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Modeling the Continuous Intention to Use Generative AI as an Educational Tool for EFL Learners among Vocational College Students in Guangzhou, China

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Abstract: This study aims to model the continuous intention to use generative AI (GenAI) as an educational tool among English as a Foreign Language (EFL) learners in vocational colleges in Guangzhou, China, by integrating the Technology Acceptance Model (TAM) and Self-Determination Theory (SDT). Data were collected from 419 vocational college students in Guangzhou enrolled in EFL courses. A structured questionnaire measured autonomy, relatedness, competence, perceived usefulness, and continuous intention. The analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results show that autonomy, relatedness, and competence significantly influence perceived usefulness, which, in turn, positively affects students' continuous intention to use GenAI. Furthermore, perceived usefulness mediates the relationships between the three independent variables (autonomy, relatedness, and competence) and continuous intention. The study is limited to vocational college students in Guangzhou, which may restrict the generalizability of the findings. Future research could expand the sample to different educational contexts. The findings provide valuable insights for educators and policymakers on how to enhance GenAI adoption in vocational education by fostering student autonomy, relatedness, and competence. This study extends TAM by incorporating SDT to explain both external and intrinsic factors influencing the continuous intention to use GenAI in educational settings, focusing on vocational students in a Chinese context.

Keywords: Continuous Intention; Generative Artificial Intelligence; Technology Acceptance Model; Self-determination Theory; EFL Learners.

1. Introduction

1.1. Background of Study

The rapid development of generative artificial intelligence (GenAI) has created new possibilities for enhancing educational experiences across various contexts. In recent years, AI-powered tools like ChatGPT, DALL-E, and Bard have been increasingly integrated into education, particularly in assisting language learning through personalized content generation and intelligent tutoring systems (Zhou & Wang, 2022). For English as a Foreign Language (EFL) learners, the application of GenAI in educational settings offers opportunities to improve language skills, foster autonomous learning, and provide real-time feedback tailored to individual needs (Sun et al., 2023).

Vocational college students, particularly in urban centers like Guangzhou, face unique challenges in mastering EFL. These students often balance rigorous practical training with the demands of acquiring English proficiency, making efficient and flexible learning tools essential. Generative AI could fill this gap by providing EFL learners with continuous, personalized support, but the factors influencing students' continuous intention to use GenAI for educational purposes remain underexplored. Understanding these factors is crucial for effective implementation of GenAI tools in vocational education (Chen & Li, 2021).

1.2. Problem Statement

Despite the promising potential of GenAI in education, limited research has investigated its application among EFL learners in vocational settings, particularly in China. While many studies have focused on the use of AI in higher education (Huang & Zhang, 2020), little is known about the vocational sector, where students' needs differ from those in traditional academic settings. Additionally, although previous research has examined technology adoption through the lens of the Technology Acceptance Model (TAM), few studies have integrated this framework with self-determination theory (SDT) to explore how intrinsic factors like autonomy, relatedness, and competence influence perceived usefulness and, consequently, continuous intention to use GenAI in EFL learning (Gao & Wu, 2022).

Given the educational significance of AI in supporting EFL learners, it is imperative to investigate what drives vocational students to continue using such tools (Gao et al., 2024). Autonomy, relatedness, and competence are key components that could shape students' perceived usefulness of GenAI in their language learning journeys, yet empirical evidence on these relationships is scarce. This research aims to address these gaps by modeling the continuous intention to use GenAI as an educational tool among vocational college EFL learners in Guangzhou.

1.3. Significance of Study

This study contributes to the growing body of literature on AI in education by focusing on a less-studied population: vocational college students. It provides insights into how intrinsic factors such as autonomy, relatedness, and competence, as well as perceived usefulness, influence students' intention to continue using GenAI for EFL learning.

By exploring these dynamics, the study not only extends the application of the Technology Acceptance Model but also incorporates self-determination theory, adding a novel perspective to the field of educational technology research (Li & Zheng, 2023).

Practically, the findings of this study are expected to inform educators and policymakers about the factors that encourage sustained engagement with GenAI tools in vocational education(Yu et al., 2024). As China continues to promote technological integration in education, understanding the motivations behind vocational students' adoption of AI-based tools will be critical for designing more effective learning environments (Wang & Sun, 2023).

1.4. Research Questions

This study seeks to address the following research questions:

1)How do autonomy, relatedness, and competence influence perceived usefulness (PU) of generative AI as an educational tool among vocational EFL learners in Guangzhou?

2)How does perceived usefulness (PU) affect students' continuous intention (CI) to use generative AI for EFL learning?

3)Do autonomy, relatedness, and competence indirectly influence continuous intention through the mediation of perceived usefulness?

2. Literature Review

2.1. Current Development

Generative Artificial Intelligence (GenAI) has emerged as a transformative force in education, especially in language learning. GenAI technologies, such as ChatGPT, DALL-E, and Bard, have redefined how students interact with learning materials, providing personalized feedback and adaptive learning paths (Li & Wang, 2021). These tools are particularly valuable for English as a Foreign Language (EFL) learners, who often require tailored assistance to master language nuances(Gao,2024). The global integration of AI in education is accelerating, and China is at the forefront, pushing for AI-enabled education in both academic and vocational settings (Zhou et al., 2022). However, the continuous intention to use GenAI as a learning tool, particularly among vocational college students, has not been adequately explored, presenting an important research gap.

