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Research Article

AI adoption in accounting education: A UTAUT-based analysis of mediating and moderating mechanisms

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This study investigates the adoption and usage of artificial intelligence [AI] technologies among Chinese undergraduate accounting students, focusing on the roles of Social Influence [SI], Behavioral Intention [BI], and Actual Usage [AU], while examining the mediating effect of BI and the moderating effect of Voluntariness of Use [VOU]. By extending the Unified Theory of Acceptance and Use of Technology [UTAUT] model, it addresses gaps in understanding the social and behavioral factors influencing AI adoption within the educational context. A quantitative research design was employed, utilizing Partial Least Squares Structural Equation Modeling. Data was collected through a self-administered survey distributed via the Wenjuanxing platform, with responses from 362 Chinese undergraduate accounting students analyzed to test the hypothesized relationships. The findings reveal that SI significantly affects both BI and AU, with BI serving as a partial mediator in the SI-AU relationship. However, VOU did not exhibit a significant moderating effect on the SI-BI pathway. These results provide insights into the dual role of SI and the importance of fostering positive attitudes toward AI adoption among students. This study contributes to the literature by extending the UTAUT model in an educational setting, emphasizing the interplay of cultural and social dynamics in influencing AI adoption. It offers actionable recommendations for educators, policymakers, and technology vendors to promote AI integration in accounting education and prepare students for AI-driven professional environments.

Keywords: Artificial intelligence; Accounting education; Behavioral intention; Chinese undergraduate accounting students; Social influence; Voluntariness of use

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1. Introduction

The 21st century has witnessed unprecedented advancements in AI, a transformative force reshaping industries and redefining professional landscapes. Accounting, a traditionally structured and data-intensive field, is among the professions undergoing profound transformation through AI integration (Alshdaifat et al., 2024; Kavitha & Joshith, 2024; Saleem et al., 2023). AI technologies are now enabling the automation of routine tasks, enhancing decision-making processes, and optimizing operational efficiencies, fostering a new era of digital accounting practices (Damerji & Salimi, 2021). Despite the rapid pace of technological innovation, accounting education has lagged, where traditional curricula often fail to adequately equip students with the requisite technological competencies (Kotb et al., 2019).

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As of June 30, 2020, of the 942 Chinese universities and colleges that offer undergraduate accounting programs, 23 offer AI courses, accounting for only 2% of the total (Shu et al., 2021). This limited integration highlights the early stage of AI adoption in accounting education, leaving many students unprepared for the demands of the modern accounting profession (Damerji & Salimi, 2021). The gap between academic training and industry requirements has created an urgent need for educational reforms. Accounting graduates often lack the necessary technical skills to utilize AI tools effectively, leading to a mismatch with employer expectations and hindering their career readiness (Cunha et al., 2022).

The increasing global demand for digitally skilled accounting graduates has intensified pressure on universities to address these deficiencies. Leading accounting firms such as KPMG, PwC, Deloitte, and Ernst & Young are heavily investing in AI-driven solutions and expect new hires to be proficient in leveraging advanced technologies for financial analysis and reporting (Damerji & Salimi, 2021). However, the adoption of AI by accounting students remains inconsistent, influenced by various factors including social influence and educational context.

This study seeks to address the disconnect between industry expectations and educational outcomes by examining the factors affecting AI adoption among Chinese undergraduate accounting students. It emphasizes the influence of Social Influence [SI] on Behavioral Intention [BI] and Actual Usage [AU] of AI tools. It also examines how Voluntariness of Use [VOU] moderates the connection between SI and BI.

Existing research has largely focused on AI adoption in professional contexts, often neglecting the student perspective, particularly in developing countries. Additionally, widely used frameworks such as the Unified Theory of Acceptance and Use of Technology [UTAUT] are typically used in organizational studies, overlooking the distinct challenges of educational environments. This study addresses these gaps by focusing on Chinese undergraduate accounting students, a group influenced by strong collectivist cultural norms and specific institutional expectations. The key research questions guiding this study are:

RQ1) How does SI impact BI and AU of AI technologies among Chinese accounting students?

RQ2) Does BI mediate the relationship between SI and AU?

RQ3) Does VOU moderate the relationship between SI and BI?

This study adds to the existing literature by incorporating SI, BI, AU, and VOU within a cohesive model, exploring their interactions specifically in accounting education. Through an analysis of BI as a mediator and VOU as a moderator, this research provides novel perspectives on the social and psychological factors influencing AI adoption among students. Beyond validating established frameworks like the UTAUT, this study extends the model by highlighting the interplay of cultural and educational dynamics unique to the Chinese context. The outcomes of this research are intended to guide curriculum design, offering practical strategies for educational institutions to prepare students for the swiftly evolving technological advancements in accounting.

