Assessing Student Acceptance of an LLM-Integrated VR Public Speaking Simulation via Extended UTAUT

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Abstract

Public speaking anxiety (PSA) is a common issue among the youth due to a lack of confidence, fear of strict evaluation, and concerns about self-image. This can cause negative effects, such as shyness, reduced social skills, and limited career goals. Past researchers asserted that virtual reality (VR) simulation with a virtual public speaking environment for practicing increases confidence. Moreover, other researchers applied artificial intelligence (AI) to enhance communication and foster student learning. To our understanding, there are currently few studies on integrating large language models (LLMs) in VR within the public speaking realm. In addition, analysis of behavioral intention to use the simulation is also essential before widely applying new technologies in educational environments. Therefore, we conducted a study based on the Unified Theory of Acceptance and Use of Technology (UTAUT) approach, using an LLM-integrated VR simulation system. In this study, we recruited 30 students from two public speaking sections and asked them to experience and rate the system. Results revealed that effort expectancy, facilitating conditions, and hedonic motivation are significant predictors of behavioral intention. Gender and prior VR experience were not moderating factors for connections between UTAUT constructs and behavioral intention. In addition, our results also highlighted the critical role of two antecedent variables: academic major and GPA levels, which had a significant effect on performance expectancy, effort expectancy, and hedonic motivation. Our research findings offer beneficial theoretical and practical implications for applying novel technologies to students.

CCS Concepts

• **Human-centered computing** → **Virtual reality**; **User studies**.

Keywords

Virtual Reality, Artificial Intelligence, Large Language Models, Public Speaking Anxiety, Simulation, Intention to Use, Technology Acceptance

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1 Introduction

Public speaking remains an essential technique for effective communication and professional growth in academic and workplace settings [Blöte et al. 2009]. Yet many undergraduates experience public speaking anxiety (PSA), a form of social anxiety marked by intense fear when addressing a live audience [Lucas and Stob 2020]. This apprehension can undermine course performance and shape students' emerging professional identities and daily interpersonal interactions [Behnke and Sawyer 2004]. Conventional public-speaking courses excel at teaching theory, structure, and delivery techniques, but often lack psychological and experiential dimensions of speaking in front of real audiences [Allen and Bourhis 1996].

To address the issue, numerous studies suggest that virtual reality (VR) offers promising remedies. Learners can experience modern VR systems that closely approximate real-world scenarios [Behmadi et al. 2022]. Prior studies' results have emerged that VR simulation enhances safety and efficiency in skills training [Paszkiewicz et al. 2021; Smutný 2022], improves learning quality and satisfaction [Yerden and Akkuş 2020], and mitigates constraints found in physical settings [Taçgın 2020]. Importantly, researchers have found that VR exposure can reduce PSA in simulated speech environments [Lim et al. 2023]. In addition to VR systems, artificial intelligence (AI) has gradually gained attention as a robust assessment and feedback tool [Bakhuis et al. 2023]. Researchers have linked educational applications of large language models (LLMs) to increasing learner engagement and knowledge retention [Kadaruddin 2023], more personalized instruction, and reduced administrative burden for educators [Su and Yang 2023]. AI-driven speech-analysis platforms have also helped students refine delivery skills while lowering PSA [Cherner et al. 2023].

Nevertheless, understanding students' acceptance of such technology remains essential [Lazim et al. 2021], as students have the autonomy to choose the most fitting learning method they prefer. Understanding the intention to use new technology and the motivation behind students' decisions can help with designing a more optimized learning strategy [Wang et al. 2024]. The Unified Theory of Acceptance and Use of Technology (UTAUT) is one of the most replicated frameworks for examining technology adoption [Venkatesh et al. 2003]. Although individual UTAUT constructs have been explored in VR-specific [Nurlaela et al. 2025] and AI-specific contexts [Acosta-Enriquez et al. 2024], and several studies have explored further into the intention of AI-VR hybrid systems [Bakhuis et al. 2023; Sougato and Biplab 2024], to the best of our knowledge, no study to date has investigated acceptance in an LLM-integrated VR simulation in the context of public speaking. Therefore, we developed a full LLM-integrated VR public-speaking simulation and conducted a research study to investigate the factors driving behavioral intention. Our study brings insightful implications for applying novel technology in educational environments. This study pursues two objectives:

- Using the extended UTAUT model to examine students' behavioral intentions toward using an LLM-integrated VR public-speaking simulation in a university setting.
- Investigating how demographic factors influence our UTAUT model as moderators and antecedent variables to clarify students' attitudes and intentions to use the system.

All in all, our study refines UTAUT for LLM-integrated VR public-speaking simulation, using a domain-novelty and academic achievement lens to help explain the value of our simulation. LLM feedback can serve as a meaningful design element that shifts attention towards experiential qualities of the simulation, offering a successful case for how UTAUT constructs behave in AI-VR learning environments.

