Research on the Acceptance of Generative Artificial Intelligence Based on SECI Theory

A Case Study of Accounting Students in an Applied University

Tingwei Lu[1] Dongmei Luo[2]

[1,2] *Business School of Chengdu University, Chengdu, Sichuan 610106, China*
[1]*Corresponding author, Email: lutingwei@cdu.edu.cn*

ABSTRACT

This study employs the SECI model(socialization, externalization, combination, and internalization) as the theoretical foundation to investigate the acceptance level of generative artificial intelligence among Accounting Students in application-oriented universities, and its efficacy in facilitating knowledge creation processes. By integrating the four stages of the SECI model with the four dimensions of the Technology Acceptance Model (TAM), the research constructs a theoretical framework for assessing the acceptance of generative AI. Using a highly reliable and valid five-point Likert scale questionnaire, the study surveyed 88 accounting students from an applied university in China. The results indicate that students exhibit higher acceptance levels during the explicit knowledge integration phases (“Combination and Internalization”), with “Performance Expectancy” at 94.48% and “Effort Expectancy” at 77.73%. In contrast, acceptance is lower in the tacit knowledge transformation stages (“Socialization and Externalization”), with “Facilitating conditions” at 75.76% and “Social influence” at 61.82%. The findings suggest that generative AI tools demonstrate advantages in facilitating explicit knowledge management but exhibit limitations in supporting interpersonal interaction and critical thinking, which are crucial for tacit knowledge conversion.

Keywords: *SECI theory, Generative artificial intelligence, Acceptance scale, Accounting education.*

1. INTRODUCTION

1.1 AI Technology and Education

Artificial Intelligence (AI) and AI-based chatbots (e.g., ChatGPT) are transforming pedagogical approaches, with university students widely adopting ChatGPT to assist in completing academic tasks (Putra et al., 2023; Baidoo-Anu et al., 2024; Zulfiqar et al., 2025)[1][2][3]. Romero-Rodríguez et al. (2023) [4]conducted an online survey of 400 Spanish university students aged 18-64 (mean age = 21.80±6.40 years), revealing that ChatGPT, with its massive data processing capacity and interactive learning mechanisms, has become a crucial intelligent learning tool for students. Lelepary et al. (2023)[5] demonstrated that students can leverage ChatGPT’s deep learning capabilities to generate contextually appropriate natural language dialogues, thereby enhancing oral expression and textual interpretation skills. Their research highlighted ChatGPT’s unique value in educational settings, particularly for Arabic language acquisition in higher education.

Yilmaz et al. (2024)[6] developed a generative artificial intelligence acceptance scale based on the Unified Theory of Acceptance and Use of Technology (UTAUT) model, incorporating four key dimensions: performance expectancy, effort expectancy, facilitating conditions, and social influence. The multi-phase study, conducted during the 2022-2023 academic year, enrolled 627 university students from diverse disciplines who had prior experience with generative AI tools, aiming to comprehensively investigate students’ acceptance levels of generative AI applications.

Putra et al. (2023)[1] empirically demonstrated that while ChatGPT provides substantial pedagogical benefits for learners, its latent risks concurrently pose significant threats to student populations. The study particularly identified that excessive reliance on this AI tool engenders multifaceted cognitive hazards, with the progressive deterioration of higher-order thinking skills emerging as the most salient concern.

Complementing these findings, Baidoo-Anu et al. (2024)[2] psychometrically developed and validated the Student ChatGPT Experience Scale (SCES), specifically designed to assess non-academic usage patterns. The application of ChatGPT primarily for non-academic purposes has precipitated multiple concerning issues, including: (a) violations of academic integrity policies, (b) excessive technological dependency, (c) deficiency in creative thinking, and (d) potential security risks. Moreover, a critical training gap exists, as users predominantly lack systematic instruction on the secure and effective utilization of this AI tool.

