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Research Article

What drives VR use in English learning? Examining the impact of perceptions and attitudes

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Virtual reality (VR) technology has attracted attention due to its advantages in educational fields, and its adoption in English learning can enhance students' learning outcomes. Thus, strengthening VR adoption is conducive to promote learning efficiency and improve the quality of English education. This study analyzes the factors affecting VR adoption and examines the association between factors and students' behavioral intention to adopt VR, as well as the mediating effect of attitude toward using VR in English education. A quantitative research method was employed in the study, with a total of 424 vocational students participating. Their responses were collected through a survey questionnaire using 5-points Likert scale. Using PLS-SEM approach on the collected data, the study identified the significant relationships between factors and behavioral intention of VR adoption, as well as with attitude toward using VR. The findings highlight the importance of factors such as perceived benefit, perceived sacrifice and external factors in shaping students' behavioral intention to adopt VR, while also revealing the insignificant mediating effect of attitude toward using VR among vocational college students. This study provides important implications for educators and policymakers, offering insight into how influencing factors affect VR adoption and providing suggestions to promote its use in English learning to enhance students' learning efficiency.

Keywords: English learning; Factors; Virtual reality; Vocational students

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1. Introduction

VR technology has been developed and attracted increasing attention across various fields in recent years (Li et al., 2023). In the educational domain, VR is rapidly emerging as a powerful tool due to its capacity to create immersive and interactive learning environment, thereby enhancing student engagement and participation (Ali et al., 2021). Among various educational contexts, vocational education has become a promising area for VR adoption, including in English instruction in vocational colleges. Considering the nature of vocational education, integrating VR into this field has also received attention, as it considered as a potential approach to enhancing learning performance through VR learning environment with different working scenarios (Wang & Wang, 2023). The primary educational objective of vocational education, which emphasizes the

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cultivation of students' practical competencies and workplace readiness, aligns with the social and industry demands (Yang, 2024).

This objective makes English instruction in vocational colleges serves both communicative and occupational functions (Tan et al., 2021). The integration of VR in this context introduces a novel platform for contextual language learning, allowing students to access diverse language resources and practical language-use scenarios (Lee, 2023). Moreover, VR supports self-spaced individualized learning methods, enabling vocational students to acquire language skills efficiently and independently. Prior studies have indicated that VR can stimulate students' interests, boost their confidence and improve their overall language acquisition outcomes.

Despite the pedagogical advantages, VR adoption in English education among vocational college students remains limited. While previous research has examined VR adoption in education contexts, little empirical attention has been distracted toward the unique setting of vocational colleges, especially in non-English speaking countries. The specific factors that affect vocational students' willingness to adopt VR for English learning have yet to be systematically explored.

Therefore, this study aims to investigate the key factors and how these factors affecting VR adoption in English learning among vocational college students. Furthermore, the study also examines the mediating effect of attitude toward using in this relationship, thereby offering a nuanced understanding of how these factors interact. The findings are expected to provide valuable recommendations for educators and policymakers, emphasizing the crucial factors that should be considered to facilitate the effective integration of VR into students' English learning in vocational colleges.

2. Literature Review

VR has been widely developed for a period and nowadays applied across various domains, like entertainment, engineering and education (Al Farsi et al., 2021). The ability of VR enhancing education efficiency and improving learning outcomes is well recognized. Within vocational education, VR enables students to practice knowledge in an immersive virtual learning environment, fostering experiential learning and skill acquisition (Chen et al., 2021). Compared with traditional approaches, VR enables students to engage in real-world simulations, aligning with the goal of vocational institutions to cultivate industry-ready talent.

Several studies have highlighted the multifaced benefits of VR in education. For instance, (Chang et al., 2024) pointed out that VR has significant advantages in providing advanced learning methods and personalized learning environments, facilitating talent to cultivate to meet educational goals. Additionally, (Qiu et al., 2024) underscored that VR-based learning effectively integrates academic knowledge with practical skills, accommodating students' diverse requirements and backgrounds. Thes finding resonate with the broader shift toward learner-centered pedagogies. However, while the consensus supports VR's potential, there remains a lack of agreement on how these advantages translate into language educational outcomes.

In English learning, the three-dimensional VR learning environment can cultivate comprehensive language skills and cross-cultural competence, which are essential but challenging in language education settings (Annamalai et al., 2023). Consequently, promoting VR adoption in English learning, especially in vocational colleges where students' practical skills are emphasized is of significant academic and practical value (Shi, 2022). Despite these potentials, VR adoption remains limited within vocational colleges, suggesting the presence of influential factors. The gap indicates that an in-depth investigation into the determinants of VR adoption in vocational English education is needed. This study examines the impact of influencing factors on VR adoption and determine the effectiveness of factors and mediators in VR adoption in English learning among vocational college students.

2.1. Perceived Benefit Factors

Perceived benefit factors play a crucial role in influencing the adoption of new technologies (Srivastava et al., 2023). Given the students' diverse backgrounds of using VR in English learning, understanding these perceived benefit factors is essential as previous studies suggest they significantly impact on the utilization of VR (Lim et al., 2022). As the sound factors, perceived benefit consists of two sub-elements, motivation and attitude. Based on (Abdeen & Albiladi, 2022), motivation determines students' willingness to engage with VR in their English learning process. In other words, while VR integrate into English learning, it has the potential to boost students' motivation and stimulate their interests in VR supported language learning (VanDerSchaaf et al., 2023). Consequently, motivation should be considered. Meanwhile, attitude as another construct of perceived benefit factors, which encompasses students' perception of value and utility of VR in English learning (Du et al., 2022). Both motivation and attitude could positively affect VR adoption when students get benefits from using VR. Therefore, by jointly examining the two elements, this study contributes to a holistic understanding of perceived benefit factors and their influence on students' adoption behavior.