2 Related Work

Public Speaking Anxiety. PSA is one of the most common forms of anxiety among university students [Plandano et al. 2023]. This anxiety typically stems from fear of negative evaluation [Puspitasari et al. 2018], making mistakes, and concerns about self-image [Priya 2024]. Prior research also shows that non-conducive learning environments with stringent instructor critique, limited practice opportunities, and unsupportive classroom climates can exacerbate anxiety [Stewart and Tassie 2011]. As a solution, providing regular rehearsal opportunities and constructive feedback from peers and instructors within classroom settings can help build confidence [Gebre 2024]. Such approaches gradually increase students' exposure to public-speaking situations and offer repeated opportunities for skill refinement. Traditional public-speaking coursework, however, is limited in its ability to recreate realistic speech scenarios [Halim 2024]. Overcoming these limitations is therefore critical, and VR has emerged as a widely adopted solution.

Virtual Reality. Virtual reality has become an effective and accessible option for educational and training contexts because it delivers immersive and interactive experiences. Moreover, VR also enhances knowledge acquisition, psychomotor performance, and spatial ability [Howard et al. 2021]. VR platforms have likewise proved valuable for developing practical competencies [Holuša et al. 2023] and refining soft skills such as teamwork and leadership [Kumar et al. 2021]. In public speaking settings, VR-based exposure and practice reliably reduce PSA, elevate confidence, and improve real-world speaking performance by simulating authentic speech settings. VR exposure therapy (VRET) allows users to rehearse in customized environments with various audiences and has significantly decreased PSA, social anxiety, and fear of negative feedback [Reeves et al. 2021; Stupar-Rutenfrans et al. 2017]. Public-speaking rehearsal with supportive virtual audiences has also shown reductions in anxiety, increases in self-confidence, and measurable gains in live presentation scores [Kroczek and Mühlberger 2023]. While VR provides realistic rehearsal opportunities, AI can supply the detailed feedback missing from most VR studies.

Artificial Intelligence. Researchers have shown that AI can analyze learner data to provide feedback to individual needs [Aryadoust et al. 2023; Harry and Sayudin 2023]. It can also automate tasks such as grading assessments, thereby saving instructors' time and effort [Ahmad et al. 2024]. Moreover, AI tools foster collaborative learning by engaging peer interaction, enhancing communication, and supporting cooperative objectives through social robots and chatbots [Ahmad et al. 2021]. Because AI systems provide real-time feedback, tailored guidance, and extended opportunities for deliberate practice, learners tend to value and readily adopt these tools [Zou et al. 2023]. AI applications are available to support interview preparation and public-speaking skill development and improve English-speaking proficiency by offering immediate and reliable feedback [Jadhav et al. 2023]. Collectively, these studies demonstrate AI's capacity to deliver feedback calibrated to a learner's current level [Nhan 2024]. A more recent line of research integrates AI with VR to simulate authentic speaking scenarios, such as job interviews or conference presentations, while analyzing voice modulation and facial expressions to generate formative feedback [Halim 2024]. Taheri's and Tan's [Taheri and Tan 2024] AI-VR system, for example, enhanced participants' presentation skills and confidence by delivering dynamic, voice-to-text feedback. Although these results are encouraging, the question of whether students are willing to adopt such technology remains unsolved. Thus, exploring user acceptance of AI-VR hybrids is essential.

UTAUT, Research Hypothesis, and Proposed Model. Researchers need to evaluate students' acceptance of different technologies before implementing them [Liu et al. 2024]. Thus, we adopted the UTAUT, originally synthesized by Venkatesh et al. [Venkatesh et al. 2003] from Technology Acceptance Model (TAM), TAM2, and Theory of Planned Behavior (TPB) to explain behavioral intention toward new information systems. Current research extensively utilizes the UTAUT2 model with additional factors to investigate technology adoption elements for VR and AI [Farsi 2023]. For our project, we implemented an LLM in our VR public-speaking simulation to provide instructor-style feedback, enabling us to explore whether immediate AI feedback significantly influences UTAUT constructs. The original UTAUT posits four determinants: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC), with age, gender, and experience as moderators [Venkatesh et al. 2003]. UTAUT2 adds hedonic motivation (HM), price value, and habit [Farsi 2023]. Figure 1 shows our proposed model.

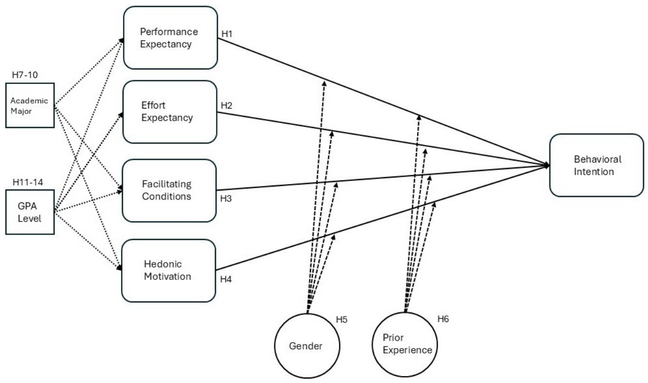

Figure 1: Proposed UTAUT Model for LLM-integrated VR public speaking system. H1-H4 refers to the direct effect of each construct on BI. H5 and H6 refer to gender and prior VR experience's moderating effect on the relationship between constructs and BI. H7-10 and H11-14 refer to the effect of academic major and GPA level on individual UTAUT constructs.

