A Virtual Reality-Based Simulation Tool for Assessing the Risk of Falls in Older Adults

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Abstract: Falls are considered a significant cause of disability, pain, and premature deaths in older adults, often due to sedentary lifestyles and various risk factors. Combining immersive virtual reality (IVR) with physical exercise, or exergames, enhances motivation and personalizes training, effectively preventing falls by improving strength and balance in older people. IVR technology may increase the ecological validity of the assessments. The main goal of our study was to assess the feasibility of using a KAVE-based VR platform combining simulations of Levadas and a cable car to perform a balanced assessment and profiling of the older adult population for high risk of falls and the related user experience. A VR-based platform using a Wii balance board and a CAVE was developed to assess balance and physical fitness. Validated by the Biodex Balance System (BBS), 25 older adults participated in this study. The usability and presence were measured through the System Usability Scale and ITC-SOPI questionnaires, respectively. The IVR system showed a high presence and a good usability score of 75. Significant effects were found in the maximum excursion of the centre of pressure (COP) on the anterior–posterior axis during the cable car simulation (CCS), correlating with BBS metrics. Multiple discriminative analysis models and the support vector machine classified fall risk with moderate to high accuracy, precision, and recall. The system accurately identified all high-risk participants using the leave-one-out method. This study suggests that an IVR-based platform based on simulations with high ecological validity can be used to assess physical fitness and identify individuals at a higher risk of falls.

Keywords: virtual reality; balance assessment; posturography; ecological validity; physical fitness; senior fitness tests

1. Introduction

Falls are becoming a global health problem because they create injuries and especially affect the lives of older people, their families, and society. According to the World Health Organization (WHO), approximately 684,000 fatal falls occur every year, making them the second leading cause of accidental injury death after road traffic accidents. More than 80% of fall incidents occur in low and middle-income countries. Some 60% of deaths occur in the regions of the Western Pacific and Southeast Asia. The death rates are the highest among people aged 60 and above all over the world. Age is one of the risk factors for falls in older adults. The risk of serious injuries or death is associated with falls, which increase with age. The changes in physical, sensory, and cognitive capacity are associated with aging, and a lack of customized environments for the older population may add to the risks of falls.

Falls among the elderly population occur because of the interaction of several risk factors, such as a sedentary lifestyle, loss of balance, overuse of alcohol, and environmental...
barriers, e.g., narrow stairs, socioeconomic conditions, and multiple comorbidities. Medical conditions such as neurological and cardiac ones are also part of the risk factors for falls [1]. Some other risk factors include older age [2], poor muscle strength [3,4], gait disorders [5], cognitive deficits [6], and balance disorders [7]. Older adults with difficulties in daily life activities are particularly vulnerable to falls, leading to injuries, disabilities, poor quality of life, mortality, and financial dependency. Addressing these risk factors through interventions like physical exercise, home modifications, and medical management can help reduce the incidence and impact of falls among the elderly [8].

In particular, physical exercise has been identified as one of the best solutions to reduce the risks of falls. Some exercises that can minimize the risks of falls are body stretch, strength and balance training, tai chi, and treadmill workouts [9]. Cognitive impairments, including low memory, self-control and response, are also linked with falls among older people [6,9]. Thus, cognitive-motor interference (CMI) challenges the ability of older adults to execute tasks effectively, such as walking and speaking simultaneously [10,11], putting them at higher risk of falls and experiencing difficulties executing those cognitive tasks [12,13].

Several organizations such as the Joint American and British Geriatric Society (ABGS), the British Geriatric Society (BGS) (Panel on Prevention of Falls in Older Persons, the American Geriatrics Society and British Geriatrics Society, 2011) and the National Institute of Clinical Excellence (NICE) UK have introduced a set of guidelines to assess and reduce the risk of falls [14]. It is also suggested that older adults should have moderate-to-high-intensity balance training in their multi-tier exercise program [15]. One study conducted home-based training sessions, which were successful for both men and women. It helped to reduce the risk of falls and associated injuries by about 35–45%. These sessions had multiple exercises, such as walking, muscle strength, and balance training, which health professionals and trained nurses at home advised. However, the need for health professionals to administer the training sessions is a known limitation [16].

