Enhancing VR-Based Language Learning: Linking Task-Technology Fit, Expectancy Disconfirmation, and EEG Insights

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***Abstract*—This study investigates the structural relationships between task characteristics, technological features, task–technology fit, performance, satisfaction, and expectation within a Virtual Reality (VR) environment for English as a Foreign Language (EFL) learning. Grounded in the task-technology fit and expectancy disconfirmation theories, we further explore the moderating role of Electroencephalography (EEG)-detected Frontal Alpha Asymmetry (FAA) in these relationships. A total of 159 participants engaged in a 20-minute VR-based EFL course, and the data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). Results demonstrated the reliability and validity of the measurement model, and six of ten hypothesized pathways in the structural model were supported. Notably, FAA significantly moderates the relationship between expectation and satisfaction, highlighting the potential of physiological measures in understanding user experiences. This study offers a novel contribution by integrating EEG data into SEM analysis to examine EFL learners' perceptions of VR-based language learning, providing critical insights into the interplay between cognitive and technological factors in immersive educational environments.**

***Keywords*—Virtual Reality (VR)-based language learning, task-technology fit theory, expectancy disconfirmation theory, educational neuroscience, Frontal Alpha Asymmetry (FAA)**

I. INTRODUCTION

In recent years, the development of digital technology has created many unprecedented learning platforms and contexts, with a growing focus on Virtual Reality (VR) for language learning [1]. Head-mounted VR can create immersive 3D virtual environments where users can interact and converse with virtual objects or components via electronic devices, thereby enhancing the realism of the environment and increasing the opportunities for language learners' scaffolding via communication complexity and accuracy [2]. This is beneficial for foreign language learners and has positive effects on learning [3–6]. Lan [7] pointed out that the application of VR facilitates English as a Foreign Language (EFL) learning via language correctness and appropriate expressions of foreign languages. However, few empirical studies on the development of VR for foreign language learning content have argued that current VR technology is not applicable to all educational environments [8]. Hence, this study combined the Task-Technology Fit theory (TTF) [9–11], which is widely used by scholars to investigate the relationship between technology use and performance outcomes, along with the expectancy disconfirmation theory [12–15] to investigate issues related to technology use, digital course learning expectations, and education.

Language learning utilizes extensive brain neural networks [16, 17], modifying the neural connections of the brain during learning and memory. Over the past 30 years, new technologies for research on the brain and neuroscience have emerged. Neurophysiological signals and brain imaging techniques such as the Electrical Encephalogram (EEG), Positron Emission Tomography (PET), functional Magnetic Resonance Imaging (fMRI), single photon computer tomography (SPECT), Magnetoencephalography (MEG) have been used to further investigate brain regions related to neural function and link them to emotional and mental activities (thoughts, emotions, reasoning processes, and understanding) in conscious subjects [18]. Utilizing EEG for direct measurements of learners' cognitive processes and emotions expands the scope of educational neuroscience [19], leading to greater insights. The role of Frontal Alpha Asymmetry (FAA) has been particularly identified to significantly moderate the relationship between behavior and mental states, such as anxiety [20] or emotional stimuli [21]. FAA presents theories and methods typically utilized in approach/withdrawal motivation research and consolidates research on applied FAA with an emphasis on product design, marketing, brain-computer communication, and mental health studies, where approach motivation is of interest. However, the role of EFL learners' FAA in their learning has been underexplored. To bridge this academic gap, this study intends to combine the perspective of educational neuroscience with the catering tourism English VR learning scenario developed and applied to address the following research questions:

1) What are EFL learners' perceptions of the suitability of VR for English learning?
2) Is there any expectancy disconfirmation regarding EFL learners' thoughts on using VR for English learning?
3) What is a comprehensive model of VR task fit, EFL learners' expectations, and brainwave data after experiencing VR-based language learning?

II. LITERATURE REVIEW

A. VR and L2 Learning

An immersive VR-constructed language learning environment would not only enable learners to hear sounds but also directly use language for exploration and socialization [22]. Consequently, learners can focus more on their communication abilities [5]. Cheng *et al.* [23] used VR to teach Japanese greetings and bowing behavior, emphasizing its potential for cultural interaction, benefiting L2F learning. Garcia *et al.* [24] combined immersive VR games with Spanish language teaching to reduce the

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expenses of traveling to achieve immersion in a foreign language context; they reported that VR could be applied to any language learning and extended to most scenarios and fields. Chen [25] evaluated the learning outcomes of Taiwanese students using a virtual reality English learning platform and found that VR helps learners develop more complex and higher-level thinking; improves students' cognition of English phonology, morphology, syntax, and sentences; and positively affects their L2 learning. Current research on applying VR to L2 learning is focused on learning outcomes or learners' subjective feelings; however, the underlying mechanism of learners who experience VR-based language learning remains unknown. Neuroscience can bridge this research gap, as it evaluates the effectiveness of a specific method for education and enhances teaching methods and outcomes [26]. Hence, this study utilized data on EFL learners' neuronal activities in the brain while undertaking VR-based language learning.

