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[Muhammad Asif Ahmad](#)^{*}, [Élvio Rúbio Gouveia](#), [Sergi Bermúdez i Badia](#)

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Article

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

Muhammad Asif Ahmad ^{1,*}, Élvio Rúbio Gouveia ^{2,3} and Sergi Bermúdez i Badia ¹

¹ Faculdade de Ciências Exatas e da Engenharia & NOVA LINCS, Universidade da Madeira, Funchal, Portugal; Agência Regional para o Desenvolvimento da Investigação, Tecnologia e Inovação, Funchal, Portugal; masifnrs@gmail.com; sergi.bermudez@uma.pt

² Department of Physical Education and Sport, University of Madeira, 9020-105 Funchal, Portugal; erubiog@staff.uma.pt

³ LARSYS, Interactive Technologies Institute, 9020-105 Funchal, Portugal

* Correspondence: masifnrs@gmail.com

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 most common in older adults and cause injuries that are the leading factor of disability, pain, dependency, and early death. According to the World Health Organization (WHO), 28-35 % of older adults aged 65 and above fall annually, increasing to 32-42% for those aged 70 and above [1]. Falls are becoming a global health problem because they create injuries and affect especially the lives of older people, their families, and society. Falls among the elderly population occur because of the interaction of several risk factors, such as a sedentary lifestyle, overuse of alcohol, and environmental barriers, e.g., narrow stairs, socioeconomic conditions, and multiple comorbidities. Neurological diseases such as Parkinson's disease, multiple sclerosis, and traumatic brain injuries 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, is 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), British Geriatric Society (ABGS) (Panel on Prevention of Falls in Older Persons, 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 well-known that poor strength and balance cause an increase in the risk of falls [15], and the efficacy of neuromuscular exercises has been tested to reduce falls [16]. It is also suggested that older adults should have moderate-to-high-intensity balance training in their multi-tier exercise program [17]. 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 [18].

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 [20–22]. VR may increase older adults' motivation for their physical rehabilitation, which may be a valuable tool for achieving active aging goals [21].

To summarise, 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 for 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 for falls to customize or implement assessments and interventions [21]. 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 risk assessment of falls [22]. However, it can be used for certain populations and takes longer to complete. Literature also highlighted other physical functional tests, such as the Timed-Up-and-Go (TUG) test, Berg balance scale or walking speed, as profiling tools [21]. However, these mobility tests require trained healthcare professionals to evaluate the risk of falls in healthy community-dwelling older adults [23]. 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 value information on postural controls [24]. The multivariate logistic regression may not be feasible to get the optimal fall risk classification as the posturographic parameters are highly correlated and may be no-linear. Therefore, utilizing Artificial Intelligence (AI)- based methods such as machine learning may solve the complexity of the data set [25]. The posturographic parameters and AI-based methods have been used in several studies for multiple types of elderly populations belonging to different groups or organizations [26–30] such as osteoporotic [31], parkinsonism [32], and multiple sclerosis [33]. The posturography systems comprise multiple hardware components such as force platforms [29,32,33], pressure platforms [28], inertial sensors [28,34], or depth cameras [30] 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 neighbours [28,29,33]. The receiver's operating characteristic (ROC) analysis [28] shows that these algorithms can get accuracy between 80 and 99.9% [29,31,33,35] 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 (F) and non-fallers (NF) based on the features of the sensor data. The following criteria were used to classify participants as F and NF: quantitative evaluation of the standard function procedure (e.g., BBS and Tinetti Gait and Balance Scale), self-reported fall incidents, and hospitalization history [55,56,57]. Wearable Sensor-based tools have been developed recently and are available commercially to assess the risk of falls in older adults. One recent instrument, FallSkip, assesses the risks of falls in the elderly. The tool modified the TUG test following the clinical protocol and used inertial sensors to record the metrics such as time and sway of COP [58]. Another tool is Mobility Lab™ (ML, APDM, Inc., Portland) [36], which comprises six wirelessly synchronized Inertial measurement units (IMUs) [37].

It has been considered that older people have low motivation for traditional physical exercise programs [38]. However, combining immersive VR (IVR) and physical exercise could be a suitable training program for older people's physical needs and requirements [39]. The literature is scarce for the 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 [40] and as a treatment option for multiple types of unhealthy subjects [41,42]. 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 [43,44,45]. Habibnezhad et al. 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 [46]. 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 greater than the stance with the eyes closed [47]. 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 [48]. One study assessed the validity and reliability of the data from the 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 change 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 [49].