Performance expectancy refers to the learner's belief that the system will improve task or learning performance [Utomo et al. 2021; Vacca and Ko 2025]. In immersive learning environments, students adopt VR technologies when they expect tangible benefits such as higher grades or improved mastery of skills [Noble et al. 2022]. Another study indicated that AI-generated instant feedback can accelerate perceived learning by making progress visible after each speech attempt [Alsaiari et al. 2024]. Effort expectancy indicates the perceived ease of use, which is the mental and physical effort to conduct specific tasks [Davis 1989]. EE reflects an individual's perception of a seamless and effortless operation process [Qasim and Abu-Shanab 2016]. Researchers have asserted that EE is a significant predictor of behavioral intention [Du et al. 2022]. Facilitating conditions refer to the degree to which learners believe that necessary resources, knowledge, and support are available to perform specific behaviors [Venkatesh et al. 2012]. Researchers have found that equipment support, on-site assistance, and clear tutorials can enhance learners' intention to adopt novel technologies [Teng et al. 2022]. Hedonic motivation reflects the fun, enjoyment, and pleasure that users experience when engaging with the system [Nurlaela et al. 2025]. Recent studies on generative AI acceptance have identified HM as a key UTAUT2 variable that contributes significantly to technology-learning models [Cabero-Almenara et al. 2024]. Because of the positive psychological experiences, HM is often a significant predictor of behavioral intention [Tamilmani et al. 2019]. Social influence refers to the extent to which important others, such as peers, instructors, and institutions, believe the learner should use the system [Bozan et al. 2016]. In our study, however, the use of VR simulation was a mandatory course activity. Because every participant faced the same requirement, individual differences in perceived peer or instructor pressure were likely minimal, producing restricted variance and undermining SI's explanatory value. We therefore excluded SI from the present study. Based on the previous findings, we propose the following hypothesis:

- H1-H4: UTAUT constructs (PE, EE, FC, HM) affect the intention to use the LLM-integrated VR public speaking simulation.

For our moderating factors, we selected gender and prior VR experience as they are standard moderating variables in the original UTAUT model. Gender can reflect social differences in attitudes toward technology [Portuguez-Castro and Santos Garduño 2024], while prior VR experience can shape self-efficacy and perceptions of novel technologies [Hertwig et al. 2024]. As all participants belonged to the same age group, we did not consider age as a moderating variable in this study. We propose the following hypotheses.

- H5: Gender has a moderating effect on UTAUT construct paths.
- H6: Prior VR experience has a moderating effect on UTAUT construct paths.

Furthermore, we explored the antecedent variables for our UTAUT model. Researchers from a previous study suggested the extended model with factors affecting the UTAUT constructs can help understand potential reasons behind students' perception of technology and use behavior [Qiu and Luximon 2025]. In addition, by analyzing antecedent variables, we would be able to find implications of certain demographic discrimination on technology adoption [Rioch and Tharp 2022]. We included academic major as a factor, as previous research has shown that domain relevance influences both the novelty effect and perceived instrumentality [Qu et al. 2024]. We also introduced grade point average (GPA) level as another antecedent factor, as previous UTAUT studies' results suggested GPA has a strong correlation with technology adoption and performance expectancy [Wu et al. 2024; Zeng et al. 2023]. We then propose the following hypotheses:

- H7-H10: Academic major has a significant effect on individual UTAUT constructs (PE, EE, FC, HM).
- H11-H14: GPA level has a significant effect on individual UTAUT constructs (PE, EE, FC, HM).

3 Methodology

3.1 Participants

We recruited 30 participants from two randomly selected sections of a public speaking course. All students are native English speakers. All the students are within the 18-26 age group (M = 21, SD = 1.53). The sample included eight male students (26.67%) and 22 female students (73.33%). For prior VR experience: seven students (23.33%) reported none, 17 (56.67%) reported "a little experience," and six (20.00%) reported "some experience." For academic majors: 17 students (56.67%) are from the communication major, while 13 students (43.33%) come from non-communication majors. For GPA level: 21 students (70%) reported a high-level GPA (above 3.0), and nine students (30%) reported a low-level GPA (below 3.0). The study was approved by the Institutional Review Board (IRB) of our university.

3.2 LLM-Based VR Public Speaking Simulation

We developed our VR public-speaking simulation in Unity game engine version 2020.3.48f using the OpenXR plug-in, with an immersive environment where students can present their speech to our virtual agents. Our virtual characters were from Adobe Mixamo. Level geometry and props were assembled from Fab (formerly the Unity Asset Store), ensuring visual fidelity and smooth performance on the target hardware. For the LLM part, we applied the ChatGPT-4 model for speech evaluation. We ran the simulation on a workstation PC fitted with an Intel i7-14700k CPU and an NVIDIA RTX 4060 GPU. We paired this workstation with a Meta Quest 3 headset, which served as the students' primary interface, delivering clear visuals and spatial audio, and a built-in microphone that captured each speech. Meta Quest 3's hand controllers fed directly into Unity, allowing participants to perform gestures. To ensure everything functioned seamlessly during the experiment, a lab assistant was available in person to help students with any technical issues.

