

Fig. 4. Proposed research model. *Source: The authors*

3 Methodology and Data

3.1 Samples

The convenience sampling method was employed using the Google Forms online survey tool, with a sample size of 294 samples from the target students from various universities across Ho Chi Minh city who have utilized GenAI for learning purposes.

3.2 Measurement scales

Based on measurement scales from previous studies, the research team adjusted the scale to suit the research context.

Perceived Autonomy Scale consists of five items: four items (PA2, PA3, PA4, and PA5) are based on the research of Hew and Kadir (2016); item PA1 was added by the authors from the study of McAuley et al. (1989). The items was adapted by replacing “the chatbot”,”this activity” with “GenAI”; "learning” with “self-learning”.

Perceived Competence Scale consists of five items: PC1, PC2, and PC5 are based on the research of Hew and Kadir (2016); items PC3 and PC4 were taken from the study of McAuley et al. (1989). The authors adjusted the items by replacing “learning” with “self-learning”; “the chatbot” with “GenAI”.

Perceived Relatedness Scale consists of four items coded from PR1 to PR4 based on the research of McAuley et al. (1989). The authors adjusted the items by replacing “this person” with “GenAI”.

Intrinsic Motivation Scale consists of four items coded from IM1 to IM4 based on the research of Dysvik and Kuvaas (2008). The authors adjusted the items by replacing “ChatGPT” with “GenAI for self-learning”.

Perceived Usefulness Scale consists of five items: PU1 and PU4 are based on the research of McAuley et al. (1989); PU2, PU3 and PU5 were taken from the study of Davis et al. (1989). The authors adjusted the items by replacing “ChatGPT” with “GenAI”; “this activity” with “using GenAI for self-learning”

After the qualitative research, the authors found that there was no existing scale that accurately measured the construct of Self-learning Motivation. Therefore, we adapted the Writing Motivation Scale to fit the research context by replacing "writing in English" with "self-learning" and making other minor changes. The scale consists of six items coded SLM1 to SLM6, based on the study by Waller and Papi (2017).

3.3 Questionnaire Design

The questionnaire was designed to collect data for the quantitative analysis phase, consisting of three parts.

Screening Questions: To ensure that the survey was completed by the target population, two screening questions were included: "You are currently a student studying in which area?"; "Have you ever used GenAI (ChatGPT, Gemini, Claude AI, etc.) for learning?". Only respondents who answered "Ho Chi Minh City" to the first question and "Yes" to the second question were allowed to proceed with the rest of the survey.

Personal Information: This section collected demographic information such as gender, year of study, and the most commonly used GenAI tool. Additionally, respondents were asked to provide their email address for follow-up purposes (This was an optional question).

Main Survey Questions: This section focused on the impact of using GenAI for learning on self-learning motivation. Respondents were asked to indicate their level of agreement with various statements. The questions for these factors were based on scales that were adapted from the qualitative study. To measure the students' level of agreement, the questionnaire used a 5-point Likert scale, as follows: "1: Strongly disagree”, “2: Disagree”, “3: Neutral”, “4: Agree”, “5: Strongly agree”.

4 Results and Discussions

4.1 Sample characteristics

The survey results show a gender disparity with 213 female respondents (72.4%) and 81 male respondents (27.6%), indicating a higher usage of GenAI for self-learning among female students. Year-wise, the distribution among 294 respondents was fairly balanced: 93 Juniors (31.6%), 74 Freshmen (25.2%), 70 Sophomores (23.8%), 52 Seniors (17.7%), and a minimal 1.7% from other categories, suggesting a representative sample for Ho Chi Minh City's student population. In terms of GenAI tools, ChatGPT led with 269 selections, significantly outpacing other tools like Gemini, Bing Chat, and Claude AI, highlighting its predominant usage despite the availability of other emerging technologies.

4.2 Evaluation of the measurement quality of scales

Results of Scale Reliability Testing Using Cronbach's Alpha Coefficient

Initially, we conducted an exploratory factor analysis (EFA) using Promax rotation to preliminarily assess the concepts and eliminate items that did not meet the requirements. The EFA results indicated that the variables loaded onto the following factors: Perceived Autonomy, Perceived Competence, Perceived Relatedness, Intrinsic Motivation, and Perceived Usefulness. One variable, specifically IM1 ("I find using generative AI enjoyable"), was excluded from further analysis due to a factor loading coefficient below 0.5, failing to meet the convergence requirement. The results showed a total variance extracted of 64.799%, surpassing the minimum standard of 50% according to Gerbing & Anderson (1988), thus emphasizing the reliability of the scale.

