A VIRTUAL REALITY-INTEGRATED SYSTEM FOR BEHAVIORAL ANALYSIS IN NEUROLOGICAL DECLINE

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ABSTRACT

Understanding natural human behavior in daily living scenarios is crucial for assessing and monitoring neurological and age-related functional declines. However, conventional observational and behavioral studies often lack ecological validity and control in addressing the complex real-world challenges of analyzing mobility, cognition, and behavior. In this work, we present an AI-enhanced virtual reality (VR) system for behavioral analysis of elderly people. Our system simulates high-fidelity daily living environments incorporating dynamic weather and traffic conditions, and simultaneously records 3D human behavior with motion capture technology. Multimodal analysis revealed the influence of dynamic and adjustable VR interactions on behavioral performance in individuals at risk of neurological declines, underscoring its potential for assessing and detecting motor and behavioral dysfunctions in aging and neurological populations. Our findings also highlight the capability of the proposed VR-integrated system as a platform for studying natural human behavior and cognitive-motor integration, and advancing AI-assisted behavioral research and health assessments.

1 INTRODUCTION

With the increasing aging of the world's population, the rising prevalence of age-related neurological declines, including cognitive, motor, and behavioral impairments, has become a critical public health concern. These impairments progressively affect the functional ability of aging individuals, limiting their mobility, daily behavior performance, and independent living. Analyzing and detecting age-related declines from natural human behavior can inform the development of effective interventions and support disability prevention, and thus play an important role in addressing the healthy aging challenges. Optical motion capture technology, which facilitates the precise recording of movement, provides a useful tool for quantifying motor and behavioral functions (Vun et al., 2024). Meanwhile, advancements in virtual reality (VR) present new opportunities to enhance research through immersive, task-dependent, and controllable virtual environments that simulate real-world scenarios (Schiza et al., 2019; Quan et al., 2024).

VR technology integrates head-mounted displays, motion controllers, spatial tracking systems, and advanced computer graphics to construct multisensory, three-dimensional environments. The applications of VR span diverse domains including neurorehabilitation (Campo-Prieto et al., 2022; Kim et al., 2005; Gao et al., 2020; Thunström et al., 2022), motor skill training (Tayal et al., 2023; Pustovoit et al., 2021; Lee & Kim, 2018), and behavioral neuroscience (Zhou et al., 2022). Its capacity to simulate complex environmental conditions enables the development of novel experimental paradigms. When combined with motion capture systems, it allows for a rigorous investigation of movement behaviors in controlled laboratory settings (Jicol et al., 2019), which could guide precise functional analysis and therapeutic interventions, and ultimately seek approaches to improve quality of life (QoL) for older adults with age-related neurological dysfunctions (Hemmerling et al., 2024).

However, current VR implementations for movement and behavior analysis face significant limitations in environmental fidelity (Vun et al., 2024; Yee et al., 2024). Many simulations rely on

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oversimplified representations that deviate substantially from real world contexts, which is a critical shortcoming given that stylistic discrepancies between virtual and physical environments can alter natural gait patterns and behavioral responses (Mousas et al., 2020). The ecological validity of research findings could be compromised by artificial experimental conditions, limiting the clinical generalizability. Existing VR systems may also fail to replicate the dynamic challenges of daily living environments, including hazard navigation and obstacle avoidance, which are important for functional assessment (Quan et al., 2024). Moreover, inadequate environmental realism may hinder the risk factors that could induce symptoms and falls during rehabilitation. Therefore, enhancing the fidelity of virtual environments represents a crucial step toward improving the applicability of VR-based systems.

To address these limitations, we introduce a framework that leverages AI-assisted 3D modeling techniques to construct photorealistic digital twins of real-world environments. Our VR system incorporates dynamic traffic objects and weather conditions across various outdoor walking environments, with environmental fidelity validated by community-dwelling elderly people. When synchronized with Vicon motion capture technology (Vun et al., 2024), this system enables millimeter-level precision in movement tracking during virtual tasks. This study represents the integration of high-fidelity environment modeling with full-body motion capture to create a multi-scenario experimental platform for the behavioral analysis of individuals at risk of neurological decline.

2 Methods

2.1 High-fidelity modeling of real-world environments

We implemented a series of modeling steps to create virtual environments that incorporate the complexity and richness of real-world settings. Figure 1 outlines the procedure we adopted for scene and pedestrian modeling.

