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System Trust or Self-Efficacy? Behavioral Intention Toward Wearable Devices in Immersive Embodied VR for Upper-Limb Training: An Integrated Cognitive-Affective Perspective

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Abstract

Although virtual reality (VR) and motion capture technologies are increasingly being applied in rehabilitation training, existing research has largely focused on analyzing users' experience. The underlying mechanisms of cognitive-emotional trust resulting from the synergistic effects of technological features and in-depth gamification design remain unclear. This study aimed to examine the determinants that influenced behavior in immersive VR upper-limb training by integrating the stimulus-biological-response and cognitive-emotional-behavioral models. Furthermore, we combined technical features, the situational learning theory, and two-dimensional trust (based on the trust and self-efficacy theories) from an attribution perspective. We developed an immersive VR training system and obtained experimental data from 280 users. Analysis employed Partial Least Squares Structural Equation Modeling (PLS-SEM), Necessary Configuration Analysis (NConfA), and Artificial Neural Networks (ANN). Results revealed that Environmental Embeddedness had a significantly greater effect on the situational cognition dimension than Embodied Interactivity. However, Perceived Incentives had no significant effect on Affective Trust in Technology. NConfA results identified four necessary configurations that promoted high levels of behavioral intention. Furthermore, ANN findings illustrated strong non-linear relationships between Immersion, learning motivation, and task-specific self-efficacy, demonstrating Immersion's crucial role in the overall formation mechanism. Based on a cognitive-affective trust perspective, this study provides guidance for all relevant stakeholders: Immersion and interactive experiences should be strengthened to promote self-efficacy, thereby fostering behavioral intentions.

Keywords: Virtual reality; Technical features; Situational learning theory; Affective trust model; SEM-NConfA-ANN

1. Introduction

The upper limbs are a core component of the human musculoskeletal system and key structure for enabling interaction between the body and external environment; they perform complex and precise tasks and maintain overall functional integrity (Xiong et al., 2026). Furthermore, they play an irreplaceable and vital role in physiological activities, daily living, and social participation. However, traffic-related injuries, repetitive occupational strain injuries, and increasing incidence of stroke among younger adults have become major causes of upper limb dysfunction (Dhillon et al., 2022; Fraser et al., 2023; Wang et al., 2024), particularly in developing countries, such as China (Zhang et al., 2026). Virtual reality (VR), with its immersive interaction, three-dimensional (3D) visualization, and scene simulation capabilities (Gonçalves et al., 2023), has become a powerful driver for enhancing efficiency in various fields, such as industrial manufacturing, education and training, architectural design, and cultural tourism (Alani et al., 2026; Ho & Wong, 2026; Phadke et al., 2026; Y. Yan & Du, 2025). In medical rehabilitation, substantial research has confirmed that highly engaging VR game-based interventions can effectively increase patients' active participation and improve their cognitive function (Bonab et al., 2026; Vanbellingen et al., 2026). With technological advancements, the potential for applying virtual gaming environments and narrative-driven mechanisms in clinical settings (Ammanabrolu & Riedl, 2021; Gu et al., 2025) has garnered significant attention (Kang et al., 2026; Toh, 2023). Therefore, drawing on the training philosophy of the integrated occupational therapy (Maden et al., 2025; Xu et al., 2025), the design of game modes, supporting environments, and narrative contexts tailored to daily, occupational, and recreational settings has become key to extending the integration of cognitive training and physical exercise (L. Li et al., 2025; Zhang et al., 2024).

Motion synchronization technology based on motion capture is a fundamental technology for building virtual interaction systems (Park et al., 2024) and typically encompasses two approaches: visual and non-visual (Gu et al., 2023). Current mainstream systems, such as Kinect-based systems, are susceptible to various factors, such as ambient lighting, image quality, and limb occlusion (Weibel et al., 2024), resulting in significant limitations regarding perceptual stability and applicability (L. Yan & Du, 2025). In contrast, wearable inertial measurement units (IMUs) that integrate accelerometers, gyroscopes, and magnetometers can capture 3D kinematic data in real time with high accuracy, precisely calculate joint poses, and reduce ergonomic risks (Karasheva et al., 2025). Thus, they have significant advantages in rehabilitation medicine (Alenjareghi et al., 2026). Second, IMUs can be mounted on key joints without spatial constraints, supporting their deployment across multiple scenarios and quantitative assessment of rehabilitation training (Joung et al., 2026; Lee & Lee, 2025). Thus, wearable IMUs are a reliable technological foundation for upper-limb rehabilitation systems integrating VR and serious games (Lim et al., 2026; Yin, 2026).

In Human-Computer Interaction (HCI), embodied interaction emphasizes that interaction is a contextual coupling process involving the body, environment, cognition, and digital systems (Dourish, 2001; Genay et al., 2022). Technological integration of VR and IMUs provides an effective digital platform for contextualized training in embodied interaction (Bian et al., 2023). Furthermore, it allows users to enhance interaction efficiency and experience through embodied interactivity (touch in the virtual environment) and environmental immersion (perception within the virtual environment; (Y. Lin et al., 2026). Studies have examined whether VR training can enhance users' motivation (Sun & Ke, 2025; Wu et al., 2026). Results have generally supported the notion

that VR technology can provide users with multidimensional experiences and satisfaction and foster intentions to continue use (Bai et al., 2024; Y.-L. Lin & Wang, 2024; Wu et al., 2026; Xu et al., 2026). However, existing research has primarily focused on comparing VR with traditional media; the psychological recovery mechanisms resulting from the integration of technological features and game design remain unclear (Cao et al., 2021; Ramalho et al., 2026). Limited studies have explored how narrative-rich, perspective-guided game design, when supported by technology, can enhance cognitive and emotional recovery (Nie et al., 2026; Tao et al., 2021). This issue is important: technological stimuli alone can only provide temporary sensory gratification; high-quality game design is the key driver for maintaining adherence and ensuring the long-term effectiveness of interventions.

Thus, technological stimulation does not directly trigger emotional responses; rather, it reshapes individuals' cognitive processing through contextualized narratives, exploratory engagement, and sensory immersion embedded in game design, thereby indirectly modulating their emotional responses (Andreatta & Pauli, 2021). VR-based training and gamified learning research (Ponciano Núñez, 2025; Wen et al., 2023; Yan et al., 2024) has adopted the situational learning theory as a key theoretical framework for system development (C. Liu et al., 2026; Naderi & Shojaei, 2025; W. Yan et al., 2024). Learning scenarios essentially involve reshaping participants' cognition by simulating physical environments and corresponding events (Li et al., 2020). Furthermore, some studies have emphasized the use of technology as an intervention tool for cognitive remediation (Yee et al., 2025). However, existing VR literature does not elucidate how the characteristics of integrated technologies shape situational cognition, particularly in serious games. Furthermore, cognition and emotion are inherently intertwined, with emotion representing the emotional responses generated by cognition (Shiau et al., 2022). Although trust is a key emotional factor in HCI relationships, the concept remains ambiguous (Kaplan et al., 2023). Drawing on the dual and attribution perspectives in interpersonal communication (Lipkin, 2016; Quiñones & Rojas, 2023), trust in HCI can be divided into trust in the technological system and individuals (Leichtmann et al., 2024; Zijlstra & Payne, 2025). Users' trust in technology reflects their degree of reliance on external systems (Kim et al., 2020); trust in individuals, that is self-efficacy, refers to an individual's belief in their ability to complete tasks in a technology-supported context (Zalazar-Jaime et al., 2023).

Although substantial research has explored technological trust in various VR systems (Chakraborty, 2026; Derakhshan et al., 2025; Y. Liu et al., 2026), limited studies have adopted a perspective focused on interaction and attribution and incorporated self-efficacy and technological trust into a unified analytical framework. Higher sense of self-efficacy can significantly improve adherence to task training; therefore, it is crucial for effective intervention (Singleton & McAllister-Deitrick, 2023). Simultaneously, research supports the view that trust is a core factor in users' adoption of platforms for assisted training (Koren et al., 2022). Therefore, investigating the impact of situational cognition on the two dimensions of affective trust, Affective Trust in Technology and Task-specific Self-efficacy, is theoretically significant and provides important practical guidance for optimizing allocation of cognitive and affective resources in VR training systems.

Therefore, this study constructed an explanatory framework to explore how the characteristics of VR technology shaped individual cognition within contextualized game designs that integrated narrative, exploration, and sensory aesthetics. We also explored how this influenced trust across two dimensions. The framework aimed to reveal the cognitive-trust mechanisms underlying the synergy between technological attributes and deep game design. To clarify the interrelationships between

the variables in the proposed framework, this study reviewed VR-related literature and found that the Stimulus-Organism-Response (SOR) model is the dominant framework for explaining user behavior (Jookyung Kwon, 2019). Although the SOR is flexible and capable of encompassing emotions, attitudes, motivation, and perception, (Jacoby, 2002), its conceptualization of the "organism" is too broad and underdefined. In contrast, the Cognitive-Affective-Behavioral (CAB) model focuses on internal psychological mechanisms, and emphasizes that attitudes are a combination of cognition, emotion, and behavior (B. Liu et al., 2021). Since this study focused on cognitive-trust mechanisms in technology and design integration, the CAB model was adopted as the core framework; however, the indispensable role of technological features and CAB model's lack of an external stimulus perspective cannot be overlooked. Therefore, this study integrated the SOR and CAB models to propose a novel Stimulus-Cognitive-Affective-Behavioral (S-CAB) integrated model and aimed to systematically investigate how the technical features of VR based on gamified design shaped the relationships between cognition, emotion, and behavior.

