



## Research on Continuance Intention for Business Undergraduates to Use Simulation Practice Teaching System

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### Abstract

**Background and Aim:** The rapid integration of simulation technologies in business education has highlighted the need to understand psychological factors driving students' sustained use of such systems. Existing research lacks focus on continuance intention mechanisms in Chinese business education, particularly in simulation-based learning contexts. This study addresses this gap by integrating the Technology Acceptance Model (TAM), Expectation-Confirmation Model (ECM), and Information Systems Success Model (ISSM) to examine how perceived usefulness (PU), perceived ease of use (PEOU), confirmation (CON), interactivity (INT), and system quality (SYQ) influence satisfaction (SAT) and continuance intention (CNI).

**Materials and Methods:** A quantitative survey was conducted with 756 business undergraduates from Zhanjiang University of Science and Technology who completed simulation-based courses. Data were collected using a validated 5-point Likert scale (28 items) and analyzed via structural equation modeling (SEM) and confirmatory factor analysis (CFA) in AMOS 24 and SPSS 26. Judgmental sampling ensured representativeness, with reliability (Cronbach's  $\alpha > 0.8$ ) and validity (Fornell-Larcker criteria) rigorously tested.

**Results:** All six hypotheses were supported: PU ( $\beta=0.184$ ,  $p<0.001$ ), PEOU ( $\beta=0.224$ ,  $p<0.001$ ), CON ( $\beta=0.196$ ,  $p<0.001$ ), INT ( $\beta=0.205$ ,  $p<0.001$ ), and SYQ ( $\beta=0.215$ ,  $p<0.001$ ) significantly influenced SAT, explaining 75.3% of its variance. SAT strongly predicted CNI ( $\beta=0.775$ ,  $p<0.001$ ), accounting for 60% of its variance. The impact hierarchy ranked PEOU > SYQ > INT > CON > PU, with system ease of use being the strongest driver.

**Conclusion:** This study validates the pivotal role of satisfaction in mediating the relationship between cognitive evaluations (e.g., ease of use) and continuance intention. Practical implications emphasize optimizing interface simplicity and system stability to enhance user experience. Limitations include sampling bias (76.6% accounting majors) and cross-sectional data. Future research should explore longitudinal effects and cross-cultural comparisons to generalize findings.

**Keywords:** Simulation Practice Teaching System; Continuance Intention; Satisfaction; Structural Equation Modeling; Business Education

### Introduction

The rapid development of modern information technology has posed significant challenges to traditional educational models. Fragmented content, such as short videos and social media, has cultivated multitasking habits among students, making it difficult for them to adapt to the linear, long-term attentional demands of traditional classrooms (Carr, 2010). Meanwhile, one-way lecture-based teaching fails to provide students with real-time interaction and feedback (Prensky, 2001). The rise of mobile device-supported microlearning further exposes the rigidity of fixed classrooms and schedules (Sharples et al., 2016). Against this backdrop, global education systems are undergoing innovations in pedagogical concepts and methods. For instance, China's Ministry of Education (2023) explicitly emphasized "building a new-generation information technology-supported framework for learning innovation" in its 2023 Education Informatization Work Priorities.

Simulation-based learning, as a technologically empowered educational innovation, demonstrates unique practical value. First, it reduces resource barriers through virtual environments (Dalgarno & Lee, 2010), allowing learners to experiment and observe behavioral consequences in risk-free scenarios, thereby deepening cognitive understanding (Clark et al., 2016). Second, simulation technology constructs



realistic business scenarios (e.g., financial market fluctuations, supply chain disruptions) to stimulate learners' exploratory motivation and competitive awareness (Potter et al., 2009b), while providing closed-loop learning opportunities for decision-making skills, alternative strategy planning, and outcome evaluation (Hyman, 1978). Third, systems automatically record operational data (e.g., response time, error rates), offering objective quantitative metrics for competency assessment and reducing biases inherent in traditional subjective evaluations (Makransky et al., 2019). Fourth, adjustable parameters and instant feedback mechanisms enable learners to dynamically validate theoretical hypotheses, strengthening their understanding of complex system operations (Chulkov & Wang, 2020). These features drive the transformation of experimental courses toward simulation and digitization.

Business education, due to its high demand for dynamic practical competencies, has become a core domain for simulation technology applications. For example, in sensitive fields such as financial compliance and business ethics, simulations can preview the consequences of noncompliant operations (Knight et al., 2017), while real-time data streams (e.g., stock market simulations) train students to navigate uncertain environments (Gartner, 2021). Research confirms that business simulations, by replicating the dynamics and complexity of corporate operations (Ranchhod et al., 2014), serve as effective tools for experiential learning (Chulkov & Wang, 2020), aligning closely with business schools' goals of cultivating practical skills (Daly, 2001; Noble, 1990; Paul & Mukhopadhyay, 2005). However, existing studies have paid limited attention to the mechanisms shaping continuance intention toward simulation systems in Chinese business education. Therefore, this study aims to investigate the psychological and cognitive factors influencing business undergraduates' use of simulation-based teaching systems, providing theoretical support for: (1) designing innovative, practical curricula by educational administrations, (2) optimizing simulation-based instructional activities by educators, and (3) upgrading system hardware and functional ecosystems by enterprises.