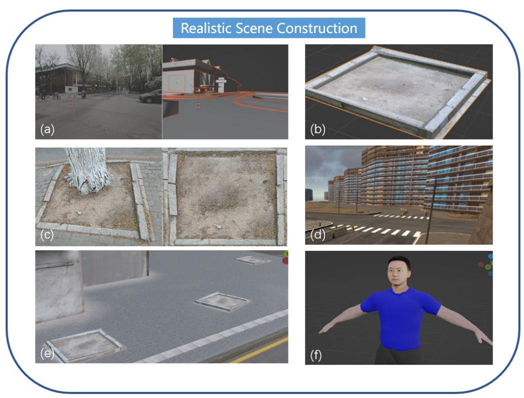

Figure 1: Virtual environment construction. (a) Extract geometry from photos. (b) Build 3D models with photos. (c) Extract texture from photos. (d) Extract nearby buildings to construct vistas. (e) Add details to the 3D model and dust effects. (f) Pedestrian model construction.

Geometry. We took photos of real outdoor environments for their static components such as buildings, roads, and plants. The camera calibration parameters were derived using *fSpy* (Per Gantelius, 2018), an open-source photogrammetric tool with camera perspective estimation algorithms. We leveraged photos to establish perspective relationships between environmental components and imported them into *Blender* (Bonatti et al., 2016) as reference to construct geometrical structures of buildings and other objects, which streamlined the modeling process.

Realistic texturing. We extracted environmental textures from real photos and imported them into *Blender* for modeling. This approach allowed us to create highly realistic object representations without the need for conventionally complex modeling steps.

Distant virtual scenery and detail optimization. To address the limitations of distant virtual scene modeling and enhance realism, we used the *Open Street Map* plugin in *Blender* that quickly generated naturalistic building landscapes (Blender OSM Community, 2021). By optimizing scene details and adding random elements, we were able to improve the overall fidelity of the environment and create more diversified and realistic backgrounds with minimal effort.

Photo-based pedestrian modeling. To overcome the lack of realistic pedestrian models, we adopted an AI-driven approach to efficiently generate lifelike head models (An et al., 2023). We then manually combined and animated the head model with the body model. This method facilitated the generation of heterogeneous models encompassing a wide range of demographic attributes, including gender and physical appearance.

2.2 Virtual Environment Control System

We developed a virtual environment control system to simulate dynamic daily living scenarios, integrating natural elements such as weather and time of day, together with interactive traffic objects like pedestrians and vehicles. These features were implemented as adjustable parameters within the virtual environment, enabling task-relevant control over factors such as the number and routes of pedestrians and vehicles, weather conditions, and temporal settings.

Weather and time control. We utilized the *Unistorm* plugin in *Unity* to dynamically manage weather and time settings, as well as lighting and visibility control in the virtual scene. Users can adjust these settings via the control panel once the simulation starts, with sunny weather set as the default. Alternative weather conditions such as rainy, snowy and foggy are available, each accompanied by corresponding sound effects to enhance the immersiveness (see Figure 2 for an example).

Figure 2: Environmental control effect. Left: Noon on a sunny day. Right: Snowy weather at 8 am.

Route control for pedestrians and vehicles. To maintain a consistent experimental setting and ensure controllability of environmental elements for all participants during experiments, our system included a route control feature for both pedestrians and vehicles in the virtual scene. We developed this feature using the *Nav Mesh Agent* component in *Unity* to allow waypoint settings on the map. Once the simulation begins, pedestrians and vehicles appear at their own waypoints randomly and move according to the pre-defined route sequences. We also integrated an AI-based collision avoidance mechanism for each vehicle with the collision component in *Unity* to effectively facilitate realistic interactions between them.

Traffic system. We implemented a basic traffic system comprising intersections, traffic lights, and moving objects as shown in Figure 3. Traffic light cycles last 60 seconds, with the signal color altering every 30 seconds and a flashing warning signal activated five seconds before each alternation. During the red light, cars and e-bikes/motorcycles stop before the crosswalk. When the light turns green, they gradually accelerate to their normal speed. This basic yet effective traffic system enhances the realism of the virtual street scenes and ensures smooth interaction between different types of traffic components.

2.3 Calibration and safety

2.3.1 Mixed Reality Calibration

Leveraging the SRWorks SDK and the headset camera of HTC VIVE Pro (VIVE-P130), we developed a VR real-view calibration feature controlled by the handheld controllers. During human experiments, researchers can switch the displayed view for participants between virtual and real environments at any time, enabling precise guidance on positioning and movement. Additionally, we integrated stride and view height adjustment capabilities using the VRTK package (Extend Reality Ltd, 2023), allowing quick individual adaption for participants.

