

Article

Exploring Students' Intention to Use Generative Artificial Intelligence in Business Administration Education: An Integrated TOE-TAM Model with PLS-SEM and fsQCA

Lisheng Jiang  and Shiyu Yan * 

College of Management Science, Chengdu University of Technology, Chengdu 610059, China; lsjiang@cdut.edu.cn

* Correspondence: syyan@cdut.edu.cn

Abstract

Business administration education relies on case analysis, strategic simulation, and complex decision-making, all of which generative artificial intelligence (GenAI) can substantially support. However, limited research has examined the mechanisms driving business students' intention to use GenAI tools to support their learning. To address this gap, this study aims to investigate business administration students' intention to use GenAI by drawing on an integrated Technology-Organization-Environment (TOE) framework and an extended Technology Acceptance Model (TAM) incorporating perceived trust and perceived risk. Using survey data from 385 Chinese business administration students, a hybrid analytical approach combining Partial Least Squares Structural Equation Modeling (PLS-SEM) and fuzzy-set Qualitative Comparative Analysis (fsQCA) is adopted to examine both the net effects and the configurational mechanisms underlying behavioral intention. The results show that perceived ease of use and perceived trust are the two strongest direct predictors of intention to use GenAI, jointly outweighing perceived usefulness, and that perceived trust serves as the sole significant mediator linking cognitive evaluations to intention to use. Perceived risk, in contrast, exhibits neither a direct nor a mediating effect, suggesting a risk tolerance pattern among business students. Among the TOE dimensions, environmental support (peer influence) emerges as the most potent contextual driver, whereas organizational support facilitates perceived ease of use but does not directly enhance perceived usefulness. The fsQCA findings further identify five typical pathways to high intention to use, namely TAM-driven, trust-compensated, environment-driven, organization-driven risk-tolerant, and comprehensive external-support configurations. These findings provide guidance for designing targeted GenAI-supported strategies and peer-driven interventions in higher business education.



Academic Editors: Patricio E. Ramirez-Correa and Fernando Moreira

Received: 29 June 2026

Revised: 19 July 2026

Accepted: 21 July 2026

Published: 31 July 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

Keywords: behavioral intention; business students; fsQCA; generative artificial intelligence; PLS-SEM

1. Introduction

With the rapid advancement of information technology and artificial intelligence, generative artificial intelligence (GenAI) has ushered humanity into a new era of intelligence [1]. Representative GenAI tools, such as ChatGPT [2] and DeepSeek [3], possess near-human capabilities in language understanding and generation. They have demonstrated outstanding performance across a wide range of tasks, including content creation, question answering, and code generation [4], and have rapidly become a focal point of attention for government

agencies, enterprises, and academia [5]. GenAI tools are progressively reshaping the ways in which humans acquire information and create content, fundamentally transforming the landscape of higher education and the business ecosystem.

GenAI has been widely regarded by scholars as one of the most disruptive technologies for higher education. Existing research suggests that GenAI has significantly facilitated personalized learning [6], intelligent assessment [7], tutoring [8], academic research support [9], language learning assistance [10], and innovative instructional design [11,12]. Through scenario-based simulation and real-time feedback, GenAI can create immersive learning environments, alleviate students' cognitive anxiety, and facilitate knowledge co-creation and brainstorming [13]. However, the educational benefits of GenAI do not emerge automatically; students' intention to use the technology is a critical prerequisite for its effective integration into learning and for realizing its long-term positive impact.

As a core discipline for cultivating future managers and decision-makers, business administration education relies heavily on case analysis, strategic simulation, market assessment, and team collaboration [14]. Students are required to address unstructured problems involving multiple variables and interconnected stakeholders, thereby developing systematic thinking and comprehensive decision-making capabilities [15]. The application potential of GenAI in the field of management is particularly significant: it can rapidly generate industry reports, simulate strategic choices across diverse market scenarios, provide ethical analyses from multiple perspectives, and assist in drafting business plans [16]. However, while GenAI brings efficiency and convenience, it also introduces new challenges. First, students may place excessive trust in GenAI-generated content and accept it uncritically, thereby reducing GenAI to a mere answer generator and hindering the development of their independent thinking and complex decision-making abilities. Second, when GenAI provides incorrect or misleading responses, it may trigger a crisis of trust, which in turn undermines students' intention to continue using it. Therefore, it is essential to gain an in-depth understanding of the complex factors underlying students' intention to use GenAI and to promote its effective use in supporting learning.

Although existing studies have begun to examine the acceptance and usage behavior of GenAI in higher education, this line of inquiry has predominantly focused on specific disciplinary contexts such as medical education [17], engineering education [18], and second-language learning [19], while business administration remains comparatively underexplored [20]. Theoretically, existing models focus primarily on the usability and perceived usefulness of the technology itself, drawing predominantly on single frameworks such as the TAM [21] or the Unified Theory of Acceptance and Use of Technology (UTAUT) [22]. They rarely integrate external contextual factors (e.g., technical, organizational, and environmental supports) together with users' internal cognitive and trust-risk mechanisms into a unified analytical architecture [8,23]. Methodologically, most existing studies employ linear net-effect models, such as regression analysis or structural equation modeling, which assume that the effects of various factors on usage intention are symmetric and independent [24]. In practice, students' intention to use GenAI is often shaped by combinations of multiple conditions, and different configurations may lead to the same outcome. Recent methodological advances have introduced configurational approaches capable of capturing such nonlinear and asymmetric relationships, including fsQCA [25,26] and artificial neural networks (ANN) [27]. Yet, these methods have rarely been applied to the study of GenAI intention in the context of business education.

To address these gaps, this study draws on an integrated TOE-TAM framework incorporating perceived trust (PT) and perceived risk (PR), and adopts a hybrid PLS-SEM and fsQCA approach. Accordingly, the following research questions guide the analysis:

- (1) How do cognitive perceptions, including perceived usefulness, perceived ease of use, perceived trust, and perceived risk, influence business administration students' intention to use GenAI?
- (2) How do contextual supports, including technical, organizational, and environmental support, shape business administration students' cognitive evaluations of GenAI tools?
- (3) Do perceived trust and perceived risk mediate the relationships between cognitive evaluations and behavioral intention?
- (4) What configurational combinations of antecedent conditions lead to high behavioral intention?

This study makes three main contributions. From a theoretical perspective, it develops a comprehensive analytical framework that integrates the TOE framework with an extended TAM incorporating PT and PR, thus systematically identifying the factors influencing business administration students' intention to use GenAI and providing a theoretical reference for future research. From a methodological perspective, it employs a hybrid approach combining PLS-SEM and fsQCA to reveal both net effects and configurational pathways, deepening the understanding of the complex and asymmetric mechanisms underlying behavioral intention. From a practical perspective, it offers actionable recommendations for business educators, curriculum designers, and GenAI platform developers and thereby promotes the sustainable integration of GenAI in higher business education.

2. Theoretical Underpinning and Hypotheses Development

2.1. Perceived Ease of Use, Perceived Usefulness, and Behavioral Intention

According to the TAM, the decision to adopt a new technology is primarily shaped by whether the tool is useful for accomplishing tasks and whether it is easy to operate. These two cognitive assessments, termed perceived usefulness (PU) and perceived ease of use (PEOU), together drive users' behavioral intention (BI) to engage with the technology [21].

PU captures the degree to which students think that GenAI tools can supply useful information for studying, including case analysis and solution development. A growing body of work confirms the link between PU and BI in educational settings [8]. One recent study of over 400 participants, for example, reported that PU, together with enjoyment and trust, was a significant driver of GenAI use among programming learners [28].

PEOU reflects the ease or effortlessness with which students interact with GenAI tools. When a technology feels intuitive and requires little technical skill, users are more inclined to incorporate it into their learning routine [29]. Moreover, ease of use tends to enhance PU. A tool that is simple to operate allows students to discover its practical benefits more readily, which in turn strengthens their overall evaluation of its value [30]. Taken together, these theoretical considerations and existing evidence motivate the following hypotheses:

H1a. *Perceived usefulness is positively associated with business administration students' behavioral intention to use GenAI.*

H1b. *Perceived ease of use is positively associated with business administration students' behavioral intention to use GenAI.*

H1c. *Perceived ease of use is positively associated with perceived usefulness.*

2.2. Perceived Trust, Perceived Risk and Behavioral Intention

Although the traditional TAM does not explicitly incorporate PT and PR, numerous studies have emphasized that PT and PR are critical psychological factors influencing users' intention, particularly in data-sensitive educational environments [31]. For GenAI tools, the possibility of inaccurate outputs, embedded biases, or hallucinations may directly shape students' judgments of system reliability and subsequent usage behavior [32].

PT is generally defined as users' confidence in the competence, integrity, and reliability of a technological system [33]. Unlike conventional computing technologies that primarily rely on real-time user input, GenAI is capable of generating outputs with limited direct human intervention [34]. Accordingly, PT constitutes a central psychological construct in human-AI interaction. In the context of GenAI-assisted learning for business administration students, PT is reflected in students' beliefs that AI-generated industry reports, strategic recommendations, or financial analyses possess sufficient accuracy and contextual relevance. When students exhibit a high level of PT in GenAI, they are more likely to rely on its outputs for complex decision-making and to demonstrate a stronger willingness to continue using the tool. Conversely, a lack of PT may lead students to frequently verify AI-generated outputs or even discontinue use altogether, thereby reducing both learning efficiency and their intention to use the technology. Based on the above rationale, the following hypothesis is proposed:

H2a. *Perceived trust is positively associated with business administration students' behavioral intention.*

PR refers to users' expectations of potential negative consequences arising from technology use, including privacy breaches, academic integrity concerns, decision-making errors, and overreliance [35]. For business administration students, the use of GenAI tools in learning may involve several potential risks, such as inaccurate data or incorrect citations in generated content that may reduce assignment quality, unintentional plagiarism resulting from AI-generated materials that violates academic norms, and long-term dependence on AI that may weaken students' analytical and judgment capabilities [36]. Such risk perceptions may significantly reduce students' positive evaluations of GenAI and, consequently, weaken their BI. Prior empirical studies have consistently confirmed the negative effect of PR on technology adoption [31,37]. Accordingly, the following hypothesis is proposed:

H2b. *Perceived risk is negatively associated with business administration students' behavioral intention.*

2.3. TOE Framework

The TOE framework was originally developed to analyze the factors influencing organizations' adoption and implementation of technological innovation [38]. The framework posits that technology adoption behavior is jointly shaped by technological, organizational, and environmental characteristics. Although conceived at the organizational level, the TOE framework has been increasingly adapted to individual-level technology acceptance research in educational settings because the three contextual dimensions are equally salient in shaping students' technology adoption decisions [39,40]. In the present study, the TOE dimensions are positioned as external antecedents to the TAM belief constructs of PEOU and PU, based on the premise that students' cognitive evaluations of a technology do not form in isolation but are embedded in, and shaped by, the broader technical, organizational, and social environment in which learning takes place. Drawing on this logic, each dimension and its hypothesized relationships with PEOU and PU are defined as follows.

