Exploring the Continuous Intention to Use Generative AI: The Influence of Expectation Confirmation and AI Self-Efficacy

Shih-Ming Pi*, Kuo-Chen Li, and Min-Jie Hsieh
Department of Information Management, Chung Yuan Christian University, Taiwan
*Corresponding Author: happypi@gmail.com

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Abstract

With the rapid development of generative AI, natural language processing models like ChatGPT are gaining increasing attention in the field of education. This study aims to explore university students' expectations, satisfaction, and continuous intention to use ChatGPT, as well as to analyze the differences in AI self-efficacy among students from different academic backgrounds, which in turn affect their acceptance and continuous use intention of AI tools. The study surveyed 902 valid responses from students at a private university in Taiwan to understand their attitudes toward the use of generative AI. The results indicate that most students show a positive attitude toward the application of ChatGPT in learning and are willing to continue using the tool. High expectations of ChatGPT significantly enhance their satisfaction and confirmation, further strengthening their continuous use intention. Students from information-related disciplines have higher expectations and AI self-efficacy regarding ChatGPT, leading to greater satisfaction and continuous use intention. In contrast, students from non-information-related disciplines primarily use ChatGPT for summarization and language translation, with lower expectations and AI self-efficacy. Based on the findings, this study provides recommendations aimed at helping educational institutions and AI developers better understand users' needs and expectations regarding generative AI. These recommendations include integrating AI technology into curricula, offering technical training to boost students' confidence in using technology, and improving AI tools to meet students' expectations and needs. These suggestions will contribute to the broader application of generative AI in the educational field.

Keywords: Generative AI, expectation confirmation, AI self-efficacy, continuous intention

1. Introduction

In recent years, generative AI has rapidly evolved, with applications like large-scale language models (e.g., GPT series) and Diffusion-based models (e.g., GANs) generating highly realistic text, images, and videos. One notable innovation is ChatGPT, launched by OpenAI in 2022, which gained over a million users in just one week and reached 100 million active users within two months, making it the fastest-growing consumer app in history (Grant & Metz, 2022; Hu, 2023). ChatGPT's capabilities have revolutionized natural language processing and content creation, impacting fields from education to business (Zhou et al., 2022). Despite its success, concerns about AI replacing human jobs persist (Krugman, 2022), though experts like Fei-Fei Li suggest AI will assist rather than replace humans.

In education, AI has been widely used in teaching and learning (Fitria, 2023), with studies showing AI tools enhance student engagement and performance (Patil & Abraham, 2010; Srinivasa et al., 2022). ChatGPT can serve as a teaching assistant by answering questions, correcting grammar, modifying code, and providing translations (Rudolph et al., 2023). However, most research focuses on user acceptance (Menon & Shilpa, 2023; Sallam et al., 2023), with limited exploration of how students from different academic backgrounds vary in their confidence in using ChatGPT.

This study investigates how students' confidence in ChatGPT affects their attitudes, particularly across different academic disciplines. It aims to explore AI self-efficacy and its influence on students' expectations and continuous usage of ChatGPT. By comparing students' experiences across disciplines, this research will provide insights into the specific demands and challenges of integrating ChatGPT in educational settings. The findings will offer recommendations for educators and institutions to improve the integration of generative AI in curricula, boost students' technological confidence, and enhance AI tools to meet educational needs.

2. Literature Review

2.1 Generative AI in the Field of Education

Generative AI technology creates content such as natural language texts and images by mimicking human thinking, rather than just analyzing existing data (Cao et al., 2023). One notable application is ChatGPT, which uses the GPT model with over 100 billion parameters, utilizing natural language processing techniques (Fitria, 2023). Trained with Reinforcement Learning from Human Feedback (RLHF), ChatGPT simulates conversations, responds to questions in context, and exhibits creativity (Kohnke et al., 2023; Patel et al., 2023).