## Research Objectives

1. To explore the significant impact of perceived usefulness, perceived ease of use, system quality, interactivity, and confirmation on the satisfaction of business undergraduates with the simulation practice teaching system.
2. To explore the significant impact of satisfaction on the intention of business undergraduates to continue using the simulation practice teaching system.

## Literature review

### Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), proposed by Davis (1989), posits that users' perceived usefulness (PU) and perceived ease of use (PEOU) are core determinants of their attitudes and behavioral intentions. This model provides a theoretical framework for understanding students' acceptance of simulation-based learning technologies in business education (Charness & Boot, 2016). While other variables (e.g., perceived user efficacy) may intervene, PU and PEOU remain critical predictors of technology adoption (Masrom, 2007). For instance, Davis (1989) validated the direct causal relationship between PU and user satisfaction, while expectation-confirmation theory (ECT) research demonstrates that PU mediates the effect of confirmation (CON) on satisfaction (SAT) through cognitive evaluation mechanisms (Yuan et al., 2016; Susanto et al., 2016).

### Expectation-Confirmation Model (ECM)

Initially developed by Oliver (1980) and later adapted to information systems research by Bhattacharjee (2001), ECM emphasizes the role of congruence between user expectations and actual experiences (i.e., confirmation, CON) in driving satisfaction. Chen and Wang (2018) found that in business simulation games, CON exerts a stronger influence on SAT than affective variables (e.g., enjoyment). Lee and Cheung (2014) highlighted that alignment between technological functionality and learning objectives (CON) serves as a key predictor of SAT in team collaboration contexts. Mtebe and



Gallagher (2022) confirmed that instructors' CON positively influences students' satisfaction with digital technologies, while Daneji et al.'s (2019) cross-national study demonstrated ECM's efficacy in explaining users' continued technology usage intentions.

### **Information System Success Model (ISSM)**

ISSM evaluates technological effectiveness through dimensions including system quality (SYQ), information quality, and service quality (DeLone & McLean, 2003). Alyoussef (2023) validated ISSM's applicability to technology adoption in higher education. Petter and McLean (2009) applied it to business simulation environments, demonstrating that SYQ (e.g., ERP system stability) is essential for students' understanding of supply chain dynamics. Yang and Lin (2015b) developed an ISSM-based evaluation model that comprehensively maps six dimensions to business simulation teaching scenarios, while Chiu and Wang (2008) emphasized SYQ's quantifiable contributions to financial trading simulation systems. Cheng (2019) proposed that ISSM offers a structured improvement pathway for business simulation course design (e.g., optimizing decision-making authenticity).

### **Perceived Usefulness (PU) and Perceived Ease of Use (PEOU)**

PU refers to users' belief in a technology's capacity to enhance work efficiency (Davis, 1986), driving satisfaction through cognitive mechanisms (Bhattacharjee & Premkumar, 2004). PEOU reflects users' assessment of a technology's operational simplicity (Davis, 1989), particularly critical in business simulations. Faria et al. (2009) noted that business simulations require balancing multi-source data processing, team collaboration, and interface simplicity. Watkins and Beckem (2012) emphasized the importance of real-time feedback and low latency for maintaining PEOU. Ohliati and Abbas (2019) demonstrated that user satisfaction in private education platforms is jointly influenced by PEOU, information accuracy, and support quality.

### **Confirmation (CON) and Interactivity (INT)**

CON is defined as the consistency between expectations and actual experiences (Bhattacharjee, 2001a), operationalized in business simulations as "goal-functionality alignment" (Chen & Wang, 2018). Lee and Cheung (2019) found that dynamic feedback delays weaken CON, necessitating instructor intervention for compensation. Bhattacharjee and Lin (2014) verified that team collaboration clarity (CON) independently explains 12% of SAT variance. INT denotes users' ability to manage roles during interactions (Williams et al., 1988), with responsiveness (Wu & Wu, 2006) and perceived control (Chen & Wang, 2019) significantly enhancing SAT. Sun and Hsu (2012) confirmed that interactive market prediction.

### **Tools yield higher user satisfaction than traditional teaching methods.**

#### **System Quality (SYQ) and Satisfaction (SAT)**

SYQ reflects a technological platform's stability and efficiency (Chen, 2010), indirectly enhancing continued usage intentions by reducing frustration (e.g., lagging or crashes; Al-Fraihat et al., 2019). DeLone and McLean (2016) proposed SAT as a common outcome variable of SYQ, information quality, and service quality, fully mediating their effects on continued intentions. Lin (2012) validated that SYQ enhances SAT by supporting learning autonomy (e.g., multi-device synchronization). Bhattacharjee (2001) confirmed within ECM that SAT fully mediates CON's effect on continued intentions, while Tam et al. (2018) identified SAT, rather than PU, as the core driver of continued technology use.