B. Task-Technology Fit Theory

Task-Technology Fit (TTF) theory posits that the alignment between task characteristics and technology functionalities enhances performance and user satisfaction [27, 28]. In educational contexts, TTF has been applied to evaluate how technologies, such as Virtual Reality (VR), support specific learning tasks [29]. For English as a Foreign Language (EFL) learning, VR offers immersive environments that simulate real-world communication scenarios, potentially improving vocabulary acquisition and communicative competence [30]. Recent studies have further explored VR's efficacy in language learning. For instance, Tai *et al.* [31] demonstrated that a VR application significantly enhanced EFL learners' vocabulary retention compared to traditional methods, attributing this to the immersive and interactive nature of VR environments. Similarly, Baceviciute *et al.* [32] used EEG to investigate cognitive engagement during reading tasks in VR, finding that environmental embeddedness in VR increased cognitive load and knowledge transfer compared to non-immersive settings. Hofmann *et al.* [33] used EEG to decode emotional arousal in immersive VR experiences, finding heightened emotional responses compared to 2D environments, which supports VR's potential to elicit strong affective states. Similarly, Cao and Luo [34] combined VR with EEG biofeedback to enhance EFL proficiency, reporting that real-time FAA adjustments improved learner engagement and vocabulary acquisition. These studies highlight the synergy between VR and EEG in capturing affective and cognitive processes, yet few have applied FAA to examine the expectation–satisfaction relationship in EFL learning, as proposed in this study. Moreover, the cognitive and affective mechanisms underlying these benefits, such as neurophysiological responses measured via EEG, remain underexplored, warranting further investigation in EFL contexts.

C. Expectancy Disconfirmation Theory

Expectancy disconfirmation theory is a widely accepted model of consumer behavior that is often used to explain and predict consumer satisfaction and repurchase intentions for services or products [35–38]. Initially proposed by Yuce *et al*. [39, 40], and found in the literature related to psychology and marketing, this theory has now been adopted by many different fields, including public administration and civic service [41–44], online game design and evaluation [45, 46], corporate image and social responsibility [47, 48], and teacher vitality and expectations [49]. When considering the technology integration in education, the expectancy disconfirmation theory contributes to the current learning of digital technology. In addition to learning outcomes, the model incorporates student expectations of digital courses into the analysis, considerably increasing the applicability of the theoretical model in investigating education-related issues [50]. Previous studies [51, 52] have confirmed the predictive capacity of the expectancy disconfirmation theory model for the continued use of technology-based services. Until now, there has been no relevant research on applying the expectancy disconfirmation theory to VR-based language teaching and learning, as elucidated by the previous discussion. Therefore, this study uses expectancy disconfirmation theory to investigate the expectations, perceived effectiveness, failure, and satisfaction of students using VR-based language learning to learn EFL courses.

D. Frontal Alpha Asymmetry

Neuroscience is recognized for its potential to improve our quality of life and learning development [53], and educational neuroscience helps us understand brain function, which is essential for enhancing learning and teaching processes [54]. In terms of EFL teaching and learning, language learning and acquisition research have been inseparable from the human mind and neuroscience research [55, 56]. Most related research on using VR for language learning also utilizes objective physiological measurements, such as EEG, for detecting users' affective responses in VR environments [57]. In this study, we focus on Frontal Alpha Asymmetry (FAA), a score indicating the difference between the right and left prefrontal cortex activities [58]. FAA was chosen as the primary EEG metric due to its well-established role as a biomarker of emotional responsiveness and approach/withdrawal motivation, which are critical for understanding learners' affective states in immersive VR-based language learning [59, 60]. Unlike other EEG metrics, such as theta power (associated with cognitive load) or beta power (linked to attention), FAA specifically captures motivational and emotional processes that align with the expectancy disconfirmation theory's focus on satisfaction and affective outcomes [61, 62]. For instance, FAA has been used to assess approach motivation in product design, marketing, and mental health studies [63–65], making it particularly relevant for evaluating learners' engagement with VR technology.