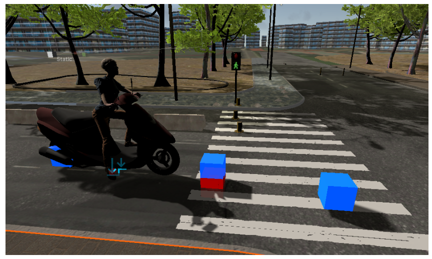

Figure 3: An example scene of the traffic system with traffic lights.

2.3.2 Safety Range Marking and Alerting

Given the invisibility of the real experimental environment for participants navigating in the virtual scene, we introduced a feature for marking and alerting the safety range to minimize hazards. During calibration, walking around the boundaries of the experimental area while holding down the trigger button on the HTC VIVE controller enables the virtual environment control system to automatically record the controller's coordinates and define the safety range. If the participant approaches the boundary during the experiment, the virtual system will display a safety alert to prevent collisions with real-world objects such as walls.

2.4 Data recording and analysis

Our system features the capability to export graphs of positions, orientations, and speed information of participants. Coordinate recording and video replay are available for analysis and visualization. We also developed the following functions in our integrated system:

Integration with motion capture system. Our VR system was synchronized with the motion capture system via a serial port. The VR host monitors the motion capture recording status by detecting 0/1 signals from a self-developed synchronizer, using *.NET 4.x API Compatibility Level* in *Unity* to handle serial communication. Serial port parameters such as the baud rate and data bits were configured through the *Unity* interface. Real-time signal reception could be easily observed in the VR system control panel to verify synchronization functionality. Running the synchronization script allowed serial signals to be recorded and saved, facilitating more accurate timestamp alignment during offline analysis of virtual interactions with physical movements. Notably, this synchronization protocol works with any motion capture system that can send serial signals.

Collision detection. We integrated a collision detection feature utilizing *Unity*'s collision component. If contact was detected between the participant's collision body and that of other objects, our system would record the timestamp and spatial coordinates of the event.

Behavioral comparison under various affecting factors. By controlling variables such as scenes, environmental conditions, and interactive objects, and setting impact labels and coefficients according to these variables' effects and risk levels on elderly mobility, an impact factor matrix could be generated. Within different events and under the impact factor matrix, we compared the changes in participants' movement trajectories and behavioral decisions across single or multiple variables.

3 Experiments

We conducted daily walking experiments using our VR-integrated system with 100 community-dwelling older adult participants (53 males and 47 females) aged 60 to 87 years, which covered gender differences and a broad age range. All participants signed their informed consents before participating. No motion sickness, VR dizziness or cognitive overload was reported. During the experiment, we collected their head orientations, virtual positions, and 3D motion capture data simultaneously with latencies shorter than 10 ms (Figure 4).

Each participant engaged in an experimental study comprising three distinct scenarios: (1) a walking street environment, (2) a road intersection with traffic lights, and (3) a crossroad without traffic light signals. The first scene includes a pedestrian-only street with buildings on both sides. Eight pedes-

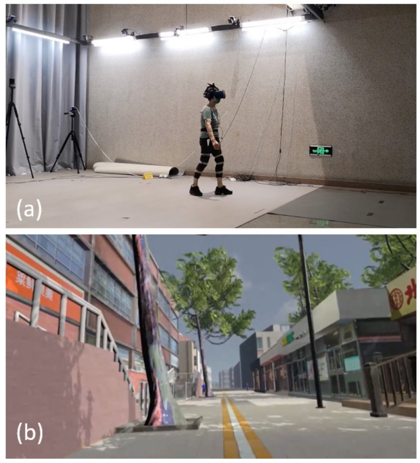

Figure 4: Human experiments. (a) The experiment settings, including the VR and the motion capture systems. (b) The virtual scene that the participants see in VR.

trians would appear on the street, moving in their pre-defined routes. In each experiment trial, the participant started from the entrance of this street and walked forward until they approached the end of the experiment field. The participant then returned to the starting point. The second scene mainly includes an intersection with buildings and tree-lined roads. Several cars and e-bike/motorcycles would travel along the road. The participant started at the crosswalk facing the traffic light, and walked across the road when the light turned green. Vehicles on the road obey the normal traffic rules. The third scene also comprises an intersection with buildings and trees. Two cars and sixteen e-bikes/motorcycles would travel along the road. The participant started at the crosswalk and needed to safely cross the road while being mindful of vehicles.