Novel tech-based applications can effectively promote these training programs. Recent reviews and meta-analyses exposed new technologies such as virtual reality (VR), artificial intelligence (AI), and exergames that introduced new training programs specially designed to avoid incidents of falls [17–19]. VR may increase older adults’ motivation for their physical rehabilitation, which may be a valuable tool for achieving active aging goals [18].

To summarize, the literature highlights how common commercial exergames fall short in addressing the particular needs of older adults. The relevance of adequate, objective, and automated user profiling is essential for effective personalization of an exergame intervention designed for older adults.

2. Related Work

The fall risk classification can be defined as a single or group of assessments performed to evaluate the risk of falls to individuals and to provide feedback if follow-up assessments or training are required. The standard methods are followed based on the individual’s level of risk of falls to customize or implement assessments and interventions [20]. Some common fall risk classification methods include self-reported questionnaires, physical exercise tests, and posturography procedures. These methods have some limitations, advantages, and drawbacks. For example, the Stay Independent Brochure is a valid and reliable instrument for the risk assessment of falls [17]. However, it can only be used for certain populations and takes longer to complete. The literature also highlighted other physical functional tests, such as the timed-up-and-go (TUG) test, and the Berg balance scale or walking speed, as profiling tools [20]. However, these mobility tests require trained healthcare professionals to evaluate the risk of falls in healthy community-dwelling older adults [18]. Computer-based posturography is another way to assess the individual’s balance and quantify body sway. The posturographic parameters can be acquired for static and dynamic balance conditions, providing valuable information on postural controls [19]. Multivariate logistic regression may not be feasible to obtain the optimal fall risk classification as the posturographic parameters are highly correlated and
may be non-linear. Therefore, utilizing artificial intelligence (AI)-based methods such as machine learning may solve the complexity of the data set [21]. AI-based methods may still require trained professionals, but the goal of AI-based methods may increase the autonomy of those professionals and help to solve the complexity of the data set generated during the tests. Posturographic parameters and AI-based methods have been used in several studies for multiple types of elderly populations belonging to different groups or organizations [22–26] such as osteoporotic [27], parkinsonism [28], and multiple sclerosis [29]. The posturography systems comprise multiple hardware components such as force platforms [25, 28, 29], pressure platforms [24], inertial sensors [24, 30], or depth cameras [26] to acquire posturographic data. The common machine learning algorithms are mostly used in studies of random forests, decision trees, neural networks, support vector machines (SVMs), and k-nearest neighbors [24, 25, 29]. The receiver’s operating characteristic (ROC) analysis [24] shows that these algorithms can reach accuracy between 80 and 99.9% [25, 27, 29, 31] or an area under the curve (AUC) between 85 and 88%.

Some studies evaluated the efficacy of wearable sensor-based functional assessments for predicting the risk of falls. The machine learning models were implemented to classify participants as fallers (Fs) and non-fallers (NFs), based on the features of the sensor data. The following criteria were used to classify participants as Fs and NFs: quantitative evaluation of the standard function procedure (e.g., Berg Balance Scale (BBS) and Tinetti Gait and Balance Scale), self-reported fall incidents, and hospitalization history [32–34]. Wearable sensor-based tools have been developed recently and are available commercially to assess the risk of falls in older adults.

It has been considered that older people have low motivation for traditional physical exercise programs [35]. However, combining immersive VR (IVR) and physical exercise could be a suitable training program for older people’s physical needs and requirements [36]. The literature is scarce on VR simulations to assess the risk of falls. However, most of the studies used VR-based exergames through interventions to reduce the risk of falls. Exergames are game-based physical training performed in a virtual environment and have been shown to improve physical fitness [37] and as a treatment option for multiple types of unhealthy subjects [38, 39]. VR is an ideal platform for cognitive-motor interference because it offers physical exercise, joy, and cognitive functions in one platform, increasing the intervention’s ecological validity, safety, and acceptance.