Section 2 presents the relevant theories and models, constructs a comprehensive framework, and proposes research hypotheses to examine the effects of VR technical characteristics on cognition, two-dimensional trust, and behavioral intentions in situational game design. Section 3 introduces the self-developed non-immersive VR upper-limb training system and describes the research process and methods. Sections 4 and 5 present the empirical research results and comprehensive discussion of the research findings, respectively. Section 6 summarizes the theoretical and practical implications. Section 7 discusses the limitations of this study and suggests directions for future research.

2. Literature Review and Hypothesis Development

2.1 Stimulus-Cognitive-Affective-Behavioral Integrated Model

To explore the effects of VR technology characteristics integrated with game design on specific cognitive, emotional, and behavioral aspects, this study proposed an S-CAB model that integrated the SOR and CAB frameworks. The SOR model is a structural framework proposed by Mehrabian and Russell (1974) from the perspective of environmental psychology to understand complex human behavior. It views user responses as a sequential process: external environmental cues serve as stimuli (S), triggering changes in the organism's (O) internal emotions and attitudes, which ultimately lead to individual responses (R). This three-stage SOR framework has been widely applied in research on user behavior in VR environments (Deng et al., 2025; R. Lin et al., 2024; Tian et al., 2025); however, existing studies have typically focused only on single-dimensional internal mental processes at the organism stage. Roh (2024) used the flow experience as the sole organismic-level variable to explore users' behavioral intentions regarding continued use of the metaverse. Sultan (2021) examined food consumption and argued that attitude is the core organismic factor driving organic food consumers' behavioral intentions. Furthermore, although the organismic level encompasses various internal states, such as emotions and attitudes, connections between these internal mechanisms are often overlooked. Conversely, the CAB model elaborates on the sequential relationships between users' cognition, emotions, and behavior in specific contexts and has been used in research on the impact of emotional fluctuations on user behavior (Bagozzi, 1992; Oliver, 2010). Abumalloh (2024) found that customer loyalty toward recommendation algorithms, including perceptions of recommendation quality and perceived accuracy, was a key determinant of emotional responses, such as trust, which influenced customers' use of recommendation agents in

metaverse environments. Qin and Liu (2025) examined virtual consumption and reported that users' perceptions of virtual hosts, such as perceived warmth and competence, fostered a psychological contract between the two parties and ultimately influenced users' consumption decisions and behaviors. Therefore, from the perspective of technological convergence, this study attempted to shape users' situational cognition through the optimized design of game narratives and interaction modes to trigger trust factors, Affective Trust in Technology and Task-specific Self-efficacy, and influence users' sustained behavioral intentions. This study integrated the SOR and CAB models and mapped VR technical characteristics, situational cognition, two-dimensional trust model, and behavioral intention to the four dimensions of S, C, A, and B, respectively, to construct a preliminary S-CAB model, as shown in Figure 1.

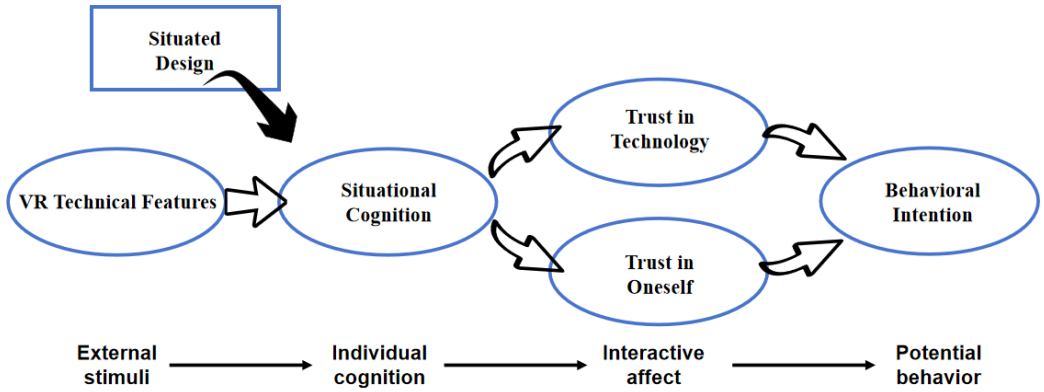

Figure 1. Integrated Abstract of the S-CAB Theoretical Model

2.2 VR Technical Features

VR technology creates artificial 3D virtual environments (VEs), providing users with an immersive, lifelike experience. It serves as a powerful educational and training tool and offers opportunities for immersive learning and training (Chen, 2022). Dourish (2001) referred to the patterns of user behavior in VEs that mimic interactions in the physical world as embodied interaction, its core lies in the subject's perception of and dynamic interaction with the VE. Building on the embodied theory, Lin et al. (2026) further mapped these core characteristics to embodied interactivity and environmental embeddedness, and classified them as technical features of VR. This perspective is underpinned by the synergy in wearable devices, high-precision motion tracking systems, and VR technology (Lee-Cultura & Giannakos, 2020). Considering the technological framework used in this study and objectives of the game design, we adopted Lin's foundational framework and treated embodied interactivity and environmental embeddedness as technical characteristics of VR.

2.2.1 Embodied Interactivity

Embodied interactivity stems from the broader concept of interactivity (Heeter, 2000). As a technical feature of VR, interactivity reflects user's ability to actively engage with the VR system's content (Lee et al., 2021). Conversely, embodied interactivity places greater emphasis on users interacting with virtual avatars and objects within a virtual environment (Kilteni et al., 2012); furthermore, it requires support for whole-body engagement to provide greater interactive possibilities (Paes et al., 2021). However, interactivity itself plays a crucial role in enhancing users' perceptions during the use of VR systems, regardless of the interaction mode or technology (Qiu et

al., 2024). Arghashi and Yuksel's (2022) study on virtual consumption identified interactivity as a primary predictor of consumer experience and usage motivation. Similarly, Payal's (2024) research on the metaverse found that interactivity fostered users' trust in and attachment to brands within virtual communities (cognitive and emotional outcomes). Li and Lv (2024) examined virtual museums and emphasized the significant impact of interactivity on various perceptual factors, such as perceived enjoyment and ease of use. Furthermore, König (2021) established that high levels of embodied interactivity helped users better understand spatial information and perceive spatial relationships while moving and interacting within virtual environments. Therefore, this study proposed the following hypotheses regarding the elements of situational cognition in Embodied Interactivity:

H1a: Embodied Interactivity is positively associated with Immersion when using the system.

H1b: Embodied Interactivity is positively associated with Learning Motivation when using the system.

H1c: Embodied Interactivity is positively associated with Interactive Experience when using the system.

H1d: Embodied Interactivity is positively associated with Perceived Incentives when using the system.

2.2.2 Environmental Embeddedness

Environmental embeddedness's core lies in constructing creative VEs that provide situational narrative settings (Irimiás et al., 2021); this concept stems from a synthesis of the concept of "presence" and embeddedness perspective (Tussyadiah et al., 2018). Robbins (2001) was the first to emphasize, from an embedded perspective, that the external environment is a key factor in shaping individual cognition. Conversely, presence is defined as the psychological state in which users are immersed in VEs (Slater, 2009); this state may be a causal factor influencing human information processing capabilities and other cognitive variables (Kim & Biocca, 2006). Baceviciute (2021) summarized the aforementioned research and defined environmental immersion as the ability of immersive VR to surround users within VEs and emphasized its crucial role in educational and training systems. According to Dalgarno and Lee (2010), environmental simulation inherently possesses the ability to contextualize learning. VR technology immerses users in VEs to provide rich sensory stimulation and fosters engagement during the exploration of VEs and enhances users' motivation to use the technology (Martin et al., 2022). Second, when immersed in VEs, users focus on their own goals and fully perceive environmental cues while receiving environmental information (Bian et al., 2022). These cues and information create a continuous interactive experience and positive motivation, which drives users to complete the predetermined tasks (Azini et al., 2026; Luan et al., 2024). Therefore, this study proposed the following hypotheses regarding the role of Environmental Embeddedness in situational cognitive elements:

H2a: Environmental Embeddedness is positively associated with Immersion when using the system.

H2b: Environmental Embeddedness is positively associated with Learning Motivation when using the system.

H2c: Environmental Embeddedness is positively associated with Interactive Experience when using the system.

H2d: Environmental Embeddedness is positively associated with Perceived Incentives when using the system.

2.3 Situational Cognition

Situational cognition stems from the situational learning theory. From the perspective of situational cognition, immersive learning environments that replicate real-world application scenarios should be constructed to enable learners to perceive the practical utility of knowledge (Cook & Brown, 1999). Research has demonstrated that cognition does not exist in isolation; its generation and maintenance are based on the continuous interaction between an individual's mental model and external environment (Lant, 2017; Zhu et al., 2019). Since VR can provide immersive environments, when created within a reasonable framework, these can support contextual and experiential education and training (Schott & Marshall, 2018). Research on Metaverse-based Learning (MTS) has used situational learning to explore how to reshape users' cognition, learning, and social interactions (Onu et al., 2024; Rho et al., 2020). Henz (2022) reported that specific experiences and interactions positively shaped users' cognition in the metaverse. Furthermore, Valencia et al. (2019) emphasized that designing learning environments with the necessary stimuli were crucial; in addition, these scenarios could be customized and adjusted according to actual needs, thereby influencing cognitive, emotional, and behavioral outcomes (Onu et al., 2024). Since users' cognitive experiences in VEs are multifaceted (Luong et al., 2022), environmental factors and design objectives may influence multidimensional elements of situational cognition. VR motor training aims to provide users with realistic environments and corresponding learning activities to achieve restoration of motor function (Garzón et al., 2020). This aligns with the concept of MTS that simulates diverse educational scenarios and provides context-relevant stimuli (Onu et al., 2024). Therefore, drawing on relevant research on situational learning and MTS, this study incorporates Immersion, Learning Motivation, Interactive Experience, and Perceived Incentives into the situational cognitive dimensions of VEs (He et al., 2025).