We also incorporated three distinct environmental conditions in each scenario — sunny daylight, evening twilight, and rainy — to evaluate the influence of varying lighting and weather effects on participant behavior. Figure 5 shows the sample scenes of different VR scenarios and conditions.

Figure 5: Scenes with different conditions. A total of nine experimental conditions, including three different virtual scenarios combined with three different weather conditions.

4 RESULTS

4.1 HUMAN MODEL BASED ON MOTION CAPTURE DATA

Through the SOMA pipeline (Ghorbani & Black, 2021), we could reconstruct an individual 3D human model consistent with the body of the participant. The original motion capture data were in the format of coordinates and labels of markers attached to the participant's body in a series of time frames, shown as the point cloud in Figure 6. We fit these data to the human model, which captured and represented the body pose and shape of the participant. The resulting SMPL-based model (Loper et al., 2023) was then converted into standalone FBX files for use in 3D graphics tools like *Blender*. This process included rigging the SMPL-based model in *Blender*, enabling realistic animations and visualizations for further analysis and applications.

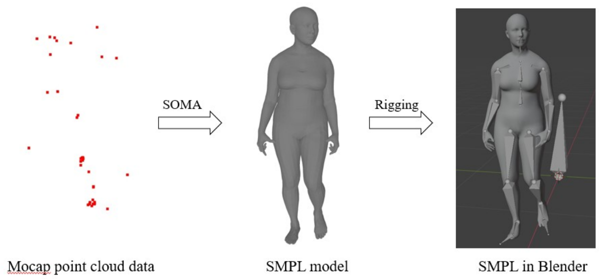

Figure 6: The 3D human model was obtained via SOMA, and rendered in the animation file.

4.2 Data replay

Our system features an additional interface that displays the virtual scene overhead map and representations of interactive elements (vehicles, pedestrians, participant positions). It automatically loads all position recordings and creates objects in a new scene to represent different interactive elements with the same names and quantities. This feature also allows visualization of participants' movement paths and orientations during the recording period. Furthermore, the 3D human model derived from motion capture data can be imported to enable the reproduction of physical movements and behaviors of the participant in the virtual environment. This approach, compared to using only internally recorded data, offers a direct visualization and analysis tool for the participant's actions throughout the experiment (see Figure 7).

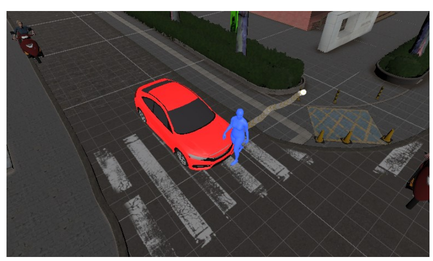

Figure 7: Replay of virtual scene with imported participant model

4.3 Predicting the Risk of Mild Cognitive Impairment (MCI)

In addition to the VR-motion capture experiments, we also conducted assessments of MCI risk using the Montreal Cognitive Assessment (MoCA) and Mini-Mental State Examination (MMSE), as well as a 6-meter round-trip walk (GA6M) with motion capture gait analysis. Through cognitive assessments, we identified two participants at risk for MCI. We selected another two participants as healthy controls matched by gender, age, and similar height, to compare motor performance between the two groups. The demographic information of the two groups of participants is shown in Table 1.

For each experiment, we derived kinematic data throughout gait cycles and calculated essential spatiotemporal gait parameters, including the stance phase, double support phase, cadence (steps/min), stride time (s), stride length (m), and walking speed (m/s).

The key parameters obtained from the motion capture data collected during the GA6M experiment and intersection-evening scene VR experiment were compared. The two types of experiment in-

Table 1: Demographics of participants

Category	Gender	Age	Height
Group 1 Participants			
Category	**Gender**	**Age**	**Height**
MCI Risk (H139)	M	68yrs	163 cm
Matched Control (H144)	M	68yrs	165 cm
Group 2 Participants			
Category	**Gender**	**Age**	**Height**
MCI Risk (H142)	M	67yrs	171 cm
Matched Control (H153)	M	67yrs	167 cm

volved a similar motion process, namely, after walking forward for a distance of about six meters, turning around and returning to the starting position.