The literature highlighted commercial VR-based exergames for multiple physical activities, such as balance and strength training for older adults. Thus, the efficacy and feasibility of VR technology have been acknowledged to minimize the risks of falls [40–42]. Habibnezhad et al. [43] created a VR simulator to evaluate the risk of falls for construction workers. The VR system comprised three trackers, a VR headset, and a virtual environment. The inverse kinematic method was used for the body–joint simulations to create the virtual leg movements. The study showed that the VR simulator performed better than the traditional VR systems to assess upper-limb stability during gait movements [43]. Another study investigated the effect of multiple VR-based visual stimuli on postural control while standing in an upright posture. The participants’ postural stability was quantified by measuring the center of pressure (COP) in a VR environment. The authors created the virtual simulation of the rotary optokinetic drum and observed that visual stimuli invoked by the rotary optokinetic drum may enhance the instability more than the stance with the eyes closed [44]. Yeh et al. examined the impact of delayed visual feedback and cognitive performance on postural control in healthy young and elderly populations. The participants were asked to position their COP (upright posture with eyes open) in a fixed target as precisely as possible with the visual and delayed-visual feedback of their COP position. They also performed arithmetic tasks (cognitive dual tasks). An increase in postural sway was observed in older adults with delayed visual feedback, which indicates that older adults rely more on vision to control their posture [45]. One study assessed the validity and reliability of the data from a Wii balance board (WBB) against a force platform (FP) in older adults with type 2 diabetes mellitus. The regression model showed that the WBB was able
to describe most of the changes in COP sway of the force platform between 42 and 72% for all test cases. The authors suggest that WBB is a valid and reliable tool for quantifying the COP excursion [46].

Another study created a VR-based tool to assess the risks of falls. A head-mounted display (HMD) was used along with motion sensors to record kinematic data during the tests. The results indicated that the participants who were at high risk of falls took a longer execution time for interventions and a number of steps [47]. Garcia introduced a VR tool to assess the risk of falls in the elderly. The author implemented the choice stepping reaction time task (CSRT) and used an HTC Vive headset (VR headset), suggesting that the highly immersive VR tool can concentrate more on cognitive and motor tasks instead of the technology being used [48]. Similarly, an Oculus Rift headset was used in another study to assess dynamic balance through head mobility. A virtual park scene was created where participants had to ask to save their heads from approaching the balls. The objective of the task was to stimulate the vestibular function to quantify head movements and assess dynamic balance. The results indicated significant between-group differences in head paths, head accelerations, and peak frequencies. However, no significant differences were found in the postural sway parameters [49]. Another study used non-immersive VR and treadmill training to improve cognition and body movements and identified fewer incidents of falls when compared to treadmill training without VR [50]. Some studies showed the efficiency of novel tech-based intervention programs in improving balance [51,52] and locomotion in older adults [50,53].

Aspects such as the visual representation of the user’s body in a virtual environment affect the perception of spatial presence and may decrease the presence level if the user’s virtual body is not represented in the VR environment [54]. Augmented reality (AR) can offer a higher sense of presence and realism than VR. Applications for motor rehabilitation are an excellent example of the benefits of using AR [55]. It allows users to interact with real-world objects by implementing an adapted virtual environment, which is more ecologically valid, accessible, and feasible for older adults [50].

Therefore, in this research, we created a custom immersive VR-based platform based on validated protocols and propose a high ecological validity to assess physical fitness and static balance for older adults to enable adequate exergame personalization to avoid the occurrence of falls. The VR environment [56] has a high user perception of presence, which may be used to create a highly ecological environment. We also examined the usability and the presence level of the VR application. The use of simulated functional activities in VR may enhance the validity of balance and fitness assessment. The following section of this paper describes methods (hardware and software) and the results of our study.