The subsequent sections of this study commence with a comprehensive review of the theoretical framework, which serves as the foundation for developing hypotheses based on prior research. This is followed by a detailed explanation of the methodology, outlining the survey structure and data collection procedures. The findings are then analyzed using Partial Least Squares Structural Equation Modeling [PLS-SEM]. The discussion section interprets these findings considering existing theoretical and empirical studies, highlighting their contributions to accounting education and AI adoption, while also addressing the study's limitations and proposing directions for future research. The study concludes by summarizing its key contributions and insights.

2. The Theoretical Background of the Study

As technological advancements continue at an unprecedented rate, higher education must adapt to ensure that students, educators, and administrative staff remain equipped to handle these changes. AI is being progressively adopted in higher education, providing valuable benefits to students, faculty members, administrative personnel, and researchers across the globe. Incorporating AI into education is anticipated to improve learning outcomes, streamline administrative processes, and promote innovation (Dwianto et al., 2024; Popenici & Kerr, 2017). Consequently, there is a growing demand for AI technology in both developed and developing countries, driven by governmental initiatives to improve educational quality (Chatterjee et al., 2020). Such advancements can be realized by embedding contemporary technologies, including AI, into the education system (Sevnarayan, 2024; Vincent-Lancrin & Van der Vlies, 2020).

To effectively adopt future technologies like AI in education, it is essential to identify the factors that shape users' acceptance or rejection. Various theories, including Innovation Diffusion Theory, Social Cognitive Theory, the Theory of Planned Behavior [TPB], the Technology Acceptance Model [TAM], and UTAUT, have been used to explain technology adoption (Chao, 2019; Dwivedi, 2019; Rahi, 2019). Notably, the UTAUT model has frequently been employed in educational studies to pinpoint the factors influencing students' acceptance and use of technology in diverse cultural contexts (Xue et al., 2024).

The UTAUT model is adopted in this study to investigate AI adoption among Chinese undergraduate accounting students. UTAUT was chosen for its integrative approach, as it synthesizes eight prominent technology acceptance models (Venkatesh et al., 2003). Incorporating constructs from prior models, UTAUT provides a robust structure for analyzing factors affecting technology adoption and user behavior. The UTAUT model has demonstrated its predictive strength by explaining more than 70% of the variance in software adoption behaviors (Tian et al., 2024; Venkatesh et al., 2003).

UTAUT outlines four key factors directly influencing technology usage: Performance Expectancy, Effort Expectancy, SI, and Facilitating Conditions. Additionally, it includes four moderators which include gender, age, experience, and VOU—which influence the intensity of relationships among the model's constructs. This study hypothesizes that SI has a significant effect on BI to adopt AI technologies, and BI in turn influences the AU of AI tools in accounting education. Additionally, VOU is expected to moderate the SI-BI relationship, with stronger effects in contexts where AI adoption is perceived as voluntary rather than mandatory.

The theoretical framework for this study aligns with UTAUT's comprehensive approach to examining factors driving AI adoption within accounting education. The study seeks to uncover critical insights into AI adoption among Chinese undergraduate accounting students, contributing to the ongoing conversation about AI integration in educational settings.

3. Hypothesis Development

3.1. Direct Effects

SI refers to "the degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh et al., 2003). Venkatesh et al. (2003) identified SI as a direct influencer of BI, acting as a pivotal factor in the adoption of emerging technologies. This construct highlights how environmental factors, including feedback from friends, family, and supervisors, in shaping decisions to adopt specific technologies (Rocha et al., 2024). In the context of AI adoption, SI reflects the pressures or encouragements students may feel from their peers, instructors, and societal norms to engage with AI technologies. Empirical evidence from various studies has consistently shown that SI significantly impacts the adoption of new technologies across different contexts (Moriuchi, 2021). Studies on AI adoption reveal that SI critically influences attitudes and intentions to utilize AI tools (Andrews et al., 2021). Almahri et al. (2020) found that an individual's BI is heavily shaped by the expectations of significant others, especially in educational environments. Furthermore, recent studies suggest that SI not only affects BI but can also have a direct impact on the AU of AI technologies. In addition to shaping intentions, the expectations and encouragement from peers and instructors can directly motivate students to actively use AI tools in their academic activities (Li, 2023; Nassar & Othman, 2019). When students feel socially supported or perceive social validation for using AI technologies, they are more likely to integrate these tools into their learning processes, even beyond their initial intention. These findings emphasize the dual role of SI in influencing usage intentions and actual engagement with AI technologies. As such, this study proposes the following hypotheses:

Hypothesis 1: SI significantly influences students' BI to adopt AI technologies.

Hypothesis 2: SI significantly influences students' AU to adopt AI technologies.