2.2. Theory Related to Study

This study is grounded in two theoretical frameworks: the Technology Acceptance Model (TAM) and Self-Determination Theory (SDT). TAM, introduced by Davis (1989), posits that perceived usefulness (PU) and perceived ease of use (PEOU) influence users' acceptance of technology (Venkatesh et al., 2021). In the context of education, TAM has been applied to understand how students adopt new technologies like AI (Sun & Gao, 2023). However, TAM alone may not capture the intrinsic motivations driving students' continuous use of educational tools, which is where SDT comes into play.

SDT focuses on intrinsic motivation, emphasizing three core needs: autonomy, relatedness, and competence (Deci & Ryan, 2000). When these needs are fulfilled, individuals are more likely to engage in activities, perceiving them as valuable and enjoyable (Ryan & Deci, 2020). This theory complements TAM by providing a deeper understanding of why students perceive GenAI as useful, especially when they feel autonomous in their learning process, connected to their peers and instructors, and competent in their ability to use the technology.

2.3. Dependent Variable: Continuous Intention

Definition and Conceptualization: Continuous intention (CI) refers to the sustained willingness of individuals to use a particular technology over time. In the educational context, it represents students' ongoing commitment to use technological tools like GenAI to support their learning objectives (Bhattacherjee, 2001).

Past Studies and Overview: Previous research has shown that CI is influenced by both external factors, such as the perceived ease and usefulness of the technology, and intrinsic motivators, like autonomy and competence (Chen & Huang, 2021). In a study on mobile learning adoption among EFL students, Zhang et al. (2022) found that students' continuous intention was closely tied to their perception of the technology's usefulness in improving learning outcomes. Similarly, Pappas et al. (2020) demonstrated that intrinsic motivation plays a critical role in determining CI, particularly when students are given control over their learning process.

2.4. Independent Variables: Autonomy, Relatedness, and Competence

2.4.1. Autonomy

Definition and Conceptualization: Autonomy refers to the degree to which individuals feel they have control over their actions and decisions (Deci & Ryan, 2000). In the context of education, autonomy reflects the extent to which students feel empowered to make choices about their learning, such as how and when to engage with GenAI tools.

Past Studies and Overview: Numerous studies have highlighted the importance of autonomy in fostering continuous engagement with educational technologies. For instance, Kim et al. (2022) found that when students felt autonomous in their use of e-learning platforms, they were more likely to continue using the tools. Similarly, in a study on AI in education, Liu and Tang (2021) discovered that autonomy significantly influenced students' perceived usefulness of AI tools, which in turn impacted their intention to use the technology.

2.4.2. Relatedness

Definition and Conceptualization: Relatedness is defined as the feeling of connection with others, particularly in a social or educational setting (Ryan & Deci, 2020). In this study, relatedness refers to the degree to which students feel supported by their peers and instructors while using GenAI tools.

Past Studies and Overview: Past research has demonstrated the importance of relatedness in educational technology adoption. Wang et al. (2021) showed that students who felt socially connected while using online learning platforms were more likely to perceive the technology as useful and were more inclined to continue using it. Similarly, Zhang and Li (2023) found that relatedness had a significant positive effect on students' continuous intention to engage with AI-powered learning tools.

2.4.3. Competence

Definition and Conceptualization: Competence refers to the feeling of efficacy and mastery over a particular task or

technology (Deci & Ryan, 2000). In educational settings, competence is the extent to which students feel capable of using GenAI effectively for their learning needs.

Past Studies and Overview: Competence has been widely recognized as a critical factor influencing the adoption of educational technologies. In a study on the use of AI for language learning, Sun and Gao (2023) found that students' perceived competence in using AI tools was a strong predictor of their perceived usefulness and continuous intention. Furthermore, Pappas et al. (2021) demonstrated that students who felt more competent in using e-learning technologies were more likely to engage with them over time.

2.5. Mediator Variable: Perceived Usefulness

Definition and Conceptualization: Perceived usefulness (PU) refers to the extent to which a person believes that using a specific technology will enhance their performance (Davis, 1989). In this study, PU is conceptualized as students' belief that GenAI will improve their learning outcomes in EFL.

Past Studies and Overview: Numerous studies have established a strong link between PU and continuous intention to use educational technologies. For instance, Chen and Li (2022) found that PU significantly influenced students' intention to use AI-based tools in their language studies. Similarly, in a study on mobile learning adoption, Zhang et al. (2022) demonstrated that PU was a key determinant of students' continuous intention to engage with learning technologies.

2.6. Relationships between Variables

Building on the literature, the relationships between autonomy, relatedness, competence, perceived usefulness, and continuous intention are well established (Gao et al., 2023). Autonomy, relatedness, and competence are expected to positively influence perceived usefulness, which, in turn, impacts students' continuous intention to use GenAI. The self-determination theory provides a strong foundation for understanding these relationships, as the fulfillment of autonomy, relatedness, and competence enhances intrinsic motivation, leading to greater perceived usefulness of GenAI tools (Ryan & Deci, 2020).