3. Methods
3.1. Participants

Following a repeated measures samples design, 25 participants (19 females, ages: M = 71.2 SD = 7.8) were recruited from a local senior gymnasium in Funchal, Portugal, by invitation of the sports science professionals who work at this gymnasium. The balance assessments were performed at the University of Madeira, Laboratory of Pedagogy and Optimization of Sports Performance. The participants were healthy Portuguese older adults, were provided with informed written consent before the study, and received no compensation for their participation. Six participants were removed because they lost their heart rate data due to connectivity issues of the chest band sensors to the system application. Following the Declaration of Helsinki, the procedures were implemented and supervised by experienced, trained staff and approved by the Faculty of Human Kinetics Ethics Committee, CEIFMH Nº3/2023.
3.2. Apparatus

3.2.1. Hardware

We used a KAVE (Kinect-cave Automatic Virtual Environment) [51], designed and implemented at the NeuroRehabLab, to create an immersive virtual environment for our application. To project a virtual environment display, three white walls were built with a width and height of 2.2 and 2.8 m, respectively. Four HD projectors, external speakers, and a processing personal computer were the core parts of the Kave system (Figure 1a). The KAVE application integrates a Unity 3D plugin comprising scripts, prefabs, objects, and the Microsoft Kinect libraries (https://assetstore.unity.com/packages/tools/camera/kave-113090, accessed on 8 April 2024). Unity 3D is a cross-platform game engine with features such as advanced animations, particle systems, high-definition audio, and tools to create 2D and 3D games. The Kinect V2 tracking sensor (Microsoft, Redmond, WA, USA) was used for full-body tracking to interact with the virtual environment and create a parallax effect.

![Figure 1. Hardware Setup (a) Schematic diagram of the KAVE Setup; (b) Nintendo Wii Balance Board.](image)

A Wii Balance Board (WBB) platform (Nintendo Co., Ltd., Kyoto, Japan) was used to examine the static balance of the participants by computing the displacement of the center of pressure (COP). It works with Bluetooth technology, comprises four platform sensors, and has been used for commercial games such as WII. It has two variants with weight support limits of 135 kg and 156 kg. The maximum weight limit for the platform is 300 Kg (WiiBalanceBoardOperationsManual.Nintendo) [52] (Figure 1b).

The heart rate was measured using a chest band Polar H10 (Polar Electro Oy, Kempele, Finland) for cardiorespiratory endurance. The Polar H10 connects with ActiGraph’s WGT3X-BT accelerometer (Actigraph Corporation, Pensacola, FL, USA) to measure the intensity (magnitude vector) and the motion of the physical exercise. The accelerometer data (metrics) were processed by an ActiLife6 computer application (version 6.13.4, ActiGraph, Cary, NC, USA).

3.2.2. Software

A VR-based cable car simulation (CCS) was created in Unity 3D (unity3d.com, accessed on 8 April 2024) to simulate a realistic and more ecologically valid environment to examine the static balance in older adults. The virtual environment has 3D assets such as mountains, trees, grass, cable car poles, wires, stations, etc. Some virtual environment assets of the simulation were created in the open-source 3D computer graphics software tool Blender (v.4.1) (Blender Foundation, Amsterdam, The Netherlands). (Figure 2a,b.) The simulation application communicates with WBB through Bluetooth technology and records the COP at 30 Hz during the study. The CCS circuit consists of five straight segments at five turning angles (0, 45, 90, −45 and −90 deg). The CCS circuit is performed four times at different
speeds (3, 5, 7 and 9 m/s). After finishing a lap, the simulation restarts automatically at a
different speed. The CCS measures the displacements of the COP for each combination of
displacement speed and turning angle, which will then be used to assess the static balance.

Figure 2. Software Setup (a) Cable Car track Top View; (b) Cable Car Inside View; (c) Biodex Balance
System (BBS).

