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Board 300: Impact of Virtual Reality on Motor-Skill Performance in Children with Autism Spectrum Disorder

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Impact of Virtual Reality on Motor Skill Performance in Children with Autism Spectrum Disorder

Abstract

Autism Spectrum Disorder (ASD) is a neurodevelopmental condition often associated with delayed motor skills. The Motor Assessment Battery for Children – Second Edition (MABC-2) is a standardized motor assessment for identifying motor delays pertaining to ASD. It evaluates fine and gross motor tasks across three domains: Manual Dexterity, Aiming & Catching, and Balance. These tasks are categorized into three age bands: 3-6, 7-10, and 11-16. Virtual Reality (VR) has emerged as a promising intervention in the ASD realm. This study aimed to investigate the potential of VR to assist children with ASD in performing the gross motor skills (i.e., ball skills and balance) in the MABC-2. The children who participated in the study were attendees of a local Autism Summer Camp. Our research focused on adapting motor tasks for ages 7-10 (i.e., Age Band 2) to VR, as most campers fell in this age range. Within the VR environment, children could observe avatar demonstrations and practice motor skills in a highly immersive setting.

The VR environment featured avatars demonstrating ball skills and balancing tasks. Developed with the Unity game engine, 3D software Blender, C# scripting, and mixed reality toolkits, this environment was tested on the Meta Quest 2 Oculus. The children's gross motor skill performance was scored before and after VR interactions. The test standard scores were categorized through a traffic-light scoring system comprising red, amber, and green zones. A standard score ≤4 is classified in the red zone, indicating a significant movement difficulty; a standard score >4 and ≤7 is classified in the amber zone, indicating a risk for movement difficulty; and a standard score >7 is classified in the green zone, indicating no movement difficulty detected. Following the VR intervention, we observed a notable improvement in the balance score ($p < 0.05$). Furthermore, using the Random Forest machine learning model, we analyzed a combined dataset of MABC-2 scores from 250 children across all age bands from the Autism Summer Camp in previous years and the MABC-2 scores from the 18 children in the present study. Our analysis revealed that Balance was crucial in classifying children with ASD with motor delays, with an importance score of 0.195, nearly double that of Manual Dexterity and Aiming & Catching. When the model was exclusively applied to the Balance component score, it achieved an impressive accuracy rate of 91% in identifying children with ASD.

In summary, our findings underscore the promise of VR in enhancing balance among children with ASD. The Random Forest analysis reaffirmed the significant role of balance in identifying children with ASD. Given its precision in detecting children with ASD based on their balance performance, we anticipate the potential of future machine learning advancements in this field. Our research validates the effectiveness of a VR-based approach and emphasizes the significance of collaborative research in providing valuable support to the underserved ASD population.

Introduction

Autism spectrum disorder (ASD) is a neurological and developmental condition affecting socialization, interaction, learning, and behavior [1]. According to CDC estimates, about 1 in 36 children have ASD [2]. Individuals with ASD present a heterogeneous range of symptomatology, including persistent deficits in social communication and interaction, such as differences in eye contact and body language, a lack of verbal communication, and restrictive, repetitive behaviors or fixations on routines, interests, or activities [3]. These deficiencies are classified into levels of severity, from Level 1 requiring support to Level 3 requiring very substantial support [3]. Children with ASD exhibit temporal dyscoordination in grip strength [4] and impairments in reaching and grasping [5], visual-motor integration, and fine motor control [6], including handwriting and object control skills [6], [7]. Severe motor impairment is widespread among children with ASD, at 79%, and may be detected as early as 12 months of age [8], [9].