3.2.1 Tutorial Level. Before the formal speech began, students entered a guided tutorial session (see Figure 2). A virtual agent introduced the simulation workflow (i.e., voice recording, hand movement, and LLM-driven evaluation) and then invited each learner to deliver a brief sample speech about themselves. Students had ten minutes to explore motion, practice microphone techniques, and observe how the ChatGPT-4 feedback pipeline operates. Immediately after the sample recording, the agent provided concise formative comments so that participants knew what to expect at subsequent levels.

Figure 2: Tutorial level and three speech levels. Top-left: the tutorial level with the virtual agent. Top-right: self-introduction speech level in a classroom environment (level 1). Bottom-left informative speech level in an outdoor environment (level 2). Bottom-right: persuasive speech level in a large hall environment (level 3).

3.2.2 Practice Topics and Narrative Framing. The simulation comprised three continuous scenarios: level 1 asked students to deliver a self-introduction in a virtual classroom; level 2 shifted to an open forum, where students presented an informative talk on "double agents" after listening to a brief NPC dialogue; and level 3 culminated in a persuasive speech set in a hallway scene, requiring students to defend the value of a "double agents." Across these levels, we designed the consistent use of LLM-mediated feedback, contextual storytelling, and incremental complexity to foster both skill acquisition and engagement in an academically authentic yet psychologically safe environment.

Recorded audio was processed through Azure Speech to Text (STT), evaluated via ChatGPT, and delivered back to users through Azure Text to Speech (TTS). Audio captured by the Meta Quest 3's built-in microphone was first passed to Azure STT; the resulting transcript was then forwarded to ChatGPT. ChatGPT-4 generated feedback via a predetermined evaluation prompt covering the speech's introduction, credibility statement, main points, supporting evidence, and conclusion (see Figure 3). The model returns a structured critique, in which Azure TTS immediately converts into an audible response voiced by an on-screen virtual agent (see Figure 4).

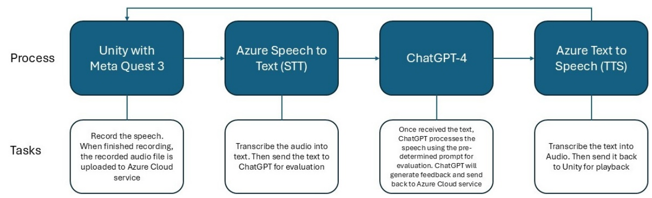

Figure 3: Speech data processing diagram.

Figure 4: Speech evaluation screen with results panel. The left panel shows the transcribed speech. The right side shows the LLM-generated feedback.

3.3 Measurement

Our data analysis followed a two-stage plan. First, we ran a multiple-regression model to identify which construct exerted the strongest influence on BI and potential moderating effects. Reliability checks (i.e., Cronbach's α, average variance extracted [AVE], composite reliability [CR], and Fornell-Larcker criterion) ensured the metric integrity of each scale before we interpreted the regression coefficients. Second, we examined whether antecedent variables (i.e., academic major and GPA level) impacted UTAUT constructs with independent sample t-tests. The UTAUT questionnaire items are in Table 1. All the questions are answered on a 7-point Likert scale, with one being "strongly disagree" and seven being "strongly agree."

We expected a large effect size due to reports on strong UTAUT indicator influence [Khusaini et al. 2023]. An a priori G*Power calculation (α = .05, f^2 = .35, four predictors) indicated that a

Table 1: UTAUT questionnaire on the adoption of LLM-integrated VR simulation using a 7-point Likert scale.

UTAUT Construct	Items
Performance Expectancy (PE)	PE1: I would find the LLM-integrated VR system useful for my class. PE2: I think using VR with LLM will help me save practice time. PE3: If I use the LLM-integrated VR system, I will increase my chances of getting a better grade.
Effort Expectancy (EE)	EE1: My interaction with this system was clear and understandable EE2: It would be easy for me to become skillful at using this system EE3: I would find this system easy to use.
Facilitating Conditions (FC)	FC1: I have the resources and equipment necessary to use the system. FC2: I have the knowledge necessary to use the system. FC3: A specific person (or group) is available for assistance with system difficulties.
Hedonic Motivation (HM)	HM1: I think using VR with LLM is fun. HM2: I think using VR with LLM is entertaining HM3: I think using VR with LLM is enjoyable
Behavioral Intention (BI)	BI1: I intend to use the system for future semesters BI2: I would recommend the LLM-integrated VR system to my peers.

sample of 30 would yield 80% power, confirming the adequacy of our sample size. Because our sample was modest, we deliberately chose not to employ structural-equation modeling (SEM), which was the technique most often used to trace UTAUT pathways to behavioral intention [Venkatesh et al. 2003]. However, a smaller-scale technology adoption study could still detect meaningful effects with regression analysis [Khusaini et al. 2023]. From the above, the precedent supported our measurement decision.