Additionally, a VR-based Virtual Levada simulation application previously created in
our lab [53] assessed cardiorespiratory endurance and lower body strength. The virtual
Levada tracks comprise computer-generated 3D objects such as trees, mountains, tunnels,
and irrigation canals, designed and developed in Unity3D Engine and Blender software
(Blender Foundation, Amsterdam, The Netherlands). It simulates virtual hiking based
on in-place stepping. Based on the assessments from the senior fitness tests (SFTs) [32], a
two-minute step test (2MST) was implemented. The participants had to raise their knees at
a certain height, which Kinect computed during the in-place stepping exercise, to navigate
into virtual Levada tracks. Additionally, aversion of the 30-s chair sit-stand (30SCST)
exercises was implemented to examine lower body strength.

As a means of comparison and validation of the system, we used a Biodex Balance
System (BBS) SD (biodexrehab.com, accessed on 8 April 2024) as a reference (Figure 2c). It
offers both static and dynamic balance assessment and the risk of falls. The advantages of
BBS are the development of muscle tone, balance and agility improvement and treatment
for various pathologies. It is highly user-friendly, has a touch screen, and a step-by-step
guide for executing static and dynamic balance training and protocols. The BBS can only
be operated or serviced by qualified, trained personnel. However, subjects may require
minimal supervision. The BBS is quick and efficient in profiling older adults for the risk of falls and has been extensively validated in this population [33].

3.3. Questionnaires and Balance

The 7-point Likert scale questionnaire was used to evaluate the participant’s cybersickness. Similarly, the system usability scale SUS [34] questionnaire was used to measure the system’s usability.

The ITC-SOPI is a 5-item Likert scale (Strongly Disagree, Disagree, Neither Agree nor Disagree, Agree, and Strongly Agree) questionnaire used to assess a participant’s level of presence in an immersive virtual or a displayed environment, and it comprises four components: Spatial Presence, Engagement, Naturalness, and Negative Effects.

The balance assessment used the Biodex Balance System (Biodex, Shirley, NY, USA). Before each testing session, the equipment was adjusted according to the participant’s height. Participants underwent a single training session to ensure they understood the protocol and to mitigate learning effects during subsequent testing phases. A 60-s rest interval separated the testing sessions. Participants performed the protocol in a unilateral stance while barefoot for bilateral comparison. The assessment measured the overall stability index (OSI), the anteroposterior stability index (APSI), and the lateromedial stability index (LMSI). Each index was assessed under four levels of platform stability, ranging from level 4 (most stable) to level 1 (most unstable). Lower scores on these indexes indicate better balance, reflecting less deviation from the horizontal position [57].

3.4. Procedure

The participants were randomly assigned to one group, and informed consent was provided before the study. The study protocol and the two-minute demo session were given at the start of the study. The participants performed the static balance assessment tests on the BBS platform for 15–20 min. They were provided a 10-min break after finishing BBS assessments.

Subsequently, participants performed the 2MST (Figure 3a) and 30SCST in the KAVE-based VR environment (Figure 3b). During the tests, they were asked to wear a Polar H10 chest band and an Actigraph device to monitor heart rate (minimum and maximum) and physical activity. A 10-min rest was provided after finishing the fitness tests.

![Figure 3](image-url)

**Figure 3.** The KAVE-based VR Simulations Include (a) Two-minute Step Test; (b) 30-s Sit-Stand; (c) Cable Car Simulation Balance Assessment.

Participants were asked to stand on the WII balance board in an upright standing position for approximately five minutes during the CCS (Figure 3c). They were instructed not to move their body while standing on the balance board. However, they were allowed to
move their head and eyes. The cybersickness, system usability scale [34] and ITC-SOPI [56] questionnaires were provided afterwards.

3.5. Statistical Analysis

The means (M) and standard deviation (SD) were computed for SUS, ITC-SOPI questionnaires, the number of steps, magnitude vector, and heart rate, respectively.