Technological characteristics refer to the external technical conditions and usability support on which students rely when using GenAI tools. Factors such as convenient operation, the ability to meet basic learning needs, and the availability of rapid solutions through official help documentation or online tutorials when technical issues arise constitute the fundamental technological environment for students' engagement with GenAI tools. Prior studies have shown that when these basic technical conditions are satisfied, users' perceived operational barriers are significantly reduced, thereby enhancing PEOU [41]. Meanwhile, prior empirical studies based on the TOE framework in educational AI adoption have indicated that relative technological advantage is a critical factor influencing the further diffusion of AI innovation. This suggests that when the free functionalities of GenAI tools can cover most learning tasks and technical issues can be resolved efficiently, students are more likely to recognize the practical value of such tools in supporting learning activities, thereby enhancing PU [39]. In this study, the technological dimension is operationalized as technical support (TE). Accordingly, the following hypotheses are proposed:

H3a. *Technical support is positively associated with perceived usefulness.*

H3b. *Technical support is positively associated with perceived ease of use.*

Organizational characteristics refer to the institutional support and resource investment provided by universities and instructors to facilitate students' use of GenAI tools, such as relevant training, usage guidance, and explicit encouragement to adopt such tools [42]. These forms of organizational support can reduce students' operational barriers and uncertainty when facing new technologies, thereby enhancing PEOU [43]. When institutions explicitly communicate supportive attitudes and provide relevant resources, students are more likely to regard GenAI tools as legitimate and recognized learning aids [44]. Consequently, they are more likely to perceive their practical usefulness in completing course tasks and optimizing the learning process, thereby strengthening PU. In this study, the organizational dimension is operationalized as organizational support (OR). Accordingly, the following hypotheses are proposed:

H4a. *Organizational support is positively associated with perceived usefulness.*

H4b. *Organizational support is positively associated with perceived ease of use.*

Environmental characteristics refer to the normative influence exerted by users' external interpersonal networks and the surrounding social climate on their use of GenAI tools [40]. Previous studies have shown that peer influence plays a significant role in technology adoption contexts and may amplify or weaken the effects of other determinants [45]. When students observe peers or instructors actively using and recommending GenAI tools, others' successful usage experiences may reduce students' subjective perceptions of tool complexity, leading them to perceive the tool as easier to use and thereby enhancing PEOU. At the same time, external signals from social discourse and authoritative recommendations may lead students to perceive the use of GenAI tools as valuable for both learning and future career development, thereby strengthening PU. In this study, the environmental dimension is operationalized as environmental support (EN). Accordingly, the following hypotheses are proposed:

H5a. *Environmental support is positively associated with perceived usefulness.*

H5b. *Environmental support is positively associated with perceived ease of use.*

2.4. Mediating Role of Perceived Trust and Perceived Risk

According to the TAM and Social Cognitive Theory, PT and PR are conceptualized not only as direct antecedents of behavioral intention but also as mediating mechanisms through which cognitive evaluations influence behavioral intention [46]. For example, PT has been identified as the most important factor influencing students' acceptance of ChatGPT for assessment purposes, whereas moral obligation and PR have been identified as major inhibiting factors [47]. In addition, prior studies suggest that individuals' awareness of potential risks may shape their behavioral intention by promoting more cautious and deliberate technology adoption decisions rather than inducing simple resistance [48]. These studies collectively highlight the mechanisms through which trust and risk perceptions influence technology adoption behavior.

Specifically, when students perceive GenAI as easy to use and practically useful for learning tasks, they are more likely to develop trust in the system. A high level of PT strengthens students' confidence in relying on GenAI to complete academic tasks such as case analysis, report writing, and research papers, thereby enhancing their BI [49]. Meanwhile, higher levels of PU and PEOU may help alleviate students' concerns about potential risks, such as inaccurate information and academic misconduct, because students who feel competent in using GenAI may believe they are better able to identify and avoid such risks. A lower level of PR is therefore expected to further strengthen their intention. In summary, PT and PR are posited to play mediating roles through which PU and PEOU influence BI. The following hypotheses capture these proposed pathways:

H6a. *Perceived trust mediates the relationship between perceived usefulness and behavioral intention.*

H6b. *Perceived trust mediates the relationship between perceived ease of use and behavioral intention.*

H6c. *Perceived risk mediates the relationship between perceived usefulness and behavioral intention.*

H6d. *Perceived risk mediates the relationship between perceived ease of use and behavioral intention.*

2.5. Behavioral Intention and Actual Usage

In the TAM, BI is defined as the degree to which a user plans or is willing to perform a specific behavior, whereas actual usage (AU) refers to the extent to which the technology is genuinely and continuously used in terms of frequency, duration, or depth of application. A substantial body of empirical research has consistently demonstrated that BI is the most direct and stable antecedent of AU [21]. When users exhibit a strong intention to use a particular information system, such intention is typically translated into actual and sustained usage practices.

In the context of GenAI-assisted learning, business administration students' BI reflects their planned future reliance on GenAI for completing course-related tasks, such as case analysis, report writing, and data interpretation. Such intention is expected to translate into AU, including frequency of use, duration of interaction, depth of functional exploration, and breadth of application across different course tasks. When students demonstrate a high level of BI, they are more likely to actively engage with GenAI tools, repeatedly refine prompts, evaluate generated outputs, and integrate AI into their routine learning workflows. In contrast, lower levels of BI may lead to reduced use or even complete discontinuation.

Although the relationship between intention and behavior may be attenuated by external conditions such as time pressure, task complexity, and network accessibility, meta-analytic evidence consistently supports a robust positive pathway from BI to AU in technology acceptance research [50,51]. In the specific context of GenAI use in higher

education, recent empirical studies have further confirmed that students' BI is a strong and direct predictor of their actual and sustained GenAI usage [52]. Accordingly, the following hypothesis is proposed:

H7. Behavioral intention is positively associated with actual usage.

Figure 1 depicts the proposed research model and the hypothesized relationships.

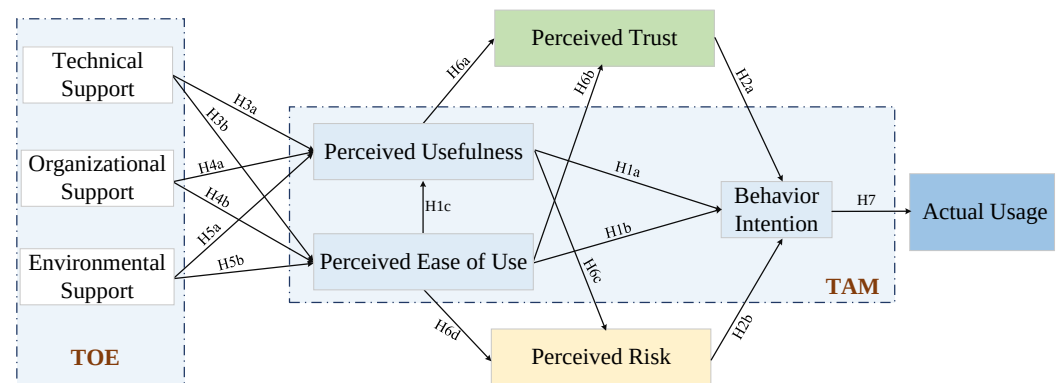


Figure 1. Research model and hypotheses.

3. Methodology

3.1. Constructs and Scales

Every construct was measured with several items taken from previously published and validated instruments, with minor rephrasing to match the GenAI and business administration setting. Participants responded on a five-point scale from 1 ("strongly disagree") to 5 ("strongly agree").

To establish content validity, the draft questionnaire was sent to a panel of five reviewers, three from business administration and two from educational technology, who evaluated each item on wording clarity, how well it represented the intended construct, and whether it matched the construct's definition. Based on their comments, problematic items were reworded. The updated instrument was then tested with 64 business administration undergraduates to verify that all items were understandable and internally consistent. The complete item list is provided in Appendix A.

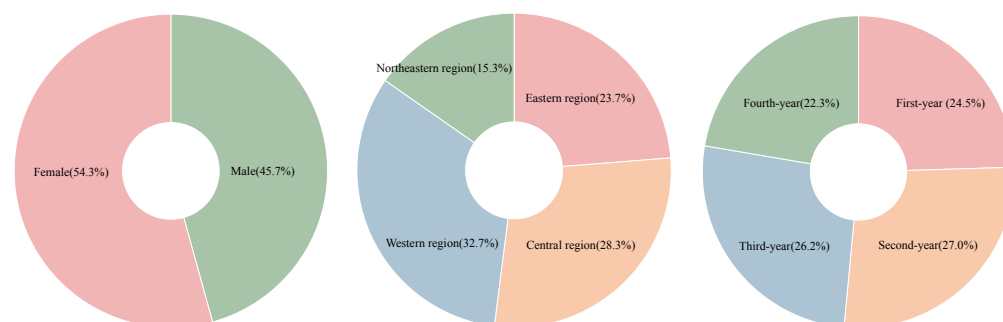
3.2. Data Collection and Sample Characteristics

The survey was fielded through Wenjuanxing, a widely used online data-collection service in China, targeting business administration undergraduates. On the opening screen, participants read a briefing about the study's aims, were told that responses would remain anonymous, and were informed that the data would serve only academic purposes. After providing consent, they proceeded to a screening item that verified their enrollment in a business administration program, then to demographic questions, and finally to the construct measures.

Several steps were taken to safeguard response quality. The platform prevented duplicate submissions from the same IP address. Cases with implausibly fast completion times or invariant response patterns were discarded during data cleaning. The final analysis sample comprised 385 valid records. This exceeds the minimum of 120 required by the ten-times rule for the 12 structural paths [53] and also surpasses the recommended threshold of 200 for adequate statistical power in PLS-SEM [54].