FAA is calculated by subtracting the natural log (ln) of the Power Spectral Density (PSD) of the alpha brainwave (8–13 Hz) at the left prefrontal site (F3) from the right prefrontal site (F4) in the International 10–20 System [58]. A positive FAA score indicates greater relative left frontal activity, associated with positive emotions and approach-related behaviors, whereas a negative FAA score indicates greater right frontal activity, linked to negative emotions and withdrawal-related behaviors [61, 62]. Prior studies have established that FAA values typically range from −0.5 to 0.5 in educational and emotional response contexts, with positive values indicating a propensity for approach motivation [62]. This makes FAA an ideal metric for examining how affective states moderate the relationship between learners' expectations and satisfaction in VR-based EFL learning. Although other EEG metrics, such as the Theta/Alpha ratio for cognitive load [66], could provide insights into cognitive effort, FAA's focus on affective processes aligns more closely with the study's objectives of integrating cognitive (TTF) and affective (EDT) frameworks. To the best of our knowledge, no prior research has included FAA in a structural equation model for VR-based language learning, making this study a novel contribution. Recent conceptual models, such as the Cognitive-Affective Theory of Learning with Media (CATLM) [67], emphasize the role of affective factors in multimedia learning, further supporting FAA's inclusion as a moderator in our model [68, 69].

E. Model Development and Research Hypotheses

Based on research questions and reviewed literature on the integration of Task-Technology Fit (TTF) and Expectancy Disconfirmation Theory (EDT), we propose a conceptual framework that synthesizes these models to explain EFL learners' experiences in VR-based language learning. TTF posits that the alignment between task characteristics (e.g., immersive language learning requirements) and technology characteristics (e.g., VR's interactive and immersive features) enhances task-technology fit, which positively influences performance [70]. In contrast, EDT focuses on the psychological process where learners' expectations of technology influence their perceived performance and subsequent satisfaction, moderated by disconfirmation [39, 40]. In this study, TTF provides a structural lens to assess how VR supports EFL learning tasks, while EDT captures learners' affective and evaluative responses to the VR experience.

The integration of these frameworks is grounded in the assumption that cognitive (task-technology alignment) and affective (expectations and satisfaction) processes are interdependent in technology-mediated learning [67]. For instance, a high degree of Task-Technology Fit (TTF) may enhance learners' perceived performance, which aligns with EDT's performance construct, subsequently influencing satisfaction. Additionally, learners' expectations (EDT) may shape their perceptions of Task-Technology Fit (TTF), as prior beliefs about VR's capabilities influence how learners evaluate its suitability for EFL tasks. The inclusion of Frontal Alpha Asymmetry (FAA) as a physiological moderator further bridges these frameworks by capturing affective responses (e.g., approach/withdrawal motivation) that modulate the expectation-satisfaction relationship [59].

To illustrate this integration, we present Fig. 1, which depicts the conceptual interplay between TTF and EDT. The diagram shows how task and technology characteristics (TTF) feed into task-technology fit and performance, which interact with expectations, performance, and satisfaction (EDT). FAA is positioned as a moderator influencing the EDT pathway, highlighting the role of affective states in shaping learner outcomes. The ten hypotheses are presented as follows:

- H1: VR task characteristics have a significant association with the perceived task-technology adaptability of VR-based language learning.
- H2: The technological characteristics of VR are significantly associated with the perceived task-technology adaptability of VR-based language learning.
- H3: Task characteristics of VR will positively influence learner satisfaction with VR-based language learning.
- H4: Technological characteristics of VR will positively influence learner satisfaction with VR-based language learning.
- H5: Adaptability of VR and VR task technology has a significant association with the applicability of VR-based language learning.
- H6: Participants' expectations of VR-based language learning are significantly associated with their perceived performance of VR.
- H7: Participants' expectations of VR-based language learning are significantly associated with their perceived course satisfaction.
- H8: Participants' perceived performance of VR-based language learning is significantly associated with their perceived course satisfaction.
- H9: The FAA of the participants calculated during VR-based EFL learning has a moderating effect on the association between their expectations and performance.
- H10: The FAA of the participants calculated during VR-based EFL learning has a moderating effect on the association between their expectations and satisfaction.

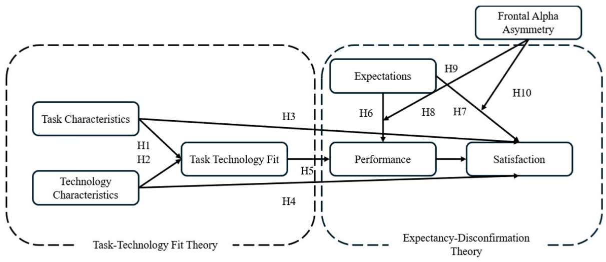

Fig. 1. Proposed research model.

