International Journal of Instruction *January 2026 ● Vol.19, No.1*
e-ISSN: 1308-1470 ● www.e-iji.net *p-ISSN: 1694-609X*
pp. 293-320

Article submission code: 20250515132456
Received: 15/05/2025
Revision: 04/08/2025
Accepted: 11/08/2025
OnlineFirst: 03/10/2025

Exploring Student Satisfaction in Digital Business English Courses: A TAM-Based Mediation Model of Perceived Usefulness and Ease of Use

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The construction of digital learning resources for "Business English" effectively avoids the limitations of the selection of learning materials, realises the targeted learning of digital teaching resources under the teacher's control, breaks the limitations of time and space, brings into play the leading role of the teacher, and promotes students' initiative, positivity and creativity, and satisfaction. The technology acceptance model has been utilised in various research to investigate learners' acceptance of e-learning systems in higher education due to the development of information communication technology. Nonetheless, studies on the influence of external factors in digital learning on students' satisfaction through perceived ease of use and perceived usefulness in Business English Courses are hardly found in China. This study aims to investigate the mediating effect of perceived usefulness between external factors in digital learning and student satisfaction and examine the mediating effect of perceived ease of use between external factors in digital learning and student satisfaction in Business English Courses in China. The researcher chose quantitative methodology, the study was a cross-sectional survey, and the sample size was 409 from College A in China. Based on the ethical approval from the researcher's university, the data was collected by an online platform (Questionnaire Star) and also spread physically by teachers, the data was analysed using structural equation modelling to test the hypothesized relationships. The findings reveal that both perceived usefulness and perceived ease of use significantly mediate the effect of external factors on student satisfaction.

Keywords: TAM, BEC, external factors, perceived ease of use, perceived usefulness

INTRODUCTION

The demand for Business English study in the form of Business English Courses (BEC) in China is high due to numerous factors: China's fast-rising economy and expanding global commercial relations, which necessitate more individuals skilled in business-related (Yang, 2021). The construction of digital learning resources for "Business

Citation: Qiaoqiao, L., & Asniza, I. N. (2026). Exploring student satisfaction in digital business English courses: A TAM-based mediation model of perceived usefulness and ease of use. *International Journal of Instruction*, *19*(1), 293-320. https://doi.org/10.29333/iji.2026.19115a

English" effectively avoids the limitations of the selection of learning materials, realises the targeted learning of digital teaching resources under the teacher's control, breaks the limitations of time and space, brings into play the leading role of the teacher, and promotes students' initiative, positivity and creativity, and satisfaction (Xu & Sarino, 2023). Digital learning in BEC can better integrate with actual learning needs, enrich learning resources and fully open and share, provide an interactive platform for teachers and students, and make the resources of the programs more applicable and easy to use, and thus improve the student's satisfaction (Gao, 2020).

TAM has been utilised in various research to investigate learners' acceptance of e-learning systems in higher education due to the development of information communication technology (ICT) (Hsu & Chang, 2013).

Studies indicate that digital learning courses, including extensive interactivity, result in increased student engagement, enhanced learning results, and more satisfaction compared to less interactive learning settings in TAM (Croxton, 2014). Meanwhile, BEC combines English instruction with business knowledge, incorporating language training and business-related material into a cohesive unit. Students should acquire knowledge of English and business etiquette, business meetings, and all aspects of company operations. Proficiency in business English vocabulary is essential. The training should emphasise developing students' listening and speaking skills in a business context using interactive, visible, content-rich, and engaging activities (Zhang & Wang, 2016).

Despite the increasing prevalence of digital learning platforms and the extensive application of the Technology Acceptance Model (TAM) in higher education, there is a paucity of research examining how external factors affect student satisfaction in Business English Courses (BEC) via the mediating roles of perceived usefulness (PU) and perceived ease of use (PEOU). Previous research has predominantly concentrated on general e-learning environments or isolated external variables (Alshahrani, 2025; Symposium, 2024), frequently overlooking the synergistic impact of elements like as technical support, interactivity, social influence, and game-based learning within the BEC context in China. Moreover, although the TAM has been expanded in numerous research, its application to Business English digital learning settings is still inadequately examined. This study examines how external factors influence student happiness using Technology Acceptance Model components, addressing a significant gap in light of China's swift digital revolution in higher education and the specific requirements of BEC programs. The results are anticipated to provide theoretical advancements by expanding the Technology Acceptance Model within a specific context and practical guidance for creating more efficient digital Business Education Course.

LITERATURE REVIEW

Theoretical framework

TAM originated from the psychological environment and expanded into business settings. Adapted from the Theory of Reasoned Action (TRA), Davis (1989) developed a new model called TAM; Davis identified two distinct constructs, perceived usefulness and perceived ease of use, which directly affect the attitude toward target system use and indirectly affect the attitude toward target system use and indirectly affect actual system use (Davis, 1989). The theory and model of technology acceptance attempt to explain how consumers may comprehend and accept new technology and how they may use it (Momani & Jamous, 2017). Several researchers have admitted that other external factors might significantly influence the promotion of the TAM model (Hsu & Chang, 2013).

SI in online learning is defined as "the extent to which interactions with peers and teachers influence learners' attitudes, beliefs, and behaviours." Research has shown that numerous social elements, such as social influence and enabling circumstances, can drastically change a user's behaviour toward accepting new technology in TAM (Kamal et al., 2020). The world is evolving rapidly, and digital learning has become the norm in BEC. Social influence on digital learning in BEC can come from teachers, students, and policymakers, particularly with the globalization of world trade, which has transformed how BEC is conducted. Factors such as COVID-19 and the emergence of ChatGPT have significantly impacted BEC.