3.4 Study Procedure

The experiment took place in the department's Emerging Media Lab. Upon arrival, each student was briefed on the study and guided through a short demographic questionnaire. The researcher then helped with headset fitting and allowed students to adjust for comfort. Students then followed a brief walk-through of the VR interface and research procedure. Then, the researcher launched the VR application. Students first completed the tutorial level. The first formal speech level began only when they indicated readiness. Before each speech, learners had several minutes to organize their thoughts. After the preparation period, students began delivering their speeches; when they finished, they ended the recording and listened to the LLM-generated feedback. Once the speech concluded and the virtual agent delivered the feedback, students removed the headset and took a five-minute break before continuing to the next topic. Then, students repeated the same process until they finished all three speeches. After the third speech, the researcher ended the simulation and distributed the post-UTAUT questionnaire, with an open comment box. All participants completed the protocol within an hour.

4 Results

4.1 UTAUT Results and Validation

For our UTAUT construct results (see Table 2), following earlier recommendations to establish the consistency of self-report measures, we began by assessing reliability. As shown in Table 2, every construct surpasses the .80 level for confirmatory analysis (Cronbach's α), thereby validating the reliability of all items included in our model. We further tested the convergent validity of our UTAUT constructs. Each AVE exceeds .50, indicating convergent validity across constructs. We also tested CR to check consistency and found that all values pass the .70 acceptance line. Finally, we used the Fornell-Larcker criterion to explore discriminant validity. We found that all constructs meet the requirement of shared variance between constructs lower than the square root of their AVE (Table 3).

Table 2: UTAUT construct data (M, SD, N) and construct validations (Cronbach's α, AVE, and CR values).

UTAUT Construct		β	SD	N	Cronbach's α	AVE	CR
Performance Expectancy (PE)	PE1	4.40	2.08	30	.833	.568	.795
	PE2	4.00	1.99	30			
	PE3	4.30	1.95	30			
Effort Expectancy (EE)	EE1	4.17	1.42	30	.847	.683	.866
	EE2	4.40	1.52	30			
	EE3	4.57	1.55	30			
Facilitating Conditions (FC)	FC1	5.07	2.08	30	.910	.686	.866
	FC2	4.80	1.80	30			
	FC3	5.33	1.26	30			
Hedonic Motivation (HM)	HM1	5.13	1.93	30	.849	.864	.899
	HM2	5.31	1.95	30			
	HM3	4.97	1.81	30			
Behavioral Intention (BI)	BI1	3.40	2.04	30	.832	.760	.804
	BI2	4.50	2.08	30			

4.2 Hypothesis Testing

We ran a linear regression analysis to test whether the UTAUT constructs predict Behavioral Intention (BI). Before the regression analysis, we performed a Shapiro-Wilk test and found the significance (p = .943), which is greater than .05, indicating that our residuals are normally distributed. The regression model explained 77.5% of the variance in BI (R^2 = .775; adjusted R^2 = .739; SE = .91). Results from the analysis indicated that EE (β = .632, p = .015), FC

Table 3: Fornell-Larcker criterion for the discriminant validity test.

Construct	PE	EE	FC	HM
PE	.754			
EE	.698	.827		
FC	.296	.239	.828	
HM	.666	.506	.246	.864

(β = .497, p < .001), and HM (β = .647, p < .001) were significant predictors of BI. PE (β = −.498, p = .052) was not statistically significant (Table 5). Thus, EE, FC, and HM significantly predicted students' intention to adopt the AI-VR speech simulation, whereas PE did not, indicating that H2, H3, and H4 were accepted. We then tested the potential moderating variables after centering them. Nevertheless, we did not find any moderating effect of gender or prior VR experience. Therefore, we were unable to accept H5 or H6.

Table 4: Significance of path coefficient and moderating effect (path coefficient [β], standard error [SE], t−value, and p−value).

	Path	β	SE	t−value	p−value	Result
H1	PE-BI	-.498	.24	-2.032	.052	Reject
H2	EE-BI	.632	.24	1.755	.015	Accept
H3	FC-BI	.497	.12	3.723	<.001	Accept
H4	HM-BI	.647	.14	4.365	<.001	Accept
H5	Gender	Insignificant on all pathways				Reject
H6	Prior VR experience moderating effect	Insignificant on all pathways				Reject

Finally, we conducted independent sample t-tests to analyze the effect of the proposed antecedent variables. We found significant differences in academic majors in PE (t = 2.464, p = .020) and EE (t = 2.091, p = .046). Communication major students had a higher rating in both PE (M = 4.83, SD = 1.23) and EE (M = 4.82, SD = .97) than their non-communication major counterparts (PE: M = 3.46, SD = 1.80; EE: M = 3.79, SD = 1.70). We also found significant differences in GPA levels in HM (t = 2.337, p = .027). High-GPA students (M = 6.16, SD = 1.45) reported higher hedonic motivation than their low-GPA counterparts (M = 4.65, SD = 1.69). Therefore, we were able to accept H7, H8, and H14 (Table 5).