The independent variables from the CCS were track Angle and Speed, with five and four levels, respectively. The dependent variables were the maximum excursion of the COP in the anterior–posterior (AP) and medial–lateral (ML) directions and mean velocity, which were calculated for all combinations of speed and angle variations. The metrics from BBS include EOMeanScore; ECMeanScore; Composite Mean Score; Stability Overall; Stability Anterior–Posterior; Media–Lateral; Percentage of Time in Zone A, B and C; Percentage of Time in Quadrant 1, 2, 3 and 4; Stability Index Front–Back and Left–Right. The participants were classified as high-risk and low-risk falls based on the BBS’s feature Composite–Mean score.

The linear discriminant analysis and the LeaveOneOut cross-validation method in MatlabR2023b (Mathworks Inc., Natick, MA, USA) were used to estimate the classifiers’ accuracy, precision, and recall. Therefore, a repeated-measures ANOVA was performed with Greenhouse–Geisser, Huynh–Feldt corrections applied to obtain a valid F-ratio when appropriate. The statistical analysis was performed using IBM SPSS Statistics version 26 (IBM, New York, NY, USA).

4. Results

The participants reported high presence scores in the ITC-SOPI for all the components: Spatial Presence (Mean: 2.8; SD: 0.69), Engagement (Mean: 3.28; SD: 0.88), Naturalness (Mean: 3.67; SD: 0.84), and Negative Effects (Mean: 1.55; SD: 0.83). Examining the results, participants were highly engaged and perceived an ecologically highly valid VR environment. However, the spatial presence was slightly lower. It was also observed that participants’ responses were low for the component of the negative effect of the environment (Figure 4). The mean score on the SUS was M = 73.8 (SD = 12.0) for the system’s usability. This indicates a good usability score (>68) [58].

![Figure 4](image-url)

**Figure 4.** Box Plot Indicating the Results of the ITC-SOPI Questionnaire. The asterisks and circles are the far-out and far outliers, respectively.

Table 1 shows the results from the repeated ANOVA, which was executed on all the 2MST, 30SCST, and CCS parameters. We found significant differences ($p < 0.05$) in three of the CCS speeds and track angles in the anterior–posterior axis (speed = 5, angle = −90; speed = 7, angle = 90; speed = 7, angle = −90). This indicates that the different CCS parameters can induce measurable behavioral differences.
Table 1. Maximum excursion of COP in anterior–posterior axis for cable car speed and trajectory angles.

<table>
<thead>
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<th>Cable Car Speed and Trajectory Angles</th>
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The maximum excursion of COP in the AP direction for all combinations of Angles (0, 45, 90, −45, −90) and Speeds (3 m/s, 5 m/s, 7 m/s, 9 m/s) was correlated with nearly all metrics of BBS metrics such as EOMeanScore, ECMeanScore, and Composite Mean, etc. (Table 2). However, no significant correlations were observed between the BBS metrics and the maximum excursion of COP in medial-lateral directions. The mean angles are the parameters where angles were ignored, speed limits were selected, and vice versa. The COP mean velocity for almost all combinations of Angles (0, 45, 90, −45, −90) and speed limits (3 m/s, 4 m/s, 5 m/s, 6 m/s) of the CCS was observed to be significantly correlated with the parameters of BBS. Again, these findings indicate that the CCS is effective at inducing behavioral responses and that the COP metrics of the CCS are consistent with those of the BBS.

A Discriminant Analysis (DA) was performed to assess the sensitivity of the KAVE simulations to profile and classify participants as high-risk-falls or low-risk-falls based on the assessment conducted by the BBS. The participants who were classified in the higher 50 percentile predicted Composite Mean score (11 points) were referred to as high-risk-falls, and those below were in low-risk-falls. Several DA models, such as linear, pseudolinear, diaglinear, pseudoquadratic, diagquadratic, and support vector machine (SVM), were built along with the leave-one-out cross-validation method to evaluate the performance of the models (accuracy, recall, precision, and F-score). The selected input features for the classifier included CCS speeds and turning angles, their average responses, 2MST, 30SCST, and HR. A DA with each feature was performed to establish the prediction power of each feature modality; additionally, a posterior step-wise regression approach was used to perform the feature selection.