Immersion is an important objective measure of information system quality; it reflects the system's actual effectiveness in constructing concrete VEs and diminishing users' perception of the real world (Cummings & Bailenson, 2016). Psch (2026) emphasized that immersion enabled users to become deeply engaged in VE experiences and facilitated the generation of emotions. Research on immersive VR education and training systems found that the high sense of presence and positive emotions induced by immersion enhanced users' learning efficiency and outcomes (Gorini et al., 2010; Lønne et al., 2023). Furthermore, Lehikko(2021) found that learning and training using immersive VR significantly enhanced self-efficacy. Learning Motivation is a key antecedent influencing learner performance (Hwang et al., 2023), and instructional and training interventions implemented through VR technology can effectively boost learner motivation (Wang et al., 2023). Hwang et al. (2023) found that high levels of motivation tended to enable users to focus more intently on VR-based experiential learning and demonstrate higher levels of learning attitude and self-efficacy. Similar studies also confirmed positive correlations between learning motivation and self-efficacy and between learning motivation, attitudes, and emotions (Lin & Wang, 2021; D. Liu et al., 2026). Interactive Experience can be understood as the comprehensive sensory and psychological experience generated by users' real-time, two-way interactions within Ves (Kim & Ha, 2021). In VR learning and training systems, experiences gained by users by interacting with highly realistic VEs through avatar control can significantly enhance engagement levels and positively shape their attitudes (Park & Kim, 2022). Even when such virtual interactions are not

entirely within the user's control, they still elicit positive emotional experiences (Suh, 2024). Song et al. (2021) found that immersive interactive experiences in VR training systems had a positive impact on both user self-efficacy and learning outcomes. Incentive mechanisms essentially involve encouraging and guiding an individual's behavioral intentions (Chang et al., 2019). Research on traditional educational games confirmed that incentive systems promoted sustained learning and yielded better learning outcomes by effectively motivating users (Rahimi et al., 2021). These findings are equally valuable in VR rehabilitation training; incentive mechanisms are considered a core element in gamifying the training process and play a crucial supporting role in guiding patients to actively complete rehabilitation tasks in real-world therapeutic settings (Saidi et al., 2026). Furthermore, L. Liu et al. (2026) found that incorporating incentive systems into VR training prevented the emergence of negative emotions, such as loneliness and boredom. These incentive systems allow users to intuitively perceive their own progress, such as through earning coins, receiving verbal encouragement, and clearing levels, which can foster varying degrees of sense of accomplishment and confidence in their continued training (Gustavsson et al., 2022). Based on relevant research on MTS and traditional instructional training, situational cognitive factors exerted varying degrees of influence on multidimensional emotions. However, the impact of Immersion, Learning Motivation, Interactive Experience, and Perceived Incentives on emotions during immersive VR upper limb training remains unclear. Therefore, this study proposed the following hypotheses:

H3a: Immersion is positively associated with Affective Trust in Technology when using the system.

H3b: Immersion is positively associated with Task-Specific Self-Efficacy when using the system.

H4a: Learning Motivation is positively associated with Affective Trust in Technology when using the system.

H4b: Learning Motivation is positively associated With Task-Specific Self-Efficacy when using the system.

H5a: Interactive Experience is positively associated with Affective Trust in Technology when using the system.

H5b: Interactive Experience is positively associated with Task-Specific Self-Efficacy when using the system.

H6a: Perceived Incentives are positively associated with Affective Trust in Technology when using the system.

H6b: Perceived Incentives are positively associated With Task-Specific Self-Efficacy when using the system.

2.4 Two-Dimensional Trust Model

Drawing on the dual-analysis framework and attribution theory perspectives in interpersonal communication(X. Lin et al., 2024; Wang et al., 2022), this study categorized the bonds of trust between humans and systems in HCI into two dimensions: trust in system technology and personal competence. The dual-relationship theory posits that any given pair of interacting entities involves two types of perceived objects; furthermore, when problems arise in interpersonal interactions, people tend to make two types of attributions: external (attributing the problem to the interaction partner) and internal (their own competence shortcomings) (Graham, 2020). Thus, this study applied the dual-analysis perspective to HCI contexts, establishing the "human–system" relationship as the

core unit of analysis, while the attribution theory, through external and internal attributions, underpins the logic of this dimensional classification: when users interpret the outcomes of an interaction, failures or successes can be attributed either to the system itself or their own operational proficiency. Therefore, based on this classification logic, we further deconstructed users' trust following their use of an immersive VR upper limb training system into Affective Trust in Technology and Task-specific Self-efficacy, both incorporated into the driver dimension.

2.4.1 Affective Trust in Technology

Affective trust is defined as a subjective psychological trust; this internal psychological state stems from users' perception that a platform or system values and cares about their needs and experiences (Mcallister, 1995). Bansal et al. (2015) demonstrated that users' trust in online platforms elicited emotional responses, which drove behavioral intentions. Furthermore, studies have extended this finding to various HCI platforms. Zhu et al. (2025) confirmed that users' affective trust in social media encouraged self-disclosure on the platform. Abumalloh et al. (2024) found that users' affective trust in recommendation agents within the metaverse was a key driver of their loyalty (behavior). Simultaneously, as users' perceived trust in a platform increases, the negative emotional burden induced by perceived risk is significantly alleviated (Rodríguez-Priego et al., 2023). In an immersive VR upper limb training scenario, users' trust in the system is a core prerequisite for sustaining long-term training participation. When users develop a positive perception of trust in VR training equipment and interactive programs, their psychological concerns and operational stress significantly reduce; furthermore, they may be more willing to actively engage in and persist with long-term standardized upper-limb training. Therefore, this study proposed the following hypotheses:

H7: Affective Trust in Technology is positively associated with Behavioral Intention after using the system.

2.4.2 Task-Specific Self-Efficacy

Self-efficacy refers to an individual's subjective judgment regarding their overall ability to plan and implement specific behavioral strategies to achieve their goals (Bandura, 1996). In traditional education, self-efficacy is a key predictor of academic performance and provides a theoretical basis for analyzing the internal psychological mechanisms through which learners cope with various academic challenges (Xiaoying et al., 2024). Students with higher self-efficacy are more likely to adopt deep learning strategies rather than superficial learning patterns (Long et al., 2020). Recently, empirical evidence supporting this theory has gradually extended to rehabilitation exercise research. Existing empirical studies have revealed that combining VR with traditional rehabilitation training can effectively enhance patients' self-efficacy (Long et al., 2020; Ouyang et al., 2023). Therefore, this study defined the improved self-efficacy that users gain after VR training as "Task-specific Self-efficacy." Unlike a singular, purely rational assessment of ability, in the immersive, embodied interactive VR environment, this cognitive evaluation simultaneously elicits positive emotional perceptions, such as a sense of grounding, certainty, and confidence (Vasudha & Choudhary, 2026). Users form a composite psychological construct that integrates rational judgment with subjective emotional experience, which may further promote their willingness to engage in long-term training. Therefore, this study proposed the following hypothesis:

H8: Task-Specific Self-Efficacy is positively associated with Behavioral Intention after using the system.

We deconstructed the abstract theoretical framework layer by layer and refined the intrinsic mechanisms of each variable to ultimately develop a standardized theoretical model, as shown in Figure 2.

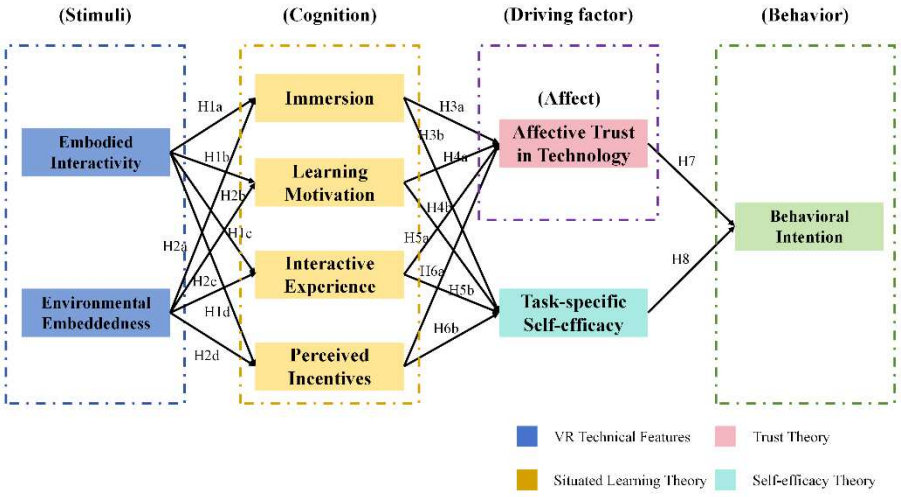

Figure 2. The Theoretical Model

3. Material and Methods

3.1 System and Game Design

3.1.1 Apparatus and Development Process

Since we emphasized the advantages and importance of IMUs in Section 1, the immersive VR upper-limb training system was developed using the Unity 3D engine and JY901P gyroscope. We positioned the JY901P gyroscope at the core of the wearable device and used a rechargeable battery to ensure power endurance. Specific implementation process began with the JY901P gyroscope transmitting limb motion data to a microcontroller unit for preprocessing. Preprocessed data were further transmitted to a personal computer via a Zigbee chip. Finally, the Unity 3D game engine received the limb motion data and mapped it to the corresponding limbs of the virtual avatar, fulfilling the technical prerequisites for embodied interaction. Simultaneously, the team secured and calibrated the wearable module based on Zigbee wireless communication to ensure the smooth operation of the experiment. Figure 3 presents the detailed hardware and software implementation procedures and synchronization calibration.