According to Venkatesh et al. (2003), it was emphasized that BI serves as a key determinant of AU, indicating that individuals' intention to use a technology often translates into AU. Prior research confirms that BI significantly impacts an individual's decision to adopt and utilize innovative technologies (Ajjan & Hartshorne, 2008; Hartshorne & Ajjan, 2009). Both the Theory of Reasoned Action [TRA] and the TAM emphasize that BI directly drives actual engagement with technology (Davis, 1989; Fishbein & Ajzen, 1975). Empirical studies on AI adoption further corroborate the critical role of BI in determining AU. Research in various contexts has shown that a stronger BI to use AI increases the likelihood of students adopting and utilizing these technologies in academic activities (Cortez et al., 2024; Li, 2023; Vărzaru, 2022). Thus, a hypothesis has been formulated as follows:

Hypothesis 3: BI significantly influences students' AU of AI technologies.

3.2. Mediating and Moderating Effects

According to Li (2023) and Nassar and Othman (2019), BI acts as an essential mediator in linking SI to AU in the context of technology usage. Specifically, these studies have shown that SI strongly affects an individual's BI regarding technology adoption. In turn, BI mediates the process by which the intention to adopt technology leads to its AU. Li (2023) suggests that in educational contexts, SI shapes students' attitudes and intentions toward adopting AI-based systems. When students perceive that others, such as their peers and instructors, believe that using AI technologies is valuable, they are more likely to form a BI to use these technologies. This intention, then, directly influences the AU of AI tools in their studies. Similarly, Nassar and Othman (2019) confirm that BI mediates the relationship between SI and ICT Adoption, meaning that the stronger the influence from others, the higher the likelihood of intention leading to AU of technology. Both studies indicate that BI serves as a bridge that translates the social pressures and norms into actual adoption behavior. This mediating effect is especially important in educational settings, where students' technology adoption decisions are often influenced by their perceptions of how others view the use of technology. Thus, the following hypothesis aligns with the findings of these studies:

Hypothesis 4: BI mediates the effect of SI on AU of AI technologies.

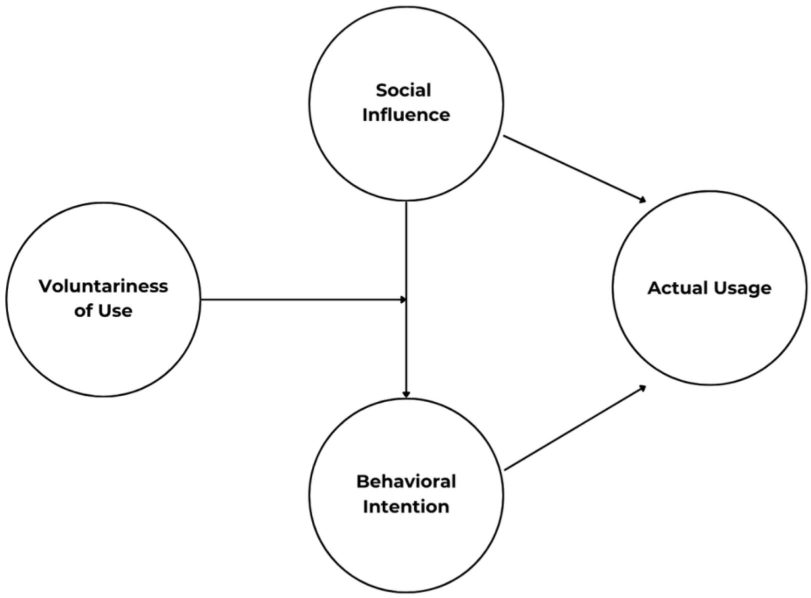
An examination of earlier research on technology adoption underscores the significant role VOU plays in influencing the connection between SI and BI. As defined within the UTAUT model, VOU is defined as the extent to individuals perceive their adoption of a technology as a voluntary choice rather than a mandatory requirement (Venkatesh et al., 2003). Studies indicate that the impact of SI on BI varies based on the context, with VOU acting as a key moderating factor. In mandatory settings, where individuals feel compelled to conform to organizational or social expectations, SI has a stronger impact on shaping BI (Ramllah & Nurkhin, 2020). For example, students in courses requiring the use of AI tools may be more influenced by peers, instructors, or institutional policies to adopt these technologies. On the other hand, in voluntary contexts, the role of SI diminishes as individuals prioritize intrinsic motivations, such as their perceived usefulness and personal interest in the technology, over external pressures. Among Chinese undergraduate accounting students, this interaction significantly influences their adoption of AI technologies. In mandatory usage scenarios, SI exerts a stronger impact on their BI to adopt AI tools due to the perceived necessity of compliance. Conversely, in voluntary settings, students' intentions are less influenced by social pressures and more driven by their evaluations of the technology's benefits. Based on this understanding, the moderating influence of VOU is hypothesized as follows:

Hypothesis 5: VOU moderates the effect of SI on BI to adopt AI technologies.