Another study created a VR-based tool to assess the risks of falls. The 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 longer execution time for interventions and a number of steps [50]. 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 [51]. Similarly, an Oculus Rift headset was used in another study to assess dynamic balance through head mobility. The 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 [52]. 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 [51]. Some studies showed the efficiency of novel tech-based intervention programs in improving balance [52,53] and locomotion for older adults [51,54].

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 [53]. 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 [54]. 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 [55].

Therefore, in this research, we created a custom immersive VR-based platform – based on validated protocols and with 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. 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.

2. Methods

2.1. 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 Optimisation 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 the connectivity issues of the chest band sensors to the system application. Following the Declaration of Helsinki, the procedures were implemented and supervised by an experienced, trained staff and approved by the Faculty of Human Kinetics Ethics Committee, CEIFMH N°3/2023.

2.2. Apparatus

2.2.1. Hardware

We used the KAVE (Kinect-cave Automatic Virtual Environment) [56], 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 width and height of 2.2 and 2.8 meters, respectively. Four HD projectors, external speakers, and a processing personal computer were the core parts of the Kave system Figure 1(a). 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>). 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, USA) was used for full-body tracking to interact with the virtual environment and create a parallax effect.

The 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) [57] Figure 1(b).

The heart rate was measured using the 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 the ActiLife6 computer application (version 6.13.4, ActiGraph, Cary, NC, USA).

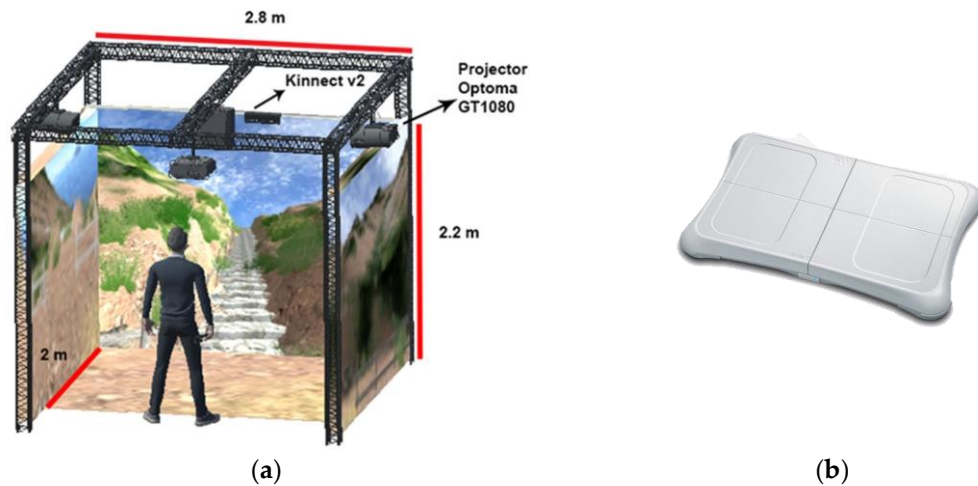


Figure 1. Hardware Setup (a) Schematic diagram of the KAVE Setup; (b) Nintendo Wii Balance Board.

2.2.2. Software

A VR-based Cable Car Simulation (CCS) was created in Unity 3D (unity3d.com) 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 (Blender Foundation, Amsterdam, Netherlands). Figure 2(a) Figure 2(b). The simulation application communicates with WBB through Bluetooth technology and records COP at 30 Hz during the study. The CCS circuit consists of 5 straight segments at five turning angles (0, 45, 90, -45 and -90 deg). The CCS circuit is performed 4 times at different speeds (3, 5, 7 and 9 m/s). After finishing a lap, the simulation restarts automatically with 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 static balance.