The sample was 54.3% female and 45.7% male, with the largest proportion of respondents coming from China's western region (32.7%), followed by the central (28.3%),

eastern (23.7%), and northeastern (15.3%) regions. The distribution across academic years was relatively balanced, spanning first-year (24.5%) through fourth-year (22.3%) students (Figure 2).



(a) Sample gender distribution (b) Sample region distribution (c) Sample grade distribution

Figure 2. Sample demographic characteristics by gender, region, and grade.

3.3. Data Analysis

The analysis proceeded in two complementary stages. The first stage used PLS-SEM to estimate the hypothesized direct and mediated paths, while the second stage applied fsQCA to explore how antecedent conditions combined into configurations sufficient for high BI.

PLS-SEM accommodates multiple latent constructs simultaneously and works with non-normal data distributions, which suits exploratory research contexts where theoretical models are still taking shape [53]. Model quality was verified on several fronts before hypothesis testing. Item reliability and internal coherence were evaluated through Cronbach's alpha and composite reliability, while the average variance extracted (AVE) confirmed that each construct captured more variance from its own items than from measurement error. Discriminant validity was assessed via the Fornell–Larcker criterion and heterotrait–monotrait (HTMT) ratios. A Harman's single-factor extraction, complemented by a full collinearity screening of VIFs, was performed to gauge the extent of shared method variance [55]. Significance testing of all hypothesized paths relied on a bootstrap procedure with 10,000 draws in SmartPLS 4.0, producing bias-corrected 95% confidence intervals around every direct and indirect coefficient.

PLS-SEM estimates the average independent contribution of each predictor, yet it rests on the assumption that these contributions are linear and symmetric. In practice, the same level of behavioral intention may result from quite different mixes of conditions, a pattern that symmetric methods alone cannot fully accommodate [56]. fsQCA was therefore introduced as a second analytical lens. Using fsQCA 3.0, all variables were transformed into fuzzy membership scores via direct calibration, after which necessity and sufficiency analyses were carried out with frequency, consistency, and PRI cutoffs set to commonly recommended values [56,57]. The intermediate solution was retained for interpretation, and conditions were designated as core or peripheral according to their appearance across the parsimonious and intermediate solutions [58,59].

4. Empirical Results

4.1. Common Method Bias

Because the data came from a single questionnaire, the possibility of shared method variance was addressed through both procedural and statistical safeguards. On the procedural side, the item pool was refined through expert review and a pilot study, and respondents were explicitly told that their answers would be kept anonymous and that no response was inherently right or wrong, steps intended to reduce evaluation apprehension and

socially desirable responding. For the statistical assessment, an unrotated factor analysis of all items showed that the first factor captured 45.7% of the total variance. Although this percentage fell below the conventional 50% benchmark [60], it is close enough that a further test was warranted. A check of variance inflation factors (VIFs) across all indicators yielded values from 1.538 to 2.608 (see Table 1), all comfortably under the 3.3 ceiling adopted in full collinearity assessments [55]. Taken as a whole, the procedural precautions and statistical diagnostics suggest that common method bias is not a dominant concern for this dataset.

Table 1. Measurement model evaluation results.

Construct	Items	Loadings	CA	CR	AVE	VIF
TE	TE1	0.838	0.847	0.848	0.685	2.316
	TE2	0.832				2.099
	TE3	0.826				2.079
	TE4	0.814				1.615
OR	OR1	0.878	0.839	0.842	0.756	2.082
	OR2	0.867				1.952
	OR3	0.863				1.662
EN	EN1	0.858	0.865	0.870	0.713	2.278
	EN2	0.828				2.088
	EN3	0.888				2.608
	EN4	0.800				1.696
PEOU	PEOU1	0.849	0.854	0.853	0.696	2.164
	PEOU2	0.857				2.077
	PEOU3	0.856				1.791
	PEOU4	0.773				2.201
PU	PU1	0.858	0.813	0.813	0.729	2.296
	PU2	0.874				2.219
	PU3	0.827				1.538
PR	PR1	0.785	0.839	0.840	0.676	1.656
	PR2	0.866				2.289
	PR3	0.848				2.116
	PR4	0.786				1.696
PT	PT1	0.797	0.851	0.864	0.690	1.901
	PT2	0.823				1.895
	PT3	0.861				2.246
	PT4	0.841				1.824
BI	BI1	0.788	0.830	0.831	0.662	1.887
	BI2	0.840				2.040
	BI3	0.828				1.609
	BI4	0.798				2.194
AU	AU1	0.899	0.858	0.860	0.778	2.136
	AU2	0.873				1.812
	AU3	0.874				1.770

4.2. Measurement Model Evaluation

Before proceeding to the structural paths, the measurement model was assessed along three standard dimensions, internal consistency, convergent validity, and discriminant validity.

Internal consistency was evaluated using Cronbach's alpha (CA) and composite reliability (CR) for each latent construct. As summarized in Table 1, all CA estimates lie between 0.813 and 0.865, while CR values span 0.813 to 0.870. Both sets of coefficients comfortably surpass

the 0.70 benchmark [53,61], confirming that the item sets reliably capture their respective constructs. Composite reliability offers a somewhat more accurate picture here because it weights indicators by their individual loading magnitudes rather than assuming equal contributions.

Convergent validity was judged through the AVE, which quantifies how much indicator variance is attributable to the latent construct relative to measurement error. Across all nine constructs, AVE estimates range from 0.662 to 0.778, exceeding the 0.50 floor recommended in prior methodological guidelines [54]. This indicates that each latent variable accounts for the majority of variation in its own indicators.

Two complementary checks were used to establish discriminant validity. The first, the Fornell–Larcker criterion, requires that each construct share more variance with its own indicators than with any other construct, which is assessed by comparing the square root of AVE against inter-construct correlations [62]. As displayed in Table 2, every diagonal entry exceeds the corresponding off-diagonal correlations in its row and column, meeting this requirement [63]. As a more sensitive supplementary check, HTMT ratios were examined, as shown in Table 3. All HTMT point estimates fall within the interval of 0.439 to 0.844, remaining below the conservative 0.85 cutoff [54]. Acknowledging that the ratios between TE and PEOU (0.786) and between TE and PU (0.798) are relatively close to this threshold, a bootstrapped HTMT inference with 10,000 resamples was conducted to verify whether the corresponding confidence intervals exclude 1.0. The 95% bias-corrected confidence interval for the HTMT between TE and PEOU was [0.710, 0.852], and for the HTMT between TE and PU was [0.716, 0.870]. Since the upper bounds of both intervals lay well below 1.0, it was concluded that students empirically distinguished their own ease of use from the external technical support available to them. Together, these checks confirmed that the nine constructs captured empirically distinguishable facets of students' perceptions rather than reflecting a single undifferentiated evaluative dimension.

Table 2. Fornell–Larcker criterion.

	TE	OR	EN	PEOU	PU	PR	PT	BI	AU
TE	0.827								
OR	0.529	0.869							
EN	0.666	0.528	0.844						
PEOU	0.671	0.546	0.697	0.834					
PU	0.666	0.489	0.660	0.705	0.854				
PR	0.575	0.477	0.634	0.616	0.584	0.822			
PT	0.668	0.598	0.637	0.667	0.693	0.550	0.831		
BI	0.486	0.371	0.492	0.492	0.478	0.406	0.483	0.814	
AU	0.590	0.399	0.566	0.605	0.597	0.513	0.535	0.701	0.882

Table 3. HTMT ratios evaluation.

	TE	OR	EN	PEOU	PU	PR	PT	BI	AU
TE									
OR	0.623								
EN	0.770	0.616							
PEOU	0.786	0.642	0.806						
PU	0.798	0.589	0.781	0.844					
PR	0.679	0.568	0.740	0.727	0.707				
PT	0.772	0.705	0.725	0.767	0.823	0.638			
BI	0.571	0.439	0.574	0.579	0.576	0.481	0.559		
AU	0.688	0.468	0.652	0.707	0.715	0.604	0.613	0.824	

4.3. Structural Model Evaluation

Once the measurement model was confirmed, the hypothesized structural paths were estimated using the entire sample of 385 respondents. Statistical inference for each path coefficient relied on a nonparametric bootstrap with 10,000 draws, from which bias-corrected 95% confidence intervals were constructed. No demographic covariates were introduced into the model because the aim was to assess the strength of the theorized associations among the focal constructs rather than to isolate their effects net of background characteristics. The resulting parameter estimates for the direct paths are summarized in Table 4.

Table 4. Path analysis results for main effects.

Construct	β	SD	2.5%	97.5%	t-Value	p-Value	Decision
H1a: PU $\rightarrow$ BI	0.149	0.066	0.023	0.277	2.267	0.023	Accepted
H1b: PEOU $\rightarrow$ BI	0.201	0.078	0.056	0.361	2.610	0.009	Accepted
H1c: PEOU $\rightarrow$ PU	0.356	0.055	0.246	0.461	6.452	<0.001	Accepted
H2a: PT $\rightarrow$ BI	0.199	0.070	0.060	0.334	2.806	0.005	Accepted
H2b: PR $\rightarrow$ BI	0.086	0.060	−0.032	0.205	1.421	0.155	Rejected
H3a: TE $\rightarrow$ PU	0.260	0.051	0.159	0.357	5.079	<0.001	Accepted
H3b: TE $\rightarrow$ PEOU	0.317	0.053	0.213	0.417	6.058	<0.001	Accepted
H4a: OR $\rightarrow$ PU	0.043	0.041	−0.036	0.126	1.037	0.300	Rejected
H4b: OR $\rightarrow$ PEOU	0.169	0.046	0.080	0.256	3.708	<0.001	Accepted
H5a: EN $\rightarrow$ PU	0.217	0.053	0.115	0.320	4.092	<0.001	Accepted
H5b: EN $\rightarrow$ PEOU	0.397	0.053	0.292	0.499	7.416	<0.001	Accepted
H7: BI $\rightarrow$ AU	0.701	0.028	0.640	0.752	24.629	<0.001	Accepted

4.3.1. Direct Effects

As reported in Table 4, among the four direct antecedents of BI, three paths reached statistical significance. PEOU exhibited the strongest direct effect on BI ($\beta = 0.201$, $p = 0.009$), followed closely by PT ($\beta = 0.199$, $p = 0.005$) and PU ($\beta = 0.149$, $p = 0.023$). These results supported H1a, H1b, and H2a. The prominence of PEOU and PT over PU suggested that, for business students, the immediate accessibility of GenAI tools and confidence in their reliability carried greater weight in shaping intention than the abstract assessment of utility. By contrast, the path from PR to BI was not significant ($\beta = 0.086$, $p = 0.155$), and its 95% bias-corrected confidence interval included zero (−0.032 to 0.205). H2b was therefore not supported. The non-significant and directionally positive coefficient indicated that risk perception, in isolation, neither suppressed nor promoted students' intention to use GenAI tools.