### **Continued Usage Intention (CNI)**

CNI is defined as users' motivation to persist with technology (Bhattacharjee, 2001), directly driven by SAT (Tan & Kim, 2015). Mtebe and Gallagher (2022) noted that educators' CNI reflects their commitment to pedagogical innovation. Chiu and Wang (2008) emphasized that CNI correlates with users' long-term perceptions of technological value (e.g., career competency enhancement). Andić et al. (2022) further conceptualized CNI as "users' sustained commitment to technological services," particularly in high-investment scenarios like business simulations, where CNI prediction requires integrating multidimensional cognitive and affective variables.

## Conceptual Framework

The conceptual framework in this research is grounded in TAM, ECM, and ISS theories and is developed by integrating the theoretical contributions of earlier scholars (Feng et al. 2023; Cheng 2020; Chang 2013). The specific conceptual framework is shown in Figure 1. In the conceptual framework proposed in this study, these variables are divided into three categories: independent variables, dependent variables, and mediating variables. Perceived usefulness, perceived ease of use, interactivity, confirmation, and system quality serve as independent variables. Satisfaction acts as the mediating variable, and continuance intention is the dependent variable.



**Figure 1** Conceptual Framework

The six research hypotheses proposed in this study are:

- H1: PU has a significant influence on SAT.
- H2: PEOU has a significant influence on SAT.
- H3: CON has a significant influence on SAT.
- H4: INT has a significant influence on SAT.
- H5: SQY has a significant influence on SAT.
- H6: SAT has a significant influence on CNI.

## Methodology

This study employed a questionnaire survey method, selected for its advantages in reducing researcher subjectivity through standardized scales (Dillman et al., 2014), enabling cost-effective large-sample coverage (Fowler, 2013), supporting statistical validation of theoretical hypotheses (Hair et al., 2017), and measuring continued usage intention via user self-reports (Venkatesh et al., 2003b). The measurement instrument comprised 28 items using a 5-point Likert scale. PU and PEOU items were adapted from Davis et al. (1989); CON integrated scales from Bhattacharjee (2001), Roca et al. (2006), and Musyaffi et al. (2022); INT referenced Liu (2003) and Pituch and Lee (2006); SYQ drew from Bailey and Pearson (1983); SAT and CNI were based on Roca et al. (2006), Lee (2010), and Joo et al. (2018b). Three associate professors with over a decade of experience in business education were invited to conduct an Item-Objective-Congruence (IOC) assessment.

The study targeted 783 business undergraduates at Zhanjiang University of Science and Technology who had completed simulation-based courses by November 2024. Judgmental sampling was adopted due





to the homogeneity of the sample population. A pilot survey (N = 50) demonstrated high reliability, with Cronbach's  $\alpha$  values exceeding 0.8 for all constructs: PU = 0.99, PEOU = 0.96, CON = 0.97, INT = 0.94, SYQ = 0.96, SAT = 0.98, and CNI = 0.98 (Hair et al., 2017). In December 2024, 783 questionnaires were distributed, yielding 756 valid responses (96.55% validity rate; 27 were excluded due to incomplete entries).

Formal survey data underwent confirmatory factor analysis (CFA) to verify convergent validity (factor loadings > 0.7) and discriminant validity (Fornell-Larcker criterion; Kline, 2016). Structural equation modeling (SEM) was applied to simultaneously test measurement models (relationships between latent and observed variables), structural models (causal relationships among latent variables), and mediation effects (Hair et al., 2017). AMOS 24 was used for CFA and SEM analyses due to its visual modeling capabilities and bootstrap robustness testing, while SPSS 26 handled data cleaning, descriptive statistics, and reliability checks. The research design adhered to established protocols for business education technology studies (Bhattacharjee, 2001), providing empirical insights for optimizing simulation-based teaching systems.

## Results

### Demographic Information

This study included 756 valid samples, with descriptive statistical analysis conducted based on gender, age, and major distributions. Gender distribution revealed that female undergraduates accounted for 71.8% (n = 543) and males 28.2% (n = 213). Age distribution was as follows: 18–20 years (2.40%; n = 18), 20–23 years (61.80%; n = 467), 23–24 years (25.60%; n = 193), and 24+ years (10.20%; n = 77). Regarding major distribution, accounting majors constituted 76.6% (n = 579), auditing majors 10.6% (n = 80), and financial management majors 12.8% (n = 97).

Data analysis indicated three key findings:

Accounting majors were significantly overrepresented compared to other business disciplines (76.6% vs. 23.4%), suggesting conclusions may be more applicable to this academic background.

Female undergraduates exceeded 70% of participants, potentially reflecting stronger acceptance tendencies toward simulation-based teaching systems compared to males.

Students aged 20+ years (including 20–23, 23–24, and 24+ subgroups) comprised 97.6% of the sample, indicating upperclassmen's preference for completing practical coursework through simulation systems.

Detailed demographic characteristics are presented in Table 1.