2.2. Perceived Sacrifice Factors

To predict intention toward a technology, perceived sacrifice considers the technology utilization from students' effort aspects (Srivastava et al., 2023). In detail, students may confront extra challenges while integrating VR into English learning, primarily reflected through learning methods and course design (Du et al., 2022). With integrating VR into education, the innovation of learning method and course design would significantly affect VR utilization. The shift in learning methods requires students to move from passive knowledge reception to active knowledge construction (AL-Oudat & Altamimi, 2022), it may cause more burdens on or stimulate interests of students and further impact their intention of VR adoption. Therefore, the learning method in VR educational setting is essential for understanding how students' intention shaped by influencing factors, especially in vocational colleges (AL-Oudat & Altamimi, 2022). To some extent, course design and learning method are intertwined. The VR-integrated course design requires both technological competence and adaptation to learning content. This may impose cognitive load on students and further influence their acceptance of VR (Sciarelli et al., 2022). Thus, to understand how factors impact on students' intention of VR adoption, the perceived sacrifice factors (learning method and course design) should be considered.

2.3. External Factors

External factors influencing technology adoption have been extensively studied, particularly within the framework of the technical acceptance model [TAM] proposed by Davis in 1986 (Qader et al., 2022). The model suggests that various factors affect the way and degree of a new technology when it is employed (Sulasmi & Dalle, 2022). External factors shape users' intentions toward using technology.

In this study, external factors including technicality, perceived cost, policy, related training and previous experience are considered. Sohn and Kwon (2020) suggested that previous experience is a useful factor in explaining technology adoption, since users are likely having positive feelings and intention of VR adoption when they have more relevant experience. Based on (Sohn & Kwon, 2020), relevant experience are more likely to develop positive perceptions and readiness toward VR utilization in English learning. Therefore, the previous experience should be put into consideration as one of external factors. Related training would enhance effects and promote VR utilization as it can offer opportunities to help students master the technology (Amrullah et al., 2023). Policy can affect educational objectives, methods and strategies, while implementation of policies would promote the popularization of VR and largely impact its adoption in vocational colleges. Perceived cost including time spend and effort for using the technology (Alfadda & Mahdi, 2021). Students will consider the benefit, effort and price of learning through VR, which influence their intention significantly (Moura et al., 2020). Technicality refers to the quality and platform that VR provided and seem as a factor affecting VR implementation in English learning (Moura et al., 2020). Students will positively be adopting VR when its design meet the requirements of language learning and the platform easy to operate. Generally, the five elements of external factors are integrated. They significantly impact on students' behavioral intention of VR adoption and are meaningful to make the research more reasonable and feasible.

2.4. Attitude toward Using

Attitude toward using usually predicts the behavioral intention to use a certain technology. (Riza & Hafizi, 2019) asserts that attitude directly users' intention and regarded as foreteller in investigating technology utilization. From previous studies, attitude toward using consists of one's knowledge of the attitudinal object, and the intent and reaction toward objects (Alshurideh et al., 2024). It also represents users' sentiments and understanding about a situation and individual's emotional responses (positive or negative). This study adopts a dynamic view of attitude, treating it as a reflection of influencing factors and as a mechanism through which those factors affect behavioral intention. In other words, it is meaningful to set hypotheses using attitude toward using and estimate the association among variables.

2.5. Behavioral Intention

Behavioral intention is commonly defined as an individual's subjective probability of engaging in a specific behavior. (Jingnan et al., 2023) argued that behavioral intention as dependent variable while examining the adoption of a certain technology. Previous studies like (Sohn & Kwon, 2020), reflect the negative impact of factors on intention through extending technology acceptance model, while (Al-Dokhny et al., 2021) analyzed the adoption of electronic services by using convergent model of value-based adoption model and suggested that behavioral intention has great influenced by variables, like perceived benefits and perceived sacrifice. Meanwhile, the behavioral intention is regarded as guidelines and predictors for promoting new technology in one field. These differing findings suggest a need for integrated models that account for both benefits and sacrifices. In the context of vocational education, where technology adoption is often pragmatic rather than aspirational, behavioral intention not only predicts usage but also informs institutional strategies for implementation.

By synthesizing diverse constructs, including perceived benefits, sacrifices, external factors, and behavioral intention. This study aims to provide a comprehensive explanation of behavioral intention regarding VR adoption in English learning among vocational students.

2.6. Research Objective and Hypothesis

This study analysis between factors and behavioral intention of VR adoption in English learning. The objective is to examine how the influencing factors impact vocational college students on their behavioral intention of VR adoption in English learning, taking into account the mediating effect of attitude toward using. It is helpful to understand whether the mediator can promote VR utilization in language learning in the context of vocational colleges. Research objectives of the study are as follow:

RO 1) To investigate the relationship between factors (perceived benefit, perceive sacrifice and external factors) and behavioral intention of VR technology in English learning in vocational college.

RO 2) To investigate the relationship between factors (perceived benefit, perceive sacrifice and external factors) and attitude toward using of VR technology in English learning in vocational college.

RO 3) To investigate the relationship between attitude toward using and behavioral intention of VR technology in English learning in vocational college.

RO 4) To investigate the mediating effect of attitude toward using on the relationship between factors and behavioral intention in English learning in vocational college.

The hypotheses of the study are as follows:

H1: Perceived benefit factors significantly impact on vocational college students' behavioral intention in VR adoption in English learning.

H2: Perceived sacrifice factors significantly impact on vocational college students' behavioral intention in VR adoption in English learning.

H3: External factors significantly impact on vocational college students' behavioral intention in VR adoption in English learning.

H4: Perceived benefit factors significantly impact on vocational college students' attitude toward using of VR adoption in English learning.

H5: Perceived sacrifice factors significantly impact on vocational college students' attitude toward using of VR adoption in English learning.

H6: External factors significantly impact on vocational college students' attitude toward using of VR adoption in English learning.

H7: Attitude toward using significantly impact on vocational college students' behavioral intention of VR in English learning.