Turning to the antecedents of the TAM belief constructs, PEOU strongly predicted PU ($\beta = 0.356$, $p < 0.001$), which upheld H1c and the core TAM premise that ease of use enhances perceived usefulness. Among the three TOE dimensions, TE was positively associated with both PU ($\beta = 0.260$, $p < 0.001$) and PEOU ($\beta = 0.317$, $p < 0.001$), supporting H3a and H3b. EN showed the strongest association with PEOU ($\beta = 0.397$, $p < 0.001$) and also predicted PU ($\beta = 0.217$, $p < 0.001$), consistent with H5a and H5b. Peer influence thus appeared to be the strongest external factor shaping how easy students found GenAI tools to use, surpassing even the contribution of technical infrastructure. OR significantly predicted PEOU ($\beta = 0.169$, $p < 0.001$) but not PU ($\beta = 0.043$, $p = 0.300$), resulting in support for H4b and rejection of H4a. This pattern suggested that while institutional training could lower the perceived barriers to using GenAI, it did not by itself persuade students of its academic value. Finally, BI was a strong predictor of AU ($\beta = 0.701$, $p < 0.001$), confirming H7.

The model's explanatory power was assessed using the coefficient of determination (R^2) and its predictive relevance by means of the Stone-Geisser Q^2 . The R^2 values indicated that the model accounted for 60.0% of the variance in PU, 58.1% in PEOU, 52.9% in PT, 43.7% in PR, 49.1% in AU, and 30.1% in BI. The R^2 for PU, PEOU, PT, and AU were in the moderate-to-substantial bracket, while those for PR and BI were moderate, based on established thresholds for PLS-SEM research [54]. A blindfolding procedure with an omission distance of 7 produced Q^2 values above zero for every endogenous construct, indicating adequate out-of-sample predictive capacity.

To gauge the incremental contribution of the extended framework, a baseline TAM-only model was estimated with PU and PEOU as the sole predictors of BI. This reduced model yielded an R^2 of 0.279 for BI, while the full model increased the R^2 to 0.301, corresponding to a modest gain of 0.022. The limited increase did not imply that PT and PR are unimportant. Rather, it suggested that their influence did not follow a simple linear additive logic and might instead operate through configurational mechanisms, wherein trust and risk combined with other conditions to shape behavioral intention. This possibility was examined in the fsQCA analysis that followed.

4.3.2. Mediation Analysis

Table 5 shows that PT carried significant indirect effects from both PU ($\beta = 0.087$, $p = 0.008$, 95% CI [0.027, 0.156]) and PEOU ($\beta = 0.070$, $p = 0.013$, 95% CI [0.021, 0.132]) to BI, thereby supporting H6a and H6b. These results pointed to a meaningful cognitive-affective route, in which students who found GenAI useful and easy to operate tended to build stronger trust in the tools, which then translated into a greater willingness to use them. The indirect effect via PU ($\beta = 0.087$) was slightly larger than that via PEOU ($\beta = 0.070$), suggesting that perceived utility is a somewhat stronger foundation for trust formation than perceived ease of operation. To further quantify the strength of these indirect pathways, the variance accounted for (VAF) index was computed. The VAF for the PU $\rightarrow$ PT $\rightarrow$ BI path was 36.9%, and for the PEOU $\rightarrow$ PT $\rightarrow$ BI path was 25.8%. Both values fall within the 20% to 80% range, indicating complementary partial mediation rather than full mediation [53]. PT does not replace the direct effects of PU and PEOU on BI. Instead, it provides an additional cognitive-affective channel through which these evaluations translate into BI. The higher VAF of the PU-mediated pathway further verifies that competence-based trust rooted in PU exerts a stronger influence on business students' GenAI adoption intention than convenience-based trust derived from PEOU.

Table 5. Path analysis results for mediation effects.

Construct	β	SD	2.5%	97.5%	t-Value	p-Value	Decision
H6a: PU $\rightarrow$ PT $\rightarrow$ BI	0.087	0.033	0.027	0.156	2.663	0.008	Accepted
H6b: PEOU $\rightarrow$ PT $\rightarrow$ BI	0.070	0.028	0.021	0.132	2.497	0.013	Accepted
H6c: PU $\rightarrow$ PR $\rightarrow$ BI	0.026	0.019	−0.010	0.066	1.348	0.178	Rejected
H6d: PEOU $\rightarrow$ PR $\rightarrow$ BI	0.035	0.025	−0.013	0.088	1.371	0.170	Rejected

By contrast, PR did not function as a significant mediator. Neither the indirect path from PU through PR to BI ($\beta = 0.026$, $p = 0.178$) nor that from PEOU through PR to BI ($\beta = 0.035$, $p = 0.170$) reached significance, leading to the rejection of H6c and H6d. Taken together with the non-significant direct effect of PR on BI, these findings consistently indicated that PR, although recognized by students, did not systematically translate into behavioral avoidance. This pattern implied a degree of risk tolerance among business students, whereby they might acknowledge the potential downsides of GenAI use (e.g.,

inaccurate information, academic integrity concerns), yet such awareness did not reliably deter their intention when trust, usefulness, and ease of use were present.

4.4. FsQCA Results

PLS-SEM is well suited to estimating the average contribution of each variable, but its linear design makes it less sensitive to the ways in which variables may interact or combine. fsQCA addresses this limitation by shifting the analytical focus from individual net effects to configurations of conditions, asking which combinations are sufficient to produce the outcome. Together, these two methods offer complementary perspectives, one symmetric and the other asymmetric, on the same underlying phenomena.

In this study, fsQCA was employed to identify combinations of antecedent conditions that lead to business administration students' high BI to use GenAI tools. By examining these configurations, the analysis provided deeper insights into the complex interplay among antecedent variables and students' behavioral intention.

4.4.1. Calibration

The first step in the fsQCA workflow was to convert each variable into a fuzzy membership score via direct calibration. In line with established guidelines [56], the 5th percentile served as the threshold for full non-membership, the 50th percentile marked the crossover point, and the 95th percentile defined full membership. After this step, every case held a membership value ranging from 0 to 1 for both the conditions and the outcome.

4.4.2. Necessity Analysis

After calibration, the analysis examined whether any individual condition was necessary to produce high behavioral intention. The standard threshold for a necessary condition is a consistency score of at least 0.90 [57]. As shown in Table 6, all antecedent conditions and their negations fell short of this cutoff. Thus, no single factor alone was indispensable for the outcome, suggesting that high BI arose from the joint contribution of several conditions rather than from a solitary cause. This finding supported moving to the sufficiency analysis.

Table 6. Necessity Analysis.

Variable	Consistency	Coverage	Variable	Consistency	Coverage
TE	0.762	0.852	~PU	0.542	0.605
~TE	0.615	0.610	PEOU	0.762	0.831
OR	0.715	0.787	~PEOU	0.609	0.617
~OR	0.628	0.631	PT	0.779	0.787
EN	0.801	0.834	~PT	0.570	0.624
~EN	0.599	0.635	PR	0.784	0.798
PU	0.811	0.804	~PR	0.575	0.624

4.4.3. Sufficiency Analysis

A truth table was built to map all logically possible configurations of conditions linked to high behavioral intention [56]. To ensure that only empirically grounded configurations entered the logical minimization, a minimum case frequency of 3 was applied. Configurations with a raw consistency below 0.80 were treated as insufficiently reliable for the outcome. The PRI further screened out configurations with ambiguous empirical support; rows with PRI above 0.70 were coded as contributing to the outcome, while those falling below were excluded as contradictory. After applying these filters, 18 truth table rows qualified for Boolean minimization. The resulting solution attained an overall consistency of 0.918.

The logical reduction step generated three kinds of output, a complex, a parsimonious, and an intermediate solution. As is typical in configurational studies [58,59], the intermedi-

ate solution served as the primary basis for substantive interpretation, offering a workable middle ground between empirical precision and theoretical coherence. When a condition surfaced in both the parsimonious and the intermediate solution, it was classified as a core element of that configuration; conditions appearing solely in the intermediate solution were regarded as peripheral contributors. Table 7 lists all resulting configurations.

Table 7. Analysis of sufficient configurations.

Conditions	S ₁	S ₂	S ₃	S ₄	S ₅	S ₆	S ₇
TE	●	●	●	●	⊗		●
OR				⊗	●	●	●
EN	●		⊗		●	⊗	●
PU	●	●	●	●	●	●	
PEOU	●	●	⊗	⊗		●	●
PT		●	●	●	●	●	●
PR		⊗	●	●	⊗	●	●
Raw coverage	0.551	0.397	0.347	0.336	0.322	0.365	0.438
Unique coverage	0.064	0.009	0.010	0.007	0.020	0.019	0.025
Consistency	0.927	0.950	0.958	0.951	0.953	0.952	0.933
Solution coverage				0.685			
Solution consistency				0.918			

Note: ● (large) indicates the core presence of conditions; ● (small) indicates the peripheral presence of conditions; ⊗ (large) denotes the core absence of conditions; ⊗ (small) reflects the peripheral absence of conditions. Blank cells indicate ‘do not care’ situations.

Table 7 shows seven configurations that lead to high BI. The overall solution coverage is 0.685 and the overall solution consistency is 0.918, indicating that these seven configurations collectively account for a substantial proportion of the outcome and exhibit a high degree of consistency. Based on shared core conditions and underlying causal mechanisms, the seven configurations can be further grouped into five typical pathways.

Configurations 1 (raw coverage = 0.551, consistency = 0.927) and 2 (raw coverage = 0.397, consistency = 0.950) share the co-presence of PU, PEOU, and TE as driving conditions, reflecting the classical TAM logic. These two configurations can be merged into a TAM-driven path, in which students’ behavioral intention is primarily shaped by the perceived utility and usability of GenAI tools, reinforced by adequate technical infrastructure. Configuration 1 represented a stronger variant of this mechanism, with PU, PEOU, and TE serving as core conditions and EN as a peripheral contributor. Configuration 2 represented a milder variant, where all conditions acted peripherally and were further supplemented by PT and the absence of PR.