In education, ChatGPT has gained attention for its ability to enhance learning efficiency and teaching effectiveness. It helps students grasp complex concepts, especially in subjects like programming, by offering quick responses and problem-solving assistance. Yilmaz & Yilmaz (2023) found that ChatGPT improves students' academic performance, although its occasional inaccuracies may impact understanding. Shoufan (2023) noted that students find ChatGPT user-friendly and motivating, though concerns about accuracy persist, particularly when precise information is needed.

Fitria (2023) also studied ChatGPT's role in English writing, showing that it helps improve grammar and tense accuracy, particularly benefiting beginners. Sallam et al. (2023) explored student attitudes toward ChatGPT in Arab countries, revealing a positive perception of its ability to enhance learning convenience and efficiency. These studies suggest ChatGPT's adaptability across different educational systems and cultural contexts.

In summary, ChatGPT has shown great potential in education by improving learning efficiency, fostering student understanding, and boosting motivation. However, users still need a certain level of knowledge to fully benefit from its capabilities, and accuracy issues remain a challenge that requires further research to improve its educational applications.

2.2 Expectancy Confirmation Theory

Expectancy Confirmation Theory (ECT), first proposed by Oliver (1980), originated from cognitive dissonance theory and evolved to explain consumer satisfaction and post-purchase behavior. ECT posits that consumers form expectations before a purchase, which serve as reference points for evaluating satisfaction. After purchasing, consumers assess the perceived performance of a product or service based on actual usage. When perceived performance is compared to expectations, it leads to confirmation—positive, neutral, or negative—that influences satisfaction and future purchasing behavior (Oliver, 1980).

Consumer expectations are shaped by previous experiences, usage of similar products, and external factors like social environment, media, and marketing (Holak et al., 1987; Howard & Sheth, 1969). Expectations are a combination of beliefs and evaluations (Fishbein & Ajzen, 1977). Perceived performance refers to subjective perceptions of a product's actual performance, which plays a role in the confirmation process (Bhattacherjee, 2001b). Satisfaction, as defined by Hunt (1977), is an emotional evaluation of whether consumer experiences meet expectations, involving both emotions and actual experience. When satisfaction is high, repurchase intention increases, while dissatisfaction reduces this tendency (Bhattacherjee, 2001a; Spreng et al., 1996). Bhattacherjee (2001b) noted that expectations can change over time, influenced by new experiences and information.

In education, ECT has been widely applied to assess student satisfaction and continued use of online learning platforms. Saxena & Doleck (2023) found that perceived usefulness and satisfaction positively impacted students' intentions to keep using ChatGPT, while subjective norms had no significant effect. Alam et al. (2022) highlighted how task skills and satisfaction influenced students' continued use of online platforms during COVID-19. Rajeh et al. (2021) found that expectancy confirmation in E-learning significantly impacted satisfaction, which in turn affected students' continued use intentions. Lu et al. (2019) confirmed that perceived usefulness, interest, and flow experience were key mediators between confirmation and satisfaction in MOOC usage.

These studies demonstrate ECT's relevance in education, particularly for online platforms like ChatGPT. This research will further explore how student expectations, experiences, and satisfaction impact continued use of ChatGPT, with a focus on differences across academic disciplines. Understanding these dynamics will be essential to improving ChatGPT's educational applications.

2.3 Social Cognitive Theory and Self-Efficacy

Social Cognitive Theory (SCT), developed by Albert Bandura, combines behaviorism, social learning theory, and cognitive perspectives to understand and influence human behavior. The theory emphasizes that individuals can learn by observing others' behaviors and outcomes without direct experience (Bandura & Walters, 1977). Human behavior is shaped by the continuous interaction between environmental, behavioral, and personal factors (Bandura, 1986; Bandura & Wood, 1989), and key to SCT is self-efficacy, the belief in one's ability to accomplish tasks in specific contexts. Bandura (1977, 1986) identified four sources of self-efficacy: past successes or failures, observing others' success, verbal encouragement, and emotional/physiological states. Positive experiences and encouragement increase self-efficacy, while anxiety and negative emotions lower it.