2.7. Hypotheses Development

Based on the literature review, the following hypotheses are proposed:

Autonomy refers to the degree of control that individuals feel over their own learning processes. In the context of education, when students feel that they have the ability to make choices regarding the tools and methods they use for learning, they are more likely to perceive these tools as useful. Self-determination theory emphasizes the importance of autonomy in fostering intrinsic motivation, which can lead to higher perceived usefulness of technological tools in educational settings (Ryan & Deci, 2020). Research has shown that autonomy plays a crucial role in the adoption of AI-based educational tools, as students who feel empowered in their learning processes are more likely to recognize the usefulness of such technologies (Liu & Tang, 2021).

H1: Autonomy positively influences perceived usefulness.

Relatedness refers to the sense of connection individuals feel with others, such as peers or instructors, during the learning process. According to self-determination theory, relatedness is a key psychological need that, when fulfilled, enhances motivation and engagement. In the context of AI tools for learning, students who feel socially supported and connected to their learning community are more likely to perceive these tools as useful (Ryan & Deci, 2020). Studies have found that relatedness fosters a collaborative learning environment, which can enhance the perceived value of educational technologies (Zhang & Li, 2023). For example, AI-powered tools that facilitate group learning or peer feedback have been shown to increase perceived usefulness through enhanced social interaction (Wang et al., 2021).

H2: Relatedness positively influences perceived usefulness.

Competence refers to individuals' belief in their ability to effectively use a tool or technology. When students feel competent in their use of GenAI tools, they are more likely to perceive these tools as useful for improving their educational performance (Sun & Gao, 2023). Previous studies have shown that competence is a significant predictor of perceived usefulness, as students who feel proficient in using educational technologies are more inclined to recognize their benefits (Kim et al., 2022). Moreover, as AI tools become more user-friendly and accessible, the sense of competence among students is expected to increase, further enhancing their perception of these tools as useful (Pappas et al., 2021).

H3: Competence positively influences perceived usefulness.

Perceived usefulness is one of the core constructs in the Technology Acceptance Model (TAM), which posits that individuals are more likely to continue using a technology if they believe it will enhance their performance (Davis, 1989). In educational settings, perceived usefulness has been found to be a strong predictor of students' continuous intention to use AI-based tools (Chen & Li, 2022). For example, studies on mobile learning and AI-assisted education have consistently demonstrated that students who perceive these tools as useful are more likely to continue using them to achieve their learning goals (Zhang et al., 2022). Therefore, it is hypothesized that perceived usefulness will positively influence students' continuous intention to use GenAI for EFL learning.

H4: Perceived usefulness improves students' continuous intention to use GenAI.

Autonomy has been shown to influence continuous intention indirectly through perceived usefulness. When students feel autonomous in their learning, they are more likely to perceive the tools they use as valuable, which in turn increases their intention to continue using these tools (Ryan & Deci, 2020). Research in the field of educational technology supports this view, indicating that perceived usefulness serves as a mediator between autonomy and continuous intention (Liu & Tang, 2021). For example, autonomous learners tend to view AI-based learning tools as more beneficial, which motivates them to continue using these technologies (Kim et al., 2022).

H5: Perceived usefulness mediates the relationship between autonomy and continuous intention.

Relatedness also affects continuous intention indirectly through perceived usefulness. Students who feel connected to their peers and instructors are more likely to perceive AI tools as useful for enhancing collaboration and engagement, which leads to a higher likelihood of continued use (Ryan & Deci, 2020). Studies have found that relatedness improves perceived usefulness in social learning environments, and this enhanced perception of usefulness drives continuous intention (Zhang & Li, 2023). For example, AI tools that foster peer interaction have been shown to increase both

perceived usefulness and continuous intention to use these tools (Wang et al., 2021).

H6: Perceived usefulness mediates the relationship between relatedness and continuous intention.

Competence is another factor that influences continuous intention indirectly through perceived usefulness. When students feel competent in their ability to use GenAI tools, they are more likely to perceive these tools as useful, which in turn encourages them to continue using them (Sun & Gao, 2023). The relationship between competence and continuous intention is well established in the literature on educational technology, with perceived usefulness acting as a key mediator (Pappas et al., 2021). For example, students who feel confident in their use of AI tools are more likely to recognize their educational benefits, which increases their intention to continue using these tools (Kim et al., 2022).

H7: Perceived usefulness mediates the relationship between competence and continuous intention.

The conceptual framework for this study integrates TAM and SDT to examine the relationships between autonomy, relatedness, competence, perceived usefulness, and continuous intention. The framework posits that autonomy, relatedness, and competence influence perceived usefulness, which in turn affects continuous intention. Figure 1 is research framework.

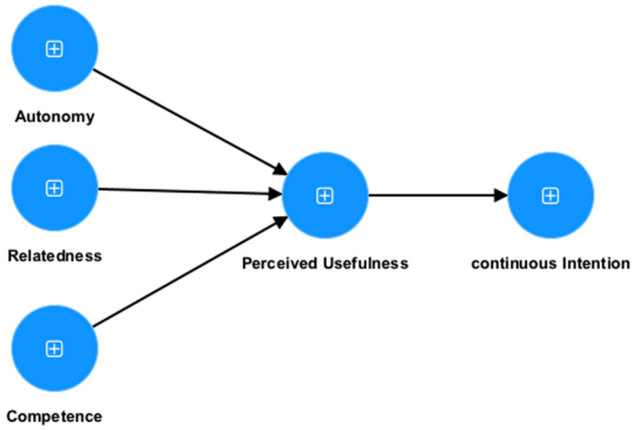

Fig 1. Research Framework

2.8. Research Gap

Despite the growing body of research on AI in education, few studies have specifically examined the factors influencing the continuous intention to use GenAI among vocational college students, particularly in the context of EFL learning. Existing studies often focus on higher education or general student populations, leaving a gap in understanding how vocational students interact with GenAI tools. This study seeks to fill that gap by focusing on the unique needs and motivations of vocational students in Guangzhou, China.