Next, following Hair et al. (1998), the factor loading (FL) in EFA should be greater than 0.5 to meet the convergence requirement when the sample size is about 100 observations. In this study, with 294 observations, we applied a criterion of FL $\geq$ 0.5 to ensure robust convergence. Additionally, the highest FL of an item on one factor must differ by at least 0.3 from its loadings on any other factor, which establishes its discriminant validity.

Evaluation of Unidimensionality

The overall fit of the model is a necessary condition to determine whether a set of items achieves unidimensionality (Steenkamp & Van Trijp, 1991). Thus, we initially assess the model's fit with the data using goodness-of-fit criteria.

CFI should be greater than 0.9, CMIN/df should be less than 2 to indicate good model fit, and GFI should be greater than 0.8 reflects an acceptable fit (Hair et al., 2010).

Hooper et al. (2008, p. 54) conclude that RMSEA < 0.06 or possibly < 0.07 indicates a common agreement among researchers.

The results of the Confirmatory Factor Analysis (CFA) provide goodness-of-fit indices, including Chi-square/df = 1.849 < 2; GFI = 0.863 > 0.8; CFI = 0.947 > 0.9; RMSEA = 0.054 < 0.06. We conclude that the model fits the data.

Further examination reveals that the residuals between the measured items are entirely uncorrelated. Thus, the model measures the concepts achieving the requirement of unidimensionality.

Evaluation of convergent validity.

Table 1 shows that the Factor Loadings (FL) of the statements have met the threshold for convergence, with FL ≥ 0.35 compared to the minimum sample size of 250 (sample size of research is 294) (Hair et al., 2010), thus meeting the convergent validity. The Average Variance Extracted (AVE) is used to recheck the internal convergence of items within the same concept. AVE needs to be > 0.5 to satisfy convergence (Bagozzi & Yi, 1988). Table 1 shows that all AVE values of the concepts exceed the threshold of 0.5.

Evaluation of Reliability.

According to Hoang Trong and Chu Nguyen Mong Ngoc (2008), Cronbach's Alpha coefficients from 0.6 and above indicate acceptable measurement scales. Our study's Cronbach's Alpha coefficients for the examined scales were as follows: Perceived Autonomy (PA) = 0.881, Perceived Competence (PC) = 0.895, Perceived Relatedness (PR) = 0.890, Intrinsic Motivation (IM) = 0.857, Perceived Usefulness (PU) = 0.890, and Self-learning Motivation (SLM) = 0.916. These findings indicate strong internal consistency and reliability in measuring the respective constructs.

Evaluation of discriminant Validity

Discriminant validity is assessed through the overall correlation coefficient test between concepts not equal to 1 (Xiong et al., 2015).

Table 2 shows that P-values are all less than 0.05 (i.e., 5%), so the correlation coefficient of each conceptual pair is different from 1 at 95% reliability. Thus, the concepts studied in the model all achieve discriminant validity.

Hypothesis Testing

A Structural Equation Modeling (SEM) model using maximum likelihood estimation method is conducted to evaluate hypotheses within the analytical framework. Referencing Table 3, hypothesis H2b does not achieve statistical significance and is thus rejected, while the remaining hypotheses are all accepted.

The model demonstrates a good fit with the observation data: with Chi-square/df = 1.865 < 2; GFI = 0.861 > 0.8; CFI = 0.946 > 0.9; RMSEA = 0.054 < 0.06, all meeting the threshold conditions discussed earlier.

Table 1. Measurement model evaluation results EFA and CFA

Variables	EFA		α	CR	AVE

[PA1] I used GenAI for self-learning because I wanted to.	0.531		0.881	0.882	0.600
[PA2] I feel like I can make a lot of input in deciding how I use GenAI in self-learning.	0.552				
[PA3] I have a say regarding what input I want to learn with GenAI.	0.853				
[PA4] I have many opportunities with GenAI to decide for myself how to self-learn.	0.758				
[PA5] I feel a sense of freedom when using GenAI for self-learning.	0.709				
[PC1] I think I am pretty good at self-learning with GenAI.	0.842		0.895	0.895	0.631
[PC2] I am pretty skillful at self-learning with GenAI.	0.876				
[PC3] After learning with GenAI for a while, I felt pretty compe-tent.	0.710				
[PC4] I am satisfied with my GenAI using skills for self-learning.	0.782				
[PC5] I have been able to learn interesting new knowledge with GenAI.	0.468				
[PR1] I felt like I could really trust GenAI.	0.775		0.890	0.891	0.673
[PR2] I'd like a chance to interact with GenAI more often.	0.790				
[PR3] I feel close to GenAI.	0.892				
[PR4] It is likely that GenAI and I could become companions if we interacted a lot.	0.820				
[IM2] I had fun using GenAI for self-learning.	0.894		0.857	0.826	0.613
[IM3] The actual process of using GenAI for self-learning was	0.469				