Configurations 3 (raw coverage = 0.347, consistency = 0.958) and 4 (raw coverage = 0.336, consistency = 0.951) exhibited a distinct pattern in which PT was present while PEOU was absent, and PR coexisted with high BI. These two configurations can be grouped into a trust-compensated path, where trust in GenAI tools compensates for the lack of ease of use, and the presence of risk does not deter continued use. The two configurations differ in the specific contextual deficit. Configuration 3 is characterized by the peripheral absence of EN, whereas Configuration 4 is marked by the core absence of OR.

Configuration 5 (raw coverage = 0.322, consistency = 0.953) represented an environment-driven low-risk path. Its core conditions consisted of EN, PU, and the absence of PR, with OR and PT as peripheral enablers. In this pathway, EN and a low-risk perception served as the primary drivers, while TE was notably absent. Configuration 6 (raw coverage = 0.365, consistency = 0.952) constituted an organization-driven risk-tolerant path. Core conditions included OR, PU, PR, and the absence of EN, with PEOU and PT acting peripherally. This pathway indicated that strong institutional backing could sustain students’ intention even when EN was weak and PR was high. Configuration 7 (raw coverage = 0.438,

consistency = 0.933) reflected a comprehensive external-support path, in which all three TOE factors (TE, OR, and EN) were present as core or peripheral conditions, alongside PEOU, PT, and PR. Notably, PU was not a necessary condition in this configuration, suggesting that robust external support could fully compensate when PU is not a differentiating factor in driving BI.

Because PT and PR exhibited skewed distributions in the present sample, the positioning of cases relative to the crossover threshold may be sensitive to the exact calibration anchor chosen. To address this concern, beyond the standard percentile-based calibration, a sensitivity analysis was performed by shifting the crossover points of PT and PR by $\pm 5\%$ and re-estimating all sufficiency solutions. As reported in Table 8, all five generalized core pathways remained fully intact under both perturbations. The addition or disappearance of only marginal fine-grained sub-configurations occurred within each pathway category, while the core condition combinations and their underlying theoretical logic were unchanged. In terms of global model performance, the overall solution consistency varied within a narrow range of 0.912 to 0.918, and overall coverage ranged from 0.685 to 0.701. The minimal variation in aggregate indicators, together with the stable retention of five core pathways, confirmed that the calibration thresholds and derived configurations were robust to moderate perturbation of the crossover anchor.

Table 8. Robustness of five generalized core pathways under $\pm 5\%$ crossover perturbation.

Five Generalized Core Pathways	Baseline	Crossover -5%	Crossover $+5\%$
P1: TAM-driven path (PU+PEOU+TE core)	(S1,S2)	✓	✓
P2: Trust-compensated path ($\sim$ PEOU+PT+PR)	(S3,S4)	✓	✓
P3: Environment-driven low-risk path (EN+ $\sim$ PR, $\sim$ TE)	(S5)	✓	✓
P4: Organization-driven risk-tolerant path (OR+PR, $\sim$ EN)	(S6)	✓	✓
P5: Comprehensive external-support path (TE+OR+EN coexist)	(S7)	✓	✓
Total fine-grained configurations	7	8	8
Solution coverage	0.685	0.701	0.694
Solution consistency	0.918	0.912	0.914

Note: “✓” indicates the core causal mechanism of the pathway remains intact under the corresponding calibration threshold. The codes in parentheses represent specific fine-grained configurations belonging to this pathway. Baseline = original crossover anchor; Crossover -5% = PT & PR crossover values reduced by 5%; Crossover $+5\%$ = PT & PR crossover values increased by 5%.

5. Discussion

5.1. Cognitive Perceptions and Behavioral Intention (RQ1)

The PLS-SEM results reveal the linear mechanisms behind business administration students' intention to use GenAI. Among cognitive perceptions, PEOU and PT emerge as stronger predictors than PU, departing from the conventional TAM hierarchy [21]. This suggests that the conversational interface of GenAI makes ease of use a differentiating factor, while general usefulness has become a baseline expectation rather than a discriminating variable [64]. The prominence of trust further indicates that students' confidence in system reliability is at least as important as their cognitive assessment of utility when AI operates with a degree of autonomy [34]. This hierarchy is particularly relevant to business administration education. Students routinely tackle unstructured case analyses and strategic simulations that demand rapid switching between analytical tools, making immediate accessibility more salient than abstract utility assessment. Furthermore, when these students depend on AI-generated industry reports or financial projections for coursework, the credibility of outputs directly affects both academic performance and the development of professional judgment, making trust a prerequisite rather than a secondary consideration. At the same time, PEOU remains a strong predictor of PU, confirming that

the core TAM mechanism, in which ease of use fosters PU, holds even when the relative importance of direct predictors of BI shifts.

5.2. TOE Contextual Supports, Perceived Ease of Use and Perceived Usefulness (RQ2)

Within the TOE framework, EN emerges as the strongest contextual driver of PEOU and a substantial predictor of PU, while TE plays the most robust role in shaping PU and also strongly predicts PEOU [39]. This pattern aligns with evidence that social influence dominates GenAI adoption among university students [65,66] and suggests that observing peers actively use and endorse GenAI carries more persuasive weight than institutional directives or inherent technical qualities. A striking asymmetry emerges with respect to OR. While institutional training can lower operational barriers and enhance PEOU, it does not by itself persuade students of the academic value of GenAI tools, a decoupling pattern consistent with recent evidence [67,68]. The effect size for the OR → PU path was negligible ($f^2 = 0.003$), far below Cohen's small-effect benchmark of 0.02 [69], confirming that the null result stems from a substantively trivial relationship rather than insufficient power. OR therefore functions more as an enabling condition than as a direct driver of PU.

For business education, this implies that generic workshops are insufficient; meaningful adoption requires embedding GenAI into case-based pedagogy and strategic exercises rather than offering stand-alone technology orientation. The measurement emphasis on training provision rather than curriculum integration may partly explain the pattern, and the effect of OR on PU could be further conditioned by unmeasured factors such as students' prior AI literacy.

The primacy of peer influence over institutional directives, as well as the weak translation of OR into PU, is further shaped by the Chinese institutional landscape. The dominance of peer influence over organizational support resonates with a collectivist cultural orientation [70], in which peer networks serve as trusted sources of behavioral validation. The fragmented regulatory environment across Chinese universities, where some institutions embrace GenAI while others restrict or ban foreign platforms, may explain why OR does not consistently translate into perceived usefulness. Concurrently, the rapid emergence of domestic GenAI platforms such as DeepSeek, Kimi, and Doubao has created a distinct technological ecosystem in which trust-building mechanisms may leverage pre-existing user trust in familiar parent companies.

5.3. Mediating Roles of Perceived Trust and Perceived Risk (RQ3)

The mediation analysis offers a nuanced picture of how cognitive evaluations translate into behavioral intention. PT serves as a significant mediator linking both PU and PEOU to BI, revealing a cognitive–affective pathway in which positive evaluations foster trust, which in turn heightens behavioral intention [71]. The indirect effect via PU is slightly larger than via PEOU, suggesting that competence-based trust outweighs convenience-based trust [33]. This mediating role of trust is particularly salient for business administration students, as tasks such as drafting business plans, analyzing competitive landscapes, or formulating strategic recommendations involve outputs with direct academic and early-career implications, making trust in the reliability of AI-generated content a necessary cognitive gateway. In contrast, PR does not function as a significant mediator, and both its direct and indirect effects are directionally positive rather than negative. This counterintuitive pattern suggests a risk tolerance phenomenon, in which students who engage more extensively with GenAI become more aware of its risks, yet this awareness does not deter continued use when trust is present. From a cognitive appraisal perspective [72], some students may frame GenAI-related risks as challenges to be managed rather than threats to be avoided. PT and PR therefore represent separate evaluative dimensions, not opposite poles of a single trust–distrust continuum. This

finding resonates with the privacy paradox literature [73] and, as elaborated below, is further illuminated by the configurational analysis.

5.4. Configurational Pathways for High Behavioral Intention (RQ4)

5.4.1. Core Pathways to High Behavioral Intention

The fsQCA results provide a configurational perspective that both reinforces and extends the PLS-SEM findings. Seven configurations are identified and grouped into five typical pathways. The TAM-driven path, encompassing two variants with differing condition strength, corroborates that PU, PEOU, and TE are central drivers of BI. The trust-compensated path reinforces the mediating role of trust identified in the PLS-SEM analysis, while the environment-driven low-risk path corroborates the primacy of peer influence.

5.4.2. Divergent Roles of Perceived Risk and Organizational Support

Beyond this broad convergence, two points of divergence are particularly revealing. First, PR exhibits no significant net effect in PLS-SEM, which might suggest it is inconsequential. The fsQCA results, however, show PR playing a pronounced dual role, in which it appears as a core present condition in two pathways and as a core absent condition in one. Risk perception can coexist with high BI when buffered by strong trust, organizational support, or comprehensive external infrastructure, or be absent when peer influence and ease of use suffice. The null net effect reflects averaging rather than irrelevance, demonstrating that conditions deemed unimportant by net-effect models may nonetheless be decisive for specific subgroups.

Second, OR's non-significant direct effect on PU in PLS-SEM is contextualized by fsQCA. OR acts as a core condition specifically in the organization-driven risk-tolerant path, where it compensates for the absence of peer influence and the presence of high risk. In other configurations, OR is absent, confirming that OR is not a universal requirement but a targeted compensatory resource decisive for only a specific student segment.

These findings underscore the complementary value of integrating PLS-SEM and fsQCA [58,74]. PLS-SEM identifies average net effects, establishing which factors matter across the full sample; fsQCA uncovers multiple equifinal pathways and reveals asymmetric, context-dependent roles that net-effect models necessarily average out [75]. The five pathways illustrate that high intention arises from qualitatively different configurations rather than a single dominant mechanism [52]. More concretely, some students are driven primarily by the perceived utility and usability of GenAI tools, requiring little external support; others persist because they trust the outputs even when the tools are difficult to use; a third group is sustained mainly by strong peer networks and low risk perceptions; a fourth relies on institutional support as a lifeline in the absence of peer influence; and a fifth thrives only when all three TOE supports are simultaneously present. These distinct profiles underscore that no single intervention strategy works for all students.