Henceforth, the research framework, grounded in the UTAUT model and validated through empirical evidence, is illustrated in Figure 1. This figure highlights how the study expands the traditional UTAUT model by incorporating both direct and indirect effects on AU. Specifically, the model hypothesizes that SI not only influences BI but also has a direct impact on AU, thereby expanding the framework to capture additional pathways for understanding AI adoption among Chinese undergraduate accounting students. The theoretical model also incorporates BI as a mediating variable, allowing for the examination of how SI indirectly influences AU through BI. Additionally, VOU is included as a moderator to evaluate its role in shaping the connection between SI and BI. This addition draws upon earlier research. This extension is inspired by previous studies (e.g., Ramllah & Nurkhin, 2020; Venkatesh et al., 2003), which suggest that the strength of SI's influence on BI may vary depending on whether AI adoption is perceived as mandatory or voluntary.

Figure 1 reflects a focused analysis of individual-level adoption behaviors, distinct from multi-level frameworks that include group or organizational dynamics. It highlights the direct effect of SI on AU, the mediating effect of BI in the connection between SI and AU, and the moderating role of VOU on the SI-BI pathway. This adaptation of the UTAUT model enables the study to reveal novel perspectives on the social and psychological elements influencing the adoption of AI within educational environments, particularly in understanding how mandatory versus voluntary adoption scenarios shape students' engagement with AI technologies.

Figure 1
Conceptual Framework



4. Method

4.1. Study Design

This study adopted a quantitative approach and a deductive methodology to investigate the adoption of AI technologies among Chinese undergraduate accounting students. The choice of this target population was influenced by the prominence of accounting as one of the most widely offered disciplines in China, with 74.47% of universities offering related programs (Shu et al., 2021). Undergraduate accounting education plays a critical role in preparing future professionals capable of adapting to technological advancements, including AI. Additionally, China's emphasis on AI integration in education, with over 2,300 AI courses launched by 2023 (Cortese, 2023) and projected demand for 4 million AI-skilled professionals by 2030 (Weilan, 2024), makes it an ideal context to study AI adoption in accounting education. The study utilized a cross-sectional design to examine hypothesized relationships between variables, collecting data at a single point in time. The survey was administered via the Wenjuanxing platform, a widely used and reliable tool for online surveys in China, ensuring accuracy and minimizing biases in data collection. A nonprobability purposive sampling method was applied to recruit participants with relevant exposure to AI concepts within their academic programs. This approach ensured the sample met the study's objectives, including undergraduate students from diverse academic levels (freshmen to seniors) and institutional types (key universities and general undergraduate institutions), to achieve representativeness. Following the recommendations of Bentler and Yuan (1999) and Hair et al. (2009), a minimum sample size of 200 was deemed necessary for structural equation modeling (SEM). This study exceeded this requirement, collecting 362 valid responses, and providing sufficient statistical power for robust analysis. Ethical standards were strictly adhered to, with participants fully informed about the study's objectives and their rights. Anonymity and confidentiality were ensured, and informed consent was obtained before data collection, aligning with ethical research practices (Alhasnawi et al., 2024).

4.2. Instrument Development and Measurement

To ensure respondents could adequately answer the questionnaire items, a brief description of the research goals was provided at the beginning of the survey. Demographic questions were included to collect information such as gender, year of study, family background, institutional type, and other relevant characteristics. These questions aimed to provide a comprehensive understanding of the respondents' backgrounds. The study instrument included items measuring the primary constructs of the research model, adapted from established scales in prior studies to ensure validity and reliability. To ensure content validity, the questionnaire was reviewed by two experts in accounting education fields. Additionally, a pilot study was conducted, which confirmed the reliability of the measurement instrument. The results showed that Cronbach's alpha for all constructs exceeded 0.7, indicating high internal consistency. All constructs were measured on a 7-point Likert scale ranging from 1 ("strongly disagree") to 7 ("strongly agree"). To maintain clarity and consistency in the survey items, back-to-back translation was conducted by two experts, translating the instrument into Chinese and back into English. This process ensured cross-cultural measurement reliability and minimized language-related biases (Cruchinho et al., 2024). The detailed measurement scales and the sources of the adapted items are presented in Table 1.

Table 1
Measurement of Items

Constructs	*Number of Items*	*Sources*
Social Influence	5	(Celik et al., 2014; Shorfuzzaman & Alhussein, 2016; Wang et al., 2009)
Behavioral Intention	3	(Venkatesh & Bala, 2008)
Actual Usage	5	(Agarwal & Prasad, 1997; Hubona & Kennick, 1996; Moon & Kim, 2001)
Voluntariness of Use	4	(Moore & Benbasat, 1991)

4.3. Respondents

The details of the respondents' demographic statistics are shown in Table 2. It covers eight variables: gender, major, year of study, annual family income, area of living, parents' working company, highest family education level, and school category. Most respondents are female (69.3%) and in their junior year of study (50.8%), with 86.2% majoring in accounting. Most respondents come from families earning between 100,000 and 200,000 RMB (35.9%) or 50,000 and 100,000 RMB (34.3%). The majority reside in urban areas (59.9%), and nearly half (47.0%) have parents working in private companies. In terms of family education, 66.9% of respondents' families have at least a bachelor's degree. Additionally, 79.0% are enrolled in general undergraduate institutions, while 21.0% attend key universities.