During the conventional movement task (GA6M), the two participants at risk of MCI did not exhibit significant differences in performance compared to healthy controls. However, when switching to the VR experiment, we observed notable differences, as shown in Table 2 and Table 3. We used the gait features in the GA6M experiment as the reference value and calculated the differences. The MCI-risk participant (H139) exhibited significantly greater gait alternations in the VR experiment compared to the matched control (H144). He showed markedly reduced cadence (-39.34 vs. -6.99), prolonged double support phase (34.34 vs. 4.84) and stance phase (17.01 vs. 2.79), indicating impaired motor coordination or hesitancy during movement. In the second group, although the difference was smaller compared to the results in the first group, we also observed a similar trend.

Table 2: Gait parameter differences of Group 1 in VR experiment.

Parameter	**ΔH139**	**ΔH144**
Cadence (steps/min)	-39.3390	-6.9937
Double Support (%)	34.3400	4.8400
Stance Phase (%)	17.0100	2.7900
Stride Time (s)	0.9050	0.0950
Stride Length (m)	-0.8027	-0.1536
Walking Speed (m/s)	-0.8297	-0.1922

Table 3: Gait parameter differences of Group 2 in VR experiment.

Parameter	**ΔH142**	**ΔH153**
Cadence (steps/min)	-17.6575	-13.104
Double Support (%)	12.6700	10.130
Stance Phase (%)	7.7800	5.060
Walking Speed (m/s)	-0.5179	-0.6429
Stride Time (s)	0.2350	0.120
Stride Length (m)	-0.4743	-0.5467

Limited by the number of participants, the ability of VR experiments to identify the risk of MCI needs to be further explored. However, the current results show potentials of the VR paradigm to enhance the detection sensitivity for at-risk individuals with: (1) dual cognitive-motor loading; (2) ecological validity; and (3) parameter sensitivity.

4.4 Prediction of risk factors for natural behavior

In order to evaluate the influence of weather and dynamic interaction factors on participant behavior in the virtual environment, we further analyzed the distribution of the minimum avoidance distance under different weather conditions and three major interaction factors (pedestrian, car, motorcycle). Our VR system recorded the spatial coordinates of the participant and the nearest interactive object during the experiment and calculated the minimum Euclidean distance between them. Here, we chose the scene of the intersection without traffic lights for analysis, as it required participants to perform relatively richer interactions with the three interactive elements. When analyzing each type of interaction, we excluded data with a minimum distance of more than 10 m (too far for interaction). The distribution of the minimum distance is shown in Figure 8.

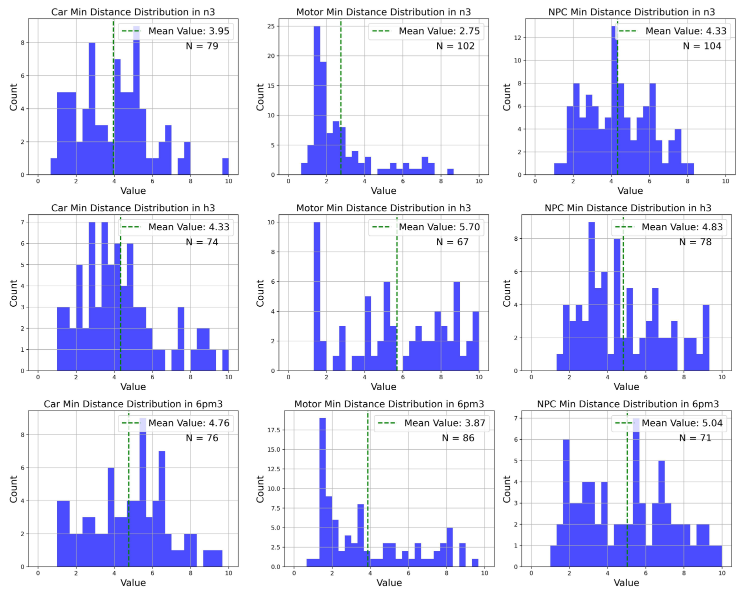

Figure 8: The histogram of the minimum distance distribution between participants and different interactive elements under different conditions. The figure shows the minimum distance distribution of the Car, motorcycle (Motor), and pedestrian (NPC) under three different weather conditions (n3: normal, h3: heavy rain, 6pm3: evening). Each subgraph shows the data distribution (blue bar with width of 0.33 m) and the corresponding average (green dashed line). N represents the number of valid data in each set of experiments.

In order to further compare whether the three weather factors (normal, heavy rain, evening) have influence on minimum distances between participants and the three interactive elements, we conducted a comparison using Mann-Whitney U tests, as shown in Figure 9.