Self-efficacy differs from general skills; for example, a person may know how to drive but lack confidence on highways (Bandura, 1984). Bandura (1977) outlined three dimensions of self-efficacy: magnitude (task difficulty), strength (confidence in task completion), and generality (applying self-efficacy across situations). Two cognitive forces influence behavior: outcome expectations and self-efficacy. Outcome expectations push individuals toward favorable results, while self-efficacy determines the effort and persistence when facing challenges (Compeau & Higgins, 1995).

In information technology, computer self-efficacy (CSE) refers to confidence in completing computer-related tasks and significantly impacts decisions to use computers (Compeau & Higgins, 1995; Hill et al., 1987). Internet self-efficacy is defined as confidence in performing online tasks and is essential in digital learning environments (Eastin & LaRose, 2000; Tsai & Tsai, 2003). In the realm of AI, AI self-efficacy refers to individuals' belief in effectively using AI technologies. Prior experience enhances AI self-efficacy and influences the willingness to use AI tools like ChatGPT (Bartsch et al., 2012; Hong, 2022).

In education, self-efficacy plays a crucial role in students' continued use of e-learning systems (Rahmania et al., 2022) and Moodle (Rabaa'i et al., 2021). This study examines AI self-efficacy in students using AI tools like ChatGPT, exploring whether students' academic backgrounds affect their confidence and behavioral intentions. Understanding these differences is essential for promoting AI use in education.

3. Research Methods

The research model of this study (as shown in Figure 1) encompasses four variables from Expectancy Confirmation Theory, namely expectation, confirmation, satisfaction, and continuous usage intention. It also integrates AI self-efficacy and perceived behavioral control from Social Cognitive Theory and the Decomposed Theory of Planned Behavior. Through the establishment of this model, the study aims to explore the relationships among these variables and their influence on users' continuous usage intention of generative AI. There are two independent variables in this study: "expectation" and "AI self-efficacy," both of which have a profound impact on individuals' attitudes and confidence when using generative AI to assist learning. Additionally, the study includes three mediating variables: "confirmation," "satisfaction," and "perceived behavioral control," which play a critical role in explaining and linking the relationship between the independent and dependent variables. The final dependent variable, "continuous usage intention," reflects the extent to which individuals intend to continue using generative AI after initial adoption, serving as an important indicator for assessing AI's long-term impact on the learning process. A comprehensive analysis of these six research constructs will provide valuable insights into the multifaceted impact of AI on the educational field, as well as explore the potential mechanisms through which AI can influence teaching and learning. In addition, please refer to Table 1 for the operational definitions of these related research variables and their reference sources.

According to Expectation-Confirmation Theory, expectations have a positive influence on confirmation (Shiau et al., 2020). When the actual performance of ChatGPT meets or exceeds these expectations, users' level of confirmation increases accordingly. In this process, confirmation represents users’ subjective perception of whether their expectations have been validated after using ChatGPT, playing a critical role. Based on this perspective, this study proposes Hypothesis 1.

Hypothesis 1: Users' expectations of using ChatGPT will positively influence their confirmation.

According to Expectation-Confirmation Theory, expectations generally have a direct and positive impact on satisfaction (Oliver, 1980). An individual’s expectations often influence their purchasing and usage decisions. If users expect a product or service to meet their needs, they are more likely to choose to use or purchase it. Therefore, expectations can be regarded as a basis for consumers’ performance evaluation of the product they acquire (Bhattacherjee, 2001b). Based on this perspective, this study proposes Hypothesis 2.

Hypothesis 2: Users' expectations of using ChatGPT will positively influence their satisfaction.

Expectation-Confirmation Theory emphasizes that confirmation is a key determinant of satisfaction (Oliver, 1980). Previous studies have also indicated that as the level of confirmation increases, user satisfaction correspondingly improves (Bhattacherjee, 2001a, 2001b; Lu et al., 2019; Rajeh et al., 2021). Based on this perspective, this study proposes Hypothesis 3.