**Table 1** Demographic Information

Variable	Category	Frequency	Percentage
Gender	Male	213	28.20%
	Female	543	71.80%
	Total	756	100.00%
Age	18 ≤ years old < 20	19	2.40%
	20 ≤ years old < 23	543	61.80%
	23 ≤ years old < 24	194	25.60%
	24 ≤ years old	56	4.20%
Major	Accounting	579	76.60%
	Auditing	80	10.60%
	Financial management	97	12.80%



### Descriptive Statistics

This study measured latent variables using a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree), with four items per variable (see Table 2). Results showed the following mean (M) and standard deviation (SD) values: Perceived Usefulness (PU: M = 3.774, SD = 1.084), Perceived Ease of Use (PEOU: M = 3.643, SD = 1.079), Confirmation (CON: M = 3.738, SD = 1.078), Interactivity (INT: M = 3.745, SD = 1.084), System Quality (SYQ: M = 3.785, SD = 1.058), Satisfaction (SAT: M = 3.759, SD = 1.118), and Continued Usage Intention (CNI: M = 3.728, SD = 1.083). All means ranged from 3.643 to 3.785, falling between "moderately agree" and "highly agree" relative to the theoretical midpoint (3.0), indicating participants' overall positive perception of the simulation-based teaching system. Key findings included: (1) SYQ scored highest (M = 3.785) with the lowest variability (SD = 1.058), reflecting strong consensus on hardware stability; (2) PEOU scored lowest (M = 3.643), significantly trailing SYQ ( $\Delta = 0.142$ ), suggesting a need for streamlined operational workflows; (3) SAT exhibited the largest variability (SD = 1.118), highlighting divergent student expectations for system improvements. Recommendations include optimizing interface interaction logic (e.g., consolidating high-frequency function access points) while maintaining system stability and adopting modular designs to address heterogeneous learning needs, thereby enhancing usability and reducing satisfaction disparities.

**Table 2** Descriptive Statistics of Relative Advantage

Variables	No. of items	Mean	S.D.	Interpretation
PU	4	3.774	1.084	Agree
PEOU	4	3.643	1.079	Agree
CON	4	3.738	1.078	Agree
INT	4	3.745	1.084	Agree
SYQ	4	3.785	1.058	Agree
SAT	4	3.759	1.118	Agree
CNI	4	3.728	1.083	Agree

### Discriminant validity

Discriminant validity was assessed using the Fornell-Larcker criterion (Fornell & Larcker, 1981), which requires the square root of the average variance extracted (AVE) for each latent variable to exceed its correlations with other latent constructs to avoid measurement model bias due to excessive overlap. Violations of this criterion may lead to construct confusion and unreliable path analysis results (Henseler et al., 2014). The results indicated that the highest correlation coefficient between latent variables was 0.755 (see Table 3), while the AVE values were as follows: continued usage intention (CNI) = 0.893, satisfaction (SAT) = 0.914, system quality (SYQ) = 0.889, interactivity (INT) = 0.891, confirmation (CON) = 0.890, perceived ease of use (PEOU) = 0.897, and perceived usefulness (PU) = 0.898. The maximum correlation coefficient (0.755) was significantly lower than the minimum AVE value (0.889), and all AVE square roots (e.g.,  $\sqrt{0.889} \approx 0.943$  for SYQ) exceeded corresponding values in the correlation matrix. These findings confirm sufficient discriminant validity, satisfying the Fornell-Larcker criterion.

**Table 3** Discriminant Validity

Correlations	PU	PEOU	CON	INT	SYQ	SAT	CNI
PU	<b>0.898</b>						
PEOU	0.600	<b>0.897</b>					
CON	0.636	0.634	<b>0.89</b>				
INT	0.647	0.672	0.686	<b>0.891</b>			
SYQ	0.663	0.595	0.672	0.688	<b>0.889</b>		
SAT	0.706	0.716	0.728	0.748	0.735	<b>0.914</b>	



Correlations	PU	PEOU	CON	INT	SYQ	SAT	CNI
CNI	0.669	0.632	0.692	0.671	0.65	0.755	<b>0.893</b>

### Confirmatory Factor Analysis

The model was validated through confirmatory factor analysis (CFA) based on the combined criteria of CFI-RMSEA (CFI > 0.95 and RMSEA < 0.06) recommended by Hu and Bentler (1999) and the fit thresholds proposed by Kline (2016) ( $\chi^2/df < 3$  for strict fit; TLI  $\geq 0.95$  as a stringent threshold). As shown in Table 4, the absolute fit indices included  $\chi^2/df = 2.372$  ( $< 3.000$ ), GFI = 0.934 ( $> 0.900$ ), AGFI = 0.919 ( $> 0.800$ ), and RMSEA = 0.043 ( $< 0.05$ ), all meeting stringent criteria. The relative fit indices were CFI = 0.981 ( $> 0.950$ ), TLI = 0.978 ( $> 0.950$ ), and NFI = 0.967 ( $> 0.900$ ), indicating strong global fit (e.g., RMSEA < 0.05 reflecting excellent data-model alignment) and parsimony (e.g.,  $\chi^2/df < 3$  suggesting reasonable model complexity). All indices surpassed theoretical thresholds, confirming the validity of the latent variable structure and supporting the reliability of subsequent path analyses.