Current research suggests that VR may support motor and social skills in children with ASD [10], [11]. VR has also been utilized in conjunction with traditional rehabilitation strategies, with improvements in the cognitive and social communication of children with ASD [12]. While the effectiveness of VR rehabilitation and interventions varies across applications, from daily life to cognitive and social communication skills, VR training has seen improvements and great promise in individuals with ASD [13]. However, there is an apparent gap in the current literature on full-body motor performance in children with autism. Few studies have considered VR as a tool to facilitate children with ASD's understanding and subsequent replication of specific motor movements. While one such study suggested the feasibility of a motion-tracking, VR-based exercise game for children and adolescents with ASD, the researchers could not show substantial evidence of improving gross motor skills among the participants after the VR intervention [14]. Consequently, there is a clear need to expand the scope of VR-based motor performance research in children with autism to facilitate early intervention and improve outcomes in adult life.

Machine learning has broad applications in medical health, revolutionizing diagnostics [15], [16], treatment and healthcare assistance approaches [16], and exhibits promise in elevating medical decision-making [17] and enhancing patient outcomes [18]. Additionally, machine learning has been utilized to support children with conditions such as ASD [19] or Developmental Coordination Disorder [20], demonstrating its capacity for tailored and effective interventions. This utilization underscores the technology's potential to contribute to a better understanding, early detection based on medical information, and personalized assistance for individuals facing these challenges.

Thus, the main aims of this study were twofold: (1) to determine whether VR aids children with ASD's understanding and performance of motor movement tasks, and (2) to utilize machine learning to classify children with ASD based on their degree of motor delay. Using 3D modeling and animations, we developed a multimodal VR environment using Unity and applied statistical analysis to assess the motor behavior of children with ASD post-VR. We employed a Random Forest machine learning model to determine the most essential feature in determining MABC-2 scores and zones. Based on previous literature, it was hypothesized that children with ASD would have a statistically significant increase in their MABC-2 scores after participating in the VR experience.

Methods

Participants

This study included a sample of 18 children (male = 17, female = 1) with ASD between the ages of 5 and 16 from a local Autism Summer Camp. Parents and caregivers received written information about the study and provided written consent for children to participate. Research assistants received child protection training, and background checks were initiated. The study began after Institutional Review Board (IRB) approval. Only children who met the inclusion criteria: (1) could follow directions, and (2) were willing and able to perform all movement tasks took part in the study. A total of six children (aged 7-10) (male = 5, female =1) in Age Band 2 completed the VR portion of the study.

The Motor Assessment Battery for Children – Second Edition (MABC-2)

The MABC-2 is widely used to identify movement difficulties across populations, e.g., children with ASD [21], [22]. The MABC-2 is separated into three age bands (3-6, 7-10, and 11-16 years old), each with eight fine and gross motor tasks composed of Manual Dexterity, Aiming & Catching, and Balancing [21]. Each task's raw score is converted into an item standard score. The summation of the item standard scores for each of the three components of the MABC-2 is converted using age-adjusted percentiles into the standard score for each component. The sum of all items' standard scores results in the total test score expressed as a total standard score corresponding to three zones, deemed the Traffic Light system. Children with an MABC-2 standard score at or below four are classified in the red zone, denoting significant movement difficulty; those with a standard score greater than four and equal to or less than seven are classified in the amber zone and are at risk of motor delay. All children with a score greater than seven are categorized in the green zone, with no movement difficulty detected [21]. As such, identifying motor difficulties through the MABC-2 provides opportunities for early intervention. It is critical to do so as the delayed motor skills often exhibited by children with ASD can significantly impact future motor ability and social behavior [23].

Development of Virtual Environments and Scenarios

The VR development process in Fig. 1 involved five key steps. The Unity game engine and XR interaction packages created immersive environments compatible with VR hardware (i.e., the Meta Quest 2). Secondly, modeling and animation were achieved using tools like the Unity Asset Store, Mixamo, and Blender, enabling the creation of intricate 3D assets and customizable avatar movements. Additionally, the VR environment was programmed with C# within Visual Studio Code, enabling the scripting of different interfaces, interactable objects, and avatar animations to ensure dynamic user engagement. Subsequent hardware setup included configuring the Meta Quest 2 headset, a computer, and motion controllers, facilitating streamlined development and updates via the Android platform in Unity. Lastly, testing and deployment were conducted using the XR device simulator in Unity, allowing for debugging via a headset-independent preview of the VR environment.