III. MATERIALS AND METHODS

A. Measurements

This study was revised based on [70] TTF model. Given that students could not control the amount of time spent using VR in class, the utilization dimension was deleted, and task characteristics, technology characteristics, TTF, and performance were retained. The performance is similar to the effect aspect in the expectancy disconfirmation model; therefore, this study combined the two aspects of this model to form a part of the integrated mode, which covered six dimensions: "Task Characteristics", "Technology Characteristics", "Task Technology Fit Degree", "Expectation", "Performance", and "Satisfaction" (please see Table A1 in Appendix for the detailed questionnaire). This present research adopted a five-point Likert scale (Strongly Agree = 5 and Strongly Disagree = 1) except for the FAA (please see the Appendix for the detailed questionnaire with the results of reliability and validity examinations). The equipment used in this study to collect EEG data was an eight-channel EEG manufactured by Thought Technology with the ProComp Infiniti encoder along with the BioGraph Infiniti software version 6.0, which has been prevalently employed in previous academic works such as those of [71]. The VR content was presented using an HTC Vive Pro.

B. Participants

To acquire results with statistical power, G*Power was used to calculate the appropriate sample size for PLS-SEM. With the following parameters: effect size f^2 = 0.15, α err prob = 0.05, and 1-β err prob = 0.95, the result of G*Power suggested an appropriate sample size of 138 (n = 138) and this study recruited 159 participants. All participants visited a soundproof laboratory to experience a 15-minute-long VR-based EFL course. Before the onset of this study, they were informed about the nature and procedure of the study, with the assurance that they could withdraw at any time without any penalty. After completing the experiment, they were expected to sign a consent form individually, which confirmed that their participation in this experiment was in accordance with the Helsinki Declaration of 1964. This study was conducted with the approval of the Institutional Review Board (NCKU HREC-E-110-577-2).

All the participants had a TOEIC score ranging from 550–580, indicating their English proficiency levels. According to the Education Testing Service (ETS), the average TOEIC score of Taiwanese test-takers was 568 in the year 2021 [72]. Furthermore, they had no cognitive and mental deficits, prior brain surgery, or medications that would affect their neuronal activities.

C. Research Procedure

As mentioned previously, every participant experienced the VR-based language-learning program. They wore Head-Mounted Display (HMD) VR for the program with EEG electrodes positioned at F3 and F4 to measure their brainwaves, as this section of the brain oversees the underlying affective processing [73]. The baseline brainwaves were detected and captured in the first two minutes of the experiment as the resting state, wherein classical music was played, and the participants were asked to relax in this phase. Subsequently, the VR-based language learning session was conducted for 20 min. Participants' brainwave data were collected continuously throughout the study period. Subsequently, all participants completed a questionnaire. The entire process was concluded with a consent form signed by the participants, and a coupon of NTD 300 (approximately USD 10) was given to them as a token of appreciation.

The instructional content in the VR environment focused on everyday conversational English to enhance participants' communicative competence. The vocabulary covered included approximately 50 high-frequency phrases and situational terms related to travel scenarios (e.g., greetings, ordering food, asking for directions, checking into a hotel). Linguistic tasks included sentence construction exercises, where participants formed sentences using target vocabulary, and pronunciation practice with real-time feedback from the VR system. Communicative tasks involved role-playing dialogues with virtual native English speakers in simulated environments (e.g., a virtual airport or restaurant), requiring participants to respond to prompts and engage in turn-taking conversations. Interactions within the VR context were designed to be immersive and interactive, leveraging 3D visuals, spatial audio, and gesture-based controls to simulate real-world language use. For example, participants could "pick up" virtual objects (e.g., a menu) to trigger language tasks or navigate through scenarios by responding to contextual cues. These tasks were calibrated to impose a moderate cognitive load, aligning with the participants' intermediate proficiency, while fostering engagement through gamified elements (e.g., earning points for correct responses). The content was informed by communicative language teaching principles [74] and aimed to stimulate both cognitive processing (e.g., vocabulary recall, syntactic accuracy) and affective responses (e.g., motivation, confidence), which were measured via questionnaire responses and EEG-derived Frontal Alpha Asymmetry (FAA).

Prior to the VR session, participants completed a 2-minute baseline EEG recording during a resting state with classical music to establish a reference for FAA calculations. The EEG data were recorded continuously during the VR session using an eight-channel EEG system (Thought Technology, ProComp Infiniti encoder with BioGraph Infiniti software version 6.0). Post-experiment, participants completed a questionnaire to assess Task Characteristics, Technology Characteristics, Task-Technology Fit, Expectation, Performance, and Satisfaction using a five-point Likert scale (see Appendix for details).

D. Data Collection and Analysis

Data were collected from 159 participants who completed a 20-minute VR-based English as a Foreign Language (EFL) course in a soundproof laboratory. The data collection process involved two primary sources: (1) neurophysiological data via electroencephalography (EEG) and (2) self-reported data via a questionnaire. EEG data were recorded using an eight-channel EEG system (Thought Technology, ProComp Infiniti encoder with BioGraph Infiniti software version 6.0) with electrodes placed at F3 and F4 according to the International 10–20 System to capture Frontal Alpha Asymmetry (FAA). The EEG system operated at a sampling rate of 256 Hz, with a 0.1–100 Hz notch filter to remove powerline interference and a bandpass filter (8–13 Hz) applied to isolate alpha band activity. Electrode impedance was maintained below 5 kΩ, and a linked-ear reference was used. Baseline EEG data were collected during a 2-minute resting state with classical music (neutral stimulus), followed by continuous recording during the VR session.