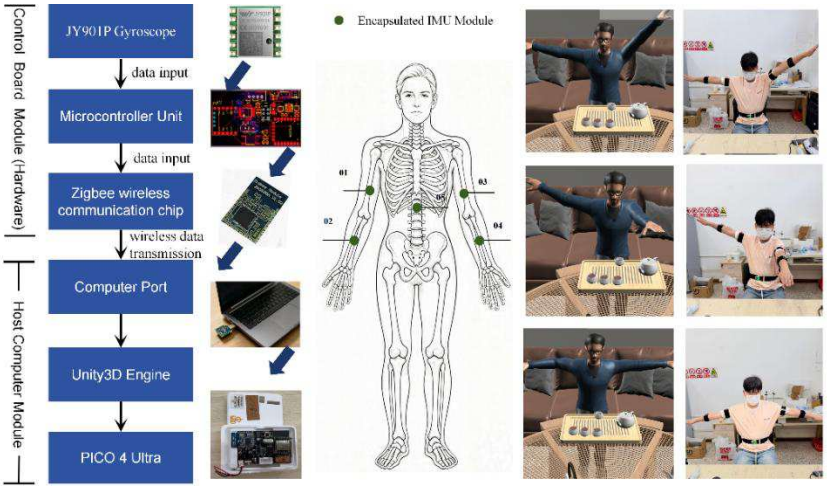

Figure 3. Development Process and Synchronization Calibration Diagram for the IMU Module

3.1.2 Game Design

Based on the concepts related to occupational therapy and serious games and incorporating theoretical guidance from situational learning, we designed a complete modern home environment, which included a fully equipped bedroom, living room, kitchen, and bathroom, and developed upper limb training games to be played within these rooms (see Figure 4). During actual use, participants simply sat in a chair and wore the PICO 4 Ultra all-in-one headset to complete the immersive VR upper limb training game; real-time motion data was displayed on the interface and synchronized to the backend for recording and storage.

The entire immersive VR upper limb training system created a complete, freely navigable virtual home environment and featured dedicated upper limb training interaction modules set up in three different rooms. The first game module was set in a virtual living room scene, where participants controlled their virtual avatar to perform a sequence of actions that involved pouring and drinking water: first, they picked up the teapot from the coffee table and poured water into an empty teacup; subsequently, they switched to the other hand to hold the cup and drink. The system randomly changed the teacup's position on the coffee table, increased the range of upper-limb movement, and unpredictability of the task. The second game module was set in a virtual bedroom, where participants sat upright at the desk to perform desktop tasks. Dolls appeared randomly on the desk, and participants sequentially performed a full set of actions, grasping, moving, and placing, to organize the dolls into the side shelf. The third game module was set in a virtual kitchen, where participants selected various ingredients that randomly appeared in front of them and placed them into a pot according to the "Today's Menu" prompts on the interface. All training modules offered both first- and third-person viewpoints. Throughout the task, the interface displayed step-by-step guidance text in sequence, providing real-time prompts for the daily-life actions to be completed, thereby lowering the barrier to understanding the operations.

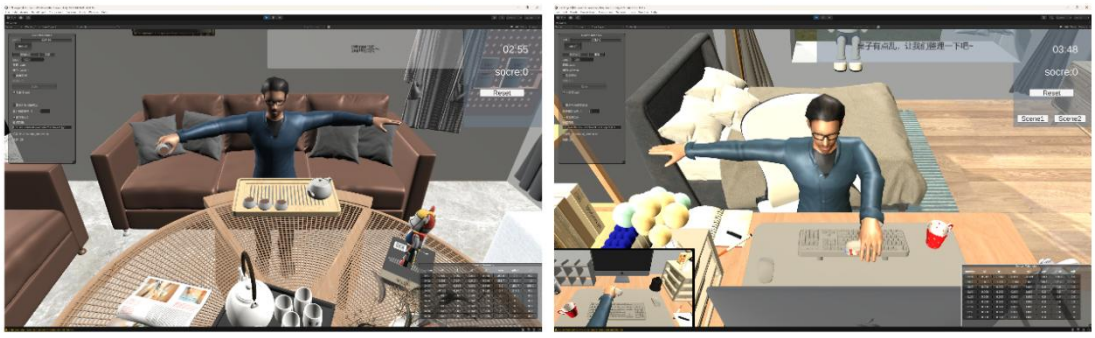

Figure 4. Embodied Interactive Games and the Virtual Space

3.2 Research Methods

Due to the complexity of the factors that influenced user engagement with immersive VR upper-limb training systems, which involved external technological stimuli and the interplay between cognitive and emotional processes, a single research method cannot fully elucidate the underlying mechanisms. Thus, combining Structural Equation Modeling (SEM), Necessary Configuration Analysis (NConfA), and Artificial Neural Networks (ANN) validated the theoretical hypotheses and uncovered more subtle and complex relationships between the factors, such as cognition and emotion. This study used the developed immersive VR training system as its experimental platform, which required recruiting participants for in-person experiments, which made it difficult to collect large-sample data. To address potential issues regarding the normality of data distribution and minimum sample size, we first employed Partial Least Squares Structural Equation Modeling (PLS-SEM) for data analysis (Hair et al., 2013). The PLS-SEM data analysis process was divided into two main stages: measurement and structural model analyses (Leong et al., 2020). We examined the scales' internal consistency, convergent validity, and discriminant validity to complete the measurement model evaluation; after ensuring that the measurement indicators met the required quality standards, path analysis of the structural model was conducted to assess the research hypotheses (Hair et al., 2019).

Although traditional symmetric statistical techniques, such as the PLS-SEM, can only capture linear effects, asymmetric analytical methods, such as fuzzy set qualitative comparative analysis (fsQCA), and necessary condition analysis (NCA) effectively addressed this shortcoming (Ragin, 2006). Increasing number of asymmetric analytical methods in social science fields, such as service research, have leveraged this unique advantage (Kang & Shao, 2023). However, neither the fsQCA nor NCA evaluate more than a single variable (Dul, 2024); thus, they cannot identify the configurations (combinations of antecedents) required to achieve the expected behavioral outcomes. Therefore, Rasoolimanesh and Olya (2025) proposed a new method, NConfA, to gain a deeper understanding of multivariate relationships and determine the necessity of configurations or factor combinations. Human judgment and decision-making behaviors regarding information systems are generally accompanied by the simultaneous interplay of cognitive and affective psychological factors; user behavioral intentions are jointly driven by differentiated configurations of multiple cognitive and affective factors, rather than governed by a single psychological variable (Pappas & Woodside, 2021). Therefore, we introduced NConfA to analyze the necessary effects of various cognitive and emotional combinations generated by users when using VR training systems, thereby supplementing the results of the PLS-SEM.

As a machine learning tool, ANN can identify complex non-linear relationships between

variables, further improving the accuracy of model predictions (Leong et al., 2025). Wang et al. (2014) indicated that ANNs can be used to validate the empirical results of the SEM, particularly in information systems; furthermore, this method can effectively supplement the analytical results of PLS-SEM, which can only capture linear effects (Li & Lau, 2025). In this study, users' intentions to adopt an immersive VR upper limb training system involved the simultaneous interaction of multiple factors, including cognitive and emotional aspects, which may involve numerous non-linear, interactive, and threshold effects. Use of ANN addressed the analytical limitations of PLS-SEM under linear assumptions and complemented NConfA, providing a comprehensive explanation of the mechanisms underlying user training behavior from multiple dimensions, including linear effects, necessary configurations, and non-linear interactions.

3.3 Participants

This research process comprised two parts: a pilot study and formal experiment. The pilot study recruited 30 participants to experience an immersive VR upper limb training system to verify the system's usability and check the items' readability. After the system operation experience was over, participants completed the questionnaire. All measurement items were adapted from established scales or previous studies. Items were rated on a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). Cronbach's alpha in SPSS version 27 was used to assess the internal consistency from the pilot test phase. Table 1 presents the complete list of items and corresponding references. Subsequently, 285 participants were recruited for the formal experimental phase. Participants received a gift worth approximately $5 as compensation once they completed the entire in-person experimental process. This experiment was conducted in-person, and participants were recruited from Fuzhou City, Fujian Province, China. Sample included undergraduate and graduate students, faculty and staff from local universities of various levels, and members of the general public from diverse professional backgrounds. Participants' were aged 18–35 years. Since the VR upper limb training system was not equipped with professional rehabilitation assistive devices, strict inclusion criteria were established: participants were required to have normal upper limb motor function (no limb injuries) and no history of VR motion sickness, thereby ensuring the quality of the experimental data. This study was approved by the university's Institutional Review Board, and all participants were informed of the experimental details.

Table 1
Statistics of construct items.

Construct	ID	Measurement Item	Sources
Embodied Interactivity	EI1	By using my physical body,I can interact with virtual objects and environments in the VR training system.	(Y. Lin et al., 2026)
	EI2	By using my physical body,I can explore what I want in the VR training system.	
	EI3	By using my physical body, I can move around in the world of the VR training system.	
Environmental Embeddedness	EE1	I immerse in the virtual world of the VR training system.	(Irimiás et al., 2021)
	EE2	I am surrounded by the virtual world in the VR training system.	