Hypothesis 3: Users' confirmation of using ChatGPT will positively influence their satisfaction.

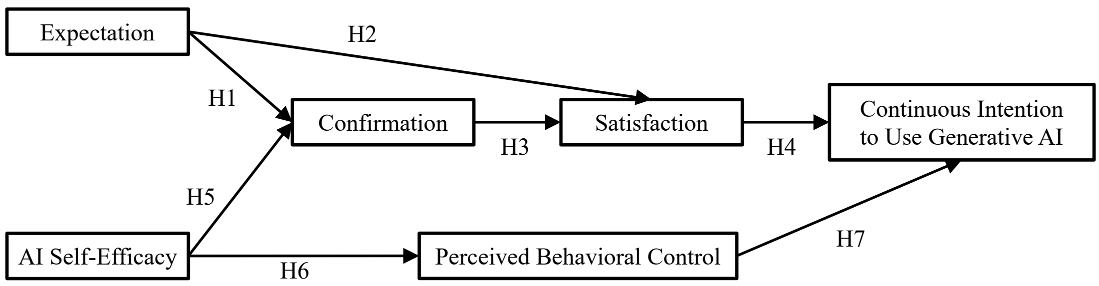

Figure 1: Research Model

Table 1: Research Variables and Operational Definitions

Constructs	Operational Definition	Reference
Expectation	The user's subjective expectations regarding the goals or performance levels that ChatGPT can achieve.	Lin and Lekhawipat (2016); Oliver (1980)
AI Self-Efficacy	The user's level of confidence in their ability to effectively use and operate ChatGPT to complete tasks.	Bandura (1988); Bhattacherjee et al. (2008)
Confirmation	The user's subjective perception of whether their expectations or anticipated outcomes have been confirmed or validated after actually using ChatGPT.	Bhattacherjee (2001a, 2001b);
Satisfaction	The user's overall evaluation of ChatGPT, including their positive or negative feelings toward it.	Lee (2010); Oliver (1980)
Perceived Behavioral Control	The user's perceived level of control or mastery when using ChatGPT.	Lee (2010); Taylor and Todd (1995)
Continuous Intention to Use Generative AI	The user's willingness and plans to continue using ChatGPT, including whether they intend to keep using it, recommend it to others, and their future usage intentions.	Bhattacherjee (2001a, 2001b); Bhattacherjee et al. (2008)

According to Expectation-Confirmation Theory, users' continued intention to use an information system is primarily influenced by their prior satisfaction with using the system (Bhattacherjee, 2001a, 2001b). Previous studies have also shown a positive correlation between user satisfaction and continued usage intention (Lu et al., 2019; Rajeh et al., 2021; Saxena & Doleck, 2023). Based on this perspective, this study proposes Hypothesis 4.

Hypothesis 4: Users' satisfaction with using ChatGPT will positively influence their continuous usage intention.

In this study, AI self-efficacy is defined as the user's level of confidence in appropriately using and operating ChatGPT to complete tasks, while confirmation refers to the subjective perception formed through the interaction between user expectations and actual experiences. When users believe they possess stronger confidence in performing specific tasks, they are more motivated to exert greater effort to achieve the expected outcomes. Previous studies have also explored the positive relationship between self-efficacy and confirmation (Rahmania et al., 2022), suggesting that users with higher levels of self-efficacy are more likely to invest effort to ensure their expectations are met and tasks are successfully completed. Based on this perspective, this study proposes Hypothesis 5.

Hypothesis 5: Users' AI self-efficacy in using ChatGPT will positively influence their confirmation.