3. Research Methodology

3.1. Population and Unit of Analysis

The target population for this study consists of vocational college students in Guangzhou, China, who are enrolled in English as a Foreign Language (EFL) courses and have had some exposure to Generative AI (GenAI) tools in their educational activities. The unit of analysis for this study is the individual student, as the study aims to explore the personal factors—autonomy, relatedness, competence, and perceived usefulness—that influence their continuous intention to use GenAI tools in their learning process.

Guangzhou is a major urban center in southern China, known for its growing focus on vocational education, making it an ideal setting for investigating how AI tools are adopted among vocational learners. These students often face distinct challenges in language acquisition due to their focus on practical skills, thus presenting a unique opportunity to explore the potential of GenAI in enhancing their EFL learning experience (Chen & Zhang, 2021).

3.2. Sampling and Sampling Technique

The study employs a purposive sampling technique, where participants are selected based on their enrollment in EFL courses at vocational colleges in Guangzhou and their experience with GenAI tools. Purposive sampling is suitable for this study, as it allows the researcher to focus on a specific group that meets the research criteria—students who have had exposure to AI-powered educational tools (Saunders et al., 2019). The target sample size is determined using the G*Power 3.1 software with the following parameters: effect size of 0.15, statistical power of 0.80, and a significance level of 0.05, which yields a minimum required sample size of 150 students (Faul et al., 2009).

Given the need for reliable and representative results in Partial Least Squares Structural Equation Modeling (PLS-SEM), this study has a sample size of 419 respondents is aimed to ensure adequate statistical power and generalizability of the findings (Hair et al., 2019).

3.3. Measurement and Instrumentation

The study uses a structured questionnaire to collect data, with all constructs measured on a 7-point Likert scale ranging from 1 ("strongly disagree") to 7 ("strongly agree"). The questionnaire consists of the following key constructs:

- Autonomy: Measured using three items adapted from the Self-Determination Theory (SDT) literature (Ryan & Deci, 2020). Sample item: "I feel in control of my learning when using GenAI tools."
- Relatedness: Measured using three items adapted from Zhang and Li (2022). Sample item: "I feel connected to my classmates when using GenAI for learning."
- Competence: Measured using three items adapted from Liu and Tang (2021). Sample item: "I feel competent in using GenAI tools for my English studies."
- Perceived Usefulness (PU): Measured using three items from the Technology Acceptance Model (TAM) literature (Davis, 1989). Sample item: "Using GenAI improves my learning outcomes."
- Continuous Intention (CI): Measured using three items adapted from Sun and Gao (2023). Sample item: "I intend to continue using GenAI for my learning in the future."

The questionnaire was pre-tested with a pilot group of 30 students to ensure clarity and relevance. Minor modifications were made to the wording of some items based on the feedback received.

3.4. Data Collection Procedures

Data collection is conducted through an online survey administered via Questionnaire Star. The survey link is distributed to vocational college students through email and social media platforms, targeting students currently enrolled in EFL courses. Participation is voluntary, and respondents are informed about the purpose of the study, ensuring that they provide informed consent before proceeding with the survey.

The data collection period spans four weeks to ensure

adequate participation. To minimize the risk of common method bias, respondents are assured of their anonymity, and the survey is structured to prevent any overlap in question content (Podsakoff et al., 2012).

3.5. Data Analysis Technique

The collected data is analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM), implemented with SmartPLS 4.0 software. PLS-SEM is chosen due to its ability to handle complex models with multiple constructs and small-to-medium sample sizes (Hair et al., 2019). The analysis is conducted in two stages:

1)Measurement model assessment: This includes evaluating the reliability and validity of the constructs. To ensure the reliability and validity of the measurement scales, the study adopts a two-step approach: Cronbach's alpha and Composite Reliability (CR) are used to assess internal consistency reliability, with acceptable thresholds set at 0.70 or higher for both indicators (Hair et al., 2019). Convergent validity is evaluated using the Average Variance Extracted (AVE), where a value above 0.50 is considered satisfactory (Fornell & Larcker, 1981). For discriminant validity, the Fornell-Larcker criterion and Heterotrait-Monotrait ratio (HTMT) are used. A HTMT value below 0.90 indicates acceptable discriminant validity (Henseler et al., 2015). The validity of the constructs is further confirmed by conducting a Confirmatory Factor Analysis (CFA) using SmartPLS 4.0 software (Sarstedt et al., 2020).