Table 2

Respondents' Demographic Statistics

Type	*Frequency*	*Percentage*
Gender		
Male	111	30.7%
Female	251	69.3%
Major		
Accounting	312	86.2%
Finance	7	1.9%
Financial Management	1	0.3%
Auditing	42	11.6%
Year of Study		
Freshman	16	4.4%
Sophomore	73	20.2%
Junior	184	50.8%
Senior	89	24.6%
Annual Family Income		
Less than 50,000 RMB	36	9.9%
50,000–100,000 RMB	124	34.3%
100,000–200,000 RMB	130	35.9%
200,000 RMB and above	72	19.9%
Area of Living		
Urban	217	59.9%
Suburban	48	13.3%
Rural	97	26.8%
Parents' Working Company		
Government Entity	42	11.6%
Private Company	170	47.0%
Own Business	88	24.3%
Others	62	17.1%
Highest Education in Family		
PhD	2	0.6%
Master's Degree	50	13.8%
Bachelor's Degree	242	66.9%
Associate's Degree	41	11.3%
Others	27	7.5%
School Category		
Key Universities (985/211)	76	21.0%
General Undergraduate Institutions	286	79.0%

4.4. Common Method Bias

Researchers have increasingly emphasized the need to address common method bias [CMB] when utilizing self-reported surveys. There is CMB when changes in responses are driven by the survey tool itself, not reflecting the true attitudes or behaviors of the respondent, which the survey intends to measure. This issue is particularly prevalent when it comes from the same respondent for both the independent variable and the dependent variable (Podsakoff et al., 2003). To detect the presence of CMB, Harman's Single-Factor Test [SFT] was applied. The results revealed that the first factor explained 42.583% of the total variance, remaining below the recommended threshold of 50% (Podsakoff et al., 2003). This finding indicates that common method variance [CMV] does not have a substantial impact on the study, thereby supporting the validity and reliability of the collected data.

4.5. Data Analysis

Data analysis was conducted utilizing PLS-SEM, adhering to the guidance provided by Hair et al. (2016). PLS-SEM is frequently applied in the behavioral and social sciences due to its capability to simultaneously estimate parameters, handle latent constructs, and address measurement errors. This study utilized SmartPLS 4.0 to assess the measurement and structural models, following the recommendations of Sarstedt and Cheah (2019) and Hair et al. (2014).

5. Results

5.1. Measurement Model Results

The measurement model, also known as the outer model, was analyzed in this study by examining individual item loadings, Cronbach's alpha, composite reliability [CR], and average variance extracted [AVE], following the recommendations of Hair et al. (2016). Internal consistency was confirmed for all constructs, as evidenced by Cronbach's alpha values above 0.81 and composite reliability exceeding the 0.70 benchmark (see Table 3), consistent with Nunnally's (1994) criteria. Results for all constructs exceeded the minimum threshold of 0.50 for AVE, supporting adequate convergent validity (Hair et al., 2016). Analysis of individual item loadings revealed values exceeding the 0.70 thresholds, validating their substantial contributions to the respective constructs ($p < .001$). An exception was item SI5 from the SI construct, which had a loading of 0.592. However, this item was retained due to its theoretical importance and contribution to the overall construct validity. The robustness of the measurement model is further corroborated by the significant loadings of all items, as outlined in Table 3. By applying the Fornell-Larcker criterion and assessing the heterogeneity-to-monomers [HTMT] ratio, discriminant validity was determined. Table 4 illustrates that the square root of AVE for each construct exceeded its correlations with other constructs, satisfying the Fornell-Larcker criterion (Fornell & Larcker, 1981). As indicated in Table 5, all HTMT ratios remained below the limit of 0.85, providing additional evidence for discriminant validity (Kline, 2011).

Table 3
Measurement Model Results

Construct	*Code*	*Loadings*	*VIF*	*p*	*CA*	*CR*	*AVE*
Social Influence	SI1	0.764	1.697	<.001	0.810	0.868	0.572
	SI2	0.832	2.082	<.001			
	SI3	0.768	1.586	<.001			
	SI4	0.803	1.812	<.001			
	SI5	0.592	1.288	<.001			
Voluntariness of Use	VOU1	0.845	2.211	<.001	0.852	0.900	0.691
	VOU2	0.803	1.916	<.001			
	VOU3	0.817	1.718	<.001			
	VOU4	0.860	2.230	<.001			
Behavioral Intention	BI1	0.882	2.140	<.001	0.853	0.911	0.773
	BI2	0.877	2.122	<.001			
	BI3	0.878	2.045	<.001			
Actual Usage	AU1	0.806	1.952	<.001	0.883	0.914	0.682
	AU2	0.790	1.909	<.001			
	AU3	0.867	2.700	<.001			
	AU4	0.793	1.747	<.001			
	AU5	0.869	2.782	<.001			