Mayer (2009) defines IY as "the extent to which the learner can participate in the instructional experience" (p. 45). He contends that interactive learning environments enable active information processing and deeper student engagement with the material (Mayer, 2009). The results in Girish et al., (2022) found that digital learning provides a high level of interactivity, which influences perceived ease of use (PEOU) and perceived usefulness (PU) and enhances the positive attitude of the students based on the TAM model. In BEC, teachers can supervise and communicate with each student. Alternatively, by broadcasting information from the Internet, arranging group discussions on a particular topic, listening to or monitoring student discussions, or even participating in a group discussion, the teacher can provide an interactive teaching environment and activate the classroom (Grecu, 2022).

In digital learning, GB entails incorporating game design elements and mechanics into non-game scenarios, such as educational or training programs, to boost engagement, motivation, and learning outcomes. It aims to utilize game-based strategies and thinking to motivate and engage learners, ultimately leading to an improved learning experience (Dicheva et al., 2015). In Business English, it is unavoidable to have numerous situational teaching methods, particularly in communication or trade. In addition to the problematic skills in BEC, the teachers can add a game in the course to motivate the student's engagement and interest in the study and then improve the students' satisfaction in BEC (Alessa, 2025).

In digital learning, Law (2021) regards technical support (TS) as the help given to students and teachers using digital tools and technologies, resolving technical problems, and ensuring the digital learning environment runs appropriately. This can involve assistance with network connectivity, access to digital resources, hardware and software issues, and other technical challenges (U.S. Department of Education, 2017). Camilleri and Camilleri (2022) report that the availability of resources, continuing training opportunities, and technical support are facilitating variables that influence respondents' participation in digital learning programs. The Internet and significant data development in recent years have provided strong technical support for BEC. The Business English case resource library can be fully utilised with advanced technologies such as mobile Internet, big data, and cloud computing, and based on the curriculum system of the professional direction, the dynamic resource system based on the cloud platform can be created by integrating online and offline teaching features in China (Ji, 2018).

Business English is a category of professional English created to meet the needs of international trade development. Unlike general English, the language style of business English is more practical. In business situations, participants in business activities use English vocabulary and grammatical resources for business purposes and to communicate (Ding, 2021). Therefore, Business English is an important tool for economic cooperation and trade negotiations in international trade.

Previous studies on the relationship

The Relationship of Social Influence, Perceived Usefulness/Perceived Ease of Use and Satisfaction among BEC Students

Bhattarai and Maharjan (2020) the relationship between social influence and positive usefulness and perceived ease of use in digital learning; it was found that social influence positively affects perceived usefulness and perceived ease of use. Meanwhile, social influence positively influenced satisfaction via perceived usefulness (Amsal et al., 2021). According to Son et al. (2012), social influence positively influenced satisfaction via perceived usefulness influence positively influences user satisfaction, PU directly influences satisfaction, while there is no direct influence between PEOU and satisfaction in digital learning. Park et al. (2021) demonstrate that PU and PEOU mediate the relationship between social influence and user satisfaction, and the positive influence between social influence and satisfaction through PU and PEOU is confirmed.

Therefore, the research assumes:

(1)There is significant influence of social influence on satisfaction through perceived usefulness among BEC students;

(2) There is the significant influence of social influence on satisfaction through perceived ease of use among BEC students.

The Relationship of Interactivity, Perceived Usefulness/Perceived Ease of Use and Satisfaction among BEC Students

Shen and Chuang (2010) employ employ the TAM model to investigate whether students' attitudes and behavioral intentions to use the system were influenced by interactivity, perceived self-efficacy, perceived ease of use, and perceived usefulness. It proves that IY can positively influence PEOU and PU. Yin and Lin, (2022) indicate three interactions: human-to-human interaction, human-to-information interaction, and human-to-system interaction. In their model, PU and PEOU exert a mediating role between interaction and satisfaction; the result shows a positive relationship among all the hypotheses. Shipps and Phillips (2013) that perceived interactivity and concentration level affect an end user's satisfaction with a social network along with antecedents from the technology acceptance model.

There is significant influence of interactivity on satisfaction through perceived usefulness among BEC students;

(2) There is the significant influence of interactivity on satisfaction through perceived ease of use among BEC students.

The Relationship of Game based on Learning, Perceived Usefulness/Perceived Ease of Use and Satisfaction among BEC

The evaluation results show that GB can increase Attitude toward Using Technology, Actual Technology Use, Behavioural Intention of Use, Perceived Usefulness, and Perceived Ease of Use of the students. However, in another research, the findings show that perceived enjoyment and perceived usefulness have a favourable impact on the decision to accept GB in education. While the intention to accept game GB is unaffected by PEOU (Zainoddin et al., 2022). In the research of Koivisto and Hamari (2014), the results indicate that perceived enjoyment and usefulness of the game based learning decline with use. Therefore, the researchers proposed:

There is significant influence of game based learning on satisfaction through perceived usefulness among BEC students;

There is the significant influence of game based learning on satisfaction through perceived ease of use among BEC students.

The Relationship of Technical Support, Perceived Usefulness/Perceived Ease of Use and Satisfaction among BEC Students

There is rare literature to show the relationship between TS and PEOU, TS and PU. At the same time, At the same time, Shah and Attiq (2016) examine a similar hypothesis between technology quality and PEOU, technology quality, and PU; it shows consumers have positive emotions for satisfaction with e-learning when it is perceived as valuable and easy to use. In the research of Ngai et al. (2007), the results demonstrate the significance of PU and PEOU in mediating the relationships between technical support and attitude and system usage (Ngai et al., 2007). Likewise, to effectively employ AI-based technology, TS is categorized into organisational factors, which indicates one of the important factors for implementing AI-based technology (Na et al., 2022). Conversely, technical support shows an insignificant relationship with PU and PEOU inside the TAM; PU and PEOU significantly correlate with learning language system usage (Sulaiman et al., 2023). Therefore, the researchers hypothesise

There is significant influence of technical support on satisfaction through perceived usefulness among BEC students;

There is the significant influence of technical support on satisfaction through perceived ease of use among BEC students.