EEG data were preprocessed to ensure high-quality signals for FAA analysis. Automated artifact rejection was applied using BioGraph Infiniti software to eliminate eye blinks, muscle movements, and electrical interference, with a threshold of ±100 µV for artifact detection. Additionally, a manual inspection by a trained technician removed residual artifacts, resulting in less than 5% data loss per participant. For power spectral density (PSD) analysis, EEG signals were segmented into 2-second epochs with 50% overlap, and Fast Fourier Transform (FFT) was applied to compute PSD in the alpha band (8–13 Hz). FAA was calculated as the difference in natural log-transformed PSD between right (F4) and left (F3) prefrontal sites: FAA = ln(PSD_F4) − ln(PSD_F3). Positive FAA values indicate greater left frontal activity, associated with approach motivation [54]. Table 1 summarizes mean PSD values and FAA scores for a subset of participants, demonstrating the quality of the EEG data.

Table 2 presents the demographic characteristics and descriptive statistics for key variables. The sample consisted of 159 participants (58% female, 42% male; mean age = 20.4 years, SD = 1.8; TOEIC scores ranging from 550–580, mean = 566.3, SD = 8.7). Means and standard deviations for the constructs are as follows: Task Characteristics (M = 4.12, SD = 0.68), Technology Characteristics (M = 4.05, SD = 0.72), TTF (M = 4.08, SD = 0.65), Expectation (M = 3.95, SD = 0.79), Performance (M = 4.15, SD = 0.62), Satisfaction (M = 4.10, SD = 0.70), and FAA (M = 0.22, SD = 0.15, positive values indicating greater left frontal activity, see Table 1 for details). These statistics provide insight into the sample's composition and the distribution of key constructs.

Table 1. Summary of EEG power spectral density and FAA scores

Participant Subset (*n* = 30)	**PSD_F3 (μV²/Hz)**	**PSD_F4 (μV²/Hz)**	**FAA Score**
Mean	2.45	2.28	0.23
SD	0.62	0.59	0.16
Range	1.80–3.50	1.70–3.40	0.05–0.45

Note: PSD values represent alpha band (8–13 Hz) power at F3 (left) and F4 (right) sites. FAA = ln(PSD_F4) – ln(PSD_F3). Positive FAA indicates greater left frontal activity.

Table 2. Demographic characteristics and descriptive statistics

Variable	**Mean**	**SD**	**Notes**
Age	20.4	1.8	Range: 18–24 years
Gender	-	-	58% Female, 42% Male
TOEIC Score	566.3	8.7	Range: 550–580
Task Characteristics	4.12	0.68	5-point Likert scale
Technology Characteristics	4.05	0.72	5-point Likert scale
Task-Technology Fit	4.08	0.65	5-point Likert scale
Expectation	3.95	0.79	5-point Likert scale
Performance	4.15	0.62	5-point Likert scale
Satisfaction	4.10	0.70	5-point Likert scale
FAA	0.22	0.15	Positive = greater left frontal activity

After the data cleansing phase, the collected data were analyzed using partial least squares structural equation modeling (PLS-SEM) with SmartPLS software (version 3.3.9). PLS-SEM was chosen due to its suitability for exploratory research and non-normal data distributions, particularly for EEG-derived FAA [71]. The analysis proceeded in two steps: (1) measurement model assessment to evaluate reliability and validity, and (2) structural model assessment to test hypothesized relationships. Bootstrapping (5,000 resamples) was used to estimate path coefficients, t-values, and confidence intervals. PLSpredict was applied to assess out-of-sample predictive power, ensuring model robustness.

IV. Result and Discussion

This study reports the measurement model first, followed by the structural model, in accordance with two-step analytical techniques [75]. This two-step process verifies that our conclusions regarding structural relationships were derived from a collection of assessment tools with appropriate psychometric qualities [76].