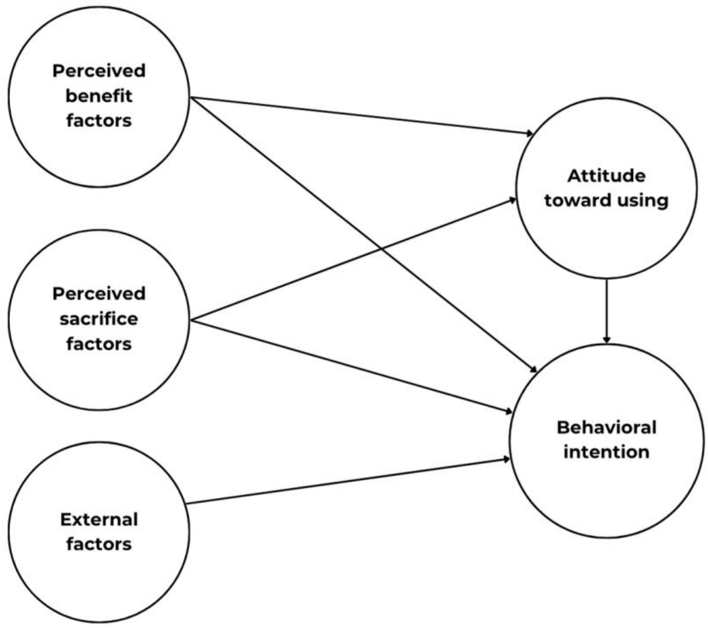
H8: Attitude toward using significantly mediates the relationship between perceived benefit factors and behavioral intention in the VR adoption in English learning among vocational college students.

H9: Attitude toward using significantly mediates the relationship between perceived sacrifice factors and behavioral intention in the VR adoption in English learning among vocational college students.

H10: Attitude toward using significantly mediates the relationship between external factors and behavioral intention in the VR adoption in English learning among vocational college students.

The research model, developed based on the literature reviewed above and the hypothesis development, is presented in Figure 1.

Figure 1
Research model



3. Methodology

3.1. Research Design

This study aims to investigate the relationship between influencing factors and vocational college students' behavioral intention to adopt VR, while the attitude toward using VR as the mediator. The factors and mediator are incorporated into conceptual research model, and testable hypotheses were proposed. The stratified random sampling method was conducted to determine the participants, as it can provide reasonable participants from a large population (Latpate et al., 2021). Then, data was collect using questionnaire and five-point Likert scale was used to measure the responses. After data collection, the structural equation model was conducted to demonstrate and test relationships between a dependent variable and an independent variable in software Smart PLS (Hair et al., 2019).

3.2. Population and Sample

The populations of this study comprised 202,570 vocational college students from 28 vocational colleges in Jilin province, China. To ensure representativeness and reduce sampling bias, stratified random sampling method was conducted (Latpate et al., 2021). This method was deemed appropriate given the heterogeneous nature of students by dividing them into subgroups based on their majors, such as engineering, healthcare and business. The rationale for choosing stratified random sampling lies in its ability to increase the precision and generalizability of the results, particularly in educational research where population subgroups may vary in their perceptions of VR. This method allows for meaningful subgroup analysis, which is essential when exploring factors such as motivation, perceived sacrifice, or external influences across disciplines (Mahmud et al., 2020). Following the stratification process, total 520 students were selected to participate in the study. This sample size was determined based on the guidelines provided by the Krejcie and Morgan Table, a widely recognized tool for calculating adequate sample sizes for large populations. The selection ensured a statistically significant and reliable representation of the overall student population, thus supporting the robustness of the findings. After data only 424 valid responses were conducted to complete the research, it still enough to do the analyzation.

The participants comprised full-time vocational college students ranging from first-year to third-year levels, with an approximately balanced gender distribution. Their academic majors were classified into eight categories, including comprehensive, engineering industry, medical, information technology, policy academy, transportation, education and financial studies. Most participants were aged between 18 and 21 years, reflecting the typical age demographic of Chinese vocational students. In terms of technological familiarity, participants displayed varying levels of exposure to digital learning tools. While some reported previous experience with VR supported learning in language or technical courses, others indicated minimal prior use, providing a balanced basis for assessing behavioral intentions toward VR adoption.

3.3. Data Collection

Data was collected using survey questionnaire that distributed through online platform “WenJuanXing”. The questionnaire is consisting of two parts. The demographic profile of respondents (Part A), which helps to understand the characteristics of respondents, including gender, grade, faculty and VR using experience, and main part for construct (Part B), which contained items related to the study’s key constructs and designed to capture quantitative data on the variable in the research model.

The development of Part B was grounded in review of prior literatures to ensure theoretical relevance. The questionnaire measured three independent variable sub-constructs, perceived benefit, perceived sacrifice and external factors, as well as one mediating variable and on dependent variable. Specifically, perceived benefit was taken from Hashim et al. (2016) and subdivided into motivation and attitude two scales with total 10 items. Perceived sacrifice was originated from Hashim et al. (2016) and subdivided into learning method and course design two scales with 10 items. External factors were adopted from Thompson et al. (2008) and subdivided into technicality, related training, policy, perceived cost and technicality five scales with 23 items. The attitude toward using VR and behavioral intention consist of three items from the study of Hashim et al. (2016) respectively.

To convince participants to answer the questionnaire and keep the scale uniform, the items were likewise based on 5-point Likert scale, with 5 representing strongly agreement and 1 representing strong disagreement. Following data collection, the instrument was checked as its reliability through assessing Cronbach Alpha value and all of items were modified accordingly. All the statistical tests were run following the instruments' validation.

A pilot study with 50 vocational college students to test the initial version of the questionnaire. This process helps in identifying ambiguous wording, measuring response time, and assessing internal consistency. Prior to pilot testing, the instrument was reviewed by four experts in educational technology. The researcher calculates the content validity index [CVI], the most widely used quantification of content validity (Sürücü & Maslakçi, 2020). Content validity index must be at least 0.70 to show higher content validity (Lynn, 1986). In this study, the overall CVI for the constructs of this study is 0.83 and each item was above the threshold of 0.70, which demonstrate that the items in the constructs are content valid. Construct validity was verified using KMO value, which closer to 1.0 are considered ideal while values less than 0.5 are unacceptable (DeVellis & Thorpe, 2021). Internal consistency of each construct should be evaluated using Cronbach's alpha, the most commonly used internal consistency measure (Streiner et al., 2024). Values above 0.70 indicating acceptable reliability, and the items in this study are all achieved the level. Results are shown in Appendix 1.