	EE3	While being there, I feel inseparable from the virtual world in the VR training system.	
	EE4	I am really inside the virtual world in the VR training system.	
Immersion	IMM1	When I use the VR training system for virtual training, I feel completely immersed in the character I am playing.	(Hudson et al., 2019; Huizenga et al., 2019)
	IMM2	My training experience in the VR training system made me forget the reality of my surroundings.	
	IMM3	My interactions when using the VR training system felt as natural as in the real world.	
	IMM4	When conducting virtual training in the VR training system, I felt that time seemed to fly by.	
Learning motivation	LM1	I want to know more about what I saw in the VR training system.	(Fokides, 2023)
	LM2	There was something about the content presented in the VR training system that made me curious.	
	LM3	I am motivated to continue my training in the VR training system.	
	LM4	I want to explore more in the VR training system.	
Interactive experience	IE1	I can interact a lot in the VR training system.	(Fokides, 2023)
	IE2	I can get a good response to my actions in the VR training system.	
	IE3	Interacting with virtual objects in the VR training system is similar to interacting with real objects.	
Perceived incentives	PI1	I think there should be incentives in the VR training system.	(Tüzün et al., 2019)
	PI2	I am concerned about rewards for completing tasks in the VR training system.	
	PI3	Receiving rewards for completing tasks in the VR training system gives me a sense of achievement in learning.	
Affective Trust in Technology	ATT1	I believe that using the VR training system can train my upper limbs.	(Zhu et al., 2025)
	ATT2	The VR training system is committed to helping me with my upper limb training.	
	ATT3	The VR training system is honest and fulfills its promises regarding upper limb training.	
	ATT4	The VR training system helped me with my upper limb training in a competent and responsible manner.	
	ATT5	The VR training system effectively helped me with my upper limb training.	
Task-specific Self-efficacy	TS1	After using the VR training system, I feel competent at completing the tasks of upper limb training.	(Zha et al., 2019)

	TS2	After using the virtual reality training system, I believe I have the expertise needed to complete the tasks.	
	TS3	After using the VR training system, I have confidence in my ability to complete the tasks.	
Behavioral Intention	BI1	I will use the VR training system regularly in the future.	(Xu et al., 2026)
	BI2	I will frequently use the VR training system to perform upper limb training in the future.	
	BI3	I will strongly recommend that others use the VR training system.	

3.4 Data Collection

After being recruited, participants visited the laboratory at the designated time to experience the immersive VR upper limb training system and complete the entire experimental procedure. The official experimental period was from May 1 to August 10, 2026. Upon arrival at the laboratory, researchers once again explained the study purpose and guided participants through the process of signing the informed consent form. Before the VR session, all participants were required to complete a baseline questionnaire that comprised six demographic items. Subsequently, staff provided a detailed explanation of the rules and exploration methods for the VR upper limb training session and assisted participants in putting on and adjusting the inertial sensors to prevent them from falling off during the experiment. Figure 5 illustrates a participant using the immersive VR upper limb training system.

Each interactive training module was limited to a maximum of 5 min. After each training set was completed, the system allowed for a rest period to alleviate physical and visual fatigue caused by continuous interactive training. Once a single training module was completed, participants could choose to repeat the current interactive task or proceed to the next training module; after all training tasks were completed, participants could also freely explore the virtual space. After all game modules were completed and virtual scenes were explored, participants completed a revised formal questionnaire. The entire experimental process took approximately 20 minutes per person. The research team excluded questionnaires with response times <3 minutes and those with obviously repetitive responses (e.g., “1” or “7” for all questions). After data cleaning, 280 valid samples were retained.



Figure 5. A Participant using the Immersive VR Upper Limb Training System

Figure 5. A Participant using the Immersive VR Upper Limb Training System

4. Results

4.1 Demographic Characteristics

Table 2 provides a comprehensive overview of the valid sample. The 280 valid respondents included 146 men and 134 women. Regarding age distribution, respondents aged 18–22 accounted for 28.21% of the sample and primarily comprised undergraduate students; those aged 23–27 accounted for 26.79% and mainly included master's degree students and entry-level employees in various industries; the 28–32 age group primarily comprised doctoral students and professionals from various industries. Those aged 33–35 were mainly young university faculty members and working professionals. Overall, our sample covered a diverse range of occupational groups within the 18–35 age range. Additionally, 58.93% had experience using VR devices, and more than half engaged in physical exercise 1–2 times per week.

Table 2
Demographics profile.

Characteristics	ID	Frequency	Percentage
Gender	Male	146	52.14%
	Female	134	47.86%
Age	18-22	79	28.21%
	23-27	75	26.79%
	28-32	72	25.71%
	33-35	54	19.29%
Education level	High school diploma or less	9	3.21%
	Bachelor's degree	129	46.07%
	Master's degree	102	36.43%
	PhD degree	40	14.29%
Experience with VR devices	Yes	165	58.93%
	No	115	41.07%
Number of times per week to engage in physical exercise	0	67	23.92%
	1-2	145	51.79%
	3-4	66	23.57%
	5 times or more	2	0.71%
Experience with an Upper Limb Injury	Yes	257	91.79%
	No	23	8.21%

4.2 Measurement Model Analysis

Before the hypothetical relationships were analyzed, we first assessed the internal consistency, convergent validity, and discriminant validity of the measurement model. We used both Cronbach's alpha and composite reliability (CR) to assess the internal consistency of each construct. Cronbach's alpha and CR values for all constructs were >0.75, exceeding the critical threshold of 0.7, demonstrating that each construct possessed excellent internal consistency, as shown in Table 3. We assessed convergent and construct validities by calculating the average variance extracted (AVE)

and factor loadings. Results revealed that all factor loadings and AVE values exceeded the recommended thresholds of 0.7 and 0.5, respectively, thereby meeting the criteria for convergent validity. Discriminant validity was assessed using two methods: the Fornell-Larcker criterion and Heterotrait-Monotrait ratio (HTMT). According to Fornell and Larcker (1981), the square root of the AVE for a single construct should be greater than its correlation coefficients with all other constructs. Henseler (2016) reported that the HTMT metric was more reliable for assessing discriminant validity in PLS-SEM models; furthermore, the ratio of all HTMT values must be <0.85. Table 4 summarizes the square roots of the AVEs and HTMT ratios for each construct, supporting the model's discriminant validity.

Table 3

Construct measures validity and reliability.

Construct	Items	Mean	S.D.	Loading	Cronbach's α	CR	AVE
Embodied Interactivity	EI1	4.86	1.117	0.851	0.850	0.91	0.77
	EI2	4.93	1.065	0.893			
	EI3	4.76	1.139	0.886			
Environmental Embeddedness	EE1	5.14	1.039	0.820	0.879	0.92	0.73
	EE2	5.24	0.983	0.874			
	EE3	5.07	1.033	0.873			
	EE4	5.13	1.066	0.860			
Immersion	IM1	4.61	1.181	0.796	0.830	0.89	0.66
	IM2	4.73	1.111	0.832			
	IM3	4.56	1.107	0.824			
	IM4	4.79	1.105	0.803			
Learning motivation	LM1	4.95	1.073	0.778	0.786	0.86	0.61
	LM2	5.03	1.019	0.817			
	LM3	4.85	1.073	0.741			
	LM4	5.10	1.032	0.785			
Interactive experience	IE1	5.11	1.009	0.759	0.775	0.85	0.65
	IE2	5.25	0.934	0.826			
	IE3	5.07	0.999	0.832			
Perceived incentives	PI1	4.45	1.167	0.783	0.749	0.86	0.67
	PI2	4.59	1.108	0.842			
	PI3	4.52	1.149	0.821			
Affective Trust in Technology	ATT1	4.80	1.116	0.742	0.817	0.87	0.58
	ATT2	4.98	1.017	0.763			
	ATT3	4.78	1.083	0.745			
	ATT4	4.86	1.072	0.767			
	ATT5	4.86	1.063	0.781			
Task-specific Self-efficacy	TS1	5.05	1.025	0.826	0.770	0.88	0.69
	TS2	5.21	0.971	0.844			
	TS3	5.14	1.022	0.813			
Behavioral Intention	BI1	5.40	0.940	0.834	0.769	0.87	0.68

BI2	5.51	0.914	0.840
BI3	5.47	0.941	0.807

Table 4

Correlation matrix and discriminant validity.

	Fornell-Larcker criterion									Heterotrait-Monotrait ratio (HTMT)								
	EI	EE	IM	LM	IE	PI	ATT	TS	BI	EI	EE	IM	LM	IE	PI	ATT	TS	BI
EI	**0.877**																	
EE	0.007	**0.857**								0.069								
IM	0.433	0.504	**0.814**							0.513	0.587							
LM	0.336	0.469	0.491	**0.781**						0.406	0.564	0.606						
IE	0.454	0.594	0.558	0.487	**0.829**					0.557	0.721	0.696	0.620					
PI	0.418	0.461	0.565	0.395	0.552	**0.816**				0.511	0.568	0.716	0.507	0.720				
ATT	0.309	0.515	0.520	0.472	0.579	0.452	**0.760**			0.367	0.608	0.629	0.586	0.724	0.573			
TS	0.425	0.488	0.587	0.552	0.584	0.520	0.505	**0.828**		0.521	0.591	0.733	0.709	0.758	0.682	0.633		
BI	0.300	0.460	0.529	0.428	0.515	0.436	0.505	0.636	**0.827**	0.372	0.559	0.661	0.551	0.669	0.576	0.631	0.826	

4.3 Structural Model Analysis

Based on the results of the measurement model, all proposed hypotheses were assessed by evaluating the structural model. To assess the significance levels of the model's path coefficients, a bootstrapping procedure was performed in SmartPLS 4, with the number of resamples set to 5,000. Additionally, we evaluated the coefficient of determination (R^2) (Hair et al., 2019) to measure the predictive accuracy of the constructs. Figure 6 illustrates that the model explained 42.0%, 50.2%, and 45.0% of the variance in Affective Trust in Technology, Task-specific Self-efficacy, and Behavioral Intention, respectively, indicating that the structural model provided a relatively good explanation of these three endogenous constructs.