**Table 4** CFA goodness of fit results

GOF Indices	Criteria	Source	Value
CFI	CFI > 0.95	(Hu & Bentler, 1999)	0.981
NFI	NFI $\geq 0.90$	(Hair et al., 2010)	0.967
TLI	TLI > 0.95	(Kline, 2016)	0.978
CMIN/DF	CMIN/DF < 3.00	(Kline, 2016)	2.372
GFI	GFI $\geq 0.90$	(Hair et al., 2010)	0.934
AGFI	AGFI $\geq 0.80$	(Sica & Ghisi., 2007)	0.919
RMSEA	RMSEA < 0.06	(Hu & Bentler, 1999)	0.043

The measurement model was tested based on the definition of factor loadings (i.e., the correlation weights between observed variables and latent constructs) by Hair et al. (2006) and the factor loading threshold ( $\geq 0.50$ ) proposed by Truong and McColl (2011). Additionally, convergent validity criteria (composite reliability, CR > 0.7; average variance extracted, AVE > 0.5) from Kline (2016) and discriminant validity standards (AVE square roots exceeding inter-construct correlations) from Fornell and Larcker (1981) were applied. Confirmatory factor analysis results (see Table 5) revealed that all observed variables exhibited factor loadings ranging from 0.873 to 0.932 (all > 0.50), indicating strong explanatory power of the observed variables for their respective latent constructs. CR values (0.938–0.953, all > 0.7) and AVE values (0.790–0.835, all > 0.5) confirmed robust internal consistency and substantial variance explained by the latent variables. Although some factor loadings exceeded 0.90 (e.g., 0.932), potentially raising overfitting concerns, Hair et al. (2017) noted that high values in large samples ( $N = 756 > 500$ ) are more likely to reflect population-level regularities than sample-specific biases. Furthermore, all AVE square roots (e.g.,  $\sqrt{0.790} \approx 0.889$ ) significantly surpassed the maximum inter-construct correlation (0.755), satisfying the Fornell-Larcker criterion for discriminant validity.

**Table 5** Results of Factor loadings, CR, and AVE (Note: \*\*\* $p < 0.001$ )

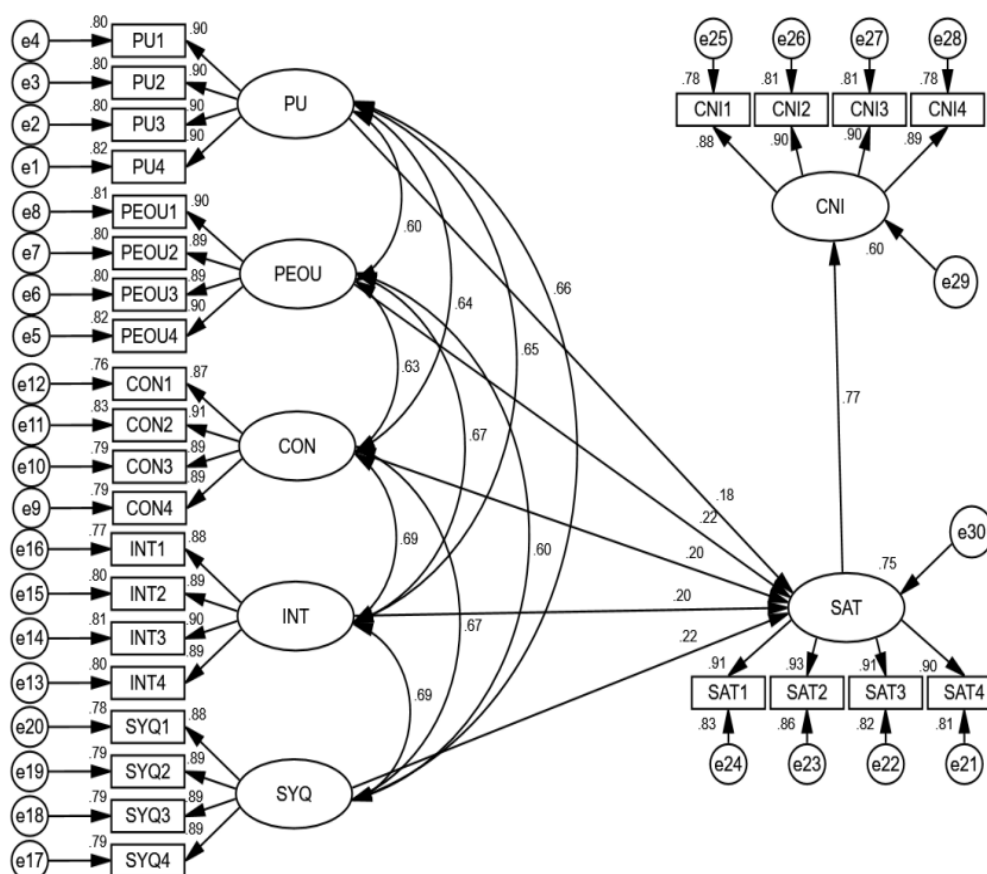
Latent Variables	Factors Loading	p	CR	AVE
PU	0.896 – 0.904	***	0.944	0.807
PEOU	0.894 – 0.903	***	0.943	0.805
CON	0.873 – 0.911	***	0.938	0.792
INT	0.877 – 0.901	***	0.939	0.794
SYQ	0.885 – 0.891	***	0.938	0.79