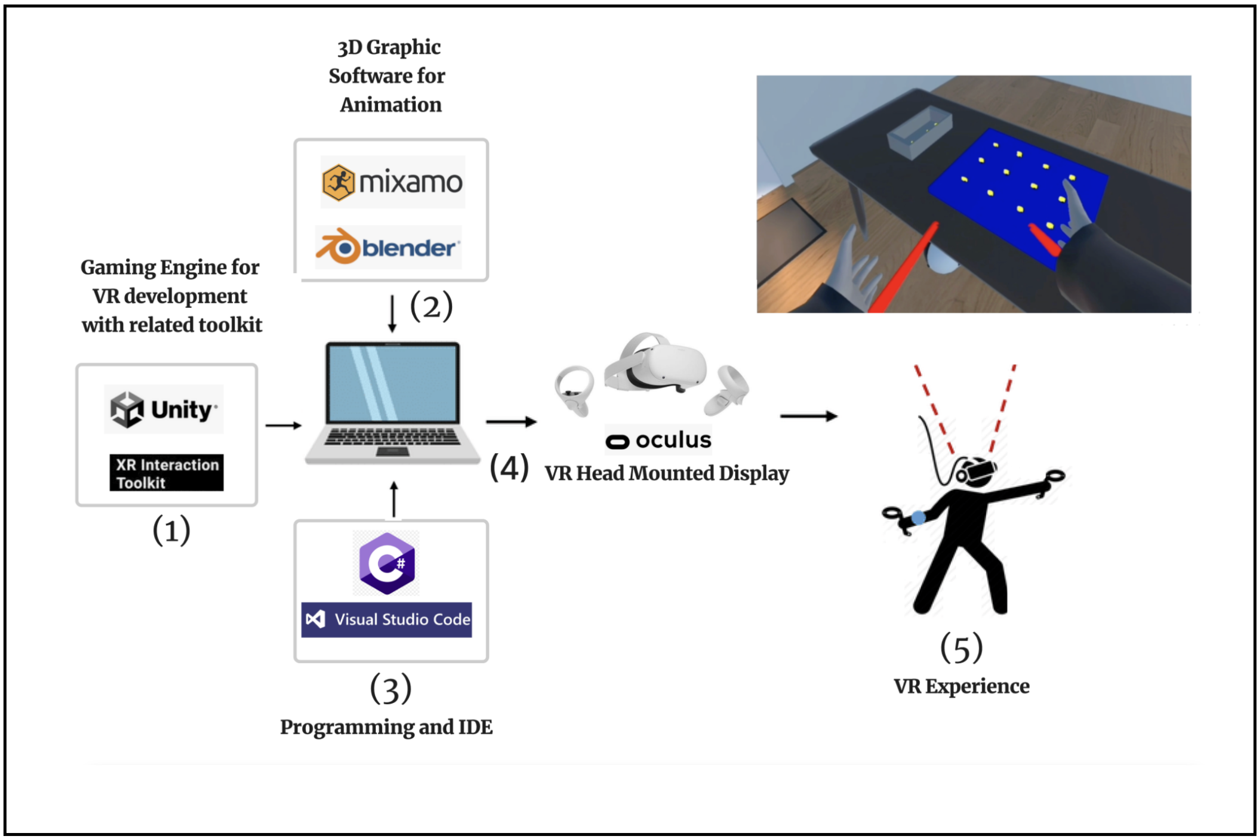

Fig. 1. Illustration of steps in the VR development process.

In Fig. 1, the Unity game engine in (1) offers a powerful platform for developing the VR environment, providing a range of features that enable the development of an immersive and interactive experience. Its seamless integration with VR hardware, including devices like the Meta Quest 2, simplified the creation of VR environments such as virtual rooms, sunlight, and scenes. In addition, the XR interaction toolkit offered pre-built components and tools specifically designed for extended reality experiences, including user hand-tracking. Integrating XR interaction packages enhanced the development of the environment, supplying pre-built components for tasks such as object manipulation and user input. Tennis balls, boards, pegs, paper, tables, pens, and other virtual objects, as displayed in Fig. 2, were collected from XR interaction toolkits. Additionally, mats and bean bags were constructed from Unity 3D objects. This comprehensive toolset ensured a cohesive and effective approach to VR development.