In this study, AI self-efficacy refers to the user's confidence in appropriately using, understanding, and operating generative AI; whereas perceived behavioral control refers to the degree of control individuals feel they have when performing a specific behavior. When users are confident in their ability to effectively utilize ChatGPT, they are more likely to believe they can manage the tool to accomplish specific tasks. This sense of confidence motivates users to actively cope with potential challenges. According to the Decomposed Theory of Planned Behavior and prior research, there is a positive relationship between self-efficacy and perceived behavioral control (Ndubisi, 2004; Tonukari & Anyigba, 2023). Based on this perspective, this study proposes Hypothesis 6.

Hypothesis 6: Users' AI self-efficacy in using ChatGPT will positively influence their perceived behavioral control.

According to the Decomposed Theory of Planned Behavior, behavioral intention is influenced by individual attitude, subjective norms, and perceived behavioral control. Prior studies have confirmed that all three factors have a significant positive effect on behavioral intention (Lee, 2010; Ndubisi, 2004; Rajeh et al., 2021; Tonukari & Anyigba, 2023). A higher level of perceived behavioral control may enhance one's willingness to adopt technology, as users believe they possess the necessary resources and opportunities to engage with AI systems. Based on this perspective, this study proposes Hypothesis 7.

Hypothesis 7: Users' perceived behavioral control in using ChatGPT will positively influence their continuous usage intention.

This study targeted students from a private university in Taiwan who had experience using ChatGPT, collecting data through an online questionnaire. The survey was distributed via the university's online learning platform to obtain broader feedback. The questionnaire items were adapted from previous studies that demonstrated good reliability and validity, with modifications made to fit the specific context of this research. Based on the results of the pilot test, ambiguous or potentially confusing items were revised or removed. The excluded items were primarily related to improving learning efficiency and resolving confusion, which may have been too abstract for respondents to comprehend. After ensuring the appropriateness and validity of the questionnaire, the final version, including the constructs and corresponding items, was established for this study.

4. Data Analysis

This study conducted a survey targeting students from a private university in Taiwan, with participants required to have prior experience using ChatGPT. The questionnaire underwent validity and reliability testing, and the results indicated good validity and reliability (See Table 2). The measurement scale used a five-point Likert scale, ranging from "Strongly Disagree," "Disagree," "Neutral," "Agree," to "Strongly Agree." The questionnaire was posted on the university's teaching platform, and a total of 1,166 responses were collected. After excluding 240 invalid responses and 24 responses from individuals who had never used ChatGPT, a total of 902 valid responses were obtained, accounting for 77.36% of the total collected questionnaires. The survey results showed that 44.35% of the respondents were male, and 55.65% were female. Freshmen accounted for 29.71%, sophomores 31.04%, juniors 18.29%, seniors 11.09%, and graduate students 9.87%. Among the respondents, 67.52% were from non-IT-related departments.

Table 2: Validity and Reliability

Construct	Indicator	Mean	SD	Factor Loading	Cronbach's α	CR	AVE
Expectation AI Self-Efficacy Confirmation	E1	3.808	1.085	0.920	0.912	0.944	0.850
	E2	3.914	1.025	0.933			
	E3	3.778	1.041	0.913			
Satisfaction Perceived Behavioral Control	AI1	3.355	0.946	0.899	0.889	0.931	0.819
	AI2	3.442	0.963	0.919			
	AI3	3.562	0.992	0.896			
Expectation AI Self-Efficacy Confirmation	CON1	3.272	0.925	0.907	0.898	0.936	0.830
	CON2	3.197	0.977	0.906			
	CON3	3.274	0.948	0.920			
Satisfaction Perceived Behavioral Control Expectation	S1	3.374	0.922	0.904	0.928	0.949	0.822
	S2	3.426	0.913	0.907			
	S3	3.315	0.894	0.912			
	S4	3.472	0.911	0.902			
AI Self-Efficacy Confirmation Satisfaction	PBC1	3.649	0.972	0.883	0.874	0.922	0.798
	PBC2	3.481	0.921	0.896			
	PBC3	3.603	0.963	0.901			
Perceived Behavioral Control	CI1	3.504	1.046	0.908	0.902	0.939	0.836
	CI2	3.404	0.986	0.916			
	CI3	3.614	0.977	0.919			

In Table 3, the square roots of the AVE values for all constructs are greater than the correlation coefficients between each construct and the others, indicating discriminant validity. Table 4 further shows that the factor loadings for all constructs are higher than their cross-loadings, aligning with the concept of discriminant validity. Based on the results of both tables, it can be concluded that each specific construct in this study can be clearly distinguished from the others, without mutual confusion.