3.4. Data Analysis

This study conducted Smart PLS to complete the data analyzation. Meanwhile the collected data were analyzed through Structural Equation Modeling, which is a widely used approach to do exploratory research (Cheung et al., 2024). To ensure the rationality of this study, two analysis stages are involved, named as Measurement Model Assessment and Structural Model Assessment.

In the measurement model assessment procedure, convergent validity and reliability were reported based on the results of factors loadings, composite reliability [CR] and Average Variance Extracted [AVE] values. Then, in the following structural model assessment process, the fit of the structural model to different segments of the model as hypothesized was analyzed. In addition, the path coefficients, the goodness of fit coefficients and the relationship between variables were calculated to understand the extent of interactions. Thus, the factors impact on vocational college students' VR adoption and the mediator's role of the affection on VR adoption were elaborated through such a well-coordinated structure of the framework.

4. Results

4.1. Composite Reliability, Cronbach's Alpha and Average Variance Extracted

The construct reliability and validity were verified to ensure the reasonability of the research model. Convergent validity is checked through Alpha and composite reliability, which exposed the correlation between items within the research model. The results show that composite reliability and Alpha values are higher than 0.70 (Lai, 2021). Additionally, the factor loadings and average variance extracted were also evaluated and the values more than 0.4 and 0.5 respectively (Cheung et al., 2024). Therefore, this study suggested that the higher correlation between items. The results are shown in Appendix 1, confirm that the constructs are reliably measured and internally consistent.

4.2. Discriminant Validity

Discriminant validity was also checked as it ensures each construct is unique, meaning the indicators represent only one construct. Heterotrait-Monotrait Ratio [HTMT] is the recommended and modern method for assessing discriminant validity (Yusoff et al., 2020). Considering the advantages of it, this study decides to use HTMT to confirm the measurement. Discriminant validity can be established when HTMT value is below 0.9 (Yusoff et al., 2020). HTMT values are below 0.9 during the first stage and the results are shown in Table 2. However, during the second stage of the analysis, some of the values are greater than 0.9, which is shown in Table 3. Thus, bootstrapping is needed to test whether the confidence interval of HTMT includes the value 1 or not. Bootstrap HTMT is significantly different from 1and the results are shown in Table 4. Hence, the discriminant validity is supported.

Table 2
First stage HTMT values

	A	*ATU*	*BI*	*CD*	*LM*	*M*	*P*	*PC*	*PE*	*RT*	*T*
A											
ATU	0.353										
BI	0.326	0.272									
CD	0.253	0.365	0.434								
LM	0.420	0.349	0.331	0.303							
M	0.339	0.386	0.306	0.309	0.293						
P	0.326	0.469	0.305	0.350	0.389	0.379					
PC	0.284	0.453	0.284	0.328	0.308	0.385	0.447				
PE	0.381	0.298	0.324	0.332	0.327	0.444	0.361	0.384			
RT	0.349	0.414	0.337	0.353	0.376	0.366	0.279	0.414	0.377		
T	0.419	0.411	0.314	0.389	0.453	0.443	0.456	0.407	0.404	0.437	

Table 3
Second stage HTMT values

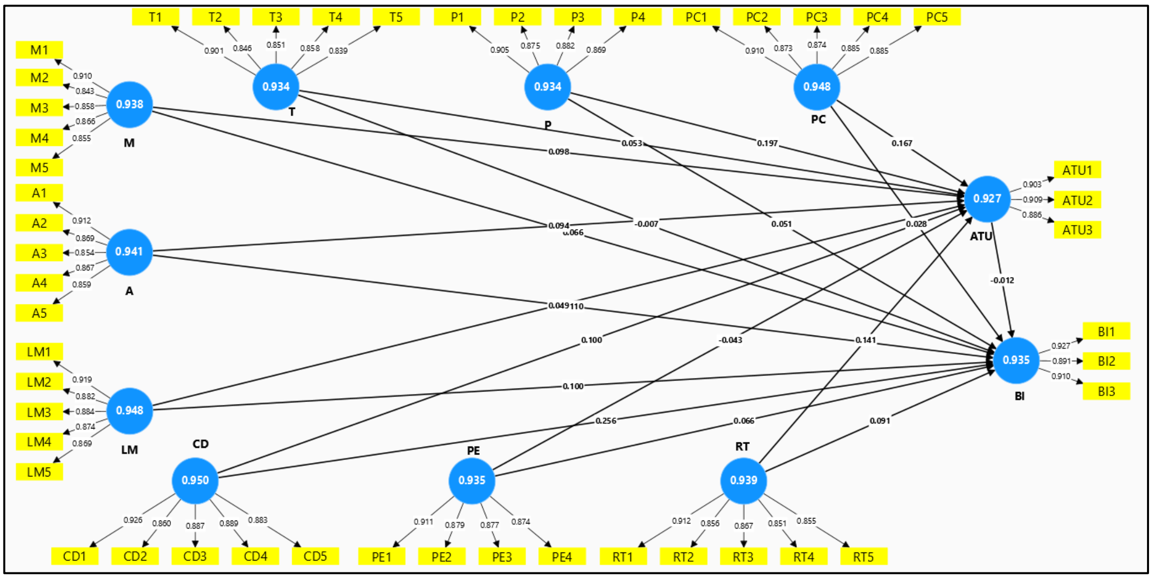
	Attitude	*Behavioral intention*	*External Factors*	*Perceived benefits*	*Perceived sacrifice*
Attitude					
Behavioral intention	0.158				
External Factors	0.354	0.619			
Perceived benefits	0.589	0.338	**1.183**		
Perceived sacrifice	0.556	0.455	0.859	**0.986**	