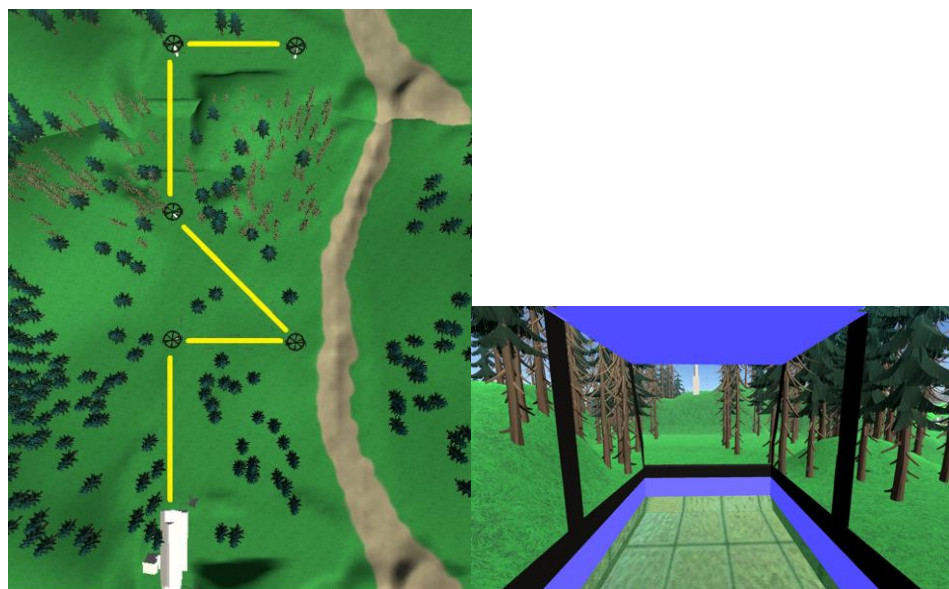




Figure 2. Software Setup (a) Cable Car track TopView; (b) Cable Car Inside View; (c) Biodex Balance System (BBS).

Additionally, a VR-based Virtual Levada simulation application previously created in our lab [58] 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, Netherlands). It simulates virtual hiking based on in-place stepping. Based on the assessments from the Senior Fitness Test (SFTs) [59], 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-second chair sit-stand (30SCST) exercises was implemented to examine lower body strength.

As a means of comparison and validation of the system, we used Biodex Balance System (BBS) SD (biodexrehab.com) as a reference (Figure 2(c)). 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 is quick and efficient in profiling older adults for the risks of falls and has been extensively validated in this population [60]

2.3. Questionnaires and Balance

The 7-point Likert scale questionnaire was used to evaluate the participant's cybersickness. Similarly, the System Usability Scale SUS [61] 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-second 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 [62].

2.4. 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 minutes. They were provided a ten-minute break after finishing BBS assessments.

Subsequently, participants performed the 2MST (Figure 3(a)) and 30SCST in the KAVE-based VR environment (Figure 3(b)). 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 ten-minute rest was provided after finishing the fitness tests.

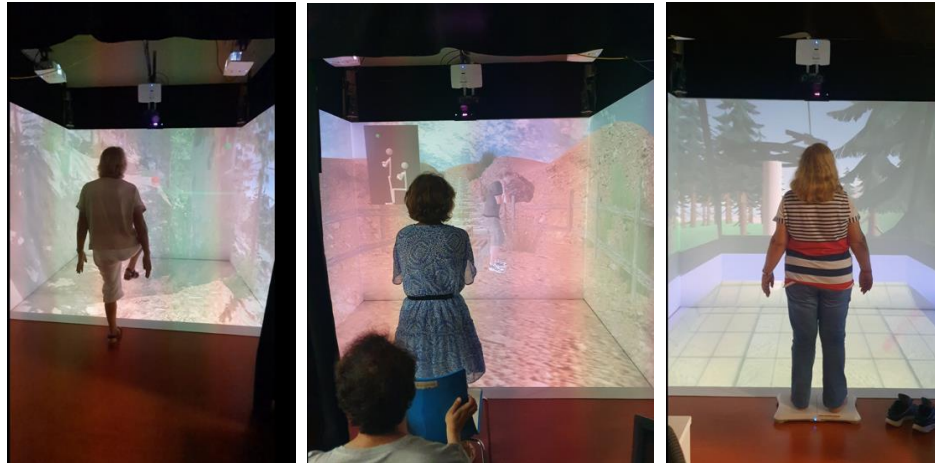


Figure 3. The KAVE-based VR simulations include (a) Two-minute Step Test; (b) 30-Sec Sit-Stand; (c) Cable Car Simulation balance assessment .

Participants were asked to stand on the Wii balance board in an upright standing position for approximately five minutes during the CCS (Figure 3(c)). 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 [61] and ITC-SOPI [63] questionnaires were provided afterwards.