1.2 Integration of the SECI Model with AI Technology

The SECI theory, proposed by Japanese scholars Ikujiro Nonaka and Hirotaka Takeuchi, constitutes a seminal knowledge creation framework that elucidates the dynamic conversion process between tacit and explicit knowledge. This model operationalizes knowledge transformation through four distinct phases: Socialization (tacit-to-tacit knowledge transfer), Externalization (tacit-to-explicit knowledge articulation), Combination (explicit-to-explicit knowledge integration), Internalization (explicit-to-tacit knowledge embodiment).[7]

The SECI model represents a dynamic process of novel knowledge creation (Bandera, 2017; Mardiani, 2023)[8][9]. As a knowledge management framework, the SECI theory systematically elucidates the codification and transformation of teachers' tacit knowledge (i.e., knowledge acquired primarily through direct experience or informal exchanges) into discipline-level or institutional-level explicit knowledge (i.e., knowledge systematically articulated through formal channels) (Mendoza, 2022)[10]. The SECI theory has demonstrated significant efficacy across multiple educational domains: Cultivating students' innovative consciousness and competencies (Xie et al., 2020; Li, 2024; Li et al., 2025)[11][12][13], Facilitating regional networked collaborative teaching research (Jing et al., 2024)[14], Enhancing academic community development and collaborative knowledge conversion in higher education (Fang et al., 2019; Chen, 2023; Gan et al., 2024)[15][16][17], Innovating accounting talent cultivation models (Cheng et al., 2018; Han, 2024)[18][19]. In a complementary study, Chen (2025)[20] conducted a multi-phase survey involving 495 participants, revealing that utilizing AI for instrumental support tended to exacerbate job insecurity, which subsequently increased knowledge-hiding behaviours. Conversely, employing AI for emotional support was found to mitigate these adverse effects.

Barreto (2025)[21] conducted a systematic investigation into the integration pathways between ChatGPT and the SECI model, establishing a dual-enabling mechanism through which ChatGPT facilitates both complex concept acquisition and practical application transfer. Grounded in the four-stage SECI theoretical framework, the study innovatively conceptualized ChatGPT's multifaceted roles in enhancing financial literacy competencies: (a) during the Socialization phase, it functions as an interdisciplinary knowledge community Moderator facilitating peer interactions; (b) in the Externalization phase, it serves as an Idea Facilitator for articulating tacit experiences; (c) throughout the Combination phase, it operates as an Organizational Assistant for knowledge systemization; and (d) in the Internalization phase, it provides Knowledge Integration Support for contextual knowledge application.

This study establishes a theoretical framework for analysing generative AI acceptance by adopting the four knowledge conversion phases of the SECI model - Socialization, Externalization, Combination, and Internalization. Through systematically mapping these SECI phases onto the four core dimensions of the Technology Acceptance Model (TAM) - Performance Expectancy, Effort Expectancy, Facilitating Conditions, and Social Influence (Yilmaz et al., 2024)[6], we examine accounting majors' acceptance and application effectiveness of generative AI from a SECI perspective. Our findings not only enrich the application research of the SECI model in digital learning environments, but also provide innovative instructional design insights for effectively integrating generative AI tools into practice-oriented accounting curricula at application-oriented universities.

2. METHODOLOGY

2.1 Participants

This study examined the acceptance and application effectiveness of generative artificial intelligence tools among sophomore accounting majors at Application-Oriented University C in China. Utilizing an online survey methodology, we distributed 90 questionnaires and obtained 88 valid responses, yielding a high response rate of 97.8%. Two participants were excluded due to failure to submit the questionnaire within the designated research window.

The participant selection was theoretically grounded in three key considerations: First, the practice-oriented educational philosophy of application-oriented universities aligns naturally with the technical characteristics of generative AI through their specialized practical curriculum. Second, the target cohort had completed the *Intermediate Financial Accounting Simulation Experiment* course, establishing essential professional knowledge foundations. Third, as digital natives, the participants possessed widespread prior experience with generative AI tools in daily life, providing empirical basis for investigating technology acceptance.