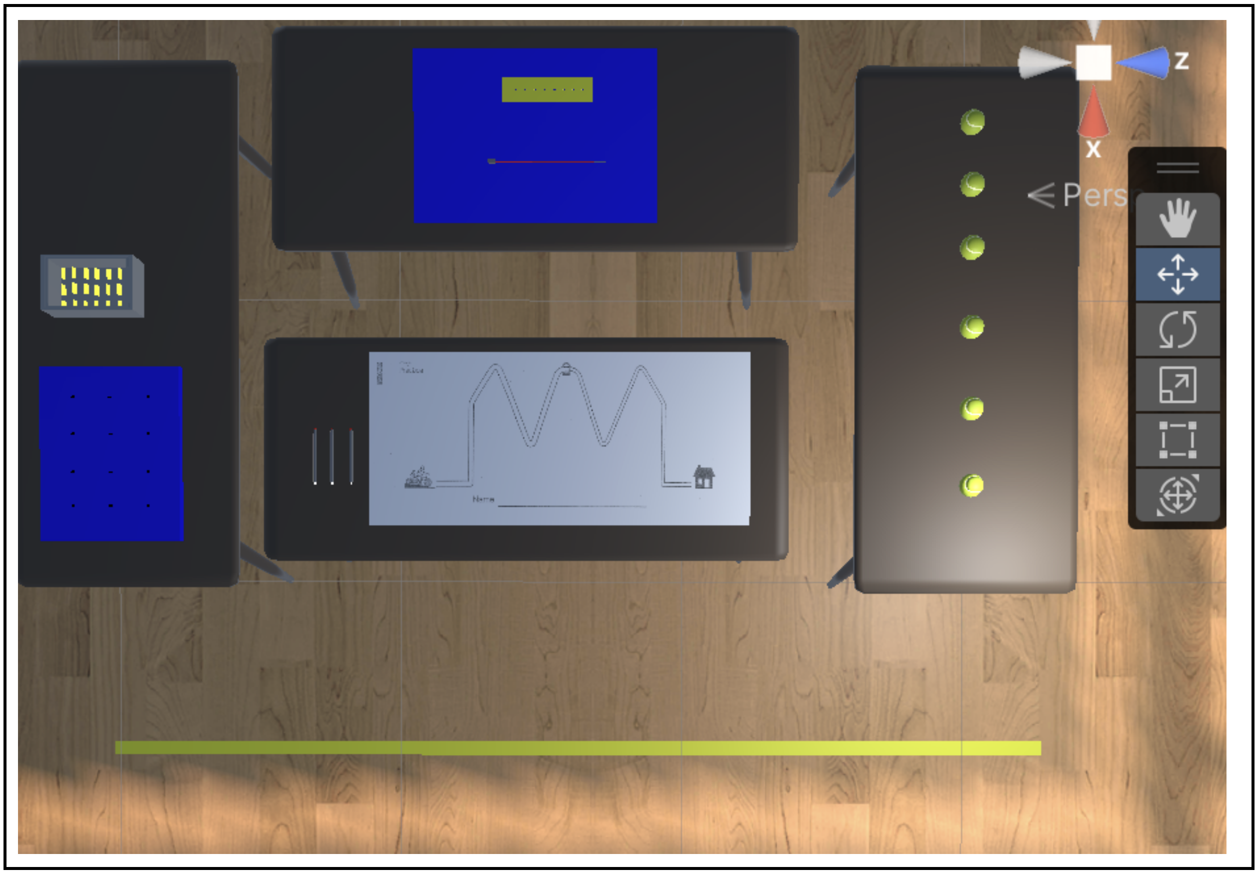

Fig. 2. Interactable Objects in VR.