2)Structural model assessment: The structural relationships between autonomy, relatedness, competence, perceived usefulness, and continuous intention are tested. Path coefficients, t-values, and p-values are generated through bootstrapping with 5,000 resamples (Chin, 1998). In addition, R^2, Q^2, and f^2 effect size metrics are used to assess the model's explanatory power and predictive relevance (Hair et al., 2019). Multicollinearity is checked using the Variance Inflation Factor (VIF), with a threshold value of less than 3.3 considered acceptable (Kock & Lynn, 2012).

3.6. Ethical Considerations

This study follows strict ethical guidelines to ensure the protection of participants' rights and data confidentiality. Ethical approval for the research is obtained from the relevant ethics committee at the university where the study is conducted. Informed consent is obtained from all participants before they begin the survey, and they are assured that their participation is voluntary, anonymous, and that they can withdraw at any time without penalty.

The data collected is stored securely, and only the research team has access to it. The findings will be presented in aggregate form, ensuring that no individual responses can be traced back to specific participants. All procedures comply with the General Data Protection Regulation (GDPR) and local privacy laws (Zhou & Wang, 2021).

4. Results

4.1. Descriptive Analysis Results

Table 1 shows the results of our descriptive and correlation analyses. The descriptive statistics indicated above-average mean scores for Autonomy, Relatedness, Competence, PU, and CI, which were 4.291, 4.827, 4.137, 4.522, and 4.392, respectively. Consistent with prior studies, the skewness and kurtosis parameters were below 3.0 and 10.0, respectively (Kline, 2011). Additionally, the highest correlation among the underlying factors was 0.711, confirming the absence of high correlation and supporting the suitability of the model for subsequent statistical exploration.

Table 1. Descriptive statistics and correlation analysis

	Mean	SD	Skewness	Kurtosis	1	2	3	4	5
1. Autonomy	4.291	0.793	0.774	-0.638	1				
2. Relatedness	4.827	0.814	0.509	-0.493	0.659	1			
3. Competence	4.137	0.662	0.922	-1.324	0.683	0.541	1		
4. PU	4.522	0.870	0.784	-1.879	0.657	0.752	0.669	1	
5.CI	4.392	0.853	-0.171	-1.893	0.589	0.663	0.682	0.711	1

Source: Authors' calculation.

4.2. Common Method Bias

To mitigate potential common method bias (CMB) during the data collection process, we implemented procedural adjustments following the recommendations of Podsakoff et al. (2003). First, the survey provided clear instructions on how to answer the questions and urged respondents to provide their most accurate responses while ensuring confidentiality, anonymity, and voluntary participation. We also emphasized that there were no right or wrong answers. Additionally, we carefully reviewed each item to ensure clarity and conciseness, avoiding any unusual or ambiguous language. We also altered the sequence of statements to minimize the likelihood of respondents making educated guesses (Malhotra et al., 2006). In this manner, we ensured that our measurement items were clear and comprehensible. In terms of statistical remedies for CMB, we conducted a post-hoc assessment using Harman's (1976) single-factor test. The analysis indicated that the highest variance explained by a component was only 43.72%, which is less than 50%. This finding confirms the absence of CMB in our data.

4.3. Measurement Model Results

The first stage in PLS-SEM is the assessment of the measurement model, wherein four tests are designed to verify item-level reliability, internal consistency reliability, convergent validity, and discriminant validity. First, the minimum and maximum factor loadings demonstrated in Table 2 and Figure 2 are 0.765 and 0.856, respectively, surpassing the threshold of 0.70 recommended by Hair et al. (2016) and Hair Jr et al. (2021). This result indicates that this research had adequate item-level reliability. Next, according to Rahman et al. (2020), the internal consistency reliability of each variable should be ascertained using Cronbach's alpha and composite reliability (CR), both of which should exceed the minimum threshold of 0.70 (Nunnally & Bernstein, 1994). The Cronbach's alpha and CR values shown in Table 2, Figure 2, and Figure 3 surpass this criterion, signifying that all the constructs were consistent, internally cohesive, and reliable.

Table 2. Construct validity and reliability.

Items	Factor Loadings	Alpha	CR rho-c	AVE
A1	0.817	0.831	0.887	0.663
A2	0.820			
A3	0.815			
A4	0.804			
R1	0.857	0.855	0.901	0.695
R2	0.856			
R3	0.813			
R4	0.809			
C1	0.837	0.851	0.900	0.692
C2	0.841			
C3	0.831			
C4	0.817			
PU1	0.783	0.864	0.901	0.647
PU2	0.797			
PU3	0.816			
PU4	0.806			
PU5	0.819			
CI1	0.825	0.886	0.913	0.638
CI2	0.765			
CI3	0.775			
CI4	0.786			
CI5	0.815			
CI6	0.825			

Note (s): Alpha = Cronbach's Alpha, CR = Composite reliability, AVE = Average variance extracted. [2] Source: Authors' calculation.