Latent Variables	Factors Loading	p	CR	AVE
SAT	0.899 – 0.932	***	0.953	0.835
CNI	0.886 – 0.900	***	0.94	0.798

### Structural Equation Model (SEM)

According to (Ainur et al., 2017), Structural Equation Modeling (SEM) is a statistical technique used to examine the connections between variables. It integrates factor analysis and path analysis to manage intricate interactions among multiple dependent and independent variables. Anderson and Gerbing (1988) pointed out that in the mathematical analysis of the Structural Equation Model (SEM), the measurement model and the structural model should be examined and evaluated as two independent stages. This is because the functions and analysis methods of these two parts of the model are different, and their emphases are also different. This technique is used to estimate the relationship between observable variables and latent variables (Bentler, 2010). In this study, the structural equation model used is shown in Figure 2. The elliptical geometric figure is the latent variable; the rectangular geometric figure is

The observed variable and the circular geometric figure are the measurement error.



**Figure 2** Structural equation model Diagram

This study constructed a structural equation model (SEM) using AMOS 24 software, grounded in the Technology Acceptance Model (TAM; Davis, 1989), the Information Systems Success Model (ISSM; DeLone & McLean, 2003), and the Expectation-Confirmation Model (ECM; Bhattacharjee, 2001). As shown in Table 6, absolute fit indices included CMIN/DF = 2.636 (< 3) and RMSEA = 0.047 (< 0.05), meeting the stringent criteria (RMSEA ≤ 0.06) proposed by Hu and Bentler (1999). GFI = 0.926 and AGFI





= 0.911 (both > 0.9) indicated that the model explained over 90% of the sample covariance. Relative fit indices, such as CFI = 0.976 and TLI = 0.973 (both > 0.95), further validated the model's superiority over the baseline model (Bentler, 1990b). All indices satisfied conventional thresholds, demonstrating strong statistical and theoretical model fit (Kline, 2016).

**Table 6** SEM goodness of fit results

GOF index	Criteria	Value
CMIN/DF	<3	2.636
GFI	>0.9	0.926
AGFI	>0.8	0.911
RMSEA	<0.06	0.047
CFI	>0.95	0.976
NFI	>0.9	0.963
TLI	>0.95	0.973

### Research hypothesis testing

According to the hypothesis testing results in Table 7, perceived ease of use (PEOU) exhibited the strongest effect on satisfaction (SAT) ( $\beta = 0.224$ ,  $p < .001$ ), followed by system quality (SYQ) ( $\beta = 0.215$ ) and interactivity (INT) ( $\beta = 0.205$ ). Notably, the significant impact of confirmation (CON) on satisfaction ( $\beta = 0.196$ ,  $p < .001$ ) fully supports the core hypothesis of the expectation-confirmation model (ECM; Bhattacharjee, 2001): students' satisfaction (SAT) significantly increases when their actual experiences with the business simulation tool (e.g., functional stability, real-time data) meet or exceed initial expectations (CON). This finding aligns with empirical studies on technology applications in business education. For instance, Wang and Liao (2008) demonstrated that the real-time feedback capability of ERP simulation systems (a key dimension of CON) indirectly enhances learning satisfaction by reducing cognitive dissonance.

Furthermore, the strong effect of satisfaction on continued usage intention (CNI) ( $\beta = 0.775$ ) reinforces the ECM framework, positing that affective experiences (satisfaction) are central drivers of behavioral continuity (Bhattacharjee, 2001). However, the weak influence of perceived usefulness (PU) on satisfaction ( $\beta = 0.184$ ) partially deviates from the core assumptions of the technology acceptance model (TAM; Davis, 1989). This discrepancy may stem from the unique context of business education, where students often engage in learning due to mandatory course requirements or professional certification pressures rather than proactive evaluations of tool utility (C. S. Lin et al., 2004b).