The modeling and animation of the VR environment were constructed using the Unity Asset Store, Mixamo, and Blender in step (2) in Fig. 1. Blender, a robust 3D modeling software, played a pivotal role in crafting the immersive virtual environment by enabling the creation of intricate 3D assets. Animations from Mixamo were edited by changing bone structures and animation clips in Blender. One such animation was altered with Blender to generate an avatar catching a ball with both hands from the initial clip of the avatar catching the ball with one hand, as seen in Fig. 3.

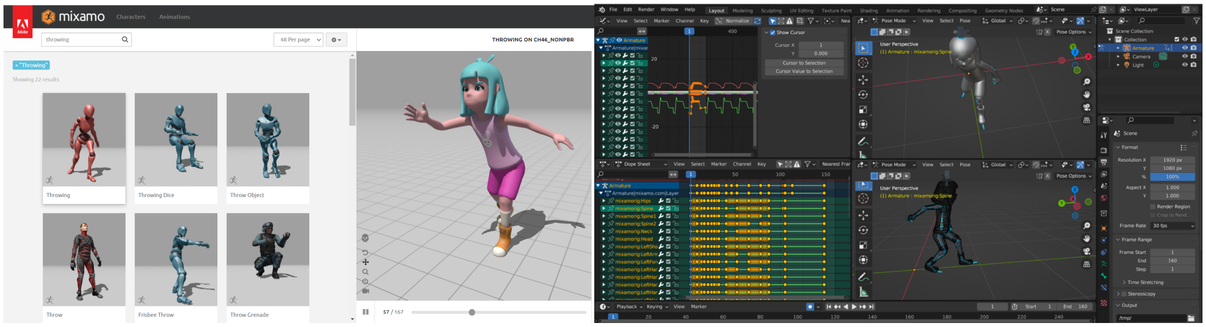

Fig. 3. Modifying character animation with Mixamo and Blender.

The programming of the VR environment, including user interface, interactable objects, VR hand-tracking, and avatar animation control, was completed using the C# programming language within Visual Studio Code in step (3) in Fig. 1. C# scripts in Unity were the backbone for implementing dynamic behaviors and interactions within the VR environment, e.g., walking, catching, and throwing. These scripts were created within Visual Studio Code, defining the functionality of *GameObjects*, such as a tennis ball, and dictating how *GameObjects* responded to user input and interacted with each other and the environment. In Fig. 4, for example, the ball was attached to a C# script, enabling it to interact with the wall and bounce back to the boy-avatar. This streamlined the development process and ensured effective user interactions within the VR environment. Seven movement tasks (Placing Pegs, Drawing Trail, Catching with Two Hands, Throwing Beanbag onto Mat, One-Board Balance, Walking Heel-to-Toe Forwards, and Hopping on Mats) in Age Band 2 of the MABC-2, two of which are displayed in Fig. 4, were replicated in VR. Additionally, male and female avatars were programmed to demonstrate these tasks, except for the fine motor tasks Placing Pegs and Drawing Trail.