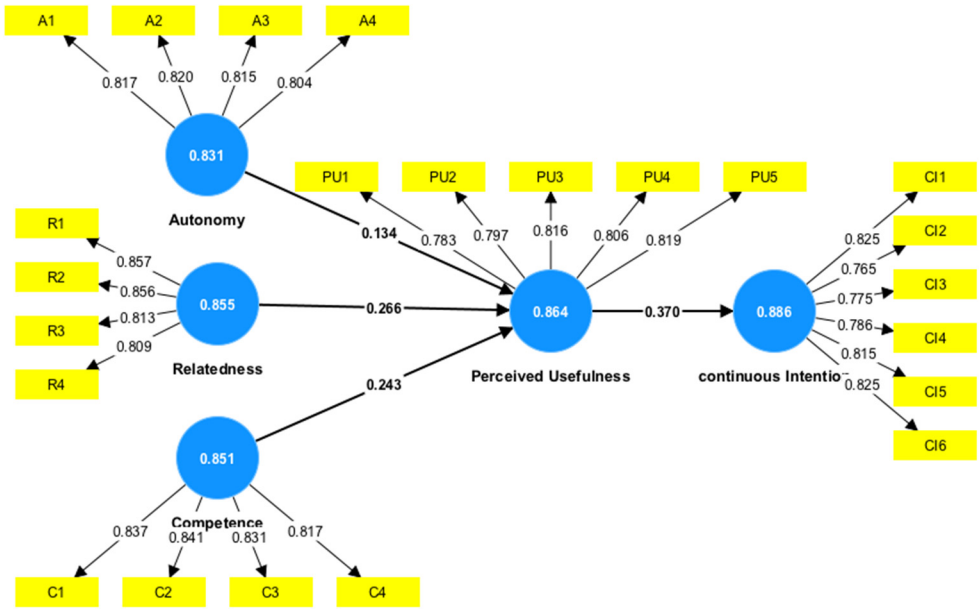

Fig 2. Factor Loadings and Cronbach's alpha.

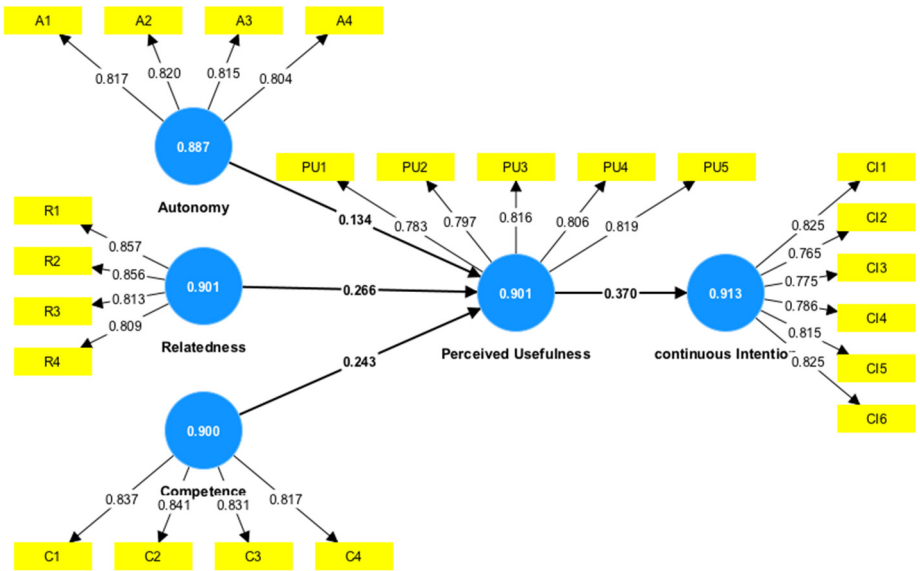

Fig 3. Factor Loadings and Composite Reliability

Third, convergent validity assesses the extent to which different items are expected to be associated with an identical construct. Table 2 and Figure 4 shows that the average variance extracted (AVE) values ranged from 0.638 to 0.695, meeting the minimum criterion of 0.50 set by Hair et al. (2021). Therefore, convergent validity was established in this study. Lastly, discriminant validity ensures that two indicators do not share a statistical identity (Hair et al., 2021). Henseler et al. (2016) recommended the heterotrait-monotrait ratio (HTMT) of correlations as an innovative method to assess discriminant validity, asserting that the traditional metric is not suitable. They recommended setting the HTMT critical point to 0.90 for the same concepts in the theory and 0.85 for conceptually different variables. In this paper, both the HTMT criterion. Table 3 indicates that the HTMT values for all constructs were below 0.85. Both these results confirm the establishment of discriminant validity as per their respective criterion. In addition, Hair et al. (2021) suggested that the value of the Variance Inflation Factor (VIF) to evaluate multicollinearity should not exceed 5.0. The test results indicated that the VIF values were all below 5, meeting the requirement for discriminant validity (see Table 4).