Table 4
Discriminant Validity Based on Fornell-Larcker Criterion

	Actual Usage	Behavioral Intention	Social Influence	Voluntariness of Use
Actual Usage	0.826			
Behavioral Intention	0.535	0.879		
Social Influence	0.559	0.559	0.756	
Voluntariness of Use	0.410	0.540	0.418	0.832

Table 5
Discriminant Validity Based on HTMT Ratio

	Actual Usage	Behavioral Intention	Social Influence	Voluntariness of Use	Voluntariness of Use x Social Influence
Actual Usage					
Behavioral Intention	0.609				
Social Influence	0.657	0.663			
Voluntariness of Use	0.465	0.624	0.487		
Voluntariness of Use x Social Influence	0.087	0.293	0.335	0.241	

5.3. Structural Model Results

The structural model was evaluated in five systematic steps to ensure a comprehensive analysis, as outlined in the flowchart (see Hair et al., 2014). These steps included assessing collinearity issues, the significance of path coefficients (β), p-values, the coefficient of determination (R^2), effect sizes (f^2), and predictive relevance (Q^2). To address potential collinearity among the constructs, the Variance Inflation Factor (VIF) was utilized as an analytical tool. The results, presented in Table 3, confirm that all values are below the threshold of 5, as recommended by Hair et al. (2016), This finding indicates no significant collinearity issues within the predictor variables.

In the hypothesis testing phase, the bootstrapping method with 5000 resamples was adopted, as shown in Table 6. The analysis revealed significant positive relationships across all direct paths. SI positively influenced BI (H1: β = 0.430, t = 8.291) and AU (H2: β = 0.386, t = 7.123), while BI positively impacted AU (H3: β = 0.324, t = 6.457).

Table 6 also shows that these direct predictors explained 43.0% of the variance in BI (R^2 = 0.430) and 38.4% in AU (R^2 = 0.384). Effect size (f^2) analysis revealed that SI had a medium effect on BI (f^2 = 0.204) and AU (f^2 = 0.159), while BI's effect on AU was small (f^2 = 0.118). Predictive relevance (Q^2) values were 0.323 for BI and 0.255 for AU, confirming the model's predictive capability.

Table 6
Results of Hypothesis Testing

Structural path	*β and t-values*	*Decision*	f^2	R^2	Q^2
H1: SI → BI	0.430 (8.291)	Accepted	0.204	.430	0.323
H2: SI → AU	0.386 (7.123)	Accepted	0.159	.384	0.255
H3: BI → AU	0.324 (6.457)	Accepted	0.118	-	-

5.4. Mediating Effect Analysis

Regarding the mediation role of BI in the relationship between SI and AU, further analysis was conducted as all relevant paths were significant. The indirect effect is obtained by multiplying the path coefficients of the external variable by the mediator and the mediator to the internal variable. For example, the path coefficient from SI to BI is 0.386, and the path coefficient from BI to AU is 0.324. Multiplying these two coefficients gives an indirect effect of 0.125. The direct effect, which represents the path coefficient from SI to AU, is 0.377. The total effect is the sum of the indirect and direct effects, resulting in 0.503 (see Table 7).

To evaluate the mediation effect, the variance accounted for (VAF) was computed as the ratio of the indirect effect to the total effect. A VAF of 0.2485, or 24.85%, was calculated, suggesting partial mediation based on the criteria established by Hair et al. (2016), where a VAF between 20% and 80% indicates partial mediation. This finding underscores the role of BI as a partial mediator in the SI-AU pathway.

Additionally, the significance of this mediation was verified through bootstrapping with 5000 resamples using SmartPLS 4.0. The results indicated that BI significantly mediates the relationship between SI and AU (t = 4.614, p < .001), with both direct and indirect effects remaining statistically significant. Thus, H4 is supported.

Table 7

Result of Mediation Analysis

Path	*Direct Effect Path Coefficient (β)*	*Indirect Effect Path Coefficient (β)*	*Total Effect Path Coefficient (β)*	*t*	*p*	*VAF*	*Decision*
H4: SI-BI AU	0.377	0.125	0.503	4.614	<.001	24.85%	Accepted

5.5. Moderating Effect Analysis

The moderating role of VOU in the relationship between SI and BI was analyzed using SmartPLS 4.0. The results are shown in Table 8 that the interaction term for VOU x SI → BI is not significant (β =−0.044, t = 0.959, p = .338), indicating that VOU does not exert a significant moderating effect on this relationship. Thus, H5 is not supported.