Table 4
CI HTMT

	CI HTMT
Behavioral intention ↔ Attitude toward using	0.147
External Factors ↔ Attitude toward using	0.545
Perceived benefits ↔ Behavioral intention	0.369
Perceived sacrifice ↔ Behavioral intention	0.472
External Factors ↔ Behavioral intention	0.379
Perceived sacrifice ↔ Attitude toward using	0.886
Perceived benefits ↔ Attitude toward using	0.473
Perceived sacrifice ↔ External Factors	0.533
Perceived sacrifice ↔ Perceived benefits	0.873
Perceived benefits ↔ External Factors	0.759

Figure 2 shows the cross-loadings of items in subscale visually. The outcomes suggested that only perceived sacrifice factors from influencing factors have a significant linkage with behavioral intention of VR adoption. It also revealed that vocational students' attitude toward using VR is related to the external factors. However, the mediating effect of ATU appeared limited and statistically insignificant as discussed below.

Figure 2
Measurement model assessment



4.3. Collinearity, R-square, F-square and Q-square

The Variance Inflation Factor (VLF) values of all the exogenous constructs should be lower than 5, which indicates collinearity is not a problem (Kock, 2020). The VIF values are shown in Table 5 and indicate that the results are falling in a reasonable range, thus, all exogenous constructs are maintained.

Table 5
Effect size and VIF

	VIF	*f-square*	*Effect size*
Attitude toward using → Behavioral intention	1.444	0.000	No effect
External Factors → Attitude toward using	2.003	0.107	Medium effect
External Factors → Behavioral intention	2.218	0.013	No effect
Perceived benefits → Attitude toward using	1.631	0.014	No effect
Perceived benefits → Behavioral intention	1.654	0.015	No effect
Perceived sacrifice → Attitude toward using	1.581	0.013	No effect
Perceived sacrifice → Behavioral intention	1.602	0.072	Small effect

Table 6 shows R^2 results, which measure model's explanatory power and its value indicates the proportion of variance in the dependent construct that is explained by the independent constructs in the model (Hair & Alamer, 2022). Generally, the value reached 0.75 means substantial power to explain, 0.50 means moderate and 0.25 refers to a weak explanatory power.

Table 6
R^2 and R^2 adjusted values

Constructs	R^2	R^2 *adjusted*
Behavioral intention	0.238	0.230
Attitude toward using	0.308	0.303

The effect size of the structural model helps to assess the contribution of each predictor construct when removing a particular predictor construct on the R^2 value of a dependent construct (Fornell & Larcker, 1981). The effect size measures the influence a selected predictor construct has on the f^2values of an endogenous construct (Table 5). The values are interpreted follow the standard: 0.02 refers to small effect, 0.15 refers to medium effect and 0.35 means a large effect (Kock, 2020).

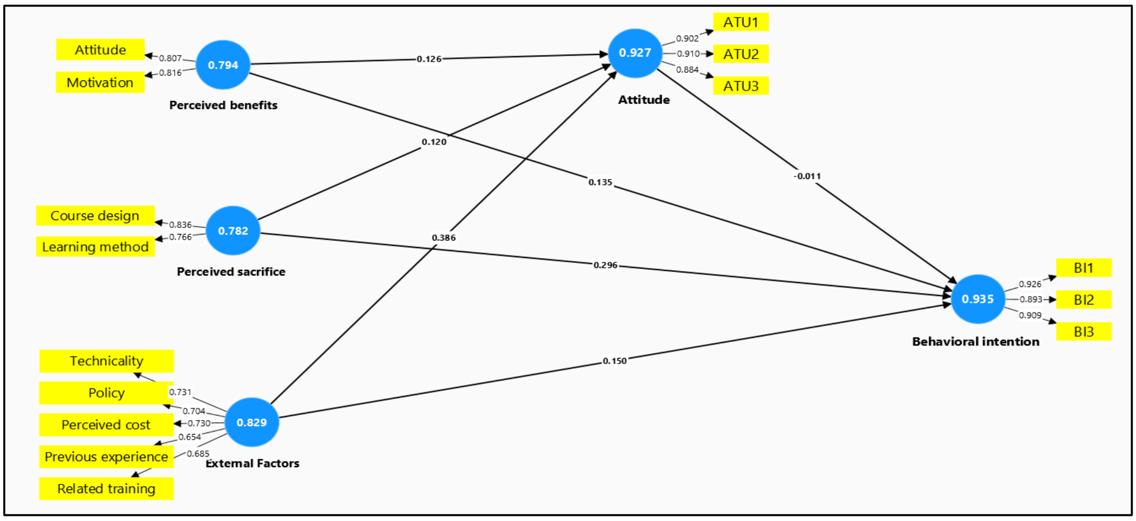
The Q^2 value assesses the predictive relevance of the model for a particular dependent construct. Q^2 value greater than 0 indicates that the model has predictive relevance for the dependent construct (Kock, 2020). Linear regression model [LM] approach regresses all exogenous indicator variables on each endogenous indicator variable to generate predictions. Meanwhile, comparison with the PLS-SEM results offers information whether using a theoretically established path model improves (or at least does not worsen) the predictive performance of the available indicator data. In comparison with the LM outcomes, the PLS-SEM results should have a lower prediction error (e.g., in terms of RMSE) than the LM. The results can confirm whether the model has predictive power or not and are shown in Table 7.

Table 7
PLS Predict result

	PLS-SEM RMSE	*LM RMSE*	*PLS-SEM RMSE < LM RMSE*
BI1	1.096	1.115	Yes
BI2	0.754	0.769	Yes
BI3	0.758	0.768	Yes

Figure 3 presents the structural equation modelling results and the relationships among variables are shown. The results help to make conclusion and suggests the hypotheses that attitude toward using can mediate relationship between factors and behavioral intention should be rejected. Notably, these results showed that the hypothesis regarding the mediating effect of ATU was not supported.