2.2 Research Instrument

This study utilized the Generative AI Acceptance Scale developed by Yilmaz et al. (2024)[6], which was theoretically grounded in the Technology Acceptance Model (TAM). The scale demonstrates satisfactory psychometric properties, with both reliability and validity indices meeting standard psychometric requirements, making it a valid tool for assessing students' acceptance of generative AI technologies.

The instrument employs a standardized 5-point Likert scale comprising 20 items ("Table 1"), requiring respondents to complete all questions. The scale consists of five ordered response options representing progressively stronger levels of agreement: A *Strongly disagree*, B *Disagree*, C *Neither agree nor disagree*, D *Agree* and E *Strongly agree.*

Table 1. Generative artificial intelligence acceptance scale

Dimension	Item	Code
Performance Expectancy	I find generative AI applications (e.g., ChatGPT, DeepSeek, Kimi) useful in my daily life.	A1
	The use of generative AI applications increases my chances of achieving the things that are important to me.	A2
	Generative AI applications help me get things done faster.	A3
	Using generative AI applications increase my productivity.	A4
	The use of generative AI applications makes my life easier.	A5
	Generative AI applications are useful for my daily life.	A6
	The use of generative AI applications increases my chances of solving the problems I face.	A7
Effort Expectancy	Learning how to use generative AI applications is easy for me.	B1
	I think it is easy to leverage generative AI applications.	B2
	Generative AI applications are easy to use	B3
	It is easy for me to become skilled in using generative AI applications.	B4
	My interaction with generative AI applications is clear and understandable.	B5
Facilitating Conditions	Generative AI applications are compatible with other technologies I use.	C1
	I can get help from others when I have difficulties in using generative AI applications.	C2
	If I experience any problems while using generative AI applications, I can access the necessary information for a solution.	C3
Social Influence	People important to me think I should use generative AI applications.	D1
	The people I model my behavior on think I should use generative AI applications.	D2
	People whose opinions I value prefer me to use generative AI applications.	D3
	People who are important to me are using generative AI applications.	D4
	People who are important to me encourage the use of generative AI applications.	D5

Following Yilmaz et al.'s (2024)[6] theoretical framework, the scale measures four key dimensions:

- *Performance Expectancy*: The degree to which students believe using generative AI tools will enhance their academic performance;

- *Effort Expectancy*: Students' subjective evaluation of the ease of using generative AI tools;
- *Facilitating Conditions*: The extent to which existing technical infrastructure and organizational environment support the use of generative AI tools;
- *Social Influence*: The perceived expectations from significant others (teachers/peers) regarding students' adoption of generative AI tools.

Building upon Barreto's (2025)[21] SECI model integration framework, this study further delineates the functional mechanisms of generative AI tools across different knowledge conversion phases:

- *Socialization* phase: Serves as a *Mediator* by leveraging the *Social Influence* dimension to stimulate students' innovative potential;
- *Externalization* phase: Acts as an *Idea Facilitator* by utilizing *Facilitating Conditions* to promote the conversion of tacit knowledge to explicit knowledge;
- *Combination* phase: Functions as an *Organizational Assistant* by incorporating E*ffort Expectancy* to construct systematic explicit knowledge systems;
- *Internalization* phase: Operates as a *Knowledge Integration Support* through *Performance Expectancy* to facilitate the practical application of knowledge.

This integrated model elucidates the dynamic process through which generative AI tools facilitate the upward spiral of knowledge via their phase-specific functionalities ("Figure 1").