Discrimination accuracies differ substantially, with the best classification for HR at 55%, CCS at 72%, 2MST and 30SCST at 72%, and 100% for the combined features through a step-wise regression (Table 3). The selected features were the maximum excursion of the COP for high speeds at high turning angles for both AP and ML, the mean of the speeds at 45-degree turning angles for both AP and ML, the mean of the angles at high speeds in the AP direction, and the COP at high speeds for no rotation.
Table 2. Correlation between the CCS’s COP in anterior–posterior direction for all angles and speed limits and BBS parameters (Pearson Correlation, Sig. (2-tailed) and N participants) Abbreviations: Percentage Time (PT).

<table>
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<th>Stability Overall</th>
<th>Stability AntPost</th>
<th>Stability Media Lateral</th>
<th>PTnZoneA</th>
<th>PTinQuad1</th>
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<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.035</td>
<td>0.011</td>
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<td></td>
</tr>
<tr>
<td>max heart rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>−0.566</td>
<td>0.011</td>
</tr>
</tbody>
</table>
Table 3. Maximum excursion of COP in anterior–posterior axis for cable car speed.

<table>
<thead>
<tr>
<th>LOO Cross-Validation</th>
<th>CCS</th>
<th>Mean of Turns</th>
<th>Mean Speeds</th>
<th>2MST &amp; 30SCST</th>
<th>HR</th>
<th>Step-Wise Feature Selection</th>
</tr>
</thead>
<tbody>
<tr>
<td>DA Model</td>
<td>Pseudolinear</td>
<td>Linear</td>
<td>Diagquadratic</td>
<td>SVM</td>
<td>Diagquadratic</td>
<td>Linear</td>
</tr>
<tr>
<td>Accuracy</td>
<td>0.72</td>
<td>0.66</td>
<td>0.66</td>
<td>0.72</td>
<td>0.55</td>
<td>1</td>
</tr>
<tr>
<td>Recall</td>
<td>0.72</td>
<td>0.66</td>
<td>0.66</td>
<td>0.72</td>
<td>0.55</td>
<td>1</td>
</tr>
<tr>
<td>Precision</td>
<td>0.72</td>
<td>0.66</td>
<td>0.66</td>
<td>0.75</td>
<td>0.55</td>
<td>1</td>
</tr>
<tr>
<td>F-score</td>
<td>0.72</td>
<td>0.66</td>
<td>0.66</td>
<td>0.73</td>
<td>0.55</td>
<td>1</td>
</tr>
</tbody>
</table>

5. Discussion

The main goal of our study was to assess the feasibility of using a KAVE-based VR platform combining simulations of Levadas and a cable car to perform a balanced assessment and profiling of the older adult population for high risk of falls and the related user experience. Overall, the participants reported high presence scores in the ITC-SOPI questionnaire, suggesting the validity of the ecological functional simulation and good usability scores with the SUS.

The participants’ level of familiarity with VR technology may impact the assessment. We did not record the participant’s VR familiarity experience; however, VR simulation sickness was monitored. The simulation sickness was classified into three categories: None, Moderate, and High. A total of 79% of participants reported no VR simulation sickness, and the rest experienced only a moderate level, indicating low simulation sickness overall.

To evaluate the feasibility and sensitivity of the system as a profiling method capable of detecting users with a high risk of falls, we used the BBS as a gold-standard reference for balance assessment and predicting the risk of falls. In addition, two senior fitness tests (2MST and 30SCST) were also implemented together with the CSS. The CCS COP data show that CCS trajectory angles and speeds impacted the participant’s balance in AP and ML directions. Significant differences in CoP metrics were observed for the higher speeds (5 m/s and 7 m/s) and turning angles (90 and −90). In addition, numerous features from the CCS were correlated with BBS features, which supports the validity of our CCS to induce behavioral responses and for balance assessment.