Figure 3
Structural model assessment



4.4. Relationships between Variables

The Table 8 displays the results of hypothesis testing among vocational college students. The path coefficients ranging from -1 to +1, while the higher value related to a stronger relationship between constructs. Typically, the path coefficient is considered significant when p-value is below .05.

From all the results, there are some conclusions about the hypotheses proposed in this study.

Hypothesis 1 was supported based on the Table 8. The path coefficient equals to 0.135, means a small and positive relationship between two variables. While the effect size is not large, the relationship is in the expected direction. Standard deviation of 0.069 shows the variability around the path coefficient is relatively low, indicating a reasonably precise estimate. *p*-value equal to .05 and 1.953 *t*-statistic meaning a significant association. The study shows that behavioral intention of VR adoption has influenced by perceived benefit factors.

Table 8
Path analysis results

		B	*SD*	*T-statistic*	*p-value*
H1	Perceived benefits → Behavioral intention	0.135	0.069	1.953	.050
H2	Perceived sacrifice → Behavioral intention	0.296	0.071	4.198	<.001
H3	External Factors → Behavioral intention	0.150	0.080	1.887	.059
H4	Perceived benefits → ATU	0.126	0.059	2.139	.032
H5	Perceived sacrifice → ATU	0.120	0.058	2.079	.038
H6	External Factors → ATU	0.386	0.071	5.443	<.001
H7	ATU → Behavioral intention	-0.011	0.057	0.199	.842
H8	Perceived benefits → ATU → Behavioral intention	-0.001	0.008	0.178	.859
H9	Perceived sacrifice → ATU → Behavioral intention	-0.001	0.008	0.178	.859
H10	External Factors → ATU → Behavioral intention	-0.004	0.023	0.194	.846

Note. B: Path Coefficient.

Hypothesis 2 was supported as path coefficient is 0.296, indicating a positive but small relationship. The *t*-statistic of 4.198 and $p < .001$ imply a relatively high significant link. Standard deviation of 0.296, indicating a reasonably estimate. Thus, students' behavioral intention significantly influenced by perceived sacrifice factors.

Hypothesis 3 was rejected. The *p*-value is .059 and *t*-statistic of 1.887, means there is no relationship between the two variables, although the small positive direction had been shown. The findings suggest that external factors cannot impact on students' behavioral intention of VR adoption in their English learning.

Hypothesis 4 was established. Path coefficient is 0.126, means a small and positive relationship. Standard deviation reflects data variability is 0.059. *T*-statistic of 2.139 with significant *p*-value is .032. These results support the idea that students' attitude toward using of VR adoption is affected by perceived benefit factors.

Hypothesis 5 was supported. Path coefficient is 0.120, means a small and positive relationship. Standard deviation reflects data variability is 0.058. *T*-statistic of 2.079 with significant *p*-value is .038. These results support the idea that students' attitude toward using of VR adoption is affected by perceived sacrifice factors.

Hypothesis 6 was supported. The path coefficient is 0.386, indicating a small and positive relationship. Standard deviation that reflects data variability is 0.071. *T*-statistic of 5.443 and $p < .001$, indicating a significant relationship between variables. These findings support the idea that externa factors impact on students' attitude toward using of VR adoption.

Hypothesis 7 was rejected. The result of standard deviation is 0.071, indicating data variability. 0.199 is an insignificant *t*-statistic with *p*-value is .842, which higher than common value .05. Meanwhile, the findings cannot support the idea that attitude toward using influence behavioral intention of VR adoption directly.

Hypothesis 8, Hypothesis 9 and Hypothesis 10 were rejected. The path coefficient of the three hypotheses shows negative mediating impact with value of −0.001, −0.001 and −0.004. The *p*-values are higher than .05. The results suggest that attitude toward using cannot mediate the relationship between perceived benefit factors, perceived sacrifice factors and external factors and behavioral intention to adopt VR.

These results elaborate the relationships between variables, helping to understand how influencing factors affect vocational college students' behavioral intention of VR adoption in their English learning, and how the attitude toward using mediate the relationship between factors and behavioral intention. Findings clarify that although ATU is shaped by perceived and external factors, it does not mediate or directly affect behavioral intention in a meaningful way. Instead, perceived sacrifice factors emerge as the most influential predictor of students' intention to adopt VR in English learning.

5. Discussion

The results of this study show that not all hypotheses were supported, and the findings reveal important theoretical and practical implications. The discussion is structured as following.

5.1. The Relationships between Factors and Behavioral Intention

The perceived benefit factors significantly affect vocational college students' behavioral intention of VR adoption in their English learning (H1) is align with the study of (Chen et al., 2021). VR offers environments for language practice, fostering strong associations between language concepts and real-world applications. Such hands-on experience positively influence students' motivation and attitude, ultimately improving promoting students' behavioral intention of VR adoption (Chang et al., 2024). In other wors, students willing to adopt VR as they perceive VR as an effective and enjoyable way to learn. The finding suggested that unlike traditional learners who may value novelty or institutional endorsement, vocational students are particularly pragmatic. They seek tools that clearly support job-related skills. Therefore, VR must be seen as directly contributing to students' practical language competencies to influence their behavioral intention meaningfully.

Perceived sacrifice factors also significantly impact on students' behavioral intention (H2). Corresponding with (Tai et al., 2022), this study suggests that students are willing to invest effort in mastering VR technology and viewing it can enhance their language leaning outcomes. Since vocational college students prioritize their working skills, timely language skills practice using VR attracted more attention of them (Ironsi, 2023). Rather than being discouraged by the effort involved in learning VR, students appear to interpret these sacrifices as worthwhile investments. In the vocational context, students' readiness to overcome technical or cognitive challenges reflects a strong orientation toward long-term gain. This finding invites reconsideration of how "sacrifice" is defined when students see the benefit as aligned with personal growth, effort becomes an enhancer, not a deterrent.