Table 5 and Figure 6 jointly present the effect coefficients and related results for all the paths. Embodied Interactivity had a significant effect on Immersion, Learning Motivation, Interactive Experience, and Perceived Incentives ($\beta = 0.430$, $p < 0.01$; $\beta = 0.333$, $p < 0.001$; $\beta = 0.450$, $p < 0.01$; $\beta = 0.415$, $p < 0.01$, respectively). Thus, hypotheses 1a–d were all supported. Environmental Embeddedness also had significant positive effects on Immersion, Learning Motivation, Interactive Experience, and Perceived Incentives ($\beta = 0.501$, $p < 0.01$; $\beta = 0.467$, $p < 0.001$; $\beta = 0.591$, $p < 0.01$; $\beta = 0.458$, $p < 0.01$, respectively). Thus, hypotheses 2a–d were all supported. Immersion had varying degrees of influence on Affective Trust in Technology and Task-specific Self-efficacy ($\beta = 0.197$, $p < 0.01$; $\beta = 0.241$, $p < 0.001$, respectively). Thus, H3a and H3b were supported. Furthermore, learning motivation had varying degrees of influence on Affective Trust in Technology and Task-specific Self-efficacy ($\beta = 0.179$, $p < 0.01$; $\beta = 0.257$, $p < 0.001$, respectively). Thus, H4a and H4b were supported. Interactive experience also had a significant positive effect on both Affective Trust in Technology and Task-specific Self-efficacy ($\beta = 0.336$, $p < 0.001$; $\beta = 0.243$, $p < 0.001$, respectively). Thus, H5a and H5b were supported. Perceived incentives had no significant effect on Affective Trust in Technology ($\beta = 0.085$, $p > 0.05$); however, it had a moderate positive effect on Task-specific Self-efficacy ($\beta = 0.149$, $p < 0.001$). Therefore, H6a was not supported; however, H6b

was supported. Finally, both Affective Trust in Technology and Task-specific Self-efficacy had significant positive effects on Behavioral Intention (β = 0.246, $p < 0.001$; β = 0.512, $p < 0.001$, respectively); therefore, both H7 and H8 were supported.

Table 5

Hypotheses testing results (N=280).

Hypothesis	Path	Path coefficients (β)	t-value	p-value	Result
H1a	EI→IM	0.430	10.171	0.000	Accepted
H1b	EI→LM	0.333	6.707	0.000	Accepted
H1c	EI→IE	0.450	11.922	0.000	Accepted
H1d	EI→PI	0.415	8.537	0.000	Accepted
H2a	EE→IM	0.501	11.927	0.000	Accepted
H2b	EE→LM	0.415	10.207	0.000	Accepted
H2c	EE→IE	0.591	16.655	0.000	Accepted
H2d	EE→PI	0.458	10.770	0.000	Accepted
H3a	IM→ATT	0.197	3.069	0.002	Accepted
H3b	IM→TS	0.241	4.173	0.000	Accepted
H4a	LM→ATT	0.179	3.418	0.001	Accepted
H4b	LM→TS	0.257	5.776	0.000	Accepted
H5a	IE→ATT	0.336	5.390	0.000	Accepted
H5b	IE→TS	0.243	4.187	0.000	Accepted
H6a	PI→ATT	0.085	1.404	0.160	Rejected
H6b	PI→TS	0.149	2.714	0.007	Accepted
H7	ATT→BI	0.246	5.227	0.000	Accepted
H8	TS→BI	0.512	11.004	0.000	Accepted

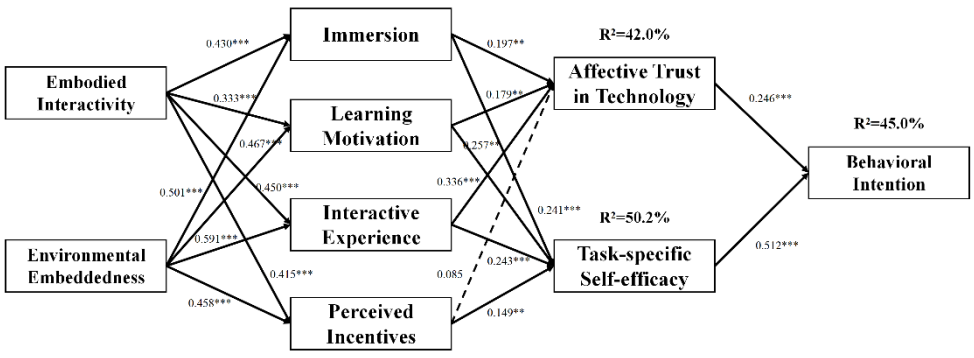

Figure 6. Results of the PLS-SEM.

Note. PLS-SEM: partial least squares structural equation modeling,*p < 0.05;**p < 0.01;***p < 0.001.

4.4 NConfA Analysis

Users' behavioral intentions toward information systems are often shaped by both cognitive and emotional factors, rather than by a linear effect of any single factor. To complement the findings of the PLS-SEM research, we employed NConfA to identify the combinations of factors that

generated high behavioral intentions and determine their actual thresholds. Rasoolimanesh (2026) proposed that NConfA should encompass three stages: configuration identification, necessity testing, and degree-of-necessity testing. Basic steps for conducting fsQCA in the first stage (Al-Emran et al., 2024) involved calibrating and transforming the raw scores of the Likert scale in the fs/QCA 4.0 software to perform necessity analysis, identifying multiple paths that lead to high behavioral intention based on the truth tables (Al-Emran et al., 2024), and identifying the factor combinations that appeared in sufficient configurations with a frequency of >50%. Table 6 presents the four pathways that drove high behavioral intention (based on the intermediate solution), in which the cognitive-affective combinations IM*TS (Immersion*Task-specific Self-efficacy), IE*TS (Interactive Experience*Task-specific Self-efficacy), IE*ATT (Interactive Experience*Affective Trust in Technology), and LM*ATT (Learning Motivation*Affective Trust in Technology) appeared in more than half of the pathways and were preliminarily identified as potential necessary configurations.

Table 6

Sufficient configurations to drive high behavioral intention.

Configuration	Construct conditional path	Raw coverage	Consistency
Conf1	IM*IE*PI*TS	0.512	0.915
Conf2	IM*IE*ATT*TS	0.514	0.914
Conf3	LM*IE*ATT*TS	0.515	0.907
Conf4	IM*LM*IE*PI*ATT	0.448	0.929

In the second stage, IM*TS, IE*TS, IE*ATT, and LM*ATT were treated as new configuration variables in the fsQCA, and their necessary consistency was assessed (Coverage ≥ 0.85)(Rasoolimanesh, 2026; Rasoolimanesh & Olya, 2025). Table 7 presents the Necessity-in-Kind Analysis for the four configurations. Results indicated that IE*TS, IE*TS, IE*ATT, and LM*ATT were all relatively strong necessary configurations for achieving a high level of behavioral intention. After the necessary configurations were identified, the third stage drew on the NCA methodology to quantify the extent to which antecedent configurations acted as “bottlenecks” that constrained behavioral intention (Dul, 2024). Based on the fuzzy set theory, the identified necessary configurations were converted into single variables and imported into R Studio for NCA calculations. We employed a stepped ceiling line (CE-FDH) to fit the data boundaries; furthermore, we calculated the effect size (d) to measure the extent to which the necessary configurations constrained the maximum possible level of behavioral intention (see Figure 7). Table 8 summarizes the effect sizes and constraint strengths for the four sets of necessary configurations. According to Dul’s criteria (2016), IE*TS, IM*TS, LM*ATT, and IE*ATT had a d value of 0.205 ($p < 0.01$), 0.152 ($p < 0.01$), 0.139 ($p < 0.01$), and 0.141 ($p < 0.01$), respectively, all representing significant moderate effects. To determine the specific requirements for these configurations, we created a bottleneck analysis table (Table 9). According to the results, the combined value of Immersion and Task-specific Self-efficacy must exceed 41.1% synergistic membership to achieve a high level (100%) of behavioral intention; furthermore, the combined value of Interactive Experience and Task-specific Self-efficacy, Learning Motivation and Affective Trust in Technology, and Interactive Experience and Affective Trust in Technology must exceed 57.2%, 50%, and 53.8%, respectively.

Table 7

Necessity in-kind analysis for potential configurations using fsQCA.

Configuration	Coverage	Consistency	Result
IM*TS	0.765	0.889	Relatively Strong
IE*TS	0.751	0.885	Relatively Strong
LM*ATT	0.729	0.859	Relatively Strong
IE* ATT	0.754	0.878	Relatively Strong

Table 8

NConfA effect size(d) and significance analysis (based on CE-FDH).

Configuration	Original effect size(d)	Permutation p-value	Constraint Strength
IM*TS	0.152	＜0.01	Medium
IE*TS	0.205	＜0.01	Medium
LM*ATT	0.139	＜0.01	Medium
IE* ATT	0.141	＜0.01	Medium

Table 9

Bottleneck table using CE-FDH for NConfA.

Behavior intention(%)	0	10	20	30	40	50	60	70	80	90	100
IM*TS	NN	3.6	3.6	3.6	14.3	19.7	19.7	19.7	30.4	30.4	41.1
IE*TS	NN	7.3	7.3	7.3	7.3	21.4	21.4	28.7	42.8	50.1	57.2
LM*ATT	NN	NN	NN	NN	6.7	15.6	20.0	20.0	20.0	38.9	50.0
IE*ATT	NN	NN	NN	NN	NN	12.2	15.2	16.9	16.9	40.0	53.8

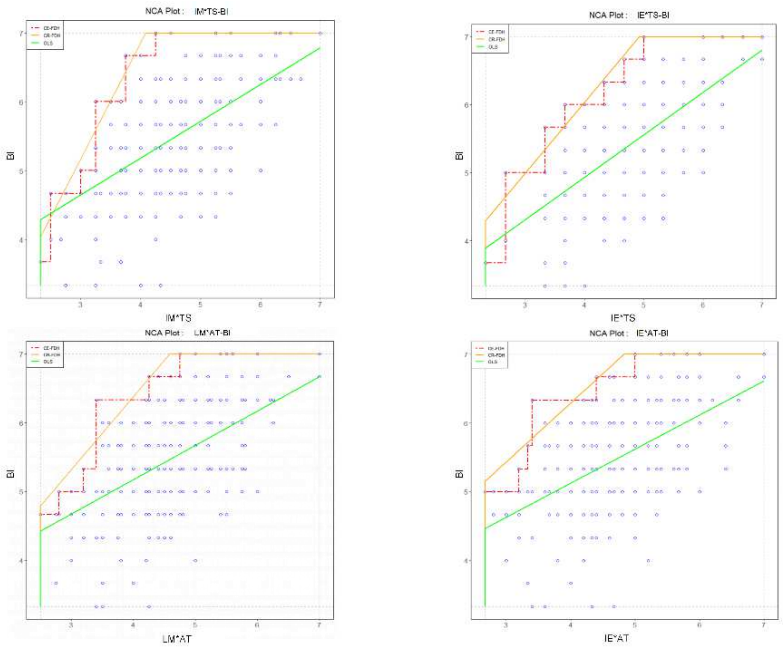

Figure 7. Scatter Plot Illustrating the Relationships Between the Four Configurations and Behavioral Intention.