Table 3: Discriminant Validity

Constructs	Expectation	AI Self-Efficacy	Confirmation	Satisfaction	Perceived Behavioral Control	Continuous Intention to Use Generative AI
Expectation	**0.922**					
AI Self-Efficacy	0.591	**0.905**				
Confirmation	0.481	0.705	**0.911**			
Satisfaction	0.561	0.736	0.844	**0.907**		
Perceived Behavioral Control	0.548	0.624	0.549	0.614	**0.893**	
Continuous Intention to Use Generative AI	0.581	0.688	0.663	0.745	0.628	**0.915**

Note: Diagonal bold values represent the square roots of AVE.

Table 4: Cross Loadings

Constructs	Indicator	Expectation	AI Self-Efficacy	Confirmation	Satisfaction	Perceived Behavioral Control	Continuous Intention to Use Generative AI
Expectation	E1	**0.920**	0.540	0.439	0.503	0.501	0.542
	E4	**0.933**	0.559	0.436	0.524	0.513	0.534
	E5	**0.913**	0.534	0.456	0.525	0.502	0.531
AI Self-Efficacy	AI1	0.533	**0.899**	0.652	0.661	0.557	0.581
	AI2	0.521	**0.919**	0.643	0.674	0.572	0.617
	AI3	0.549	**0.896**	0.617	0.662	0.565	0.669
Confirmation	CON1	0.484	0.667	**0.907**	0.778	0.534	0.651
	CON4	0.378	0.625	**0.906**	0.757	0.462	0.585
	CON5	0.451	0.632	**0.92**	0.773	0.503	0.574
Satisfaction	S1	0.511	0.664	0.781	**0.904**	0.579	0.663
	S2	0.514	0.671	0.738	**0.907**	0.584	0.692
	S3	0.491	0.662	0.780	**0.912**	0.517	0.667
	S4	0.520	0.671	0.763	**0.902**	0.548	0.678
Perceived Behavioral Control	PBC2	0.505	0.554	0.513	0.573	**0.883**	0.569
	PBC3	0.490	0.586	0.475	0.539	**0.896**	0.566
	PBC4	0.474	0.530	0.483	0.535	**0.901**	0.547
Continuous Intention to Use Generative AI	CI1	0.508	0.600	0.587	0.673	0.607	**0.908**
	CI2	0.534	0.633	0.604	0.677	0.522	**0.916**
	CI3	0.552	0.653	0.627	0.693	0.592	**0.919**

Note: The diagonal bold values represent the factor loadings of each construct.

As shown in Table 5, all seven research hypotheses demonstrate positive effects, with p-values less than 0.05 and t-values greater than 1.96, meeting the significance criteria. The path coefficients are positive, confirming that all hypotheses are supported. The R^2 value for the endogenous variable "satisfaction" is 0.744, indicating strong explanatory power. The R^2 values for "confirmation" and "continuous usage intention" are 0.503 and 0.601, respectively, indicating moderate explanatory power. The R^2 value for "perceived behavioral control" is 0.389, indicating weaker explanatory power. Overall, the conceptual model exhibits a moderate level of explanatory ability. According to Cohen (1988), within the behavioral sciences, R^2 values can be interpreted as follows: $R^2 < 0.02$ indicates a very weak effect, $0.02 \leq R^2 < 0.13$ is weak, $0.13 \leq R^2 < 0.26$ is moderate, and $R^2 \geq 0.26$ is substantial. For attitudinal research, which is applicable to this study, Chin (1998) proposed slightly different thresholds: $R^2 < 0.19$ as very weak, $0.19 \leq R^2 < 0.33$ as weak, $0.33 \leq R^2 < 0.67$ as moderate, and $R^2 \geq 0.67$ as substantial. Based on these criteria, the R^2 value of 0.389 for perceived behavioral control in this study can be interpreted as indicating a moderate level of explanatory power.