The finding of external factors cannot significantly impact students' behavioral intention of VR adoption (H3) contradicting the study of (Yang et al., 2020). Although VR motivates students with digital environments and reduces the intimidation associated with new technologies, it cannot largely impact students' intention. Considering the characteristics of vocational students, who focus more on their working skills and have less patience and interests in academic knowledge acquisition (Yeh et al., 2022), they may care more about their own feeling and experience with using VR than constraints or support from external environments, especially the policy, cost and other external factors as mentioned in the study of (Huertas-Abril et al., 2021). This finding highlight that unless external support is perceived as directly enhancing individual outcomes, it may have minimal impact on actual behavioral decisions.

From the discussion above, this study suggests that promote students' behavioral intention of VR adoption could focus more on their intrinsic factors, like perceived benefit and perceived sacrifice instead of external factors. Because vocational students are more concerned about their own learning experiences and interests that they can obtain.

5.2. The Relationship between Factors and Attitude toward Using

Perceived benefit factors significantly impact on vocational students' attitude toward using VR (H4). Corresponding with (Fussell & Truong, 2023), this study highlights VR learning positively impact their attitude through providing comprehensive, enjoyable and engaging learning environment. Moreover, VR reduces anxiety and promotes active participation, which is particularly relevant for vocational college students from diverse cultural backgrounds and varying levels of English proficiency (Kaplan- Rakowski & Gruber, 2023). Meanwhile, the personalized learning methods benefit students directly about their academic success, thus, foster students' positive attitude and further promote their intention of VR utilization in English learning (Weng et al., 2024). Therefore, this study suggests that perceived benefit factors improve students' attitude toward using VR. However, it is important to note that positive attitude alone does not necessarily guarantee behavior change. This raises critical questions about the effectiveness of attitude focused interventions and suggests that attitude may not always function as a reliable predictor of intention in pragmatic learning contexts.

Perceived sacrifice factors significantly impact on students' attitude toward using (H5). Corresponding with the idea of (Symonenko et al., 2020), students experience perceived sacrifices in terms of adopting VR-based course design and learning method, which require students to engage in dynamic and interactive experiences. Similar with the idea of (Klimova, 2021), this study suggested that students recognize the long-term benefits of enhanced skills, they may generate positive attitude toward using VR. This perspective suggests that "sacrifice" is not inherently negative and that vocational students might see challenge as an integral part of meaningful learning.

Moreover, aligning with the study of (Dağdeler & Demiröz, 2022), this study holds that external factors significantly students' attitude toward using VR in English learning (H6). Students are highly sensitive to the quality of technological infrastructure while using VR, and their positive attitude toward using improved when VR offers immersive and attractive learning environment (Xie et al., 2023). Students' attitude toward using VR affected from external aspect, like policies, which provide clear guidance for its use, previous experience could help to use VR more easy and related training that navigate students to use VR for educational purpose (Dağdeler & Demiröz, 2022). This distinction is crucial that even if external conditions promote comfort and confidence, they may not suffice to trigger adoption unless students also see a clear connection to their own learning outcomes.

Therefore, although various factors shape attitude, the translation of that attitude into intention remains uncertain, calling for a more nuanced understanding of learners' decision-making processes.

5.3. The Relationship between Attitude toward Using and Behavioral Intention

Contrary to expectations, the attitude toward using VR does not significantly translate into behavioral intention to adopt VR in students' English learning (H7). This result challenges the assumptions of traditional behavioral models, which often regard attitude as a primary predictor of intention (Mohr & Kühl, 2021). While students may appreciate and enjoy VR, these feelings do not necessarily lead to action. The finding may indicate that vocational students prioritize practical skills, the ability can benefit their future careers (Silva-Díaz et al., 2021). It means that students' behavioral intention of VR adoption will remain low if they cannot see the clear connection between VR utilization and their learning goals, despite any positive attitudes they may hold (Liao et al., 2022). It may be caused by vocational students' lower level of motivation and background of language acknowledge, which further affecting the VR utilization in the subjects.

Therefore, promoting VR adoption through attitudinal change alone may be insufficient. Practitioners must ensure that VR is clearly positioned as a practical solution that meets vocational goals. Emotional engagement, while valuable, needs to be matched by visible utility in the eyes of students.

5.4. The Mediation Effect of Attitude toward Using

In general, attitude toward using cannot mediate the relationship between factors, including perceived benefit factors (H8), perceived sacrifice factors (H9) and external factors (H10) and behavioral intention of VR adoption in English learning. The findings deviate from many established models where attitude typically serves as a bridge between beliefs and intention (Liao et al., 2022). For perceived benefit, the effect on behavioral intention appears to be direct and robust, reducing the need for mediation. Students are likely to adopt VR when they recognize its usefulness, regardless of their emotional orientation. Similarly, attitude toward using cannot mediate the relationship between perceived sacrifice factors and behavioral intention due to vocational students' attention is on acquiring practical skills, which directly impact their intention of VR adoption without considering the attitude's influence (Nisa & Solekah, 2022). External factors can directly affect students' attitude toward using and behavioral intention respectively, but attitude toward using fails to serve as a connector. This suggests that students' decision-making may involve parallel evaluations, where cognitive and emotional processes occur independently rather than sequentially. In all, these results indicate that attitude does not function as a central pathway between influencing factors and behavioral intention in vocational settings. This challenges the generalizability of traditional technology acceptance models and points to a more outcome driven decision framework in vocational learners.

Overall, the findings suggest that students' behavioral intention to adopt VR is more directly influenced by perceived benefit, perceived sacrifice, and external factors, rather than being mediated by attitude toward using VR. More importantly, attitude toward using VR fails to mediate any relationships, revealing a gap between perception and action. These results suggest that vocational students are highly pragmatic learners, guided more by practical value and perceived utility than by emotional or institutional influences.

6. Conclusion

This research aims to explore the mediating effect of attitude toward using and the relationship between factors and behavioral intention of VR adoption in English learning among vocational college students. The findings reveal that perceived benefit, perceived sacrifice and external factors on the students' behavioral intention of VR adoption, indicating the factors are powerful elements to promote VR implementation in English education and enhance the learning outcomes. Meanwhile, the factors can also affect students' attitude toward using VR, indicating vocational students' attitude largely swayed by those influencing factors. Moreover, this study also demonstrates that attitude toward using cannot mediate the relationship between factors and students' behavioral intention of VR utilization.