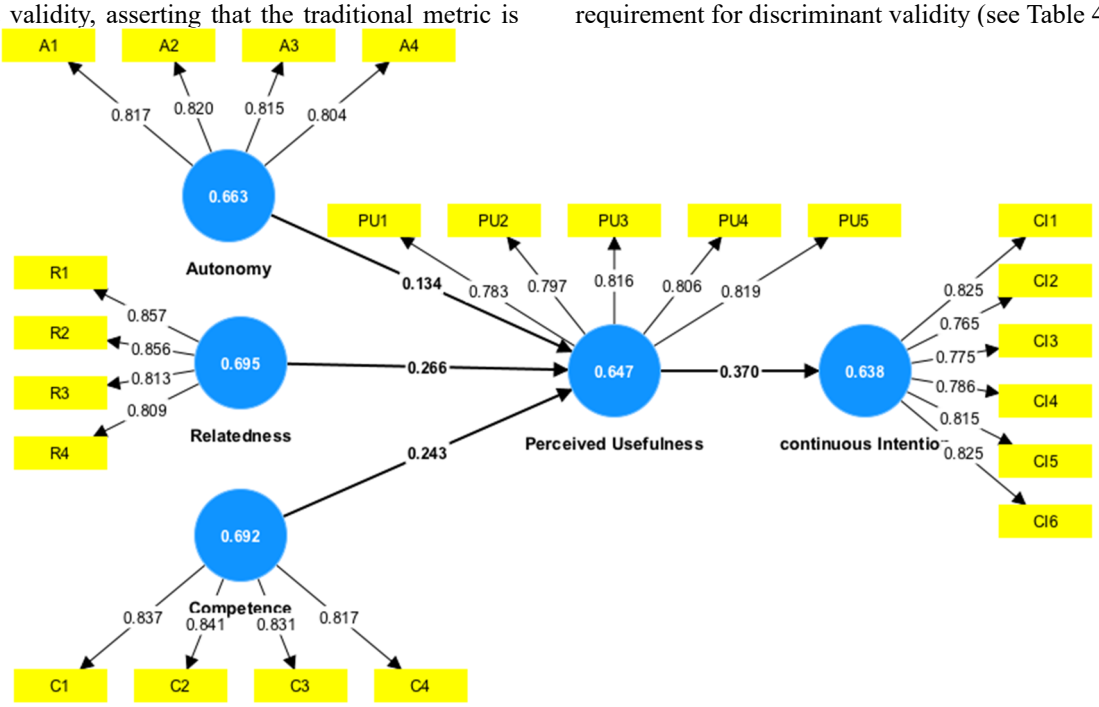

Fig 4. Factor Loadings and AVE.

Table 3. HTMT criterion and VIF.

	A	R	C	PU	CI	VIF
A						1.648
R	0.759					1.474
C	0.443	0.369				1.509
PU	0.574	0.660	0.544			1.616
CI	0.592	0.724	0.435	0.571		1.465

4.4. Structural Model Results

After establishing the measurement model, we proceeded to analyze the structural model using the bootstrapping technique in Smart PLS 4.0 with 5,000 subsamples. The inner model, used to assess the proposed hypotheses, calculates both the p-value and t-value. A hypothesis is considered supported if the p-value is below 0.05 or the t-value exceeds 1.96. The results of the analysis and corresponding hypotheses are presented in Table 4 and Figure 5.

Table 4. Direct and indirect hypotheses testing results.

Hypotheses	Structural Path	Coefficient	T-statistics	Test result
H1	A → PU	0.134**	2.949	Supported
H2	R → PU	0.266***	6.211	Supported
H3	C → PU	0.243***	5.310	Supported
H4	PU → CI	0.370***	9.044	Supported
H5	A→PU→CI	0.050**	2.774	Supported
H6	R→PU→CI	0.099***	4.599	Supported
H7	C→PU→CI	0.090***	4.243	Supported

Notes: ns =not significant. *p <0.05, **p <0.01, ***p <0.001 (two-tailed test). [2] Source: Authors' calculation

The predictive validity of the constructs is presented in Table 5, demonstrating the ability of the independent constructs in our model to make predictions of the dependent ones. Two metrics, R2 and Q2, were employed to assess predictive accuracy. According to Cohen (1992), a substantial R2 should exceed 0.26. The model accounted for 57.4% of the variance in PU, and 56.4% in CI, verifying substantial R2. Furthermore, Q2 indicates the predictive relationship among

internal variables, where a value above zero suggests predictive relevance. The results confirmed the predictive relevance of the variables examined in this study, with all Q2 exceeding zero (PU = 0.374, CI = 0.364). The model fit was considered acceptable, with the PLS-SEM SRMR coefficient at 0.040, which is below the threshold of 0.10.