4.5 Neural Network Analysis

Building on the results from the PLS-SEM and NConfA, we further explored the complex relationships between cognition and emotion and selected statistically significant predictors as input nodes for the ANN analysis to construct a network model. To address overfitting commonly associated with ANNs, we employed a 10-fold cross-validation process (Li & Lau, 2025). In ANN Model A, Immersion, Learning Motivation, and Interactive Experience were used as inputs, with Affective Trust in Technology as the output (see Figure 8). ANN Model B used Immersion, Learning Motivation, Interactive Experience, and Perceived Incentives as inputs, with Task-Specific Self-Efficacy as the output (see Figure 9). Root Mean Square Error (RMSE) was used to measure the predictive performance of each network model; a lower RMSE corresponded to stronger predictive capability. As shown in Table 10, Model A had an average RMSE of 0.110 and 0.149 during the training and testing phase, respectively. Furthermore, Model B had an average RMSE of 0.091 and 0.123 during the training and testing phase, respectively. Based on the error performance across both training and testing samples, Model B demonstrated higher predictive capability.

We used sensitivity analysis to determine the importance of each predictor and hierarchically ranked the variables based on their normalized importance scores. Table 11 presents the sensitivity analysis results for the two network models. In Model A, “Interactive Experience” exerted the most influence on “Affective Trust in Technology,” with a normalized importance of 85.40%, followed by “Immersion” (79.83%) and “Learning Motivation” (73.73%). In Model B, “Immersion” exerted a significant influence on “Task-specific Self-efficacy,” with a normalized importance of 82.50%, followed by “Interactive Experience” (82.09%), “Learning Motivation” (78.87%), and “Perceived Incentives” (70.11%).

Table 12 summarizes a comparison of the PLS-SEM and ANN analysis results, and provides a clear overview of the similarities and differences from the explanatory and predictive perspectives. For Model A, the order of importance of “Interactive Experience,” “Immersion,” and “Learning Motivation” for “Affective Trust in Technology” demonstrated a high degree of consistency between the PLS-SEM ($\beta = 0.336$; $\beta = 0.197$; $\beta = 0.179$) and ANN (85.40%; 79.83%; 73.73%). This indicated that the effects of the three types of situational cognitive factors on Affective Trust in Technology were relatively stable; furthermore, the core relationships exhibited linear characteristics. Interactive Experience was the key factor that shaped users’ affective trust in VR technology. However, in Model B, Immersion had the greatest influence on Task-specific Self-efficacy. This result is inconsistent with the findings from the PLS-SEM, in which Learning Motivation had the most significant influence on Task-Specific Self-Efficacy. This discrepancy stems from the non-linear and non-compensatory characteristics of the network model, which offers superior predictive power and analytical precision. Hence, the relationships between Immersion, Learning Motivation, and Task-Specific Self-Efficacy cannot be fully explained by linear relationships.

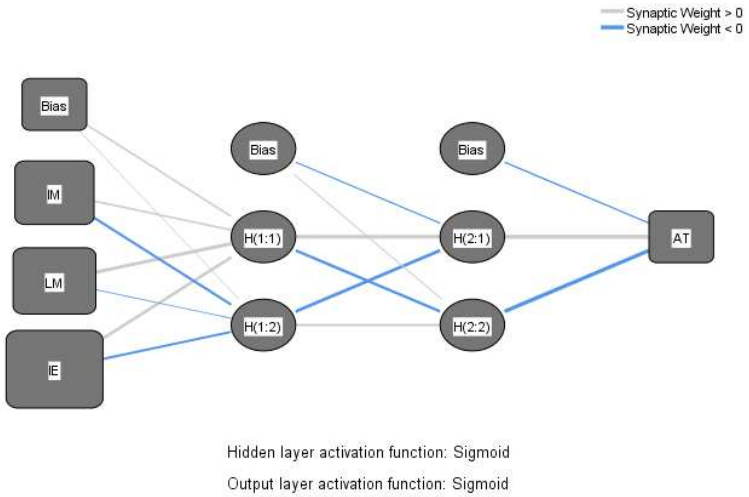

Figure 8. ANN Model A

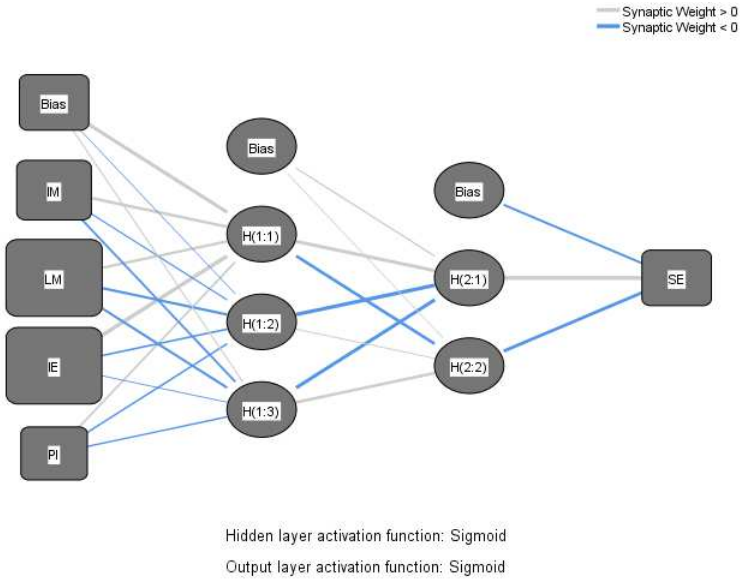

Figure 9. ANN Model B

Table 10

RMSE values of ANN models.

Network	Model A		Model B	
	RMSE(Training)	RMSE(Testing)	RMSE(Training)	RMSE(Testing)
1	0.110	0.136	0.092	0.123
2	0.131	0.156	0.091	0.122
3	0.105	0.136	0.089	0.120
4	0.107	0.129	0.096	0.121
5	0.108	0.133	0.091	0.122
6	0.108	0.145	0.091	0.120
7	0.114	0.165	0.105	0.131
8	0.101	0.178	0.092	0.125
9	0.106	0.128	0.093	0.124
10	0.111	0.183	0.089	0.120
Mean	0.110	0.149	0.091	0.123
Standard deviation	0.00814	0.02042	0.00470	0.00336

Table 11
Sensitivity analysis results.

Network	Model A			Model B			
	IM	LM	IE	IM	LM	IE	PI
1	0.357	0.256	0.388	0.303	0.201	0.296	0.199
2	0.274	0.206	0.520	0.234	0.270	0.363	0.136
3	0.275	0.205	0.520	0.225	0.275	0.306	0.194
4	0.278	0.238	0.484	0.221	0.249	0.363	0.167
5	0.225	0.316	0.458	0.241	0.293	0.320	0.146
6	0.254	0.198	0.548	0.301	0.250	0.245	0.205
7	0.289	0.335	0.376	0.251	0.336	0.210	0.203
8	0.300	0.233	0.467	0.248	0.276	0.301	0.175
9	0.326	0.247	0.427	0.255	0.294	0.210	0.271
10	0.267	0.224	0.508	0.220	0.204	0.361	0.215
Average importance	0.285	0.247	0.468	0.250	0.265	0.298	0.191
Normalized importance(%)	79.83	73.73	85.40	82.50	78.87	82.09	70.11

Table 12
Comparison between PLS-SEM and ANN results.

Model	Path	coefficients (β)	Normalized importance(%)	Ranking (PLS-SEM)	Ranking (ANN)	Remarks
A	IM→ATT	0.197	79.83	2	2	Matched
	LM → ATT	0.179	73.73	3	3	Matched
	IE→ATT	0.336	85.40	1	1	Matched
B	IM→TS	0.241	82.50	3	1	Not Matched
	LM→TS	0.257	78.87	1	3	Not Matched
	IE→TS	0.243	82.09	2	2	Matched
	PI→TS	0.149	70.11	4	4	Matched

5. Discussion

This study focused on psychological recovery mechanisms resulting from the integration of technological features and game design. First, we iteratively refined an immersive VR upper limb training system by optimizing its narrative and interactive design. Drawing on the characteristics of VR technology and situational learning, trust, and self-efficacy theories, we deconstructed and integrated the two theoretical frameworks, the SOR and CAB, to systematically analyze the specific mechanisms through which technological stimuli in VR training scenarios influenced users' situational cognition, emotional trust, and behavioral intentions. To fully elucidate the complex

internal relationships between the latent and outcome variables, this study constructed a multi-method analytical framework that integrated PLS-SEM, NConfA, and ANN.