5 Discussion

5.1 Effort Expectancy

Effort expectancy emerged as a significant driver of behavioral intention in our model: students who rated the LLM-integrated VR simulation easy to operate expressed a markedly higher willingness to use it in the future. This finding mirrors prior UTAUT studies' results on advanced educational technologies [Abbad 2021] and supports Davis's [Davis 1989] contention that perceived ease of use is a foundational determinant of system acceptance. Numerous investigations have likewise shown that when learners rate a tool as easy to use, the intention to adopt rises across VR applications [Du et al. 2022] and AI-based teaching aids [Youmei et al. 2021].

Table 5: Antecedent variables' effect on UTAUT constructs (t−value, degree of freedom [df], two-sided p−value, and result).

	Path	t−value	df	p−value	Result
H7	Academic Major - PE	2.464	28	.020	Accept
H8	Academic Major - EE	2.091	28	.046	Accept
H9	Academic Major - FC	1.586	28	.124	Reject
H10	Academic Major - HM	2.043	28	.051	Reject
H11	GPA level - PE	1.940	28	.063	Reject
H12	GPA level - EE	.824	28	.417	Reject
H13	GPA level - FC	.693	28	.494	Reject
H14	GPA level - HM	2.337	28	.027	Accept

Two design decisions likely explained why EE accounted for so much variance in intention. First, controller "press-to-start/stop" actions replicate everyday tap-and-point gestures, sharply reducing the learning curve even for VR novices [Khundam et al. 2021]. Second, the near-instant feedback loop (i.e., speech capture → transcription → ChatGPT critique → text-to-speech delivery) compresses practice and reflection from minutes to seconds, signaling tangible time savings. These features collectively lowered the perceived effort required to gain meaningful practice benefits, thereby boosting their motivation to continue using the system. We have also received feedback from students indicating that "the feedback is straightforward and easy to understand" and "the VR system operation is smooth." Taken together, our results confirm the critical role of EE in technology adoption and highlight the value of streamlining interaction and feedback cycles when designing AI-VR learning simulations. Our findings support H2, confirming that EE is a primary driver of behavioral intention in LLM-integrated VR simulation.

5.2 Facilitating Condition

Facilitating condition also exerted a significant positive influence on behavioral intention: when students understood that hardware, technical guidance, and AI-VR know-how were readily available, their willingness to continue using the simulation rose sharply. Prior work reported that sufficient technological support makes new tools easier to adopt in practice and that application-specific services that solve user problems further bolster acceptance [Pinto et al. 2022]. In educational VR, providing external resources (e.g., hardware, funding, and on-demand expertise) has been shown to raise use intentions, and comparable findings in AI initiatives highlight the value of institutional training and infrastructure [Teng et al. 2022].

Our findings conclude that visible, dependable support is critical for driving usage intention. In our experiment, support was available through three interlocking mechanisms: a VR- and AI-trained lab assistant provided real-time troubleshooting and tech support, ensuring help was always at hand; a built-in tutorial level offered self-paced rehearsal of controller gestures and voice-recording steps, and reliable infrastructure (i.e., department-supplied Meta Quest 3 headsets running on a high-specification PC) guaranteed smooth performance, eliminating worries about hardware bottlenecks or software glitches. Together, these resources created the exact environment UTAUT describes when FC translates into stronger BI.

Students' remarks such as "the lab assistant really helped," "all the system went smoothly," and "the instructions from the beginning scene were clear to follow" echoed this perception of robust support. By foregrounding technical assistance, we validated the pivotal role of FC in encouraging continued use of innovative LLM-integrated VR simulation. From the above, we were able to accept H3, indicating that the facilitating condition is also a key driver of behavioral intention.

5.3 Hedonic Motivation

Hedonic motivation surfaced as the strongest driver of behavioral intention: the more enjoyable the simulation felt, the more students planned to keep using it. This finding aligns with prior evidence that learners adopt educational VR not only for skill development but also for the positive psychological experience it affords [Du and Liang 2024]. Nurlaela et al. [Nurlaela et al. 2025] further showed that when participants report enjoyable VR encounters, hedonic motivation becomes a significant predictor of intention. Similar patterns appear in AI-enabled learning: ChatGPT and related tools increased adoption because their interactive, context-rich responses resonate with students' interests [Acosta-Enriquez et al. 2024], offering an experience that is both novel and pleasurable.

Several system features have magnified this effect. First, the narrative framework delivered by animated virtual agents turned routine speech practice into an immersive, game-like scenario that students described as "fully engaging." Second, ChatGPT supplied instructor-style evaluations in real time, blending professional feedback with a conversational tone that students found both helpful and encouraging. Students have provided comments regarding these features in the following: "It was entertaining," "I liked the system because it motivated me to continue speaking," and "I loved the story scenarios, and the 'game' feel." By coupling entertainment with learning technology, these features boosted hedonic appeal and, consistent with the literature, translated directly into stronger intentions to reuse the application. Hence, our results support H4, and we can confirm that HM is an essential factor affecting students' behavioral intention of AI-VR simulation.