Table 8

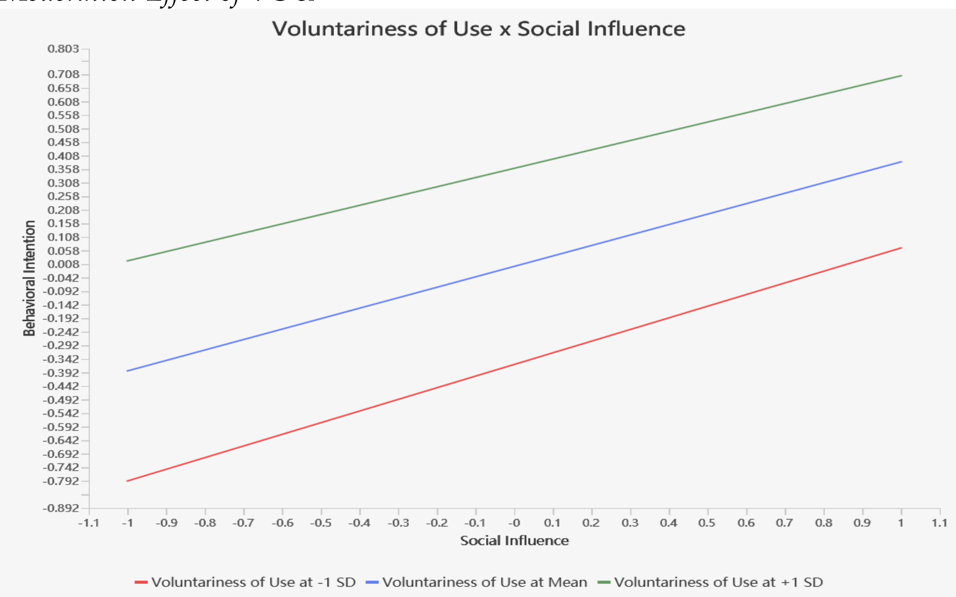
Path Coefficients for Moderation Effect Analysis

Relationships	*Path Coefficient (β)*	*T-value*	*p*
VOU × SI → BI	−0.044	0.095	0.338

To provide a clearer understanding of the results, Figure 2 visualizes the interaction consequence of VOU on the relationship between SI and BI. The graph displays three slopes corresponding to low (−1SD), mean, and high (+1SD) levels of VOU. The slopes are nearly parallel, indicating that changes in VOU do not alter the magnitude of the relationship between SI and BI. This confirms that VOU does not act as a significant moderator in this context.