The performance of DA models was evaluated to classify participants as high-risk and low-risk falls. We achieved excellent results from the classification using a step-wise feature selection. A linear DA on the selected features rendered a classification accuracy of 100%, indicating that our VR simulation of ecological and functional activities is precise in identifying the risk of falls in older adults. This also suggests that immersive VR environments can be used to implement standard procedures for fitness and balance assessments, proposing alternatives to traditional and expensive laboratory setups and creating custom environments based on functional activities with higher ecological validity. The classical functional tests (e.g., timed-up-and-go) are considered objective assessment tools without using certain equipment to acquire reliable data. These tests are not accurate in detecting minute changes because of the ceiling effect [59]. In contrast, the force platforms are commonly used for the balance assessment. However, they are time-consuming, require a laboratory setup, and cannot be used in clinical environments [59,60].

Previous research reported 86% accuracy with a WBB-based exergame to assess the physical independence of the participants. A 30-s sit–stand test was used as a reference to compare the results [61]. Seo et al. developed a balance ability diagnosis system for the elderly for balance assessment using a Wii balance board. The stability index (SI) algorithm was implemented, and the center of pressure parameter was used to predict the stability index of the balance system (Biodex SD). High accuracy was observed for the SI algorithm, and the linear regression model confirmed that the R-values ranged between 0.943 and 0.983 [62]. Similarly, another study evaluated the effect of virtual reality exercises on balance and fall in older adults. The instruments used in this study included a demographic questionnaire, the Berg Balance Scale (BBS), the Timed Up and Go (TUG)
test, the Falling Efficacy Scale (FES), and the Xbox Kinect 360 for VR exercises. The results showed that VR exercises may improve balance and reduce fear of falling among the elderly [63].

A systematic review was performed to assess the reliability and validity of the WBB. The authors confirmed the reliability of the WBB; however, they also reported the impact factors such as reference criteria, intervention duration, parameters, data acquisition platform, and sample size [64]. In one study, VR HMD and force platforms were compared to evaluate the balance of older adults. The participants at high risk of falls changed their body posture in the anterior–posterior direction significantly compared to the control group. The results showed that the VR HMD is portable with minimal VR simulation sickness, inexpensive, and provides visual perturbation compared to the traditional mechanical platforms for measuring the multiple sensory aspects of the balance [65].

6. Limitations

Both simulations use a KAVE-based VR environment, which requires an adequate laboratory setup. Hence, a mobile-based VR implementation could make this system more portable and facilitate its acceptance and widespread use. The Virtual Levada uses a Kinect sensor and sometimes does not detect gesture signals. It also requires players not to wear black clothes to facilitate the tracking. In addition, Kinect has latency issues that, although they do not affect the measurements per se, can affect the user experience. Further, Microsoft does not provide software development kit (SDK) updates. Hence, an alternative system would be ideal for improved motion detection and interaction. Although the CCS resembles an actual cable car and its environment, it does not have a realistic motion. The CCS could be improved by changing the environment, tracks, and rotation speeds, implementing only those found to induce statistically significant behavioral responses.

Nintendo has halted its production of the WBB and does not provide support any more. Some other limitations of the WBB include hardware-designed consistency and signal loss. The literature has also highlighted the limitations of the WBB, such as poor reliability and quality, and it has not been suggested that the clinical platforms be replaced completely [64].

This study was conducted on healthy older adults. However, participants with multiple pathologies could affect the balance and risk-of-fall tests. Therefore, a larger sample of older adults with different pathologies should be considered in future studies for high classification accuracy.

7. Conclusions

To conclude, in this study we showed that our KAVE-based VR platform can assess the risk of falls for older adults with very high accuracy and reliability, relying on COP data. Our system comprises multiple simulations, such as a Virtual Levada and a cable car simulation to offer low VR simulation sickness, high immersion, and usability. The Virtual Levada implemented VR-based senior fitness tests such as a 30-s sit–stand and two-minute step test. The Nintendo WBB may be used as an alternative and cost-effective tool for balance assessments and risk of falls in the elderly population.

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Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

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