5.4 Performance Expectancy

Our regression results showed that performance expectancy was not a significant predictor of behavioral intention. Students' perceived usefulness of the AI-VR simulation did not affect their intention to use it in the future. Although PE was often the strongest UTAUT driver, prior work noted that students can struggle to perceive the immediate value of unfamiliar learning tools, leading to nonsignificant PE–BI paths [Bervell and Umar 2017]. Davis [Davis 1989] argued that learners must first envision how technology fits into their study routines before the benefits become salient. More recent evidence from Owusu Kwateng et al. [Owusu Kwateng et al. 2019] reports muted PE effects when users cannot identify clear academic gains, and Utomo et al. [Utomo et al. 2021] suggest PE may only emerge over time as learners connect the tool to tangible outcomes.

In our study, participants used the AI-VR speech platform for only three speeches, which were too brief for them to appreciate broader advantages. Students did mention that "although AI was helpful, it did not suggest improvements with other speech topics." Expanding the system across additional speech topics should give students sufficient exposure to recognize how VR and AI can enhance performance, thereby elevating the relationship between PE and BI in future evaluations. Furthermore, because our LLM-integrated VR simulation is still a niche supplement rather than a mainstream instructional method, broader adoption strategies are needed. Incorporating the platform into multiple sections and framing it as a key institutional innovation would create the normative cues UTAUT associates with higher performance gain in public speaking, thereby increasing students' motivation to embrace the system. Our findings therefore reject H1, highlighting that PE is not a decisive factor.

5.5 Gender and Prior VR Experience

For the moderating effect, we found that neither gender nor prior VR experience moderates any of the structural paths in the model. This result suggests that gender difference and previous exposure fail to influence behavioral intention when it is driven by the UTAUT predictors, which is supported by previous studies [Dwivedi et al. 2019; Liu et al. 2022]. We think the possible reason is that the sample is homogeneous in terms of background (i.e., age, gender, and prior VR experience). As mentioned in previous studies, if participants all share similar levels of experience (i.e., most of our participants had experience in VR) or if the gender distribution is unbalanced (i.e., 22 female students vs. eight male students), then it can be challenging to detect moderating effects [Paszkiewicz et al. 2021]. In our future studies, a larger sample with more varied backgrounds in VR, while keeping balanced gender size, is essential to find potential moderating effects.

5.6 Academic Major and GPA Level

Academic major emerged as a significant antecedent of both PE and EE. Students majoring in communication reported significantly higher PE and EE scores than students from other majors. This finding aligns with earlier work showing that domain expertise amplifies perceptions of performance expectancy and usability when individuals encounter novel technologies [Mafa and Govender 2025]. Expertise also appears to foster perceived ease of use more strongly than prior experience alone [Goeke et al. 2018]. One explanation is that communication majors treated the simulation principally as an additional practice tool that is both useful and familiar. In contrast, non-communication majors, with less exposure to public speaking, regarded it as less valuable and more difficult to perform speeches. Unlike prior VR experience, which primarily reflects technical literacy, an academic major embodies knowledge structures that can feed directly into both PE and EE [Wei et al. 2025].

GPA level also proved to be a significant antecedent of HM. Students with a higher GPA level reported greater enjoyment when using the AI-VR system than those with a lower GPA level. GPA, an established proxy for academic achievement, has been linked to well-being in higher education [Thongsri et al. 2024]. Students with higher academic achievement are often more engaged and interested in exploring new methods and technology in improving their self-efficacy [Rioch and Tharp 2022]. Therefore, we think the potential reason behind this phenomenon is that higher grade students achieved stronger satisfaction and enjoyment with the new tools provided. We contend that high-achieving students viewed the system as an innovative learning resource, thereby deriving greater engagement and interest, and therefore rated HM higher.

5.7 Theoretical Implications

Based on our study results, we propose several theoretical implications for the UTAUT model. Our findings extend UTAUT in the context of LLM-integrated VR public-speaking simulation. First, EE, FC, and HM appear to support the traditionally proposed technology acceptance model, suggesting that ease of use, sufficient technical support, and enjoyment may serve as primary adoption factors. Second, the insignificant effect of PE indicates a shift from utilitarian drivers to experiential ones in the adoption of novel learning technologies, thereby challenging the conventional PE–BI pathway. Third, gender and prior VR experience do not have any moderating effects on the pathway between any of the UTAUT constructs and behavioral intention. Neither gender difference nor previous VR exposure moderates the effect of UTAUT constructs on BI. Fourth, the significant effects of academic major and GPA levels reveal a domain-novelty and performance dimension within the UTAUT framework. Disciplinary experts prioritize perceived usefulness and ease of use more strongly than their novice counterparts. Moreover, students exhibit higher hedonic motivation as academic performance increases. Taken together, these results suggest that UTAUT constructs, in our AI-VR simulation, should be interpreted relative to both the design of AI feedback and the learner's background, rather than as static predictors. Multiple regression and independent sample t-test analyses can still yield stable and meaningful UTAUT findings, supporting the practicality of conducting acceptance studies when SEM may be underpowered.