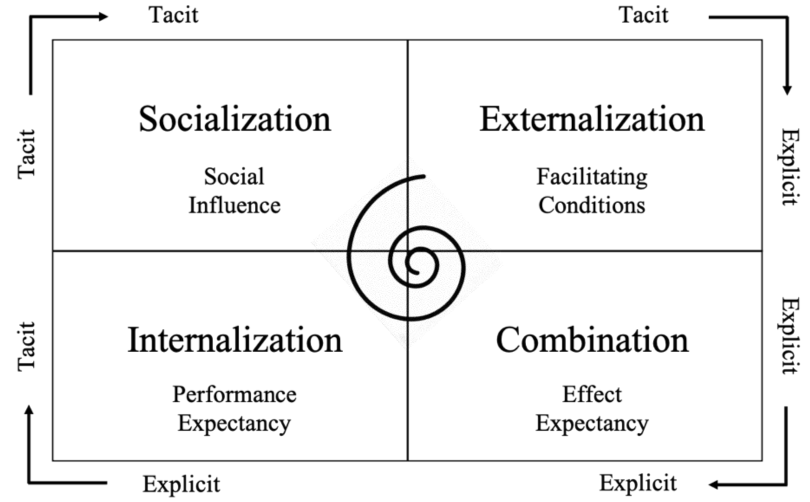

Figure 1 The SECI Integrated Model.

3. RESULTS AND DISCUSSION

3.1 *Reliability and Validity Testing of the Scale*

To further validate the applicability and effectiveness of the scale within the Chinese linguistic and cultural context for the target population, this study re-examined its reliability and validity.

3.1.1 Reliability Analysis

Internal consistency reliability was assessed using Cronbach's alpha coefficient. The analysis revealed excellent reliability for the overall scale (α = 0.954, standardized α = 0.956), significantly exceeding the threshold of 0.7, indicating exceptionally high internal consistency. Furthermore, all subscales demonstrated strong reliability with α values above 0.8. The stability of α coefficients was confirmed as no significant fluctuations were observed when individual items were deleted ("Table 2"), suggesting optimal item design without need for revision.

Table 2. Cronbach's Alpha

Dimension	Cronbach's Alpha	Standardized Cronbach's Alpha	Number of Items
Performance Expectancy	0.928	0.933	7
Effort Expectancy	0.901	0.902	5
Facilitating Conditions	0.876	0.876	3
Social Influence	0.919	0.919	5
Total Scale	0.954	0.956	20

3.1.2 Validity Testing

Given the scale's established maturity and widespread application in relevant research domains, this study primarily examined its construct validity and discriminant validity through confirmatory factor analysis (CFA).

3.1.2.1 Construct Validity

The overall model fit was assessed via CFA with the following indices: χ^2 = 2.247, RMSEA = 0.12, CFI = 0.87, GFI = 0.73, IFI = 0.87, and TLI = 0.85. Although the RMSEA was slightly elevated, other indices (e.g., CFI, TLI) approached or exceeded the 0.85 threshold, indicating an acceptable overall model fit.

To further investigate the scale's construct validity and provide a visual reference for variable relationships, standardized regression coefficients were utilized to clearly demonstrate the structural relationships between latent variables (Performance Expectancy, Effort Expectancy, Facilitating Conditions, Social Influence) and their corresponding observed variables (20 questionnaire items), as illustrated in "Figure 2".

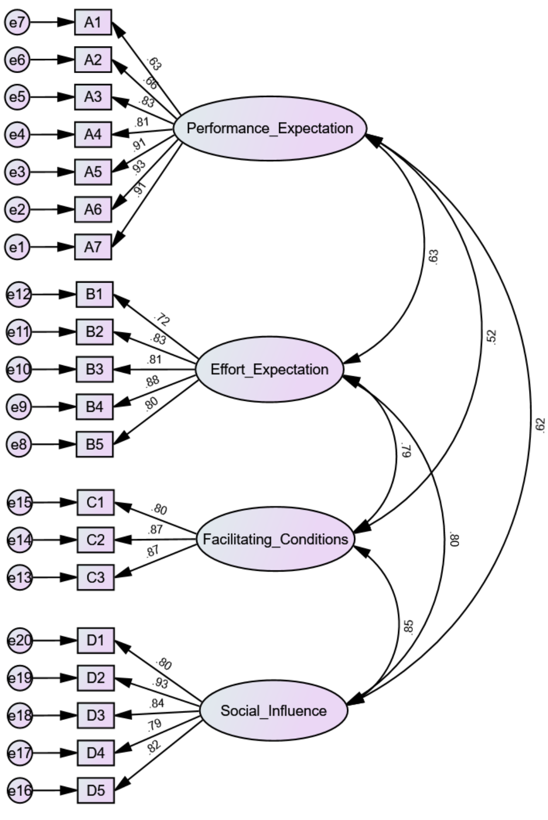

Figure 2 Structural diagram of standardized regression coefficients for the scale.