Based on all the analysis above, the researcher constructed the concept framework as follows:

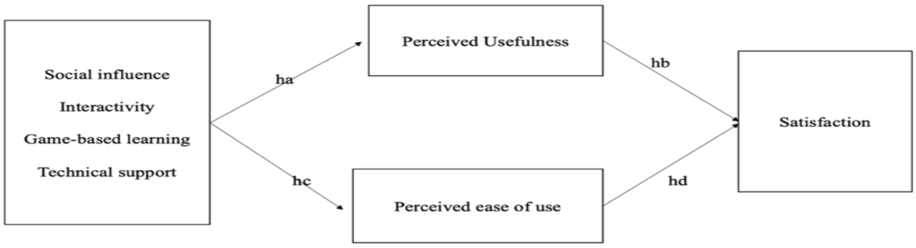

Figure 1
Conceptual framework

As can be seen in Figure 1, there are four external factors which lead to the perceived usefulness and perceived ease of use. Finally, they contribute to the satisfaction.

METHOD

Research design

Building a blueprint or structure for the research is called "research design" (Leavy, 2023). In this study, the researcher chooses quantitative methodology; the instruments for all variables are five points. The research was a cross-sectional survey; the social influence adopted the five items from Luo (2022), game-based learning had eight items from Santos-Villalba et al. (2020), interactivity had five items used by Luo (2022), Law (2021) contributed to five technical support items, the perceived usefulness had six items (Camilleri & Camilleri, 2017), the perceived ease of use was five items (Saadé & Bahli, 2005b), moreover, the researcher adopted nine items for the satisfaction from Almusharraf and Khahro (2020). The total items are 43.

Population and Sampling

This study is comprised of students majoring in Business English Course in China. It is worth noting that there were 323 undergraduate college-setting Business English majors until 2018 (Ding, 2018), while there is no specific population of BEC students. Therefore, the researcher selected purposive sampling and convenient sampling in this study. The reasons purposively and convinently to choose College A in this survey are that: 1) College A is a sample university for the combination of BEC teaching and digital technology reform in China, which has research typicality; The number of BEC students in College A is the largest among 323 universities in China, thus meeting the basic needs of sample extraction. 3) The researcher has worked at College A and can communicate efficiently with the leaders of College A and obtain accurate sample data.

Sample Size

The G* Power 3.1.9.2 statistical testing software, which is frequently used in social and behavioural research, was used to determine the minimal sample size for the study's respondents (Faul et al., 2007). The predictors to determine sample size are critical. Memon et al.（2020) indicate that "the number of predictors refers to the maximum arrows that point to a dependent variable in the model." This study has a total of four predictors with a power of 0.80, a small effect size of 0.15, and an error prob of 0.02

(Cohen, 1988). Moreover, the researcher selected linearly multiple regression: Fixed model, R^2 deviation from zero (Memon et al., 2020). The minimum sample size is 105 in this study (Figure 2).

Finally, the sample size in this study was 409, The reason is that PLS-SEM works well when distributional assumptions such as normality is not met. While for the large sample size in SmartPLS, the analysis is more likely to detect even the tiniest and most trivial effects as being "statistically significant (Jannoo et al., 2014).

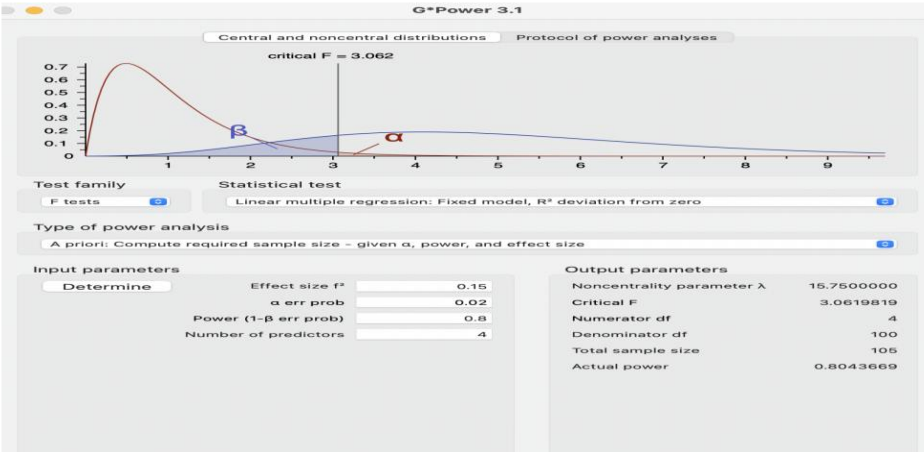

Figure 2
Sample size calculation

Data Collection and Data Analysis

The researcher gathers the data by spreading questionnaire physically and online in the college, the researcher utilised SPSS, and SmartPLS as data analysis tools, the data analysis includes data screening, dealing with missing value, and common method bias (CMB), demographic analysis, measurement model evaluation and structural model evaluation, predictive analysis, meanwhile this analysis adopted the descriptive and inferential analysis.

FINDINGS

Data Preparation

Before conducting the primary analysis, the researcher dealt with straight lining using Excel. Next, the researcher used SPSS to deal with missing values pairwise and detect outliers case-wise. The author removed missing values, and the total valid cases were 409, there was no outlier. Meanwhile, the data preparation includes demographical analysis, and common method bias (CMB).

The demographic information below includes gender, age, grade, time, and ethnicity.