6. Theoretical and Practical Implications

6.1. Theoretical Implications

This study advances the literature on GenAI adoption in higher education by integrating the TOE framework with an extended TAM that incorporates PT and PR. While prior research has examined these elements in isolation [8,23], few studies have systematically combined internal cognitive perceptions with external contextual factors at the individual student level. By situating technical, organizational, and environmental supports as antecedents to the TAM belief constructs, this study provides a more comprehensive theoretical architecture that captures both psychological and contextual determinants of

behavioral intention. This integrated framework serves as a theoretical roadmap for future research examining the interplay between individual cognition and contextual conditions in technology adoption.

The findings of this study also invite comparison with recent international research on GenAI adoption in higher education. The primacy of PEOU and PT over PU aligns with studies conducted in Korea [64] and the Middle East [17], where the conversational nature of GenAI similarly elevates ease of use above traditional utility assessments. However, this pattern diverges from findings in some Western contexts where PU remains the dominant predictor [23], possibly reflecting differences in instructional design and the degree to which GenAI is formally embedded in curricula. The risk tolerance observed in our Chinese sample echoes the privacy paradox documented in international settings [73], yet the near-zero effect of PR on BI contrasts with studies from Latin America [67] and Africa [66], where risk perceptions more consistently inhibit adoption. These cross-cultural variations suggest that the TOE-TAM framework, while broadly applicable, may exhibit context-dependent path configurations, a point that our fsQCA results further substantiate by demonstrating that identical outcomes can arise from qualitatively distinct condition combinations. The proposed framework therefore offers a flexible architecture that can be adapted and tested across diverse cultural and institutional settings.

Beyond the framework contribution, the fsQCA results offer further theoretical value. The configuration insights complement and deepen the PLS-SEM findings. These nonlinear pathways reveal the diversity of antecedent combinations underlying behavioral intention, moving beyond the single-variable determinism that characterizes much of the prior technology adoption literature. The configurational analysis shows that even under adverse conditions, such as the absence of peer influence or the presence of PR, high behavioral intention can still be achieved through compensatory mechanisms; for example, strong OR can offset weak peer influence, and high trust can buffer the presence of risk. Furthermore, the comparative analysis between the divergent roles of PR and OR across configurations demonstrates that these conditions operate through configurational logic, not linear effects.

6.2. Practical Implications

The findings offer several concrete directions for promoting students' sustained and effective use of GenAI in higher business education. Rather than pursuing a one-size-fits-all approach, stakeholders can benefit from tailoring their efforts to the different mechanisms identified in this study.

For GenAI platform developers, the priority should be making tools genuinely easy to use and trustworthy, rather than adding more functions [64]. Students in our sample value an intuitive interface and reliable output more than feature richness. Several practical steps follow from this insight. First, GenAI tools could be integrated directly into existing learning management systems, allowing students to access AI assistance from the same platform where they submit assignments. This removes the friction of switching between separate applications. Second, AI-generated responses could be accompanied by simple indicators showing the source of key claims or the degree of confidence in the output, helping students judge when to trust and when to verify. Third, for common business school tasks such as SWOT analysis, industry benchmarking, or financial ratio interpretation, pre-built prompt templates could guide students who are still learning how to interact effectively with GenAI tools. Given that trust is the sole significant mediator linking perceptions to intention, investments in transparency and reliability are likely to yield greater returns than investments in functional complexity.

For university administrators and instructors, the primacy of peer influence as a contextual driver points toward peer-led strategies rather than top-down directives [65,66].

A student AI ambassador program offers one practical model. A small group of students who are already proficient with GenAI can be trained and supported to run open workshops, hold drop-in hours, and share examples of effective AI use with their classmates. Students often find peer advice more approachable and credible than institutional announcements. At the same time, clear and specific course-level guidance on AI use is needed. Rather than issuing a blanket university-wide policy, each course syllabus could indicate the permitted level of AI assistance for different assignments, using a simple three-tier label, such as no AI allowed, AI allowed with disclosure, or AI use encouraged with reflection. This approach avoids both outright bans that students tend to circumvent and vague encouragement that leaves students uncertain about boundaries. Importantly, the fsQCA results show that different students arrive at high intention through different routes [52,75]. Some are driven primarily by the tool's perceived quality, others by peer networks, and still others by institutional support. Universities should therefore avoid treating all students the same. For students who are already comfortable with GenAI, maintaining good infrastructure and reinforcing the usefulness of the tools may be sufficient. For those who find GenAI difficult to use, providing hands-on, peer-led guidance is more effective than general training sessions. For students who lack strong peer networks around GenAI, targeted institutional support becomes essential. This group includes, for example, first-year students who have not yet built peer-learning circles or commuting students with less campus engagement.

From a resource allocation standpoint, the five equifinal pathways identified by fsQCA provide a practical framework for matching strategies to student profiles [23,74]. The largest student segment follows a TAM-driven logic and needs reliable infrastructure and clear demonstrations of utility, which is the most cost-effective starting point. A second segment, the trust-compensated group, continues to use GenAI even when they find it difficult, because they trust the outputs. For these students, trust-building measures such as transparent sourcing and accuracy indicators matter more than interface improvements. A third segment is sustained mainly by strong peer influence and low risk perceptions; here, the highest return comes from cultivating peer-learning communities. A fourth segment relies on institutional support to compensate for weak peer networks and high risk awareness, calling for dedicated one-on-one guidance. A fifth segment benefits only when all three external supports, technical, organizational, and environmental, are present simultaneously, representing the most resource-intensive scenario that well-equipped institutions may pursue. By identifying which segment a given group of students falls into, educators and administrators can allocate resources more precisely rather than spreading them thinly across uniform programs.

7. Conclusions

This study explores the mechanisms shaping business administration students' intention to use GenAI tools to support their academic work. The integration of PLS-SEM and fsQCA provides a comprehensive understanding of these mechanisms. The PLS-SEM results reveal that PEOU and PT are the strongest direct predictors of intention, while EN emerges as the strongest contextual driver of PEOU and TE plays the most robust role in shaping PU. OR exhibits a marked asymmetry, facilitating PEOU but failing to enhance PU. PT serves as the sole significant mediator, forming a cognitive-affective pathway linking cognitive evaluations to intention. In contrast, PR neither directly inhibits intention nor functions as a mediating mechanism, revealing a risk tolerance pattern among business students. The fsQCA findings complement the linear models by identifying seven configurations, grouped into five typical pathways, that lead to high BI. PR and OR, which appear non-significant in the net-effect analysis, play decisive configurational roles for specific student segments. Strong peer influence and high PT are fundamental conditions

across multiple pathways, while the absence of PU can be compensated by comprehensive external support.

Several limitations should be noted. First, the sample was limited to undergraduate students from a single discipline at Chinese universities, which restricts generalizability across academic levels, fields of study, and cultural contexts. Second, the survey did not differentiate among specific GenAI platforms; between-tool differences in inference latency may have influenced PEOU ratings in ways this study cannot isolate. Third, the present evaluation was situated in conventional campus network settings. As educational delivery increasingly moves toward advanced infrastructures such as 6G and aerial–terrestrial integrated networks [76], the GenAI access environment may shift in ways that warrant continued investigation.

Author Contributions: Conceptualization, L.J. and S.Y.; methodology, L.J.; software, L.J.; validation, L.J. and S.Y.; formal analysis, L.J.; data curation, L.J. and S.Y.; writing—original draft preparation, L.J.; writing—review and editing, L.J. and S.Y.; funding acquisition, L.J. and S.Y. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Sichuan Science and Technology Program (Grant No. 2026NSFSC1108); the Chengdu University of Technology Higher Education Talent Training Quality and Teaching Reform Project (Grant No. JG2430076); Philosophy and Social Sciences of Chengdu University of Technology (Grant No. YJ2025-CZ008); the Ministry of Education’s Collaborative Education-Industry Cooperation Project for Enhancing Practical Skills (Grant No. 241000512211223).

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki, and approved by the Ethics Review Form for Studies at College of Management Science, Chengdu University of Technology (protocol code 2026041301 and date of approval 13 April 2026).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Data will be made available on request.

Acknowledgments: During the preparation of this manuscript, the authors used ChatGPT-4o and DeepSeek-V4 for the purposes of language editing and grammar checking. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. Construct Scale

Table A1. Measurement items for all constructs.

Item	Wording	References
Technical Support (TE)		
TE1	My existing network and device conditions support the smooth use of GenAI tools for coursework and research tasks	[39]
TE2	A wide range of GenAI tools are currently available for my use	
TE3	The free features of GenAI tools are sufficient to meet my basic needs for coursework and research papers	[77]
TE4	When encountering problems with GenAI tools, I can quickly find solutions (e.g., official help documentation, online tutorials)	
Organizational Support (OR)		
OR1	My university provides adequate training and guidance on using GenAI tools (e.g., ChatGPT, DeepSeek)	[43]
OR2	My university provides the necessary resources and technical support for using GenAI tools	
OR3	My university actively encourages students to use GenAI tools to support coursework and research activities	[44]

Table A1. *Cont.*

Item	Wording	References
Environmental Support (EN)		
EN1	I would try using GenAI tools if my classmates were using them for coursework or research papers	[65]
EN2	I am more willing to try GenAI tools if instructors or advisors recommend using them for coursework or research	[66]
EN3	Discussions and recommendations on social media and academic communities influence my willingness to use GenAI tools	[40]
EN4	I believe that familiarity with GenAI tools will be important for my future career, which motivates me to use them for coursework and research	[40]
Perceived Usefulness (PU)		
PU1	GenAI tools significantly improve my efficiency in completing coursework and research papers	[21]
PU2	GenAI tools offer clear advantages over other tools in tasks such as case analysis, data analysis, literature review, and solution design	
PU3	Content generated by GenAI tools (e.g., industry analysis frameworks, paper outlines, decision-making suggestions) provides practical support for my learning and research	[28]
Perceived Ease of Use (PEOU)		
PEOU1	GenAI tools have a user-friendly interface and can be operated using natural language	[21]
PEOU2	Using GenAI tools does not require complex procedures or technical knowledge	[29]
PEOU3	Learning to use GenAI tools is easy for me	
PEOU4	I can easily get GenAI tools to understand my needs and provide responses	
Perceived Trust (PT)		
PT1	I believe GenAI tools can protect my personal information and learning data during use	[33]
PT2	I believe the information provided by GenAI tools is reliable for tasks such as business case analysis, industry research, and paper writing	
PT3	Overall, I find GenAI tools to be trustworthy	[49]
PT4	I trust the outputs of GenAI tools and am willing to use them as references for coursework and research papers	[47]
Perceived Risk (PR)		
PR1	I am concerned that content generated by GenAI tools may contain factual errors or misleading information	[31]
PR2	I am concerned that using GenAI tools for coursework or research papers may violate academic integrity requirements	
PR3	I am concerned that submitting assignments or papers containing GenAI-generated content may lead to questions about their originality	[36]
PR4	I am concerned that long-term reliance on GenAI tools may weaken my ability to analyze problems independently and think innovatively	

Table A1. Cont.