For the overall student sample, confirmation has a significant positive effect on satisfaction, and AI self-efficacy has a significant positive effect on both perceived behavioral control and confirmation. This indicates that students' confidence in using ChatGPT significantly influences their confirmation of expectations and perceived behavioral control. The effects of confirmation on satisfaction, and satisfaction on continuous usage intention, are also significant, demonstrating that expectation confirmation and satisfaction are key factors in the intention to continue using ChatGPT.

Table 5: These Path Coefficients of Research Hypothesis

Hypothesis	Path	Coefficient	t value	p value	R2	f2	q2
H1	Expectation→Confirmation	0.100	2.800	0.005**	0.503	0.013	0.009
H2	Expectation→Satisfaction	0.202	8.061	0.000***	0.744	0.122	0.064
H3	Confirmation→Satisfaction	0.747	36.164	0.000***	0.744	1.679	0.891
H4	Satisfaction→Continuous Intention to Use Generative AI	0.576	18.072	0.000***	0.601	0.518	0.343
H5	AI Self-Efficacy→Confirmation	0.645	18.399	0.000***	0.503	0.546	0.380
H6	AI Self-Efficacy→Perceived Behavioral Control	0.624	23.018	0.000***	0.389	0.638	0.443
H7	Perceived Behavioral Control→Continuous Intention to Use Generative AI	0.274	7.851	0.000***	0.601	0.117	0.078

Note: *** p<0.001; **p<0.01; *p<0.05

5. Conclusion

This study reveals that students demonstrate high expectations, perceived behavioral control, and continued usage intentions toward ChatGPT, indicating a generally positive attitude toward its educational applications. Among the factors examined, confirmation exerts the strongest influence on satisfaction, while AI self-efficacy significantly enhances both confirmation and continued usage intention. Students with higher expectations and greater confidence in using ChatGPT report higher satisfaction and are more likely to continue its use.

Academically, the study reinforces prior findings that expectation confirmation and self-efficacy are critical predictors of user satisfaction and continued usage in e-learning contexts (e.g., Shiau et al., 2020; Rahmania et al., 2022). By integrating AI self-efficacy and expectation confirmation within the framework of generative AI, this research provides empirical support for extending technology acceptance models to the domain of AI-assisted learning.

Practically, the findings suggest that educators can enhance students' satisfaction and continued use of ChatGPT by elevating usage expectations, offering targeted training, and designing achievable, yet challenging tasks to strengthen perceived control. Institutions should also implement feedback mechanisms to monitor user experience and adapt teaching strategies accordingly. Moreover, fostering AI self-efficacy through workshops and hands-on practice can further increase students' engagement and sustained usage.

For future research, expanding the sample to include students from different institutions or education levels would improve generalizability. Further studies could explore ChatGPT's applications across diverse academic contexts and investigate factors influencing users' willingness to pay for advanced features, providing insights into user preferences and informing educational technology development.

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About Authors

Shih-Ming Pi is a professor of the Department of Information Management at Chung Yuan Christian University in Taiwan. His recent articles can be found in Computers in Human Behavior, Communications of the ACM, European Journal of Information Systems, Journal of the Association for Information Systems, and other Chinese information management journals.

Kuo-Chen Li received the Ph.D. degree in Computer Science & Engineering at University of Louisville. He is currently an Associate Professor in the Department of Information Management at Chung Yuan Christian University in Taiwan. His research interests include machine learning, mobile commerce, and data analysis.

Min-Jie Hsieh is a graduate student in the Department of Information Management at Chung Yuan Christian University, Taiwan. Her research interests include business intelligence system and marketing management.