Table 1
Demographical information

Categories	Subcategories	Number	Percentage
Gender	Male	207	50.6
	Female	202	49.4
Age	16-18	61	14.9
	19-21	197	48.2
	22-24	110	26.9
	25 above	41	10
Grade	Freshman	47	11.5
	Sophomore	138	33.7
	Junior	180	44
	Senior	44	10.8
Time	1 h	59	14.4
	2-3 h	159	38.9
	4-6 h	153	37.4
	7h above	38	9.3
Ethnicity	Han	399	97.6
	The others	10	2.4
Total		409	100%

The demographic data of the participants (N = 409) in Table 1 indicates a balanced gender distribution, comprising 50.6% males (207) and 49.4% females (202). Approximately 48.2% of the responders are aged 19-21, while 26.9% are between 22-24 years old. Individuals aged 16-18 comprise 14.9% of the sample, and those aged 25 and beyond constitute the smallest cohort at 10%. Most participants, comprising 44% of the total (180), are junior students. Sophomores constitute 33.7% (138), and freshmen and seniors represent 11.5% (47) and 10.8% (44), respectively. The study time data reveals that 38.9% of individuals allocate 2-3 hours daily to their studies, while a similar percentage (37.4%) commits 4-6 hours daily. Simultaneously, 14.4% of participants engage in one hour of study, while 9.3% indicate studying for 7 hours or more daily. The predominant ethnicity among respondents is Han, with 97.6% (399), while only 2.4% (10) belong to other ethnic groups. CMB may arise when the same response method measures independent and dependent variables. Although its impact can significantly threaten a study's validity, the authors empirically demonstrate that it is often overlooked in research (Kock et al., 2021). Given that the data originated from a single source, the researcher initially evaluated the likelihood of CMB by following Kock's, (2015) guidelines through a comprehensive collinearity analysis. This method involves regressing all variables on a common variable, and a Variance Inflation Factor (VIF) of 3.3 or lower indicates the absence of bias from the unique data source (Table 2).

Table 2
Common method bias test (full collinearity)

Variable	GB	IY	PEOU	PU	SI	SS	TS
VIF	1.75	1.42	1.92	1.62	1.61	2.74	1.84

Measurement model evaluation

The measurement model was examined to determine the validity and reliability of the measurement items by assessing the individual loading (Outer loading and indicator reliability), internal consistency reliability (Cronbach alpha and composite reliability), convergent validity, and discriminant validity (Devisakti & Ramayah, 2023).

Table 3
Outer loading and indicator reliability

Items	loading	indicator reliability
GB1 <- GB	0.806	0.650
GB2 <- GB	0.772	0.596
GB3 <- GB	0.782	0.612
GB4 <- GB	0.785	0.616
GB5 <- GB	0.778	0.605
GB6 <- GB	0.828	0.686
GB7 <- GB	0.729	0.531
GB8 <- GB	0.784	0.615
IY1 <- IY	0.803	0.645
IY2 <- IY	0.81	0.656
IY3 <- IY	0.823	0.677
IY4 <- IY	0.795	0.632
IY5 <- IY	0.814	0.663
IY6 <- IY	0.846	0.716
PEOU1 <- PEOU	0.795	0.632
PEOU2 <- PEOU	0.855	0.731
PEOU3 <- PEOU	0.800	0.640
PEOU4 <- PEOU	0.800	0.640
PEOU5 <- PEOU	0.827	0.684
PU1 <- PU	0.867	0.752
PU2 <- PU	0.819	0.671
PU3 <- PU	0.857	0.734
PU4 <- PU	0.827	0.684
PU5 <- PU	0.814	0.663
SI1 <- SI	0.853	0.728
SI2 <- SI	0.826	0.682
SI3 <- SI	0.825	0.681
SI4 <- SI	0.845	0.714
SI5 <- SI	0.829	0.687
SS1 <- SS	0.814	0.663
SS2 <- SS	0.816	0.666
SS3 <- SS	0.802	0.643
SS4 <- SS	0.809	0.654
SS5 <- SS	0.808	0.653
SS6 <- SS	0.819	0.671
SS7 <- SS	0.794	0.630
SS8 <- SS	0.775	0.601
SS9 <- SS	0.801	0.642
TS1 <- TS	0.805	0.648
TS2 <- TS	0.842	0.709
TS3 <- TS	0.809	0.654
TS4 <- TS	0.846	0.716
TS5 <- TS	0.837	0.701

Outer loadings (Table 3) quantify the extent of correlation between each indicator and its corresponding construct. Most items display elevated outer loadings, surpassing the suggested threshold of 0.7, indicating robust associations with respective constructions.

Indicator reliability denotes the square of the outer loading for each item, signifying the variance in the indicator elucidated by the construct. Values typically surpass 0.5, satisfying the minimum standard for satisfactory reliability (Hair, 2021).

Internal consistency in Table 4assesses the reliability of results across factors within the test. The internal consistency reliability includes Cronbach alpha and composite reliability (CR). The cut-off value should be higher than 0.70 (Hair & Alamer, 2022). Convergent validity refers to the extent to which two measures of theoretically related constructs are correlated. In other words, a strong assessment of convergent validity demonstrates that a test measuring a particular perception is highly correlated with other tests designed to evaluate similar perceptions (Cheah et al., 2018).

Table 4
The internal consistency reliability and convergent validity

	Alpha	(rho_a)	(rho_c)	AVE
GB	0.910 (0.899,0.919)	0.911 (0.901, 0.921)	0.927 (0.919,0.934)	0.614 (0.587,0.640)
IY	0.899 (0.8840.912)	0.902 (0.889,0.916)	0.922 (0.912,0.932)	0.665 (0.632,0.694)
PEOU	0.874 (0.855，0.890)	0.875 (0.858,0.892)	0.909 (0.896,0.919)	0.665 (0.634,0.694)
PU	0.893 (0.878，0.906)	0.894 (0.880.0.908)	0.921 (0.911,0.930)	0.701 (0.672,0.728)
SI	0.892 (0.877，0.906)	0.894 (0.880,0.908)	0.921 (0.910,0.930)	0.699 (0.670,0.726)
SS	0.932 (0.922，0.940)	0.932 (0.923, 0.940)	0.943 (0.935,0.949)	0.647 (0.617,0.675)
TS	0.885 (0.870，0.899)	0.889 (0.875,0.903)	0.916 (0.906,0.925)	0.685 (0.658,0.712)

Note: The bootstrapping used 10 000 subsamples, confidence interval method was percentile bootstrap (95%), test type was one tailed

All values for each variable are higher than 0.70, which means the internal consistency reliability can be acceptable. The AVE should be higher than 0.50 (Amora, 2021), therefore, the values of AVE for each variable can be accepted in this study.