First, the overall results of the PLS-SEM analysis revealed that Embodied Interactivity and Environmental Embeddedness, the two dimensions of VR technology, exerted varying degrees of influence on all four dimensions of situational cognition. Notably, Environmental Embeddedness exerted a greater influence on all dimensions than Embodied Interactivity. This finding may be related to the nature of VR itself; users can promote active learning simply by entering a VE and observing its content (Mayer et al., 2023). Simultaneously, even when seated, users can still have a stationary experience in the VE, which allows them to explore freely and determines the outcome of the experience based on their choices and behaviors (Khorasani et al., 2023). Another significant finding is that among all the relationships between cognitive and affective factors, the motivation users felt during virtual training did not have a significant impact on Affective Trust in Technology. Wittmann (2025) found that functional antecedents, such as motivation and perspective, only influenced rational judgments regarding a system's functionality and reliability; they do not significantly affect trust at the emotional level. Thus, external motivation can only influence users' rational cognition and cannot establish a deep, emotional human-technology trust relationship. Simultaneously, we also found that task-specific self-efficacy was the core antecedent that drive behavioral intention, and had a significantly stronger influence than that of affective trust at the technological level. Adami (2023) reached a similar conclusion in a study on VR architectural training: task confidence derived from hands-on experience was the core driver that shaped users' willingness to accept the system; trust in the machine only served as a secondary, supplementary psychological factor. This suggests that when developing task-oriented VR systems, the core priority in design optimization should be placed on enhancing users' task-related self-efficacy; simply increasing users' emotional affinity for the device has a limited effect on driving their willingness to continue using it.

Second, in contrast to the symmetric linear testing logic of PLS-SEM, NConfA results identified necessary configurations that comprised combinations of cognitive and affective variables. Among these, Interactive experience*Task-specific Self-efficacy, Immersion*Task-specific Self-efficacy, Learning motivation*Affective Trust in Technology, and Interactive experience*Affective Trust in Technology were all necessary configurations for achieving high levels of behavioral intention. In the two equivalent configurations centered on "Affective Trust in Technology," total sum of the variable synergistic membership degrees was 50% and 53.8%, respectively, indicating that these were roughly equivalent in their effectiveness in facilitating high levels of behavioral intention. This suggests that "Learning Motivation" and "Interactive Experience" are cognitively-based antecedents that serve as equivalent alternatives in fostering high levels of behavioral intention. Within the configuration path that achieved high levels of behavioral intention with task-specific self-efficacy as the core driver, the Interactive experience*Task-specific Self-efficacy configuration imposed stricter requirements for very high behavioral intention (90%–100%) compared with Immersion*Task-specific Self-efficacy, and required an engagement level of 50.1%–57.2%. This suggests that although interactive experience is an important component of configuration that promotes high behavioral intention, its conversion rate is slightly lower than that of immersion. This difference may stem from the fact that interactive experience requires users to expend significant cognitive resources to parse complex operational interaction logic. Existing research confirms that responsiveness, visual realism, and intuitive navigation are core antecedents

of an immersive experience (Samsudin et al., 2026). Through a sense of presence achieved with low cognitive load, Immersion can efficiently trigger users' emotional engagement. This aligns with Makransky and Petersen's view (2021), who argue that immersion, as a catalyst for intrinsic motivation, yields higher conversion efficiency than purely functional interactions. Therefore, based on the findings from the PLS-SEM regarding the influence of the two types of emotional trust on behavioral intent, VR upper limb training systems development should prioritize refining user's sense of immersion to foster self-efficacy, thereby establishing the most cost-effective design path for achieving high training motivation.

Finally, we incorporated ANN to supplement analysis results from the PLS-SEM and NConfA. Results from both the PLS-SEM and ANN collectively indicated that interactive experience played the strongest role in predicting Affective Trust in Technology. This conclusion supports Volpato et al.'s findings (2025) that suggested people's experiences during interactions played a critical role in shaping perceptions of technological trust. Another key finding was that although the PLS-SEM identified learning motivation as the strongest antecedent that influenced task-specific self-efficacy, the ANN identified Immersion as the most influential factor. This suggests that immersion may exert a stronger non-linear influence on task-specific self-efficacy than can be captured by linear estimates. This finding aligns with He et al.'s results (2025) that identified immersion as the core variable with the greatest influence on self-efficacy in metaverse learning systems. This strong non-linear effect may also explain why the interaction between immersion and task-specific self-efficacy is a necessary configuration for generating high behavioral intention in the NConfA analysis. ANN results revealed the non-linear effects of immersion and learning motivation on task-specific self-efficacy, thereby enriching results from the SEM and NConfA analyses and enhancing the explanatory power and predictive efficacy regarding the underlying cognitive and emotional mechanisms during the use of immersive VR upper limb training systems.

6. Conclusion

6.1 Theoretical Conclusion

This study aimed to develop an immersive VR upper limb training system that integrated situational narratives as a vehicle for constructing an interpretable theoretical framework. We explored the cognitive-trust mechanisms underlying the synergistic effects of immersive VR technology features and deep situational game design, and revealed how to drive users to develop a long-term, sustained willingness to use the system. We integrated the SOR and CAB models and used the characteristics of immersive VR technology as a starting point to deconstruct and recombine theories of situational learning, trust, and self-efficacy. This study first employed PLS-SEM to examine the linear relationships between these constructs, and subsequently utilized NConfA and ANN to capture complex necessary configurations and non-linear relationships to enhance predictive accuracy. First, core findings of the PLS-SEM analysis indicated that environmental embeddedness had a more significant impact on situational cognitive factors than embodied interactivity. Although numerous past studies have repeatedly emphasized the intervention value of VEs, this linear result highlights that the VE constructed by immersive VR is a core driver in reshaping users' cognitive experiences during the training phase. Simultaneously, task-specific self-efficacy exerted a greater influence on behavioral intention than affective trust in technology. This suggests that enhancing users' task-specific self-efficacy through tailored game environments and mechanism design is key to driving long-term usage intent.

Second, this study used NConfA to identify the "cognitive-affective" factors that were necessary configurations for generating high levels of behavioral intention and as their specific thresholds. We found that four combinations, Interactive Experience*Task-Specific Self-Efficacy, Immersion*Task-Specific Self-Efficacy, Learning Motivation*Affective Trust in Technology, and Interactive Experience*Affective Trust in Technology, were all necessary configurations. This result indirectly supports the significant influence of interactive experience on both types of affective trust, as evidenced in the SEM path analysis, compared with other cognitive dimensions. Interactive experience and immersion were necessary constructs at the cognitive level; furthermore, the combination of immersion and task-specific self-efficacy yielded a higher conversion rate for generating high behavioral intentions, highlighting immersion's critical role in designing VR games.

Finally, this study explored the non-linear relationships between key situational cognitive and affective variables during VR upper limb training. Results indicated that both immersion and learning motivation exhibited complex non-linear relationships with task-specific self-efficacy; immersion was the strongest predictor of task-specific self-efficacy. Therefore, enhancing users' immersion in VR training design is a key strategy for improving their task-specific self-efficacy. This finding complements the results from the SEM and NConfA and further demonstrates that from the perspectives of interaction and attribution, an individual's trust in their own abilities remains a key factor driving their behavioral intentions. Second, immersion and task-specific self-efficacy can serve as a necessary combination for fostering high levels of behavioral intention; furthermore, considering the strong non-linear influence between immersion and task-specific self-efficacy, this jointly demonstrates the central role of immersion in the entire formation mechanism. However, in contexts with limited technical resources, optimizing the interactive experience remains a viable alternative pathway for enhancing task-specific self-efficacy and, consequently, fostering high levels of behavioral intention.

6.2 Practical Conclusion

Building on the concepts of serious games and occupational therapy, this study integrated narrative and exploratory contextualized game design paradigms to establish a comprehensive design framework for an immersive VR upper limb training system. At the technical implementation level, developers can follow our development process to select appropriate IMU chips for developing wearable devices and designing accompanying virtual games. At the product (game) design level, product managers and game designers should focus on embedding interactive behaviors within a suitable VE based on the analysis results of the theoretical model. They may leverage the VE's inherent passive guidance characteristics and reasonably expand diverse embodied interaction modes. Additionally, enhancing users' task-specific self-efficacy, thereby fostering a high level of behavioral intention should be prioritized. Finally, although immersion and interactive experience both play important roles in driving task-specific self-efficacy and influencing user behavior, the two can serve as mutually complementary strategies for enhancement, when constrained by technical and economic factors.

7. Limitations and Future Work

Although this study provides valuable insights for developing immersive VR upper limb training systems at both the theoretical and practical levels, several limitations remain. First, our participants were primarily aged 18–35, and excluded middle-aged and older adults; therefore, the generalizability of these conclusions across all age groups requires further validation. Additionally,

since participants were required to attend the experiment in person, the sample was drawn exclusively from a single city, which resulted in a geographical bias. Future studies should expand the population to include all age groups and conduct random sampling across multiple cities to enhance representativeness. Second, we relied solely on questionnaires as a single source of subjective data to collect participants' perceptual data. To improve validity, future studies should introduce objective indicators, such as physiological data, to cross-validate the analysis results of the PLS-SEM, NConfA, and ANN. Finally, although this study aimed to apply the immersive VR system and theoretical framework to individuals with upper limb functional impairments in future research, our current sample solely comprised healthy participants; thus, these results may not be directly verifiable in individuals with upper limb functional impairments. Therefore, although our team systematically developed an upper limb training robot in parallel with the immersive VR system, future research should integrate the two and recruit a sufficient number of participants with upper limb functional impairments for clinical validation.

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Informed Consent Statement

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards. Written informed consent was obtained from all individual participants included in the study prior to their participation in any research-related activities.

Statements and Declarations

No, I declare that the authors have no competing interests as defined by Springer, or other interests that might be perceived to influence the results and/or discussion reported in this paper.