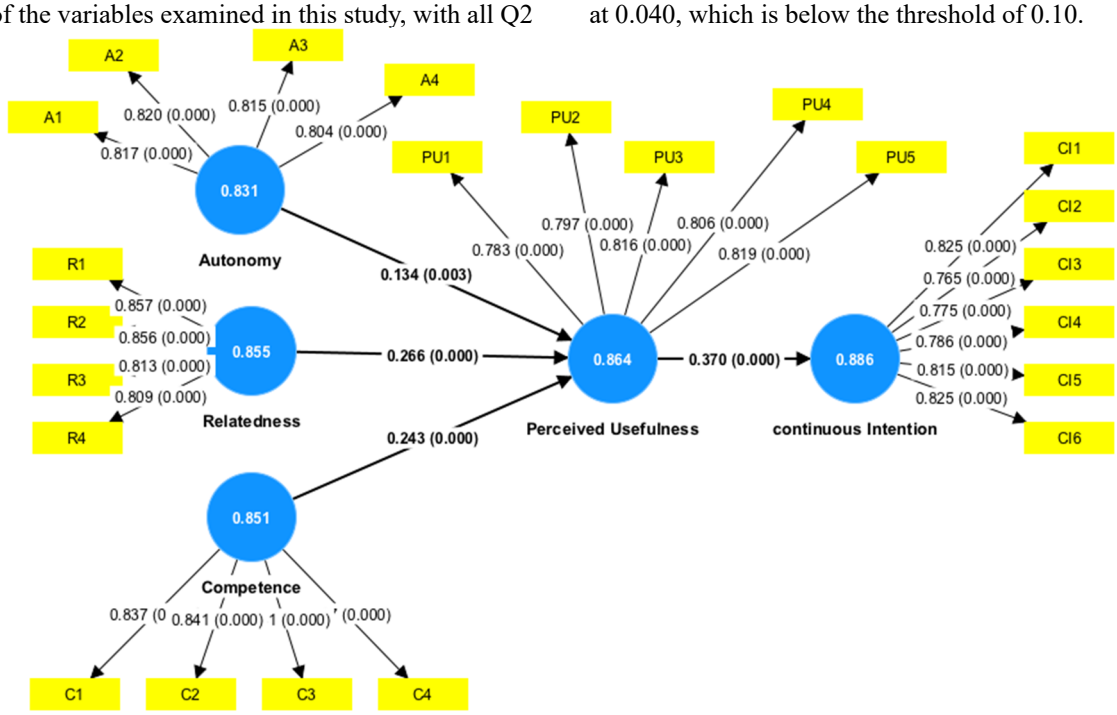

Fig 5. Structural model estimation results

Table 5. Predictive relevance of the model

	R Square	Q2 (= 1-SSE/SSO)
PU	0.574	0.324
CI	0.564	0.352

5. Discussion and Conclusion

5.1. Findings

This study aimed to model the continuous intention to use generative AI (GenAI) as an educational tool among EFL learners in vocational colleges in Guangzhou, China. Using PLS-SEM analysis, all seven hypotheses were supported. The results demonstrate that autonomy, relatedness, and competence positively influence perceived usefulness, which in turn enhances students' continuous intention to use GenAI in their learning. Furthermore, perceived usefulness mediates the relationship between each of the independent variables (autonomy, relatedness, competence) and continuous intention. These findings align with previous studies that emphasize the role of both external and intrinsic factors in driving technology adoption in educational contexts (Sun & Gao, 2023; Liu & Tang, 2021).

5.2. Theoretical Contributions

This study contributes to the growing body of research on AI in education by integrating two established frameworks: the Technology Acceptance Model (TAM) and Self-Determination Theory (SDT). While previous studies have applied TAM to explain how perceived usefulness influences technology adoption (Venkatesh et al., 2021), this research extends the model by incorporating intrinsic motivational factors—autonomy, relatedness, and competence—through SDT. The positive relationship between these factors and perceived usefulness highlights the importance of intrinsic motivation in shaping students' perceptions of GenAI's utility.

By demonstrating the mediating role of perceived usefulness, this study provides a more nuanced understanding of how intrinsic factors drive continuous intention in educational contexts. This theoretical integration of TAM and SDT offers a new perspective on how vocational students engage with AI-based tools, particularly in language learning, thus broadening the application of these theories to a new population.

5.3. Practical Implications

The practical implications of this study are significant for both educators and policymakers in the field of vocational education. First, the findings suggest that increasing students' autonomy, relatedness, and competence can improve their perceived usefulness of GenAI tools, which in turn leads to greater continuous intention to use such tools. Educators should therefore design learning environments that promote student agency, foster social connections, and build confidence in using AI-based tools. For example, allowing students to choose how they use GenAI for their language learning, such as personalizing assignments or selecting AI-generated resources, can enhance their engagement with the technology (Zhang & Li, 2023).

Moreover, policymakers should consider implementing AI training programs for vocational students to build their competence and confidence in using these tools. As the demand for AI proficiency in the workforce grows, equipping students with these skills will not only enhance their learning outcomes but also improve their employability in the future (Chen & Li, 2022).

5.4. Limitations and Future Research

Despite its contributions, this study has several limitations

that must be acknowledged. First, the sample was limited to vocational college students in Guangzhou, which may restrict the generalizability of the findings to other regions or educational contexts. Future studies should include a more diverse sample of students from different regions and types of institutions to validate these findings. Additionally, while the study employed a cross-sectional design, future research could benefit from longitudinal studies to examine how students' perceptions of GenAI evolve over time and how these changes impact their continuous intention to use the technology (Hair et al., 2019).

Another limitation is the reliance on self-reported data, which may introduce common method bias. Although steps were taken to minimize this bias, future research could incorporate objective measures of GenAI use, such as tracking students' actual engagement with AI tools over time (Podsakoff et al., 2012). Moreover, while this study focused on perceived usefulness as the sole mediator, future research could explore additional mediators, such as perceived ease of use or perceived enjoyment, to provide a more comprehensive understanding of the factors influencing continuous intention.

5.5. Conclusion

In conclusion, this study advances our understanding of the factors influencing vocational students' continuous intention to use GenAI as an educational tool for EFL learning. By integrating TAM and SDT, the findings reveal that both external factors, such as perceived usefulness, and intrinsic motivational factors, such as autonomy, relatedness, and competence, play key roles in shaping students' engagement with AI-based learning tools. The theoretical and practical implications of this research provide valuable insights for educators and policymakers seeking to leverage AI in vocational education. Future research should continue to explore the evolving role of AI in education, particularly in diverse and under-researched populations like vocational students.

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