Discriminant validity in Table 5 estimates the correlation between two constructs, assuming they are measured precisely (Hair et al., 2019). The HTMT technique stipulates a threshold of 0.90 for conceptually comparable constructs and 0.85 for conceptually dissimilar structures. Thus, when the constructions are conceptually more dissimilar, a lower, more conservative threshold value of 0.85 is recommended (Hair, 2009).

Table 5
Discriminant validity

	GB	IY	PEOU	PU	SI	SS
IY	0.407 (0.331, 0.480)					
PEOU	0.614 (0.543, 0.680)	0.474 (0.395, 0.547)				
PU	0.486 (0.409, 0.559)	0.449 (0.364, 0.527)	0.451 (0.364, 0.529)			
SI	0.469 (0.387, 0.546)	0.433 (0.359, 0.506)	0.536 (0.464, 0.603)	0.512 (0.436, 0.583)		
SS	0.654 (0.598, 0.704)	0.538 (0.461, 0.608)	0.694 (0.642, 0.742)	0.588 (0.512, 0.657)	0.616 (0.560, 0.670)	
TS	0.472 (0.394, 0.545)	0.431 (0.343, 0.512)	0.592 (0.523, 0.655)	0.557 (0.479, 0.629)	0.469 (0.392, 0.544)	0.693 (0.636, 0.745)

Note: The bootstrapping used 10 000 subsamples, confidence interval method was percentile bootstrap (95%), test type was one tailed.

In this study, all HTMT variables were lower than 0.85, which shows the acceptable values.

Structural Model Assessment

Structural model assessment in PLS-SEM focuses on evaluating the significance and relevance of path coefficients, followed by the model's explanatory and predictive power (Hair et al., 2019). The structural model evaluation includes the normality, collinearity (VIF), significance and structural model path coefficients (p-value and beta value), coefficient of determination (R^2), effect size (f^2), and predictive analysis.

The normal distribution is a continuous curve representing all a variable's potential values. It is symmetrical and bell-shaped, with nearly all (99.7%) of its values falling within three standard deviations above or below the mean (Hair et al., 2020).

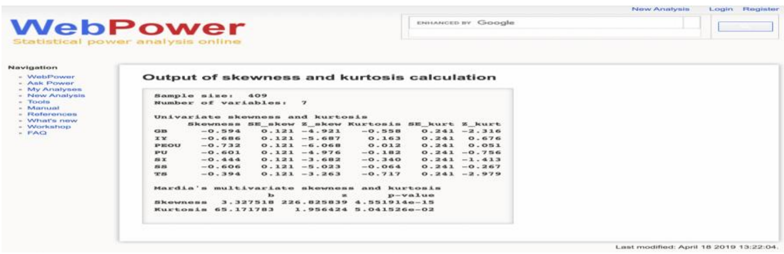

Figure 3
Normality

Hair and Alamer (2022) suggested that that the researcher assessed the multivariate skewness and kurtosis in normality. The results in Figure 3 showed that the data the researcher collected was not multivariate normal, Mardia's multivariate skewness (β = 3.328) and Mardia's multivariate kurtosis (β = 65.172), which provides the rationale for utilisation of SmartPLS. Thus, following the suggestions of Becker et al. (2012), the researcher reported the path coefficients, p-values, effect size, and R square for the structural model using a two-tailed, 10,000 sub-sample bootstrapping procedure (Karuppiah & Ramayah, 2023).

Collinearity assessment in Table 6 entails calculating the variance inflation factor (VIF) for each item by performing multiple regression, where each indicator in the measurement model of the formatively measured construct is regressed on all other items within the same construct (Sarstedt et al., 2021). Collinearity describes the situation where two or more predictor variables in a statistical model are linearly related. VIF values above 5 are indicative of collinearity.

Table 6
Collinearity

Paths	VIF
GB -> PEOU	1.387
GB -> PU	1.387
GB -> SS	1.612
IY -> PEOU	1.312
IY -> PU	1.312
IY -> SS	1.382
PEOU -> SS	1.823
PU -> SS	1.589
SI -> PEOU	1.395
SI -> PU	1.395
SI -> SS	1.524
TS -> PEOU	1.396
TS -> PU	1.396
TS -> SS	1.647

Note: The bootstrapping used 10 000 subsamples, confidence interval method was percentile bootstrap (97.5%), test type was two tailed

Based on the data analysis, all VIF values are lower than 2, therefore, there is no collinearity issues in this study.

The direct paths mean the path from independent variable to dependent variable without mediation or moderation.

Table 7
Direct path analysis

Paths	Beta	p	F^2	R^2
GB -> PEOU	0.309	0.000	0.126	0.452
IY -> PEOU	0.137	0.002	0.026	
SI -> PEOU	0.179	0.000	0.042	
TS -> PEOU	0.265	0.000	0.092	
IY -> PU	0.150	0.004	0.027	0.371
TS -> PU	0.276	0.000	0.086	
GB -> PU	0.178	0.000	0.036	
SI -> PU	0.209	0.000	0.05	
PEOU -> SS	0.491	0.000	0.399	0.492
PU -> SS	0.342	0.000	0.193	

Note: The bootstrapping used 10 000 subsamples, confidence interval method was percentile bootstrap (2.5%-97.5%), test type was two tailed test (since our hypotheses are non-direction hypotheses)

In this section from Table 7, all p-values are below 0.05, indicating significant relationships between variables. Coefficients closer to 1 indicate more substantial relationships. For example, PEOU -> SS (0.491) is the strongest predictor. The second strongest predictors are from PU -> SS (0.342), and the following strongest predictors are GB -> PEOU (0.309) and TS -> PU (0.276).