2.5. 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; Percent of Time in Zone A, B and C; Percent 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, USA).

3. 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 a highly ecologically valid VR environment. However, 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) [64].

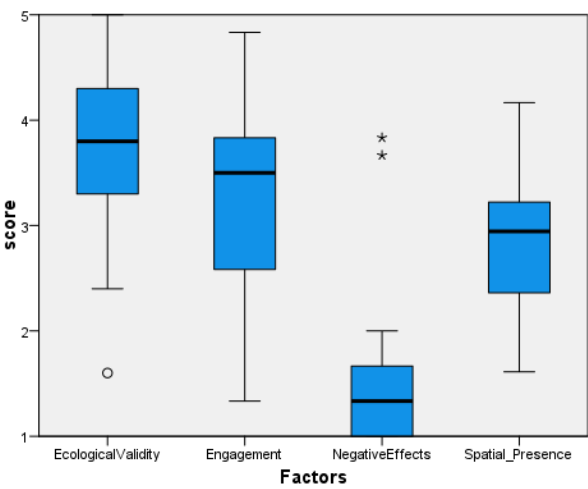


Figure 4. Box Plot indicating the results of the ITC-SOPI Questionnaire.

Table 1 shows the results from the repeated ANOVA, which was executed on all the 2MST, 30SCST and CCS parameters. We found significant differences ($p < .05$) 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.

Cable Car Speed and trajectory Angles	F	Sig.
cable_car_speed5_angle_minus_90	4.461	.050
cable_car_speed7_angle90	7.11	.016
cable_car_speed7_angle_minus_90	5.10	.037

The maximum excursion of COP in the AP direction for all combinations of Angles (0, 45, 90, -45, -90) and Speeds (3m/s, 5m/s, 7m/s, 9m/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 (3m/s, 4m/s, 5m/s, 6m/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.

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).

Pearson Correlation Sig. (2-tailed) N	Stabilit y Overall	StabilityAn tPost	Stability Media Lateral	PercentTi meinZone A	Perce ntTi mein Quad 1	PercentTimein Quad2	PercentTime inQuad4	Stability IndexFB	Stability IndexLR
mean_angle_0	.559 .013 19	.519 .023 19	.631 .004 19	-.499 .030 19	-.494 .031 19	.64 <.01 19	-.469 .043 19	.520 .023 19	.630 .004 19
mean_angle_4 5						.57 .01 19			
mean_angle_9 0						.47 .04 19			
mean_angle_ minus_45						.48 .03 19	-.46 .04 19		
mean_angle_ minus_90					-.517 .023 19	.522 .022 19			
mean_cc_spee d3						.486 .035 19	-.50 .029 19		
mean_cc_spee d5					-.470 .042 19	.566 .011 19			
mean_cc_spee d7					-.495 .031 19				
mean_cc_spee d9			.459 .048 19		-.486 .035 19	.570 .011 19			.458 .049 19
MaxHeartRat e							-.566 .011 19		

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. DA with each feature was performed to establish the prediction power of each feature modality, and also 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 step-wise regression (Table 2). The selected features were the maximum excursion of 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 AP direction, and COP at high speeds for no rotation.

Table 2. Maximum excursion of COP in anterior-posterior axis for Cable Car Speed.

LOO cross-validation	CCS	Mean of Turns	Mean Speeds	2MST & 30SCST	HR	Step-wise feature selection
DA Model	Pseudolinear	Linear	Diagquadratic	SVM	Diagquadratic	Linear
Accuracy	0.72	0.66	0.66	0.72	0.55	1
Recall	0.72	0.66	0.66	0.72	0.55	1
Precision	0.72	0.66	0.66	0.75	0.55	1
F-score	0.72	0.66	0.66	0.73	0.55	1

4. 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.

To evaluate the feasibility and sensitivity of the system as a profiling method capable of detecting users with 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 (5m/s and 7m/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 percent, 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. Previous research reported 86% accuracy with a WBB-based exergame to assess the physical independence of the participants. A 30-second Sit-Stand test was used as a reference to compare the results [65]. 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 [66]. 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 [67].

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 [68]. 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 [69].

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. The Virtual Levada implemented VR-based senior fitness tests such as a 30-second sit-stand and two-minute step test.

5. 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. Also, 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. Finally, an even larger sample of older adults could be beneficial in future studies.

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