Item	Wording	References
Behavioral Intention (BI)		
BI1	I intend to continue using GenAI tools in my future coursework	[21]
BI2	I plan to continue using GenAI tools for paper writing	[23]
BI3	I am willing to recommend GenAI tools to classmates, friends, and others	
BI4	I would actively use GenAI tools to support my learning and research even without external requirements	
Actual Usage (AU)		
AU1	I frequently use GenAI tools to assist with coursework and research tasks	[21]
AU2	I use GenAI tools across various learning and research scenarios (e.g., case analysis, literature search, data analysis, paper writing)	[52]
AU3	Using GenAI tools has become part of my daily learning and research routine	

Note: All items were measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

References

- Park, J. A systematic literature review of generative artificial intelligence (GenAI) literacy in schools. *Comput. Educ. Artif. Intell.* **2025**, *9*, 100487. [\[CrossRef\]](#)
- Alwakid, W.N.; Dahri, N.A.; Humayun, M.; Alwakid, G.N. Exploring the role of AI and teacher competencies on instructional planning and student performance in an outcome-based education system. *Systems* **2025**, *13*, 517. [\[CrossRef\]](#)
- Liu, Y.; Awang, H.; Mansor, N.S. Exploring the potential barrier factors of AI chatbot usage among teacher trainees: From the perspective of innovation resistance theory. *Sustainability* **2025**, *17*, 4081. [\[CrossRef\]](#)
- Wang, L.; Song, R.; Guo, W.; Yang, H. Exploring prompt pattern for generative artificial intelligence in automatic question generation. *Interact. Learn. Environ.* **2025**, *33*, 2559–2584.
- Arar, K.H.; Özen, H.; Polat, G.; Turan, S. Artificial intelligence, generative artificial intelligence and research integrity: A hybrid systemic review. *Smart Learn. Environ.* **2025**, *12*, 44–72. [\[CrossRef\]](#)
- Yang, M.; Luo, T.; Herman, K.; Li, B.; Chappell Moots, S.; Glaser, N.; Jiang, S. Examining non-traditional online learners' ownership of learning in the context of ChatGPT-facilitated design. *J. Comput. High. Educ.* **2025**, *37*, 1531–1563. [\[CrossRef\]](#)
- Yim, I.H.Y.; Su, J. Artificial intelligence (AI) learning tools in K-12 education: A scoping review. *J. Comput. Educ.* **2025**, *12*, 93–131.
- Hsiao, C.H.; Tang, K.Y. Beyond acceptance: An empirical investigation of technological, ethical, social, and individual determinants of GenAI-supported learning in higher education. *Educ. Inf. Technol.* **2025**, *30*, 10725–10750.
- Gu, J.; Yan, Z. Effects of GenAI interventions on student academic performance: A meta-analysis. *J. Educ. Comput. Res.* **2025**, *63*, 1460–1492. [\[CrossRef\]](#)
- Göçer, Ş.; Karabatak, S. The impact of AI-supported online classroom management (AIS-OCM) on attitudes toward english lessons, self-directed online learning, and academic achievement. *Smart Learn. Environ.* **2026**, *13*, 24–52. [\[CrossRef\]](#)
- Ruiz-Rojas, L.I.; Acosta-Vargas, P. Transforming learning: Use of the 4PADAFE instructional design methodology and generative artificial intelligence in designing MOOCs for innovative education. *Sustainability* **2026**, *18*, 2683. [\[CrossRef\]](#)
- Ramírez-Correa, P.E.; Grandón, E.E.; Mariano, A.M. Mapping the landscape of generative artificial intelligence literacy: A systematic review toward social, ethical, and sustainable AI adoption. *Sustainability* **2026**, *18*, 1429. [\[CrossRef\]](#)
- Hu, W.; Chan, C.K.Y. From user needs to AI solutions: A human-centered design approach for AI-powered virtual teamwork competency training. *Int. J. Educ. Technol. High. Educ.* **2025**, *22*, 52–81. [\[CrossRef\]](#)
- Getchell, K.M.; Carradini, S.; Cardon, P.W.; Fleischmann, C.; Ma, H.; Aritz, J.; Stapp, J. Artificial intelligence in business communication: The changing landscape of research and teaching. *Bus. Prof. Commun. Q.* **2022**, *85*, 7–33. [\[CrossRef\]](#)
- Dziubaniuk, O.; Ivanova-Gongne, M.; Nyholm, M. Learning and teaching sustainable business in the digital era: A connectivism theory approach. *Int. J. Educ. Technol. High. Educ.* **2023**, *20*, 20–42. [\[CrossRef\]](#) [\[PubMed\]](#)
- Nyberg, A.J.; Schleicher, D.J.; Bell, B.S.; Boon, C.; Cappelli, P.; Collings, D.G.; Dalle Molle, J.E.; Feuerriegel, S.; Gerhart, B.; Jeong, Y.; et al. A brave new world of human resources research: Navigating perils and identifying grand challenges of the GenAI revolution. *J. Manag.* **2025**, *51*, 2677–2718. [\[CrossRef\]](#)
- Salem, M.A. A digital sustainability lens: Investigating medical students' adoption intentions for AI-Powered NLP Tools in learning environments. *Sustainability* **2025**, *17*, 6379. [\[CrossRef\]](#)

18. Honig, C.; Rios, L.; Desu, H. Generative AI in engineering education: Understanding acceptance and use of new GPT teaching tools within a UTAUT framework. *Australas. J. Eng. Educ.* **2025**, *30*, 80–92. [\[CrossRef\]](#)
19. Ma, Q. Modelling college students' acceptance to use generative artificial intelligence for second language learning: A theory of planned behaviour perspective. *Eur. J. Educ.* **2025**, *60*, e12923. [\[CrossRef\]](#)
20. Xiao, L.; Pyng, H.S.; Ayub, A.F.M.; Zhu, Z.; Gao, J.; Qing, Z. University students' usage of generative artificial intelligence for sustainability: A cross-sectional survey from China. *Sustainability* **2025**, *17*, 3541. [\[CrossRef\]](#)
21. Davis, F.D.; Bagozzi, R.P.; Warshaw, P.R. Technology acceptance model. *Manag. Sci.* **1989**, *35*, 982–1003. [\[CrossRef\]](#)
22. Venkatesh, V.; Morris, M.G.; Davis, G.B.; Davis, F.D. User acceptance of information technology: Toward a unified view. *MIS Q.* **2003**, *27*, 425–478. [\[CrossRef\]](#)
23. Foroughi, B.; Senali, M.G.; Iranmanesh, M.; Khanfar, A.; Ghobakhloo, M.; Annamalai, N.; Naghmeh-Abbaspour, B. Determinants of intention to use ChatGPT for educational purposes: Findings from PLS-SEM and fsQCA. *Int. J. Hum.-Comput. Interact.* **2024**, *40*, 4501–4520.
24. Shomotova, A.; ElSayary, A.; Husain, S. What shapes students' AI literacy? Investigating digital competence, student background, and GenAI use in higher education. *Educ. Inf. Technol.* **2026**, *31*, 387–418.
25. Song, Y.; Zhang, S.; Zhu, Z. Configuring factors influencing science teachers' intention to use virtual experiments in China: An fsQCA-based study. *J. Sci. Educ. Technol.* **2024**, *33*, 429–443.
26. Alkaws, G.; Ali, M.; Yahaya, N.; Halim, N. Determinants of open educational resources adoption and their impact on educational sustainability: A cross-cultural comparison using SEM-fsQCA. *Educ. Inf. Technol.* **2025**, *30*, 8687–8723.
27. Bayaga, A. AI-powered platforms in STEM education, insights from UTAUT model: PLS-SEM and artificial neural networks hybrid analysis. *Comput. Educ. Artif. Intell.* **2025**, *8*, 100080. [\[CrossRef\]](#)
28. Theresiawati; Hidayanto, A.N.; Seta, H.B.; Widyatmoko, A.M.; Muhammad, M.A.; Said, M.F.A.; Adifai, S.R. Analysis of factors influencing students' adoption of generative AI as a programming learning resource. *Interact. Learn. Environ.* **2025**, *30*, 2513–2530. [\[CrossRef\]](#)
29. Ke, Q.; Gong, Y. Linking TPACK to teacher self-efficacy in EFL teacher education: Mediating roles of perceived usefulness and perceived ease of use. *J. Res. Technol. Educ.* **2025**, *30*, 1–24. [\[CrossRef\]](#)
30. Machdar, N.M. The effect of information quality on perceived usefulness and perceived ease of use. *Bus. Entrep. Rev.* **2019**, *15*, 131–146. [\[CrossRef\]](#)
31. Liu, Y.; Wang, Q.; Lei, J. Adopting generative AI in future classrooms: A study of preservice teachers' intentions and influencing factors. *Behav. Sci.* **2025**, *15*, 1040. [\[CrossRef\]](#) [\[PubMed\]](#)
32. Zhai, C.; Wibowo, S.; Li, L.D. The effects of over-reliance on AI dialogue systems on students' cognitive abilities: A systematic review. *Smart Learn. Environ.* **2024**, *11*, 28–41. [\[CrossRef\]](#)
33. Wang, F.; Li, N.; Cheung, A.C.; Wong, G.K. In GenAI we trust: An investigation of university students' reliance on and resistance to generative AI in language learning. *Int. J. Educ. Technol. High. Educ.* **2025**, *22*, 59–75. [\[CrossRef\]](#)
34. Ahn, H.Y. Modeling student loyalty in the age of generative AI: A structural equation analysis of ChatGPT's role in higher education. *Systems* **2025**, *13*, 915. [\[CrossRef\]](#)
35. Kumar, R.; Singh, R.; Kumar, K.; Khan, S.; Corvello, V. How does perceived risk and trust affect mobile banking adoption? Empirical evidence from India. *Sustainability* **2023**, *15*, 4053. [\[CrossRef\]](#)
36. Zeng, D.; Xu, X.; Zhu, T.; Li, Y.; Li, Q. A two-step structural equation modeling and explainable machine learning framework for understanding university students' adoption of generative AI: Balancing intrinsic motivations and perceived risks. *Front. Psychol.* **2026**, *17*, 1743722. [\[CrossRef\]](#) [\[PubMed\]](#)
37. Huang, X.; Cui, Y.; Jia, D.; Ma, X.; Wang, Z.; Cui, R. Weaving Cognition, Emotion, Service, and Society: Unpacking Chinese Consumers' Behavioral Intention of GenAI-Supported Clothing Customization Services. *Systems* **2025**, *13*, 829. [\[CrossRef\]](#)
38. Tornatzky, L.; Fleischer, M. *The Process of Technology Innovation*; Lexington Books: Lanham, MD, USA, 1990.
39. Sui, C.J.; Yen, M.H.; Chang, C.Y. Investigating effects of perceived technology-enhanced environment on self-regulated learning. *Educ. Inf. Technol.* **2024**, *29*, 161–183. [\[CrossRef\]](#)
40. Bai, X.; Yang, L. Exploring the determinants of AIGC usage intention based on the extended AIDUA model: A multi-group structural equation modeling analysis. *Front. Psychol.* **2025**, *16*, 1589318. [\[CrossRef\]](#) [\[PubMed\]](#)
41. Huang, F.; Teo, T.; Scherer, R. Investigating the antecedents of university students' perceived ease of using the internet for learning. *Interact. Learn. Environ.* **2022**, *30*, 1060–1076.
42. Wang, Y. Government approaches and discussions on addressing AIGC challenges in education. *Front. Educ. Res.* **2024**, *7*, 192–196. [\[CrossRef\]](#)
43. Tennakoon, H.; Hansen, J.M.; Saridakis, G.; Samaratunga, M.; Hansen, J.W. Drivers and barriers of social sustainable development and growth of online higher education: The roles of perceived ease of use and perceived usefulness. *Sustainability* **2023**, *15*, 8319. [\[CrossRef\]](#)