A. Measurement Model

The reliability and validity of the measurement model were assessed using PLS-SEM to ensure the robustness of the constructs. Reliability was evaluated through Cronbach's alpha and Composite Reliability (CR), with values exceeding the recommended threshold of 0.70 for all constructs (Cronbach's α range: 0.867–0.932; CR range: 0.890–0.940), indicating strong internal consistency [77]. Convergent validity was assessed via Average Variance Extracted (AVE), with all constructs except Expectation (AVE = 0.441) meeting the threshold of 0.50. The slightly lower AVE for Expectation is justified based on established guidelines [77], which suggest that AVE values above 0.36 are acceptable when supported by high CR (0.890 for Expectation) and factor loadings that contribute to content validity. The Expectation construct comprises six items (EX1–EX6, factor loadings: 0.665–0.792), with three items (EX3: 0.697, EX4: 0.680, EX5: 0.665) slightly below the ideal threshold of 0.70. Removing these items was considered but deemed inappropriate, as they capture essential facets of learners' expectations (e.g., improved learning outcomes, simplified learning processes, and compatibility with learning styles), ensuring content validity [77]. Retaining all items maintains the theoretical comprehensiveness of the construct, which is critical for assessing learners' expectations of VR-based EFL learning. Discriminant validity was confirmed using the Heterotrait-Monotrait (HTMT) ratio, with all values below 0.90 (range: 0.341–0.846, see Table 3), indicating that constructs are distinct [71]. Collinearity was assessed using the variance inflation factor (VIF), with all values below 3.0, confirming no multicollinearity issues. These metrics collectively demonstrate the psychometric robustness of the measurement model, supporting its suitability for structural modeling.

Table 3. Discriminant validity of PLS-SEM (the Heterotrait-Monotrait ratio, HTMT)

	EX	PP	SAT	TTF	Task	Tech
EX						
PP	0.815					
SAT	0.341	0.425				
TTF	0.736	0.759	0.415			
Task	0.707	0.712	0.562	0.770		
Tech	0.735	0.738	0.512	0.817	0.846	

Note: EX = Expectation, PP = Perceived Performance, SAT = Satisfaction, TTF = Task-Technology Fit

B. Structural Model

The structural modeling stage of PLS-SEM involved the bootstrapping of SmartPLS to obtain the path coefficient (β), R-squared (R^2), and the corresponding t-values [78]. The PLSpredict procedure was applied to assess the out-of-sample predictive power of the structural model, as recommended by [79]. The structural modeling results (Table 2) showed that the participants' expectation about the VR-based language learning significantly affected their perceived performance of VR (β = 0.494, t = 6.746, CI 95% [0.342, 0.629]). Task-Technology Fit (TTF) of VR-based language learning was also significant to their perceived performance of VR (β = 0.378, t = 5.232, CI 95% [0.244, 0.532]). In addition, the task characteristic of VR was found to be significantly associated with EFL learners' satisfaction (β = 0.351, t = 2.909, CI 95% [0.121, 0.591]). Both variables of technology and task characteristics significantly influenced the TTF (β = 0.335 and 0.487, t = 4.168 and 5.516, CI 95% [0.181, 0.498 and 0.300, 0.649] respectively). The participants' FAA was found to have a statistically marginal moderating effect on the relationship between expectation and satisfaction (β = 0.124, t = 1.990, CI 95% [−0.021, 0.227]). This preliminary finding suggests a modest influence of FAA on how expectations translate to satisfaction, potentially reflecting affective processes such as approach motivation [61]. However, given the marginal significance, this result should be interpreted cautiously, and further research with larger samples or replication is needed to confirm the robustness of this moderating pathway. Based on the report of [78], the path coefficients β indicate weak, modest, moderate, and strong effect sizes of the structural model when ranging from 0 to 0.10, 0.11 to 0.30, 0.30 to 0.50, and > 0.50, respectively. Thus, the effect sizes of the significant associations in this model were moderate, whereas the effect size of the moderating effect of FAA on expectations and satisfaction was modest and warrants cautious interpretation. The results of the structural model are shown in Fig. 2.

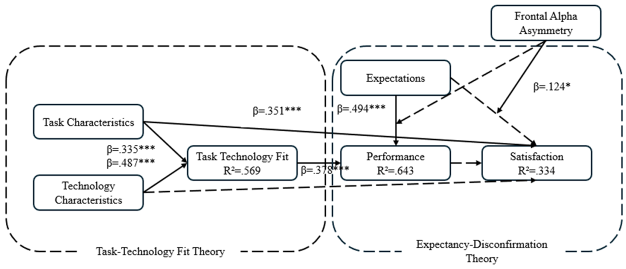

Fig. 2. Results of PLS-SEM.

Moreover, the observed FAA values in this study (M = 0.22, SD = 0.15) indicate a moderate level of left frontal activity, suggesting that participants generally exhibited approach-oriented motivational states during the VR-based EFL learning session. According to prior neuroscience literature [61, 62], FAA values typically range from −0.5 to 0.5 in studies of emotional and motivational responses, with positive values (e.g., >0) indicating greater left frontal activity associated with positive emotions and approach behaviors, and negative values (e.g., <0) indicating withdrawal behaviors. Our mean FAA value of 0.22 aligns with moderate approach motivation, consistent with participants' engagement in the immersive and interactive VR environment. This finding supports the significant moderating effect of FAA on the relationship between expectations and satisfaction (β = 0.124, t = 1.990, CI 95% [−0.021, 0.227]), suggesting that positive emotional responses enhance satisfaction when expectations are met or exceeded. These results underscore the importance of affective states in shaping learner outcomes in technology-mediated education.