Effect size measures the magnitude of an effect in a model. It quantifies how much variance in the dependent variable is explained by the independent variable, considering the exclusion of the predictor (Preacher & Kelley, 2011). Thresholds for $f^2 \geq 0.35$ are as follows: Small effect: $0.02 \leq f^2 < 0.15$, medium effect: $0.15 \leq f^2 < 0.35$, significant effect: f^2 (Hair & Alamer, 2022). In this analysis, PEOU -> SS (f^2=0.399) and PU -> SS (f^2=0.193) have the most significant effect sizes among all analyses; they have a medium influence on their SS, respectively. At the same time, IY -> PEOU (f^2=0.026) and IY -> PU (0.027) make minimal contributions to explaining PEOU and PU, respectively.

R^2 denotes the fraction of variance in the dependent variable elucidated by the independent variables (Hair et al., 2019). The R^2 criteria are 0.25, 0.50, and 0.75, indicating mild, moderate, and considerable levels, respectively.

This study reveals that GB, IY, SI, and TS account for 45.2% of the variance in PEOU, indicating a moderate explanatory level. 37.1% of the variance in PU is elucidated by TS, SI, and IY, indicating moderate explanatory efficacy. 49.4% of the variance in SS is elucidated by IY, PEOU, PU, SI, and TS, indicating a moderate to high degree of explanation.

Table 8
Indirect path coefficient and significance

Paths	Beta	p	2.50%	97.50%
GB -> PU -> SS	0.061	0.001	0.026	0.101
GB -> PEOU -> SS	0.152	0.000	0.103	0.206
IY -> PU -> SS	0.051	0.006	0.015	0.088
IY -> PEOU -> SS	0.067	0.003	0.023	0.114
SI -> PU -> SS	0.071	0.000	0.037	0.110
SI -> PEOU -> SS	0.088	0.000	0.04	0.138
TS -> PU -> SS	0.094	0.000	0.054	0.14
TS -> PEOU -> SS	0.130	0.000	0.079	0.183

Note: the test is based on two-tailed test by 10 000 subsamples

In this part as seen in Table 8, all p-values are below 0.05, signifying substantial indirect effects via the mediators. The confidence interval ranges (2.5% and 97.5%) exclude zero, underscoring the magnitude of these indirect effects.

There are several significant indirect effects: PEOU mediates the association from GB to SS, with the highest indirect effect indicated by β=0.152. TS influences SS via PEOU (β=0.130), suggesting this is the second most significant pathway.

As elevated beta values indicate, PEOU serves as a more robust mediator than PU for most constructs. Among all variables, GB and TS exhibit the most robust indirect pathways to SS via PEOU. These findings indicate that enhancing PEOU and TS constructs could improve system satisfaction.

Generating empirical case-wise out-of-sample predictions from a model and evaluating the predictive power of explanatory models is vital to theory building and evaluation (Shmueli et al., 2016).

Table 9
Predictive analysis

	Q^2predict	PLS-SEM_RMSE	LM_RMSE	PLS_SEM-LM
SS1	0.352	0.81	0.817	-0.007
SS2	0.332	0.714	0.723	-0.009
SS3	0.356	0.825	0.824	0.001
SS4	0.338	0.730	0.742	-0.012
SS5	0.396	0.805	0.783	0.022
SS6	0.356	0.801	0.81	-0.009
SS7	0.339	0.717	0.726	-0.009
SS8	0.340	0.666	0.67	-0.004
SS9	0.351	0.752	0.768	-0.016

Firstly, if Q^2 values (Table 9) are more significant than zero for a specific endogenous construct, it indicates the predictive validity of the structural model for that construct. Typically, Q^2 values exceeding 0.025, 0.15, and 0.35 indicate the PLS-path model's minor, medium, and substantial predictive importance, respectively (Urbach &

Ahlemann, 2010). Next, in this study, the prediction errors are highly symmetrically distributed. The researchers use RMSE, and if most indicators in PLS-SEM are smaller than LM, it predicts the model has medium predictive power (Evermann & Tate, 2016; Shmueli et al., 2019).

In this analysis, all values are positive; six items are more significant than 0.35, and three items are slightly smaller than 0.35, indicating medium predictive relevance for the structural model across all indicators. PLS-SEM RMSE values are consistently lower than LM RMSE for most indicators, demonstrating this study's medium predictive power. Finally, the researcher presents the graphic output

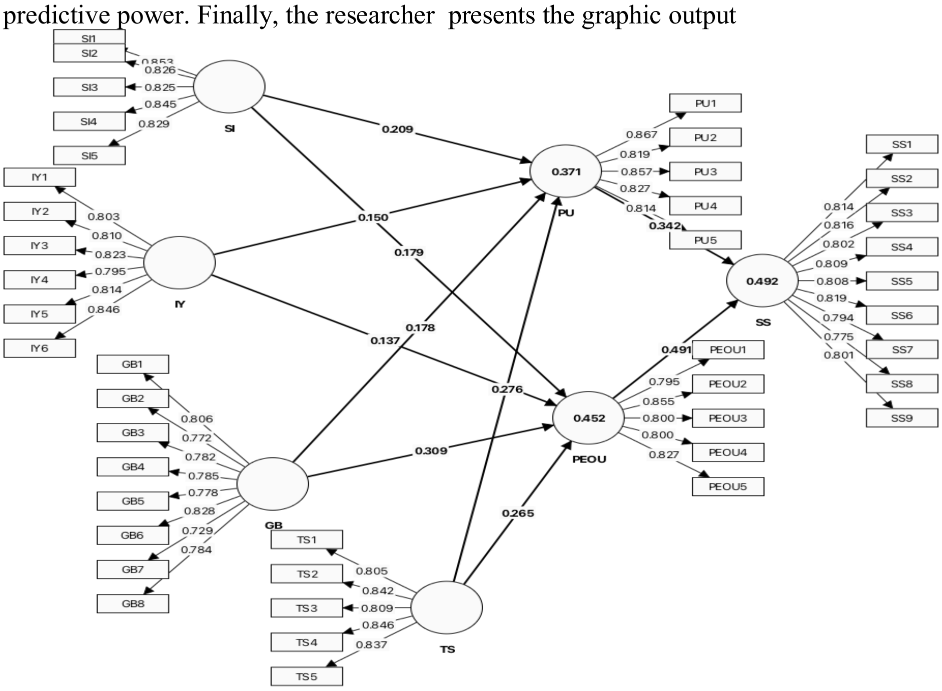

Figure 4
Graphical output

DISCUSSIONS

The distribution of male and female students in this study was nearly equal. Most students were aged 19 to 21, predominantly juniors in university. Most students reported spending 2-3 hours on digital learning; most identified as Han ethnicity.