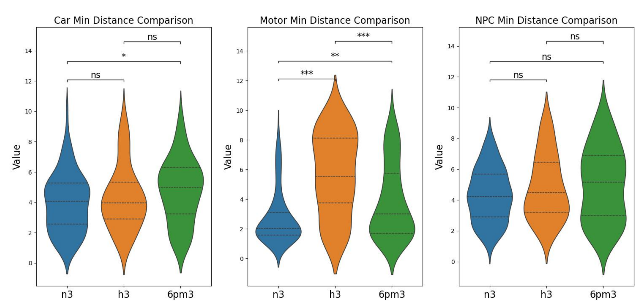

Figure 9: Comparison of the minimum distances to different interactive elements (car, motor, NPC for pedestrian) under different environmental conditions (n3: normal; h3: heavy rain; 6pm3: evening; all in the scene of the intersection without traffic lights). Violin plots show data distribution features (kernel density estimation with inner quartile lines). Intergroup comparisons were performed using Mann-Whitney U tests, with statistical significance ($*\, p < 0.05$, $**\, p < 0.01$, $***\, p < 0.001$, ns = not significant).

As illustrated in Figure 9, there is a statistically significant difference between the normal and evening conditions in the interaction with cars, but not for the other factors. For motorcycle interaction, there is a highly significant difference between normal and heavy rain, and normal and evening conditions. For pedestrian interaction, there are no statistically significant differences between all groups.

Through the above comparison, we show that the light may be a key factor for participants to change the interaction distance with the cars. For motorcycles, light and weather are both influencing factors, perhaps because the path of a motor is less predictable compared to that of a car (considering the distance between the path and the sidewalk). For pedestrians, neither light nor weather had a significant effect.

5 DISCUSSION

This study proposes an integrated framework as a multimodal approach for behavioral analysis targeting aging and neurological populations by introducing the following key innovations: (1) an advanced VR-motion capture platform designed to enable synchronized cognitive-motor performance evaluations; (2) quantitative analysis providing evidence on improved sensitivity levels when identifying functional impairments over standard clinical tests; (3) practical implementations showcasing how this system can be utilized effectively towards evaluating potential hazards linked with outdoor walking scenarios within everyday life contexts.

Our experiments demonstrated the dual utility of the VR-motion capture platform in both functional assessment and natural behavior analysis. The capacity of our system to simulate ecologically valid scenarios with adjustable parameters and dynamic factors could enable task-oriented customization at the personalized level. Crucially, the performance disparities observed between MCI-risk individuals and healthy controls were VR-only, suggesting potential effects of multimodal sensory integration in VR that may amplify subtle deficits in the at-risk population.

Our results further showed that in complex environmental simulations, the minimum safety distances between participants and various dynamic traffic elements were differentially influenced by weather conditions, with interactions involving motorized elements showing greater susceptibility. This environmental sensitivity likely reflects population-specific characteristics, as elderly individuals tend to exhibit increased vulnerability to environmental interference. Such fragility may constitute a critical predictor of daily mobility risks. Together, our findings might facilitate the establishment of new behavioral markers for understanding the interplay between environmental factors and neurodegenerative cognitive deficits, while providing experimental support for the ecological validity of VR-based multimodal assessments.

However, we also identified two key limitations. First, while our scenario library effectively probes street-crossing competencies, its ecological validity could be further enhanced through more complicated environment reconstruction. The current creation of dynamic virtual environments still requires manual effort. Future works with integration of AI-generated content (AIGC) pipelines could address this challenge by automating terrain generation (via diffusion models) (Nur et al., 2023) and asset creation (through neural radiance fields), reducing scene development time while maintaining clinical relevance (Ren et al., 2024). Second, functional evaluations from embodied VR experiences require systematic validation with a larger population and control experiments. Although preliminary data suggested that virtual body omission may amplify movement hesitancy in MCI-risk individuals, control studies comparing opaque vs. translucent avatar representations are needed to isolate visual feedback effects. Future iterations will also incorporate real-time biomechanical rendering, enabling dynamic visualizations of body positions during task performance.

In conclusion, our AI-enhanced VR-motion capture system represents a significant step forward in assessing the behavioral performance of individuals at risk for neurological declines. By addressing identified limitations and leveraging advanced technologies such as generative AI techniques, we could further refine our approach to better serve both clinical and research needs. We believe that continued advances in this integrated system will contribute to more effective tools for early diagnosis, rehabilitation, and overall management of neurological disorders.

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