**Table 7** Summary of alternative hypothesis test results (Note: \*\*\* $p < 0.001$ )

Hypotheses	Path	Stand Path Coef	Path Coef	S.E.	Z-Value	P	Tests Result
H1	PU → SAT	0.184	0.192	0.034	5.646	***	Supported
H2	CON → SAT	0.196	0.208	0.037	5.654	***	Supported
H3	INT → SAT	0.205	0.21	0.038	5.599	***	Supported
H4	SYQ → SAT	0.215	0.232	0.038	6.157	***	Supported
H5	PEOU → SAT	0.224	0.232	0.033	7.019	***	Supported
H6	SAT → CNI	0.775	0.725	0.028	25.653	***	Supported

### Direct, indirect, and overall impacts



The study results indicate that satisfaction (SAT), as a mediating variable, had an  $R^2$  value of 0.753, suggesting that perceived usefulness (PU), perceived ease of use (PEOU), confirmation (CON), interactivity (INT), and system quality (SYQ) collectively explained 75.3% of the variance in SAT. Among these predictors, PEOU exhibited the strongest effect ( $\beta = 0.224$ ,  $p < .001$ ), followed by SYQ ( $\beta = 0.215$ ), INT ( $\beta = 0.205$ ), and CON ( $\beta = 0.196$ ), while PU had the weakest influence ( $\beta = 0.184$ ). These findings align with prior research on educational technologies in business contexts.

#### Dominant Role of PEOU:

The strong effect of PEOU on SAT ( $\beta = 0.224$ ) corroborates Venkatesh et al.'s (2003b) argument that in technology-intensive business education settings (e.g., virtual stock market simulations), students prioritize tool usability (e.g., drag-and-drop financial statement generators) over functionality (e.g., complex data analytics modules), as operational complexity diverts attention from core learning objectives (Nguyen et al., 2020). For instance, in MBA case studies, tools with high usability enable students to focus cognitive resources on strategic analysis rather than technical learning, thereby improving course completion rates (Hwang & Wang, 2004).

#### Weak Influence of PU:

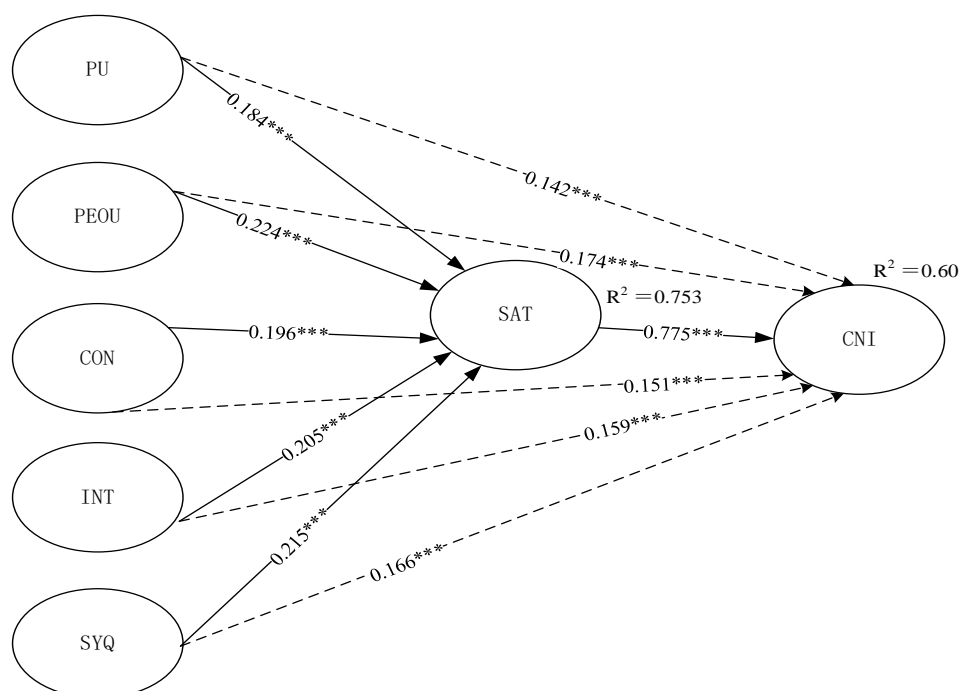
The relatively low effect of PU ( $\beta = 0.184$ ) partially deviates from the original assumptions of the technology acceptance model (TAM; Davis, 1989) but reflects the unique context of business education. Students often engage in learning due to mandatory course requirements or professional certification pressures rather than proactive evaluations of tool utility (C. S. Lin et al., 2004b).

This finding underscores the need for educational technology designs to balance functionality and usability, avoiding “over-engineering”.

For the dependent variable, continued usage intention (CNI), the  $R^2$  value of 0.60 indicates that all independent variables and SAT collectively explained 60% of the variance in CNI. SAT had the strongest direct effect on CNI ( $\beta = 0.775$ ,  $p < .001$ ), while the indirect effects of PU, PEOU, CON, INT, and SYQ via SAT were 0.142, 0.174, 0.151, 0.159, and 0.166, respectively. These results support Bhattacharjee's (2001) expectation-confirmation model (ECM), emphasizing that affective experiences (satisfaction) are central drivers of behavioral continuity, rather than mere functional evaluations of technology.

#### Practical Implications:

To enhance learning outcomes, tool operational processes could be simplified (e.g., one-click report generation) to reduce technical learning burdens. Real-time collaborative tasks (e.g., group-based market simulations) may compensate for PU's weak influence, indirectly boosting CNI. Additionally, clarifying functional boundaries of tools (e.g., data update frequency) during early course stages could mitigate unmet expectations and insufficient confirmation (CON), as overpromising may undermine satisfaction (Al-Fraihat et al., 2019).