3.1.2.2 Convergent Validity

This study assessed the scale's convergent validity by calculating the average variance extracted (AVE) and composite reliability (CR) from factor loading coefficients. As shown in "Table 3", all dimensions met the psychometric thresholds with AVE > 0.5 and CR > 0.8, confirming excellent convergent validity of the measurement instrument.

Table 3. Factor Loading Coefficients and Calculations

Path			Estimate	AVE	CR
A7	←	Performance Expectation	0.91	0.6706	0.9332
A6	←	Performance Expectation	0.931		
A5	←	Performance Expectation	0.907		
A4	←	Performance Expectation	0.813		
A3	←	Performance Expectation	0.828		
A2	←	Performance Expectation	0.657		
A1	←	Performance Expectation	0.631		
B5	←	Effort Expectation	0.798	0.6569	0.9051
B4	←	Effort Expectation	0.88		
B3	←	Effort Expectation	0.811		
B2	←	Effort Expectation	0.834		
B1	←	Effort Expectation	0.721		
C3	←	Facilitating Conditions	0.867	0.7117	0.8809
C2	←	Facilitating Conditions	0.865		
C1	←	Facilitating Conditions	0.797		
D5	←	Social Influence	0.816	0.6994	0.9206
D4	←	Social Influence	0.789		
D3	←	Social Influence	0.841		
D2	←	Social Influence	0.929		
D1	←	Social Influence	0.799		

3.1.2.3 Discriminant Validity

As presented in "Table 4", the square roots of AVE for the *Performance Expectancy* and *Effort Expectancy* dimensions are greater than the correlation coefficients between these dimensions and other dimensions, indicating good discriminant validity among them. However, the *Social Influence* and *Facilitating Conditions* dimensions exhibit a high correlation (r=0.85, p<0.001), with their correlation coefficient slightly exceeding the square roots of their respective AVEs, thus failing to meet the discriminant validity criterion. This phenomenon may reflect a potential synergistic effect between infrastructure support for technology use and the influence of social norms, suggesting that these two concepts are closely intertwined either theoretically or in practical scenarios, leading to suboptimal discriminant validity in measurement. Nevertheless, it provides valuable insights for a deeper understanding of the interplay among multidimensional factors in technology adoption contexts.

Table 4. Square roots of AVE and inter-construct correlations

Dimension	Performance Expectancy	Effort Expectancy	Facilitating Conditions	Social Influence
Performance Expectancy	0.671			
Effort Expectancy	0.634***	0.657		
Facilitating Conditions	0.519***	0.79***	0.712	
Social Influence	0.621***	0.799***	0.85***	0.699
Square root of AVE	0.819	0.810	0.844	0.836

3.2 Analysis through the SECI Theoretical Lens

This study operationalized the acceptance level by calculating the cumulative percentage of positive responses (*Agree* and *Strongly agree*) on the Likert scale. The questionnaire results(“Table 5”) revealed significant variations in acceptance across dimensions: *Performance Expectancy* demonstrated the highest acceptance rate (94.48%), indicating strong student recognition of generative AI’s efficacy in enhancing academic outcomes; *Effort Expectancy* followed at 77.73%, reflecting favourable perceptions of the tool’s usability; while *Facilitating Conditions* (75.76%) and *Social Influence* (61.82%) showed relatively lower acceptance, highlighting areas for improvement in technical support and social validation. This hierarchical acceptance pattern validates the differential receptivity to generative AI across knowledge conversion phases within the SECI theoretical framework.