Data analysis for Common Method Bias (CMB) revealed that all VIF values were below 3.3, indicating no standard method bias. The data distribution tended toward higher ratings, with few extreme responses.

In the measurement model, all item loadings exceeded 0.7, indicating strong associations with their respective constructs. The indicator reliability for each indicator was above 0.5, meeting the minimum reliability threshold.

For internal consistency reliability, all values for each variable were above 0.70, ensuring acceptable levels of Cronbach's alpha and Composite Reliability (CR). All variables' Average Variance Extracted (AVE) values exceeded 0.50, confirming convergent validity. Additionally, all HTMT values were below 0.85, indicating acceptable discriminant validity.

In the structural model evaluation, the researcher first assessed normality and collinearity, confirming the appropriateness of using SmartPLS. All hypotheses are statistically supported. Moreover, the predictive analysis demonstrated strong predictive relevance for the structural model across all indicators.

Discussion the Influence of Social Influence on Satisfaction through Perceived Usefulness among BEC Students

The results show that SI has a positive impact on PU, which subsequently improves SS. This implies that when students receive social support in using digital tools, they perceive them as more useful, ultimately leading to higher satisfaction among BEC students.

These findings are consistent with the TAM, which posits that PU is a mediator between external factors, such as social influence and satisfaction (Huang & Huang, 2017; Jimenez et al., 2021). Previous research in higher education has reported similar outcomes, highlighting those recommendations from peers and instructors shape students' perceptions of digital learning tools, ultimately affecting their overall satisfaction among BEC students (Abdullah & Ward, 2016; Alqahtani et al., 2022). Theoretically, this study expands the TAM by illustrating the mediating role of perceived usefulness in an academic setting. Universities should promote peer and instructor advocacy for digital learning tools, as social influence can positively impact students' perceptions of usefulness and satisfaction.

Discussion the Influence of Interactivity on Satisfaction through Perceived Usefulness among BEC Students

The findings indicate that IY positively influences PU, enhancing student satisfaction. This suggests that increased interaction between students and teachers when using digital tools fosters a greater sense of usefulness, ultimately resulting in satisfaction among BEC students.

These results align with the TAM, which suggests that PU mediates the relationship between external factors, such as interactivity and satisfaction (Cheng, 2020; Salleh, 2012). Previous research in higher education has similar studies, highlighting the interactivity between students and students, teachers and teachers, and students and teachers through digital learning platforms, eventually influencing their satisfaction among BEC students by perceived usefulness as a mediator variable (Irons et al., 2002; Li et al., 2021).

From a theoretical aspect, this study expands the Technology Acceptance Model by introducing interactivity as an external factor and satisfaction as an outcome variable in TAM, particularly in BEC. Practically, universities should promote interactivity through digital learning tools since it can significantly influence students' views of usefulness and satisfaction.

Discussion the Influence of Game-based Learning on Satisfaction through Perceived Usefulness among BEC Students

The results suggested that GB positively impacts PU, promoting SS among BEC students. This implies that incorporating GB into digital tools in BEC improves students' PU, ultimately leading to SS.

These results align with the TAM, which suggests that perceived usefulness mediates the relationship between external factors like GB and SS (Kuang et al., 2023; Taufiq et al., 2019). A prior study in tertiary education was similar to this research, indicating that GB through a digital platform in BEC positively influences the SS among BEC students, mediating by PU (Anggraheni et al., 2023; Edumadze et al., 2022).

This study expands the TAM by adding GB as an external factor and satisfaction as outcome variables in the TAM in the higher education context, particularly in BEC. In practice, HEIs should promote the design of game-based learning through digital learning in BEC.

Discussion the Influence of Technical Support on Satisfaction through Perceived Students

Based on the data analysis, TS has a great influence on PU, which promotes SS for BEC students. This indicates that sufficient TS in digital learning in BEC can promote students' PU and ultimately improve SS.

These outcomes match the TAM, which suggests that PU mediates the relationship between external factors, such as TS and SS (Alshammari et al., 2016; Caratiquit & Caratiquit, 2022). Previous studies in the post-secondary education environment are similar to this research, indicating that TS in digital platforms in BEC greatly influences the SS among BEC students via PU (Chiu et al., 2022; Fernando et al., 2022).

This study expands the TAM by adding TS as an external factor in TAM in higher education, particularly in BEC. In practice, the management of HEIs should strengthen the TS through digital learning in BEC.

Discussion the Influence of Social Influence on Satisfaction through Perceived Ease of Use among BEC Students

The data analysis shows that SI significantly influences PEOU, positively improving SS for BEC students. This means that SI in digital learning in BEC can positively influence students' PEOU, finally leading to students' satisfaction.

These studies align with the TAM, which indicates that external factors, namely, social influence, positively influence students' satisfaction among BEC students by mediating perceived ease of use (Beldad & Hegner, 2018; Pornsakulvanich, 2017). Some of the studies are similar to this research, highlighting SI from peers, particularly the students and teachers in digital learning in BEC, exert a positive influence on the satisfaction among BEC students by perceived ease of use (Al-Khowaiter et al., 2015; Tarhini et al., 2017).

This research expands the TAM by adding SI as an external factor, SS as an outcome variable in the TAM in higher education, and PEOU as a mediator between SI and SS in BEC in higher education. In practice, the management and policymakers in HEIs should attach the importance of social influence to students' satisfaction through perceived ease of use in BEC.

Discussion the Influence of Interactivity on Satisfaction through Perceived Ease of Use among BEC Students

The data analysis indicates that IY has a positive influence on perceived ease of use, which ultimately improves satisfaction for BEC students. This shows that IY in digital learning in BEC makes students PEOU, eventually resulting in SS.