Figure 3

Moderation Effect of VOU

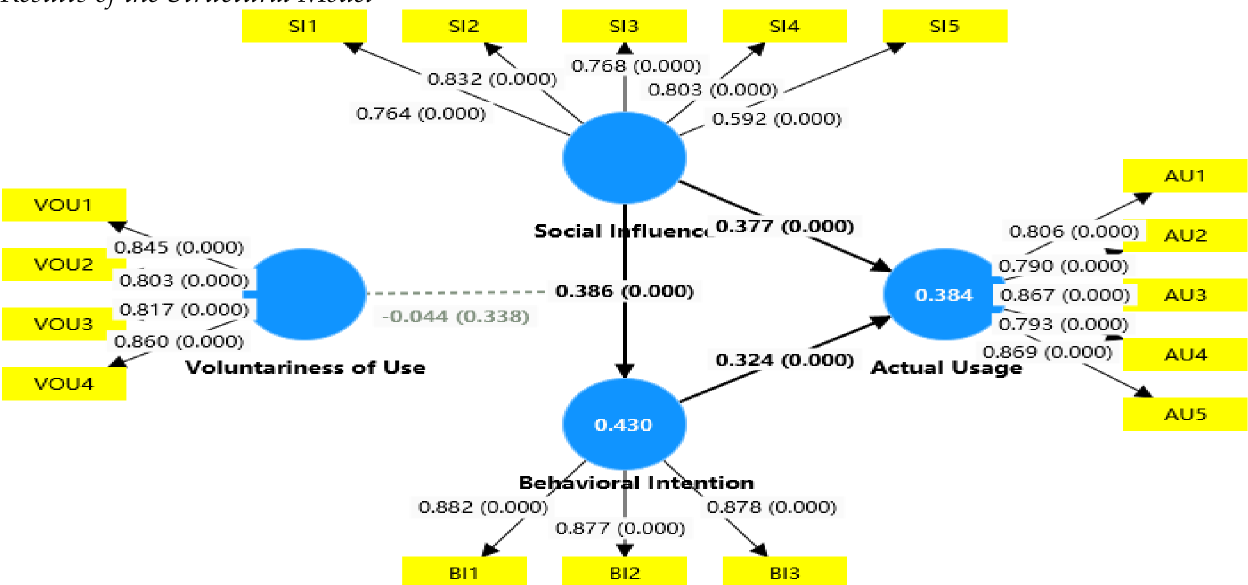


6. Discussion

6.1. Key Findings and the Theory Contributions

Surviving in the era of rapid technological advancements and digital transformation presents unique challenges, particularly in accounting education. The adoption of AI technologies is revolutionizing traditional practices by reshaping how students, educators, and institutions approach learning and professional development. By extending the UTAUT model, the present study investigates how Chinese undergraduate accounting students adopt and implement AI technologies (Venkatesh et al., 2003). Incorporating mediating and moderating mechanisms, the research uncovers factors influencing AI adoption and behavior. Using a self-administered survey and rigorous data analysis, the findings draw important implications for understanding the behavioral and structural pathways that drive AI adoption. In alignment with the UTAUT framework, this study confirms the significant roles of SI and BI in predicting AU. SI emerged as a critical predictor, influencing both BI and AU. These findings highlight the importance of peer encouragement, societal norms, and institutional support in fostering AI adoption. The strong direct effects of SI on both BI and AU align with previous studies emphasizing the social dynamics of technology acceptance (Dwivedi et al., 2019; Li, 2023). Furthermore, the mediation analysis reveals that BI partially mediates the relationship between SI and AU, with an indirect effect. This partial mediation indicates that while SI directly influences AU, a significant portion of its effect is transmitted through BI. This dual pathway emphasizes intricate interactions between social and behavioral factors in technology adoption, consistent with findings from prior studies (Nassar & Othman, 2019). However, contrary to expectations, the moderating effect of VOU on the SI-BI relationship was not statistically significant. This result suggests that whether AI adoption is perceived as voluntary or mandatory does not significantly alter the influence of SI on BI. This outcome challenges assumptions in previous research, such as Venkatesh et al. (2003), and points to the need for further investigation into the contextual factors affecting voluntariness in technology adoption. The detailed results are shown in Figure 3. These findings contribute to the literature by extending the UTAUT model to an educational context, particularly in a collectivist culture like China. The study validates the importance of social and behavioral variables in technology adoption while challenging the relevance of voluntariness as a moderating factor. By addressing these gaps, the study offers deeper insights into the dynamics of AI adoption within accounting education, aligning with the calls for further exploration in emerging technology adoption (Damerji & Salimi, 2021).

Figure 3
Results of the Structural Model



6.2. Implications for Practice

The findings offer valuable implications for educators, policymakers, and AI technology vendors. First, universities and educational institutions should leverage social dynamics to create environments conducive to AI adoption. Peer collaboration, faculty encouragement, and institutional support can significantly enhance students' willingness to adopt and use AI technologies. Integrating AI-focused learning into curricula and emphasizing its societal and professional benefits can further strengthen BI. Second, AI technology vendors should prioritize designing intuitive, user-friendly AI tools tailored to the needs of students in accounting education. The significant role of BI indicates that collaborative and interactive AI applications could further drive adoption, consistent with prior research on BI in technology acceptance. Finally, policymakers and curriculum designers must emphasize the development of AI-related competencies in accounting programs. The partial mediation effect of BI suggests that fostering positive attitudes toward AI adoption is key to bridging the gap between intention and usage. Training programs, access to resources, and practical applications of AI tools should be incorporated into accounting education strategies.

6.3. Limitations of the Study and Future Research Directions

While this research provides significant insights, certain limitations should be acknowledged. The use of a cross-sectional design restricts the ability to determine causal relationships, and reliance on self-reported data introduces potential biases. Future studies could adopt longitudinal methodologies to observe the progression of AI adoption behaviors over time, incorporating objective usage measures to complement self-reported data. Moreover, the non-significant moderating effect of VOU warrants further investigation. Exploring alternative moderators, such as age, gender, and experience, may provide additional insights into the factors that shape the relationship between SI and BI. Expanding the study to include other student populations and educational contexts would also increase the generalizability of the findings. Finally, this study relied solely on data collected through a questionnaire. Incorporating interviews could provide more meaningful insights, as they allow respondents to express their views on AI adoption and use in greater depth. Interviews also offer the advantage of enabling researchers to clarify questions and address any uncertainties directly, fostering a more nuanced understanding of the topic.

7. Conclusion

To sum up, this study underscores the critical roles of SI as a predictor and BI as a mediator in driving the adoption of AI technologies among Chinese undergraduate accounting students. The findings demonstrate that SI has both direct and indirect effects on AU, with partial mediation through BI. This emphasizes the necessity of cultivating favorable attitudes toward AI adoption to enhance usage behaviors. Additionally, the results challenge the moderating role of VOU, indicating that its influence may be context-dependent and warrants further exploration. These insights provide valuable guidance for educators, policymakers, and AI technology providers, emphasizing the development of targeted strategies to facilitate the integration of AI technologies. These strategies aim to equip accounting students with the essential skills to excel in an AI-driven digital environment.

Author contributions: All authors have sufficiently contributed to the study and agreed with the results and conclusions.

Declaration of interest: The authors declare that no competing interests exist.

Data availability: Data generated or analyzed during this study are available from the authors on request.

Ethical declaration: Authors declared that the study was approved by the Office of the Deputy Vice Chancellor (Research and Innovation) of Universiti Putra Malaysia on 21 August 2024 with approval code: UPM.TNCPI.800-2/1/7.

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