pleasant.					
[IM4] Using GenAI to address my academic inquiries is interesting.	0.438				
[PU1] I believe using GenAI for self-learning could be of some value to me.	0.639		0.890	0.893	0.625
[PU2] I find GenAI useful for answering academic inquiries.	0.473				
[PU3] Using GenAI addresses my academic inquiries more quickly.	0.756				
[PU4] I would be willing to use GenAI for self-learning because it has some value to me.	0.893				
[PU5] Using GenAI for self-learning would increase my academic performance.	0.386				
[SLM1] I enjoy self-learning.	0.611		0.916	0.918	0.615
[SLM2] Self-learning is very important to me.	0.719				
[SLM3] I always look forward to my self-learning sessions.	0.790				
[SLM4] I would like to spend lots of time self-learning.	0.940				
[SLM5] I would like to concentrate on learning more than any other topic.	0.851				
[SLM6] I actively think about what I have learned.	0.752				
[SLM7] I really try to learn how to self-learn.	0.644				

Note. EFA = Exploratory Factor Analysis, CFA = Confirmatory Factor Analysis, α = Cronbach's Alpha, CR = Composite Reliability, AVE = Average Variance Extracted.

Table 2. The correlation coefficients between constructs

O.N	Relationship	r	SE	CR	P(r)
1	SLM <--> PC	0.676	0.043	7.513	0.000
2	SLM <--> PA	0.725	0.040	6.823	0.000

3	SLM	<-->	PR	0.379	0.054	11.467	0.000
4	SLM	<-->	PU	0.766	0.038	6.220	0.000
5	SLM	<-->	IM	0.703	0.042	7.136	0.000
6	PC	<-->	PA	0.750	0.039	6.459	0.000
7	PC	<-->	PR	0.363	0.055	11.682	0.000
8	PC	<-->	PU	0.713	0.041	6.994	0.000
9	PC	<-->	IM	0.801	0.035	5.680	0.000
10	PA	<-->	PR	0.320	0.055	12.265	0.000
11	PA	<-->	PU	0.835	0.032	5.124	0.000
12	PA	<-->	IM	0.808	0.034	5.569	0.000
13	PR	<-->	PU	0.426	0.053	10.841	0.000
14	PR	<-->	IM	0.412	0.053	11.027	0.000
15	PU	<-->	IM	0.844	0.031	4.970	0.000

Note. SLM = Self-learning Motivation, IM = intrinsic Motivation, PA = Perceived Autonomy, PC = Perceived Competence, PR = Perceived Relatedness, PU = Perceived Usefulness,
O.N = Ordinal Number, r= correlation coefficients, SE= Standard Error,CR= Critical Ratio, P(r)= Probability of a relationship

Table 3. The results of hypothesis testing

Hypothesis	Relationship			Estimate	S.E.	C.R.	P	Conclusion
H1a	IM	<---	PA	0.511	0.088	5.801	***	Accepted
H1b	IM	<---	PC	0.398	0.075	5.308	***	Accepted
H1c	IM	<---	PR	0.080	0.033	2.436	0.015	Accepted
H2a	PU	<---	PA	0.518	0.101	5.112	***	Accepted
H2b	PU	<---	PC	-0.020	0.080	-0.244	0.807	Rejected
H2c	PU	<---	PR	0.074	0.031	2.404	0.016	Accepted
H3	PU	<---	IM	0.435	0.119	3.661	***	Accepted
H4	SLM	<---	PU	0.591	0.121	4.869	***	Accepted
H5	SLM	<---	IM	0.293	0.120	2.446	0.014	Accepted

Note. SLM = Self-learning Motivation, IM = intrinsic Motivation, PA = Perceived Autonomy, PC = Perceived Competence, PR = Perceived Relatedness, PU = Perceived Usefulness, SE= Standard Error,CR= Critical Ratio, P(r)= Probability of a relationship