As previously discussed, we evaluated the predictive performance of our model using the PLSpredict method. The Q^2 values for all endogenous constructs were positive, indicating that they surpassed the most basic benchmark suggested by [67]. This implies that our PLS-SEM model has predictive validity for all constructs. We also examined the PLSpredict metrics to assess the out-of-sample prediction performance of our model and obtain evidence of external validity [66]. The results of the prediction metrics revealed that the indicators had a low predictive power for the latent variables. However, the latent variables had a high predictive power at the structural level, as shown by the Q^2 values of the constructs (Performance = 0.603, Satisfaction = 0.269, and TTF = 0.579).

VR is one of the newest and most promising technologies for (language) education and training [80], which has the potential to revolutionize educational research and praxis [81]. Therefore, larger amounts of empirical evidence are required to examine its value in education [82]. This study combined the TTF model and expectancy disconfirmation theory to propose a research model with 10 research hypotheses to be examined with PLS-SEM; the novelty of this study lies in it being the first to include both physiological data and questionnaire responses.

The results of PLS-SEM indicate that both the task and technology characteristics of VR have significant associations with TTF of VR-based language learning, which reinforces the statement that TTF refers to "the degree to which a technology assists an individual in performing their tasks" [70] (p. 216). The results further reveal that in the VR-based language learning context, technology characteristics have a greater coefficient than those of task characteristics. Also, the degree of fit between task and technology have a significant influence on EFL learners' performance, which is consistent with the findings of [83, 84]. Considering the relationship between variables in the TTF model and EFL learners' satisfaction with VR-based language learning, the results demonstrate that the task characteristics of VR are significant to EFL learners' satisfaction, whereas the technological characteristics per se are not. Counterintuitively, EFL learners' expectations of VR-based language learning influence their performance but not their satisfaction with VR. However, participants' FAA is a significant moderator between their expectations and satisfaction, indicating that their relationship may vary by the existence of FAA. This implies that even if there may not be much of a direct relationship between the variables of expectation and satisfaction, the moderator of FAA is still quite important in shaping the relationship.

The theoretical implications of this study lie mainly in its two major novelties. First, it is the first study to address the issue of how EFL learners perceive the applicability of VR-based language learning via the integration of the TTF model and expectancy disconfirmation theory. Second, to the best of our knowledge, this is the first time that physiological data has been included in a structural equation model as a moderator. The moderating effect shows that, although the association between EFL learners' expectations and satisfaction with VR-based language learning may not be significant on its own, the relationship becomes substantial when considering the moderating variable. Considering this, a proper assessment of the structural relationship between physiological data, such as EEG, will require further research.

The practical implications of this study are as follows: Our results support the statement [69]: even a brief use (approximately 20 min per participant) of immersive VR applications effectively enhances foreign language vocabulary learning. EFL learners may benefit from the use of VR, and practitioners of EFL education can use VR as a part of in-class pedagogy or encourage learners to use it as a part of their assignments. Moreover, the moderating effect of the FAA highlights the importance of EFL learners' positive emotions (i.e., approach behavior). Creating a "user-friendly" or "stress-free" VR-based language-learning environment is a priority for the course designers of such materials.

V. CONCLUSION

VR technologies are known for delivering immersive online entertainment experiences. Educators also use this experience for pedagogy; however, further insights are required for optimizing VR-based language learning. The present study recruited 159 participants to collect feedback on VR-based language learning via a self-report questionnaire and physiological information from an EEG. Ten research hypotheses were proposed and examined using PLS-SEM, which revealed that six of the ten hypotheses were accepted. The findings of this present study provide new insights into the applicability of VR-based language learning in EFL learning.

The findings of this present study provide new insights into the applicability of VR-based language learning in EFL learning. Notably, the significant associations between task characteristics, technology characteristics, task-technology fit, and performance highlight the importance of aligning VR features with pedagogical tasks to enhance learner outcomes. The expectation–performance and expectation–satisfaction pathways further underscore the role of learners' prior expectations in shaping their VR experience. The preliminary moderating effect of Frontal Alpha Asymmetry (FAA) on the expectation–satisfaction relationship (β = 0.124, t = 1.990) suggests that affective states may influence satisfaction, but this finding is statistically marginal and should be interpreted with caution. Future research is needed to replicate this result with larger samples or longitudinal designs to establish the robustness of FAA's moderating role.