44. Manresa, A.; Sammour, A.; Mas-Machuca, M.; Chen, W.; Botchie, D. Humanizing GenAI at work: Bridging the gap between technological innovation and employee engagement. *J. Manag. Psychol.* **2025**, *40*, 472–492.
45. Wang, H.; Liu, T. Psychological determinants of GenAI adoption for foreign language education: An extended UTAUT2 model and sentiment analysis approach. *Front. Psychol.* **2025**, *16*, 1622926. [[CrossRef](#)] [[PubMed](#)]
46. Shata, A.; Hartley, K. Artificial intelligence and communication technologies in academia: Faculty perceptions and the adoption of generative AI. *Int. J. Educ. Technol. High. Educ.* **2025**, *22*, 14–35. [[CrossRef](#)]
47. Lai, C.Y.; Cheung, K.Y.; Chan, C.S.; Law, K.K. Integrating the adapted UTAUT model with moral obligation, trust and perceived risk to predict ChatGPT adoption for assessment support: A survey with students. *Comput. Educ. Artif. Intell.* **2024**, *6*, 100246. [[CrossRef](#)]
48. Al Murshidi, G.; Shulgina, G.; Kapuza, A.; Costley, J. How understanding the limitations and risks of using ChatGPT can contribute to willingness to use. *Smart Learn. Environ.* **2024**, *11*, 36. [[CrossRef](#)]
49. Balaskas, S.; Tsiantos, V.; Chatzifotiou, S.; Rigou, M. Determinants of ChatGPT adoption intention in higher education: Expanding on TAM with the mediating roles of trust and risk. *Information* **2025**, *16*, 82. [[CrossRef](#)]
50. King, W.R.; He, J. A meta-analysis of the technology acceptance model. *Inf. Manag.* **2006**, *43*, 740–755. [[CrossRef](#)]
51. Scherer, R.; Siddiq, F.; Tondeur, J. The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. *Comput. Educ.* **2019**, *128*, 13–35. [[CrossRef](#)]
52. Hsu, L. From experience to adoption: Modelling EFL learners' GenAI continuance through linear and configurational approaches. *Eur. J. Educ.* **2025**, *60*, e70108. [[CrossRef](#)]
53. Hair, J.F.; Hult, G.T.M.; Ringle, C.M.; Sarstedt, M. *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, 3rd ed.; Sage: Newbury Park, CA, USA, 2021.
54. Hair, J.F.; Risher, J.J.; Sarstedt, M.; Ringle, C.M. When to use and how to report the results of PLS-SEM. *Eur. Bus. Rev.* **2019**, *31*, 2–24. [[CrossRef](#)]
55. Kock, N.; Lynn, G.S. Lateral collinearity and misleading results in variance-based SEM: An illustration and recommendations. *J. Assoc. Inf. Syst.* **2012**, *13*, 546–580. [[CrossRef](#)]
56. Ragin, C.C. *Redesigning Social Inquiry: Fuzzy Sets and Beyond*; University of Chicago Press: Chicago, IL, USA, 2009.
57. Ragin, C.C. *Fuzzy-Set Social Science*; University of Chicago Press: Chicago, IL, USA, 2000.
58. Kang, W.; Shao, B. The impact of voice assistants' intelligent attributes on consumer well-being: Findings from PLS-SEM and fsQCA. *J. Retail. Consum. Serv.* **2023**, *70*, 103130. [[CrossRef](#)]
59. Hou, W.; Peng, X.; Wang, L. The influence of contractual and relational governance on the sustainable performance of public-private partnership projects: Findings from PLS-SEM and fsQCA. *J. Knowl. Econ.* **2024**, *15*, 10826–10852.
60. Aguirre-Urreta, M.I.; Hu, J. Detecting common method bias: Performance of the Harman's single-factor test. In *ACM SIGMIS Database: The DATABASE for Advances in Information Systems*; Association for Computing Machinery: New York, NY, USA, 2019; Volume 50, pp. 45–70.
61. Taber, K.S. The use of Cronbach's alpha when developing and reporting research instruments in science education. *Res. Sci. Educ.* **2018**, *48*, 1273–1296.
62. Rasoolimanesh, S.M. Discriminant validity assessment in PLS-SEM: A comprehensive composite-based approach. *Data Anal. Perspect. J.* **2022**, *3*, 1–8.
63. Afzal, B.; Wen, X.; Nazir, A.; Junaid, D.; Olarte Silva, L.J. Analyzing the impact of social media influencers on consumer shopping behavior: Empirical evidence from Pakistan. *Sustainability* **2024**, *16*, 6079. [[CrossRef](#)]
64. Jang, M. AI literacy and intention to use text-based GenAI for learning: The case of business students in Korea. *Informatics* **2024**, *11*, 54. [[CrossRef](#)]
65. Korchak, A.; Al Murshidi, G.; Getman, A.; Raouf, N.; Arshe, M.; Al Meheiri, N.; Shulgina, G.; Costley, J. The role of social influence in generative artificial intelligence ChatGPT adoption intentions among undergraduate and graduate students. *Innov. Educ. Teach. Int.* **2025**, *62*, 1559–1573. [[CrossRef](#)]
66. Changalima, I.A.; Amani, D.; Ismail, I.J. Social influence and information quality on Generative AI use among business students. *Int. J. Manag. Educ.* **2024**, *22*, 101063. [[CrossRef](#)]
67. Vargas Bernuy, J.; Nolasco-Mamani, M.A.; Velásquez Rodríguez, N.C.; Gambetta Quelopana, L.M.; Martinez Valdivia, A.N.; Espinoza Vidaurre, S.M. Relative advantage and compatibility as drivers of ChatGPT adoption in Latin American higher education: A PLS-SEM study towards sustainable digital education. *Sustainability* **2025**, *17*, 8329. [[CrossRef](#)]
68. Yu, T.; Dai, J.; Chen, X.; Wang, C. To use or not to use? Generative AI adoption in Chinese business schools. *Int. J. Manag. Educ.* **2026**, *24*, 101323. [[CrossRef](#)]
69. Cohen, J. *Statistical Power Analysis for the Behavioral Sciences*, 2nd ed.; Routledge: Oxfordshire, UK, 2013.
70. Hofstede, G. *Culture's Consequences: Comparing Values, Behaviors, Institutions and Organizations Across Nations*, 2nd ed.; Sage: Thousand Oaks, CA, USA, 2001.
71. Tang, Y.; Su, L. Graduate education in China meets AI: Key factors for adopting AI-generated content tools. *Libri* **2025**, *75*, 81–96.

72. Espinoza Vidaurre, S.M.; Velásquez Rodríguez, N.C.; Gambetta Quelopana, L.M.; Martinez Valdivia, A.N.; Leo Rossi, E.A.; Nolasco-Mamani, M.A. Perceptions of artificial intelligence and its impact on academic integrity among university students in Peru and Chile: An approach to sustainable education. *Sustainability* **2024**, *16*, 9005. [[CrossRef](#)]
73. Chen, J.; Zhang, M.; Guo, M.; Gao, Z. The role of risk attitudes in shaping digital privacy preferences: Evidence from a large-scale survey. *Humanit. Soc. Sci. Commun.* **2025**, *12*, 109–121. [[CrossRef](#)]
74. Zhao, Y.; Li, Y.; Xiao, Y.; Chang, H.; Liu, B. Factors influencing the acceptance of ChatGPT in high education: An integrated model with PLS-SEM and fsQCA approach. *Sage Open* **2024**, *14*, 21582440241289835. [[CrossRef](#)]
75. Yu, X.; Hu, Y.; Hu, Y.; Li, K. Exploring factors that influence graduate students' intention to use generative artificial intelligence in academic research: PLS-SEM and fsQCA methods. *Educ. Inf. Technol.* **2025**, *30*, 19447–19472. [[CrossRef](#)]
76. Ma, Z.; Lu, S.; Peng, Y.; Zhou, J.; Xu, J.; Luo, G.; Luo, M. Geometrical-based modeling for aerial intelligent reflecting surface-based MIMO channels. *Electronics* **2026**, *15*, 875. [[CrossRef](#)]
77. Legesse, A.; Beshah, B.; Berhan, E.; Tesfaye, E. Exploring the influencing factors of blockchain technology adoption in national quality infrastructure: A Dual-Stage structural equation model and artificial neural network approach using TAM-TOE framework. *Cogent Eng.* **2024**, *11*, 2369220. [[CrossRef](#)]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.