Attitude toward using VR does not mediate the relationship between factors and behavioral intention. This result contradicts some previous studies, emphasizing that students' actual adoption of VR is driven more by perceived advantages and sacrifices rather than their general attitude toward VR technology. The findings suggest that vocational students prioritize tangible learning benefits over abstract perceptions, and thus, interventions aimed at increasing VR adoption should focus on enhancing the practical advantages rather than fostering a positive attitude. Policymakers and educators should clear the importance of adopting VR for enhancing learning outcomes and might encourage students through focusing more on the learning method, course design, motivation and attitude that perceived benefit and perceived sacrifice factors involved instead of attitude toward using. Meanwhile encouraging students' VR adoption effectively, the support or influence from external elements should be considered either, the quality of VR technology, the policy support, the experience and training related to VR utilization and even the effort and cost for adopting VR. Educators should also put the individual characteristics of vocational students and the affection from externals into consideration while encouraging students using VR to improve learning.

The research contributes to the existing literature by providing a nuanced understanding of how factors affect students engage with VR in English learning. This study underscores the direct role of intrinsic factors and external factors in shaping students' behavioral intentions. The results provide practical implications for educators and policymakers to promote VR utilization among vocational college students. Meanwhile, this study also aims to boost students' academic performance and cultivate talents with comprehensive working skills.

7. Implications

The findings of this study offer several practical implications for educators, policymakers, and technology developers aiming to promote VR adoption in vocational college English learning. Educators should embed VR into English curriculum to meet vocational students' career-oriented goals. Emphasizing VR learning modules that stimulate real-world workplace scenarios, which can enhance students' language proficiency and job-related communication skills. Additionally, VR activities should be adaptable to accommodate students' varying ability levels and specialties and allow for ongoing language development based on individual progress.

Policymakers should ensure that adequate training, infrastructure, and financial resources are provided to facilitate seamless VR integration in vocational education. Long term stimulus policies could incentive user participation and professionalize VR-based instruction. Meanwhile, clear policy frameworks should be established to encourage vocational colleges to adopt practices in immersive learning environments. Given that external factors influence students' attitude toward using VR, institutions should ensure that technical support, training workshops, and hands-on experience opportunities are available to improve students' confidence in using VR technology.

Technology developers should work with educators to produce more suitable VR device with cultural resources, language knowledge and ensure relevance to vocational contexts. Meanwhile, the interfaces should be intuitive to accommodate diverse learner profiles. By addressing these implications, this study provides actionable insights to foster a more effective and engaging VR learning environment in vocational education.

8. Limitations and Future Recommendations

This study explores influencing factors affecting students' behavioral intention to adopt VR in their English learning. This study focuses on vocational college students in Jilin Province, which may limit the generalizability of the findings to students in other regions or higher education institutions. Future research should expand the sample scope from diverse educational backgrounds. Additionally, the study employs quantitative research design, which provides statistical insights but lacks in-depth qualitative perspectives on students' experiences with VR. Future studies could adopt mixed-method approach to provide contextual insights into VR adoption. By addressing these limitations, future research can enhance the theoretical understanding of VR adoption while providing practical recommendations for optimizing VR-based English learning.

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Appendix 1. Construct reliability and validity

Second order Construct	*First order construct/Item*	*Loadings (≥0.40)*	*CA (≥0.7)*	*CR (≥0.7)*	*AVE (≥0.7)*	*KMO & Scarlette's test*
Perceived benefit				0.794	0.658	
	Motivation	0.816	0.945	0.938	0.751	0.893
	M1	0.910	0.928			
	M2	0.843	0.842			
	M3	0.858	0.882			
	M4	0.866	0.84			
	M5	0.855	0.838			
	Attitude	0.807	0.937	0.941	0.761	0.849
	A1	0.912	0.884			
	A2	0.869	0.788			
	A3	0.854	0.822			
	A4	0.867	0.832			
	A5	0.859	0.891			
Perceived sacrifice				0.782	0.642	
	Learning method	0.766	0.894	0.948	0.785	0.789
	LM1	0.919	0.79			
	LM2	0.882	0.724			
	LM3	0.884	0.722			
	LM4	0.874	0.743			
	LM5	0.869	0.757			
	Course design	0.836	0.93	0.950	0.791	0.858
	CD1	0.926	0.927			
	CD2	0.860	0.772			
	CD3	0.887	0.781			
	CD4	0.889	0.828			
	CD5	0.883	0.847			
External factors				0.829	0.500	
	Technically	0.731	0.889	0.934	0.738	0.795
	T1	0.901	0.862			
	T2	0.846	0.548			
	T3	0.851	0.744			
	T4	0.858	0.774			
	T5	0.839	0.767			
	Policy	0.704	0.846	0.934	0.779	0.88
	P1	0.918	0.822			
	P2	0.894	0.863			
	P3	0.909	0.776			
	P4	0.892	0.868			
	Perceived cost	0.730	0.893	0.948	0.784	0.838
	PC1	0.905	0.827			
	PC2	0.875	0.772			
	PC3	0.882	0.736			
	PC4	0.869	0.685			
	Previous experience	0.654	0.887	0.935	0.783	0.805
	PE1	0.911	0.625			
	PE2	0.879	0.708			
	PE3	0.877	0.589			
	PE4	0.874	0.76			
	Related training	0.685	0.926	0.939	0.754	0.85
	RT1	0.912	0.828			
	RT2	0.856	0.819			
	RT3	0.867	0.777			
	RT4	0.851	0.813			
	RT5	0.855	0.843			
Attitude toward using			0.877	0.927	0.808	0.685
	ATU1	0.902	0.862			
	ATU2	0.910	0.698			
	ATU3	0.884	0.788			
Behavioral intention			0.845	0.935	0.827	0.694
	BI1	0.926	0.731			
	BI2	0.893	0.782			
	BI3	0.909	0.629			