**Figure 3** Pathway diagram consequences

## Discussion

The study findings revealed that student satisfaction (SAT) significantly and positively influenced continued usage intention (CNI), while perceived usefulness (PU), perceived ease of use (PEOU), confirmation (CON), interactivity (INT), and system quality (SYQ) all had significant positive effects on SAT. Although PU exhibited a relatively weak influence ( $\beta = 0.184$ ), its positive role remained consistent with prior literature (Widjaja & Widjaja, 2022; Al-Rahmi et al., 2020), particularly in business simulations where PU's value lies in aiding students' decision-making skills (e.g., risk assessment and market forecasting). For example, Yuan et al. (2016) found that ERP simulation training improved MBA students' decision-making speed by 27%; however, the weak PU effect in this study may reflect students' focus on short-term task support (e.g., financial report generation) over long-term utility (Susanto et al., 2016). In contrast, the strong effect of PEOU ( $\beta = 0.224$ ) highlighted its central role in reducing cognitive load and enhancing learning efficiency (Chandrasari, 2023; Feng et al., 2023), such as drag-and-drop tools saving 15% operational time and enabling greater focus on strategy optimization (Huang, 2021). The impact of CON ( $\beta = 0.196$ ) aligned with expectation-confirmation theory (Alshurideh et al., 2019), where students' satisfaction increased significantly when actual experiences (e.g., system stability) matched initial expectations, with dynamic feedback mechanisms reinforcing this pathway (Xu et al., 2017). The roles of INT ( $\beta = 0.205$ ) and SYQ ( $\beta = 0.215$ ) further emphasized that real-time interactions (e.g., group bidding) and system reliability (e.g., response time < 3 seconds) are critical for sustaining learning continuity (Choi et al., 2021; Hassan et al., 2014). Finally, the strong mediating effect of SAT on CNI ( $\beta = 0.775$ ) underscored affective experiences as a core driver of technology adoption (Bhattacharjee, 2001), suggesting educators should enhance satisfaction—and thereby drive sustained learning intentions—through usability optimization, expectation management, and system iterations (e.g., cross-device compatibility; DeLone & McLean, 2016; Lin & Wang, 2012).

## Conclusion

This study integrates the Technology Acceptance Model (TAM), Expectation Confirmation Model (ECM), and Information System Success Model (ISSM) to explore key factors influencing business



undergraduates' continuance intention (CNI) toward simulation-based learning systems. Analysis of data from 756 students enrolled in virtual business simulation courses revealed that satisfaction (SAT) is the core driver of CNI ( $\beta = 0.775^{***}$ ,  $R^2 = .60$ ), highlighting the dominant role of affective experience in technology adoption (Bhattacharjee, 2001). Perceived ease of use (PEOU,  $\beta = 0.224^{***}$ ) and system quality (SYQ,  $\beta = 0.215^{***}$ ) exerted the strongest effects on SAT, indicating students prioritize operational simplicity (e.g., drag-and-drop tools reducing cognitive load) and system stability (e.g., real-time data updates preventing decision interruptions; Venkatesh et al., 2003b; DeLone & McLean, 2016). Interactivity (INT,  $\beta = 0.205^{***}$ ) and confirmation (CON,  $\beta = 0.196^{***}$ ) indirectly enhanced SAT through collaborative task design and dynamic expectation management, while the weaker effect of perceived usefulness (PU,  $\beta = 0.184^{***}$ ) reflects students' prioritization of short-term task support (e.g., rapid report generation) over long-term utility (C. S. Lin et al., 2004b).

The research conclusion shows that student satisfaction has the greatest impact on the intention to continue, and the five independent variables all have a positive impact on satisfaction, and their effect sizes are perceived ease of use, system quality, interactivity, confirmability, and perceived usefulness.

## Recommendation

From a practical perspective, educational institutions should prioritize optimizing the usability design (e.g., simplifying operational workflows) and system reliability (e.g., minimizing latency and crashes) of simulation systems to reduce technological learning costs and enhance stability. Instructors should strengthen interactivity through collaborative task designs (e.g., virtual market competition) and utilize dynamic feedback (e.g., phased evaluation reports) to manage student expectations, thereby amplifying confirmation's positive impact on satisfaction. Additionally, integrating case-based teaching to highlight practical tool utility (e.g., strategic decision-making training) could mitigate the weak influence of perceived usefulness. Theoretically, future research could incorporate longitudinal analyses to explore the long-term effects of professional certification pressures on technology adoption, expand cross-cultural comparisons (e.g., differences between Chinese and American students) to validate the universality of interactivity and confirmation, and introduce moderators such as self-regulated learning capabilities or gamification elements to examine their regulatory effects on the satisfaction-continuance relationship, thereby enriching the theoretical framework of technology adoption in business education.

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