Table 5. Questionnaire results

Dimension	Code	Strongly disagree	Disagree	Neither disagree nor agree	Agree	Strongly agree
Performance Expectation	A1	1	0	4	56	27
	A2	0	1	11	57	19
	A3	0	0	2	60	26
	A4	0	0	5	59	24
	A5	0	1	3	57	27
	A6	0	0	3	59	26
	A7	0	0	3	61	24
Effort Expectation	B1	0	1	16	49	22
	B2	0	8	12	49	19
	B3	0	2	10	56	20
	B4	0	5	21	45	17
	B5	0	1	22	48	17
Facilitating Conditions	C1	0	1	22	47	18
	C2	0	2	21	50	15
	C3	0	2	16	54	16
Social Influence	D1	1	4	29	40	14
	D2	0	4	35	33	16
	D3	0	5	35	35	13
	D4	0	3	23	46	16
	D5	1	4	24	44	15

The efficacy of generative AI tools varies significantly across different knowledge conversion phases. During the socialization phase (*Social Influence* dimension), the tools' limitations primarily manifest in their inability to effectively convey non-verbal cues (e.g., body language, tone), making them inadequate substitutes for essential interpersonal interactions in collaborative learning. In the externalization phase (*Facilitating Conditions* dimension), their automated features may potentially constrain the development of students' critical thinking skills. While generative AI tools like ChatGPT can assist in tacit knowledge management, they cannot substantially contribute to the creation and internalization of tacit knowledge (Barreto, 2025)[21], resulting in relatively lower student acceptance regarding tacit knowledge acquisition during both the *Socialization* (*Social Influence* dimension) and *Externalization* phases (*Facilitating Conditions* dimension). In contrast, during the *Combination* phase (*Effort Expectancy* dimension) and *Internalization* phase (*Performance Expectancy* dimension), when systematic integration and practical application of explicit knowledge are involved, the tools' technological advantages are fully leveraged, leading to significantly higher acceptance among students. These phase-dependent differences corroborate that generative AI tools are better suited for supporting explicit knowledge operations rather than tacit knowledge transformation.

Guided by the SECI framework, application-oriented universities should adopt phase-specific pedagogical strategies when integrating generative AI tools to develop students' practical competencies: during the socialization phase, prioritize collaborative learning activities through structured group discussions and role-playing exercises to compensate for AI's limitations in non-verbal communication; in the externalization phase, leverage generative AI's cognitive scaffolding functions with carefully designed prompting to facilitate tacit-to-explicit knowledge conversion. Concurrently, a triple-safeguard mechanism should be implemented: (a) phased AI usage restrictions to prevent overreliance, (b) regular critical writing and reflective evaluation exercises, and (c) comprehensive verification of AI-generated content to ensure knowledge integration accuracy.

4. CONCLUSION

This study, grounded in the SECI theory, investigated the acceptance and application effectiveness of generative AI tools among accounting majors at application-oriented universities, validating the applicability of the SECI model in generative AI adoption research. It revealed dynamic relationships between the four knowledge creation phases—*Socialization*, *Externalization*, *Combination*, and *Internalization*—and AI technology acceptance. The results demonstrated higher student acceptance during explicit knowledge integration and absorption stages (*Combination* and *Internalization*), compared to lower acceptance in phases involving tacit knowledge conversion (*Socialization* and *Externalization*). These findings not only enrich the application of SECI theory in student learning behaviour research, but also provide critical insights for the design and optimization of AI tools.

However, the study's focus on a single cohort of accounting students from one university, coupled with a relatively small sample size, may limit the generalizability of the conclusions. Future research could expand to include diverse academic disciplines to verify the universality of the findings, as well as examine subgroup variations based on grade level, gender, and usage frequency to explore differential acceptance patterns of generative AI.

AUTHORS' CONTRIBUTIONS

Tingwei Lu designed the study, and collected the data. Dongmei Luo conducted the statistical analyses and interpreted the results. All authors reviewed and approved the final manuscript.

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