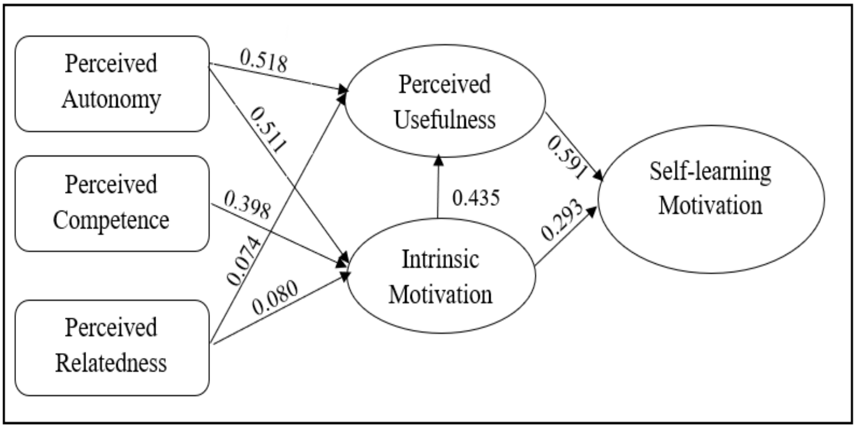

Fig. 5. Regression Model

5 Conclusion

Research results indicated that "Perceived Usefulness" has the strongest impact on self-learning motivation when students realize the benefits of GenAI reflecting their interests or needs. Internal motivation also positively influences "Perceived Usefulness", creating favorable conditions for enhancing students' self-learning motivation. Specifically, Intrinsic Motivation has a positive relationship with impacting "Perceived Usefulness".

At the same time, the "Intrinsic Motivation" variable is directly affected by three independent variables, "Perceived Autonomy", "Perceived Competence", and "Perceived Relatedness". However, statistical results and analysis revealed that among the independent variables, only "Perceived Autonomy" and "Perceived Relatedness" have a positive relationship influencing "Perceived Usefulness".

"Perceived Autonomy", "Perceived Competence", and "Perceived Relatedness" indirectly impact the effectiveness of GenAI on students' self-learning motivation. A student with perceived autonomy, perceived competence, and perceived relatedness will have better self-learning motivation when applying GenAI in their learning. Among the three factors of Self-Determination Theory, "Perceived Autonomy" has the strongest influence on two intermediate variables, namely "Perceived Competence" and finally "Perceived Relatedness". "Perceived Relatedness" has a lesser impact, as students do not demand high levels of interaction between humans and machines.

While existing research explores the impact of Generative AI (GenAI) on various aspects of learning, few studies have examined its influence on students' Self-learning motivation through the lens of Self-Determination Theory (SDT). Our research aims to address this gap by investigating how the three fundamental psychological needs outlined by SDT (autonomy, competence, and relatedness) and autonomous motivation interact with GenAI use to affect students' Self-learning motivation. Moreover, studies on GenAI and self-learning motivation are not yet widely disseminated, especially under the influence of Self-Determination Theory, the author's team's research has contributed to expanding the measurement scale assessing the impact of Self-Determination Theory on the use of Generative Artificial Intelligence (GenAI) for self-learning motivation, within the context of research in Ho Chi Minh City, accurately reflect the context of the current study.

From the research conclusions, the author's team has put forth several recommendations:

(1) For students and self-study learners:

As knowledge recipients, students must cultivate self-awareness and actively engage in their learning. This means understanding GenAI tools and taking ownership of their learning journey by setting goals and choosing suitable GenAI usage methods.

Nurturing students' intrinsic motivation to enhance the self-study motivation and leverage the utility knowledge learned from GenAI. Rather than external factors, it stems from the inherent enjoyment and learning for their own sake.

(2) For educators and educational institutions:

It is necessary to enhance students' GenAI usage skills through organizing tutorials and presentations on GenAI usage methods and effective applications in learning alongside educating students about the role of GenAI users

Educational institutions can redesign schedules to provide students with time for self-study, research, and exploration of new knowledge with GenAI to enhance the interaction between GenAI and students, which is crucial in the self-learning process with GenAI.

Support groups and online communities focusing on GenAI for self-learning can be established to familiarize students with this learning tool and enhance information exchange among students.

(3) For GenAI developers: The knowledge obtained from GenAI must be useful to students, helping them solve problems encountered during self-study. Therefore, developers of GenAI should upgrade and improve tools, including updating data on time and building algorithms, to meet users' purposes.

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