5.8 Practical Implications

Our results yield several actionable insights for instructors and AI-VR developers who wish to embed public-speaking simulations in the classroom. Because effort expectancy is a strong predictor of adoption, every design decision should protect the learner's sense of "frictionless" use: keep the interface self-intuitive, preserve the one-click start/stop mechanic, and return AI feedback within seconds so students never feel stalled between practice and reflection. Facilitating conditions came next in predictive strength, providing the value of a visible support chain. Learners must know that knowledgeable staff, tutorials, and reliable hardware are close at hand. Hedonic motivation also played a decisive role; weaving richer story arcs and playful experiences into future versions will help sustain the enjoyment that drives repeated use. Although performance expectancy did not surface as a significant driver in our pilot, its absence serves as a reminder that the AI-VR simulation should be available across broader areas to exhibit measurable performance gains.

Communication major students already perceive higher usefulness and ease of use; thus, it is reasonable to keep them engaged with advanced scenarios. Non-communication major students need stronger relevance cues. As developers, we need to import discipline-specific topics. Tailoring content and scaffolds for each discipline should raise their intention to reuse. In addition, higher GPA level students enjoy adaptive challenges (i.e., stricter time limits, tougher audiences, and live interruptions). In contrast, lower GPA level students need early confidence improvement with special functions such as shorter speeches, virtual note cards, and modified AI feedback. Calibrating the system depending on GPA levels sustains hedonic motivation across the spectrum.

5.9 Limitations

This study has several noteworthy limitations. However, the reported limitations do not invalidate the study; instead, they provide essential context for interpreting the findings and highlight avenues for future research. First, the sample size was modest for SEM analysis. Most UTAUT studies that rely on structural equation modeling recommend more than 100 cases to detect interaction effects and moderator relationships with adequate power. A larger tracking behavior across more class sections with a greater sample size would provide clearer insight into sustained adoption. Relatedly, we recruited all participants from a single institution. Future work should recruit participants from multiple universities and aim for greater demographic parity (e.g., gender, prior VR experience, major, GPA) to enhance external validity and prevent underpowered results.

Second, the platform itself contains technical constraints. Although Meta Quest 3 delivered stable performance, due to its built-in eye-tracking and hand-tracking being coarse, we could not capture additional behavioral metrics, such as heat maps and hand motion data, that could enrich our data analysis. Moreover, newer and more capable language models have become available. Integrating upgraded hardware sensors and more advanced AI engines would likely sharpen both measurement precision and user experience.

Third, our UTAUT analysis, while informative, did not encompass every factor that may influence adoption. We excluded social influence due to mandatory participation. It is necessary to prepare a background on voluntary usage and allow peers, instructors, and the university to communicate about the opinions of the system. Once SI can vary across learners, we will take this construct into account. In addition, variables such as voluntariness of use, degree of personalization, university management of support, and perceived risks associated with LLM-driven feedback were beyond the present scope. Incorporating these dimensions in future models could yield a more nuanced picture of students' technology acceptance.

6 Conclusions and Future Works

This study introduced an LLM-integrated VR public-speaking simulation. We employed an extended UTAUT framework, augmented with gender and prior VR experience as moderators, and academic major and GPA level as antecedent variables, to explore determinants of students' intention to adopt the system. Our study results revealed that EE, FC, and HM generated significant positive effects on BI, whereas PE was not significantly related to BI. For moderating effects, gender and prior VR experience were not significant moderators. Moreover, for antecedent variables, we found that academic major had a significant effect on PE and EE. Communication major students rated higher performance expectancy and effort expectancy than their non-communication counterparts. Finally, GPA levels also had a significant effect on HM. Students with higher GPAs enjoyed the system better than those with lower GPAs. These findings refine UTAUT's explanatory power in immersive learning contexts and yield a conceptual model that can guide future investigations of educational technology adoption.

As for the future work, we would like to propose the following plans. First, a broader deployment of this application across multiple universities will enlarge the sample to permit structural-equation modeling, thereby enabling a more rigorous assessment of direct, mediating, and moderating pathways. Second, the simulation will be embedded into routine coursework, with AI-generated scores incorporated into formal assessment, to test its sustained pedagogical impact. We will then put social influence back into our UTAUT model. Moreover, we intend to collect and evaluate several behavioral (e.g., pre-post PSA scores, AI instructor rating) and performance measurements (e.g., speech scores, speech time, number of errors) across multiple semesters to better understand the longitudinal effects of LLM-integrated VR public-speaking simulation on PSA reduction and actual learning gains. Third, a logical next step is a cluster-randomized controlled trial across multiple class sections, with intact classes randomly assigned to AI-VR, VR only, and traditional in-class rehearsal. We will also extend the UTAUT model with voluntariness, personalization, institutional support structures, and perceived LLM-related risk, which are variables that may play pivotal moderating roles. Furthermore, a mixed-methods study that also considers students' qualitative feedback can yield valuable insights into the LLM-integrated VR public-speaking simulation. Finally, we would also like to apply higher-fidelity headsets (e.g., Meta Quest Pro) for improved eye- and hand-tracking, and more advanced language models (e.g., GPT-4o or successors) to bolster feedback quality.

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