These studies are consistent with the TAM, which indicates that external factors, namely, IY, positively influence SS among BEC students through mediating PEOU (Cheng, 2020). Some of the prior studies are similar to this research, highlighting that interactivity between students and teachers in digital learning in BEC exerts a positive influence on the satisfaction among BEC students through the mediator variable, PEOU (Li et al., 2021; Prasetyo et al., 2020).

From the theory perspective, this study expands the TAM by inputting IY as one of the external factors in TAM and PEOU as a mediator between IY and SS in the background of BEC in higher education. In practice, educators or teachers in HEIs should pay attention to interactivity between students and teachers, thus making students perceive ease of use and ultimately improving students' satisfaction in BEC.

Discussion the Influence of Game-based Learning on Satisfaction through Perceived Ease of Use among BEC Students

The data analysis results indicate that GB has a positive influence on PEOU, which in turn positively influences SS for BEC students. This means that GB in digital learning in BEC improves students' PEOU, eventually impacting SS.

This research aligns with the TAM that GB, as one of the external factors, positively influences SS among BEC students by mediating PEOU (Lin & Hwang, 2018; Wilson et al., 2023). Some studies align with this research, showing that GB design in digital learning in BEC has ahas a positive influence on SS among BEC students by mediating PEOU (Kaimara et al., 2021; Kuang et al., 2023).

This research theoretically expands the TAM by adding GB as an external factor and PEOU as a mediator to predict SS in the context of BEC. Practically, teachers should appropriately design GB for students in BEC, thus leading to PEOU and finally improving SS in BEC in digital learning.

Discussion the Influence of Technical Support on Satisfaction through Ease of Use among BEC Students

The findings indicate that TS positively influences PEOU, which finally greatly influences SS for BEC students. This means that TS in digital learning for BEC students can improve students' PEOU and thus impact SS.

This research is in line with the TAM that TS, as one of the external factors, can positively influence SS among BEC students when perceived ease of use as a mediator variable (Alshammari et al., 2016; Caratiquit & Caratiquit, 2022; Nawaz & Khan, 2012). Current studies also align with this research, presenting that TS in digital learning in BEC positively influences the SS among BEC students through PEOU (Chiu et al., 2022; Fernando et al., 2022).

This study utilised the original TAM (Davis, 1989) as its foundational framework because of its robust explanatory capacity in assessing users' acceptance of technology in educational settings. To more accurately represent the intricacies of digital BEC in Chinese higher education, the researchers enhanced the fundamental TAM by integrating four pertinent external variables: Social influence, interactivity, game-based learning, and technical support.

The original TAM identifies PU and PEOU as fundamental determinants of technology acceptance, although it overlooks contextual and pedagogical aspects that influence learners' experiences in digitally enhanced learning environments. Consequently, our research conforms to the extensive academic history that expands the TAM to incorporate domain-specific external variables.

This study enhances the TAM literature by demonstrating that PU and PEOU work as essential mediators within a multi-factor model in a practical educational context. By incorporating contextually pertinent external variables, the researchers present a customised extension of TAM that more accurately reflects the dynamics of learner satisfaction in digital BEC contexts.

LIMITATIONS

This study utilised SmartPLS to evaluate the mediation effect between external factors and satisfaction through PU and PEOU through a cross-sectional survey in a quantitative study. The study's background only focuses on BEC in digital learning, and the sample size is also limited.

RECOMMENDATIONS

In digital times, the development of Chat GPT and other AI applications has also brought reform to BEC. It challenges the traditional course of Business English and changes the traditional communication in the Business English scenario; the educator and management must pay attention to this significant change and reform BEC according to the needs and changes of society, which includes the reform of the curriculum of BEC, and the traditional instruction method. For the TS, the educators and managers in BEC in HEIs must invest more funding and human resources to provide technical support for the teachers and students. Moreover, students need to feel PEOU and PU and finally improve SS. As to the IY, the teachers should strengthen the IY between teachers and teachers and students to improve the application of Business

English, such as communication, translating, speaking, writing, and so on. Concerning the GB, there should be a GB course in BEC to improve students' interest, thus PEOU and PU, and finally, lead to SS.

From the perspective of policy, due to the digital reform in contemporary society, BEC needs to follow the change of society in digital times; there should be related policies to enhance student satisfaction by enhancing IY, SI, designing GB, and improving SI, and thus improve students PEOU and PU, and ultimately promoting SS in digital learning in BEC.

Regarding the recommendations for future research, the researchers can focus on the longitudinal study, enlarge the sample size, and expand this model into different backgrounds in higher education; the researchers can also explore further qualitative research in this aspect.

CONCLUSION

This study explored how external factors—social influence, interactivity, game-based learning, and technical support—affect student satisfaction in digital BEC, mediated by PU and PEOU, based on an extended TAM framework. Findings from 409 university students show that both mediators significantly transmit the effects of all four external factors, with game-based learning and technical support via PEOU having the strongest influence.

The study extends TAM by integrating contextual variables relevant to BEC, offering both theoretical contribution and practical guidance for enhancing digital course design. Educators and administrators should prioritize social influence, game-based learning, interactivity, and technical support to improve student satisfaction. Future research may expand this model to other disciplines or adopt longitudinal approaches.

AUTHOR CONTRIBUTIONS

Conceptualization, L. Q. and N.A.; methodology, L. Q. and N. A.; formal analysis, L. Q.; writing—original draft preparation, L. A.; writing—review and editing, L. Q. and N. A.; supervision, N. A.

DISCLOSURE STATEMENT

The authors report there are no competing interests to declare.

FUNDING

Foshan Social Science Planning Project ≪Research on the Practical Patterns and Circular Strategies of Foshan's Participation in the Construction of the Guangdong-Hong Kong-Macao Greater Bay Area International Education Demonstration Zone under the New Dual - circulation Development Pattern≫ (2025 - GJ062).

DATA AVAILABILITY

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

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