The limitations of this study stem from its exploratory nature and several specific constraints that warrant further discussion. First, the sample was restricted to Taiwanese EFL learners with intermediate English proficiency (TOEIC scores 550–580), which may limit the generalizability of findings. Cultural factors, such as Taiwan's collectivist educational context, may influence learners' perceptions of VR-based learning environments, which emphasize collaborative and interactive tasks. Similarly, linguistic differences, such as the phonological and syntactic structures of Mandarin as a first language, may affect engagement with English in VR settings compared to learners with other linguistic backgrounds (e.g., Romance or Germanic languages). Additionally, learners with beginner or advanced proficiency levels may exhibit different responses to VR-based learning due to variations in cognitive load or language processing demands. Second, while Frontal Alpha Asymmetry (FAA) provides valuable neurophysiological data, EEG's limited spatial resolution restricts its ability to pinpoint precise brain regions compared to methods like functional Magnetic Resonance Imaging (fMRI) or functional near-infrared spectroscopy (fNIRS). These complementary methods could offer deeper insights into the neural correlations of VR-based learning. Third, the brief 20-minute VR exposure in this study may have been influenced by novelty effects, potentially inflating learners' satisfaction or performance perceptions. Longer-term VR use could produce different outcomes as learners become accustomed to technology. Finally, the relatively low R^2 value for satisfaction (0.334), though considered moderate in PLS-SEM, suggests that other factors, such as learner motivation or prior VR experience, may significantly influence satisfaction but were not included in the model. Future research should address these limitations by: (1) incorporating culturally and linguistically diverse samples, including learners with varying proficiency levels; (2) combining EEG with fMRI or fNIRS to enhance neural insights; (3) examining longer-term VR interventions to mitigate novelty effects; and (4) including additional variables, such as motivation or prior technology experience, as suggested by the Cognitive-Affective-Social Theory of Learning in digital environments (CASTLE), to improve the explanatory power of the model.

APPENDIX

Table A1. The measurement of the survey

Construct		Item	Factor Loading
Task Characteristics Cronbach's α = 0.908 CR = 0.910 AVE = 0.733	TC1	I need to learn English within immersive context.	0.752
	TC2	I often need advice from someone else about easier methods to solve academic problems	0.884
	TC3	I often learn by gathering information from others	0.860
	TC4	I often require interaction during English learning process	0.894
	TC5	I often require timely feedback during learning process	0.884
Technology Characteristics (TEC) Cronbach's α = 867 CR = 0.891 AVE = 0.605	TEC1	Learning using VR encourages active engagements with both peers and instructors	0.768
	TEC2	I constantly study at an immersive learning environment created by VR.	0.875
	TEC3	I constantly have a choice to interact with others in an immersive learning context using VR.	0.785
	TEC4	I constantly have a choice to interact using video, audio, images or text in an immersive learning context using VR.	0.890
	TEC5	Overall, VR technology characteristics are suitable for promoting effective English learning	0.657
Task-Technology Fit (TTF) Cronbach's α = 909 CR = 0.913 AVE = 0.612	TTF1	Within immersive learning using VR, I would like to solve academic tasks of English through active engagement with peer students and facilitators.	0.773
	TTF2	Within immersive learning using VR, I would like to gain critical thinking skills.	0.833
	TTF3	Within immersive learning using VR, I would like to get timely	0.802

		feedback.	
	TTF4	Within immersive learning using VR, I would like to learn English naturally.	0.840
	TTF5	Overall, I would like to gain new knowledge through the academic use of VR.	0.765
Expectations Cronbach's $\alpha = 0.873$ CR = 0.890 AVE = 0.441	EX1	Learning to work with VR is easy for me.	0.751
	EX2	It is easy for me to become skillful in the use of VR	0.792
	EX3	Using VR I can improve my learning in the Tourism English	0.697
	EX4	Using VR I can simplify my process of learning in the Tourism English	0.680
	EX5	Study by VR fits well in the way I learn	0.665
	EX6	The resources and activities of VR are compatible with the way I learn	0.694
Perceived Performance Cronbach's $\alpha = 0.932$ CR = 0.939 AVE = 0.601	PO1	The layout and user interface of VR are friendly	0.874
	PO2	It is easy to navigate through VR	0.842
	PO3	The VR offers the services I need	0.837
	PO4	I feel comfortable using the services offered by the virtual platform	0.804
	PO5	VR provides information that is easy to comprehend.	0.806
Satisfaction Cronbach's $\alpha = 0.932$ CR = 0.940 AVE = 0.709	SAT1	I am satisfied with the performance of the VR-based language learning course	0.884
	SAT2	I am satisfied with the experience of participating in a VR learning course.	0.846
	SAT3	My decision to do an undergraduate VR distance was wise.	0.877

CONFLICT OF INTEREST

The author declares no conflict of interest.

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