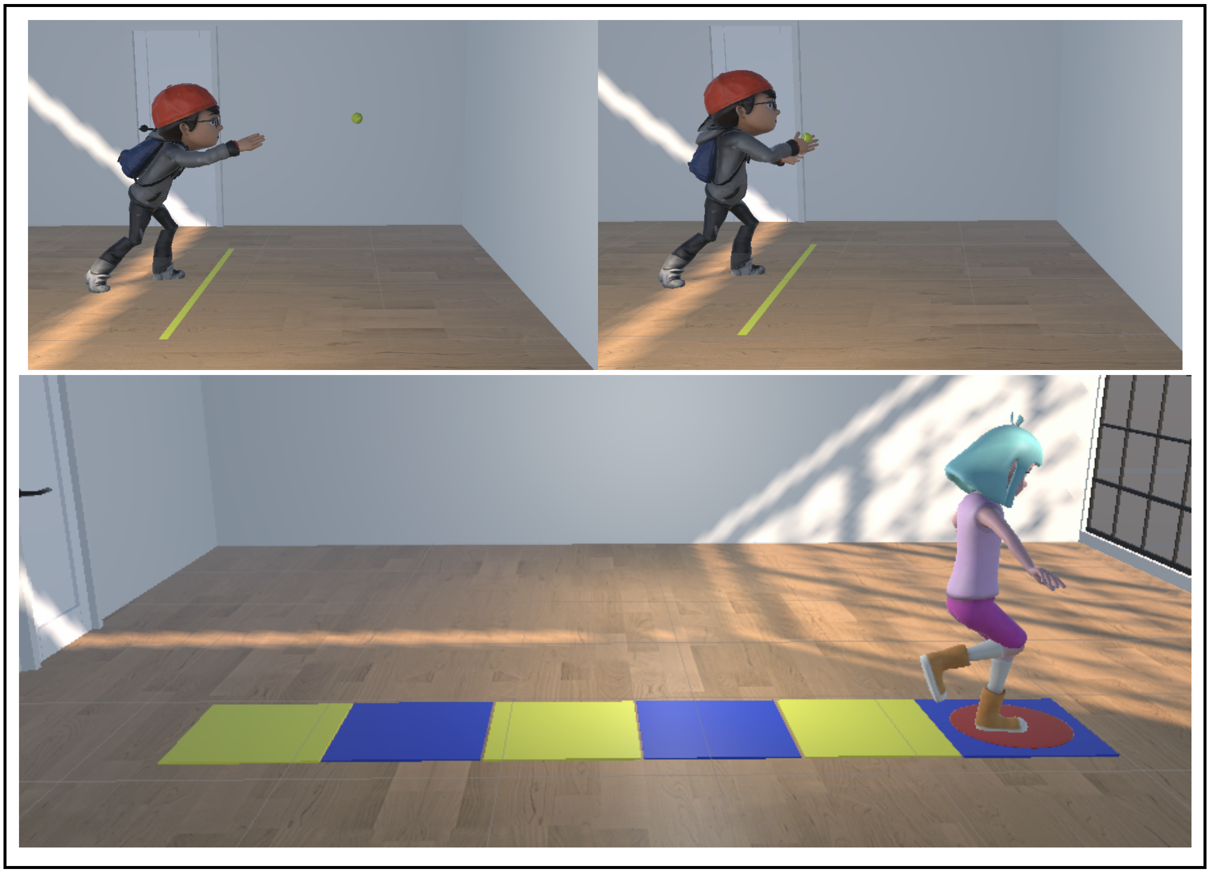

Fig. 4. Avatars performing the MABC-2 Tasks Catching with Two Hands (*top*) and Hopping on Mats (*bottom*) in VR.

The hardware setup for the VR environment consisted of the Meta Quest 2 headset, a computer, and motion controllers in step (4) in Fig. 1. The computer was connected to the Meta Quest 2, allowing for ease of access in setting up the VR environment, making updates to the code, and adding 3D animations. Because the Meta Quest 2 operates on the Android platform, the VR environment was deployed and updated using the Android platform in Unity.

The VR environment was tested using the XR device simulator in Unity, allowing for the testing and previewing of the VR experience within the Unity editor before deploying the code to a physical VR headset in step (5) in Fig. 1. Doing so enabled adjustments to avatar and virtual object placement within the environment and for scripting and animation issues to be identified and addressed. Additionally, to observe users while immersed in the virtual environment, the computer seamlessly streamed wirelessly through devices, utilizing the support provided by Meta's application.

Procedures

Children's performance was assessed at a local elementary school gym. The MABC-2 was administered by the primary investigators and trained research assistants. During MABC-2, chronological age was calculated to determine the appropriate movement tasks according to the corresponding age band. The primary investigators used the MABC-2 Examiner's Manual to score each task accurately. Each child received verbal instructions and demonstrations before performing each motor skill task. They were also provided additional training and practice trials as needed. Before the assessment, each child was asked to write their name on a sheet of paper to determine their preferred hand. The order of evaluation generally followed that as listed on the MABC-2 Examiner's Manual, testing fine motor before gross motor skills.

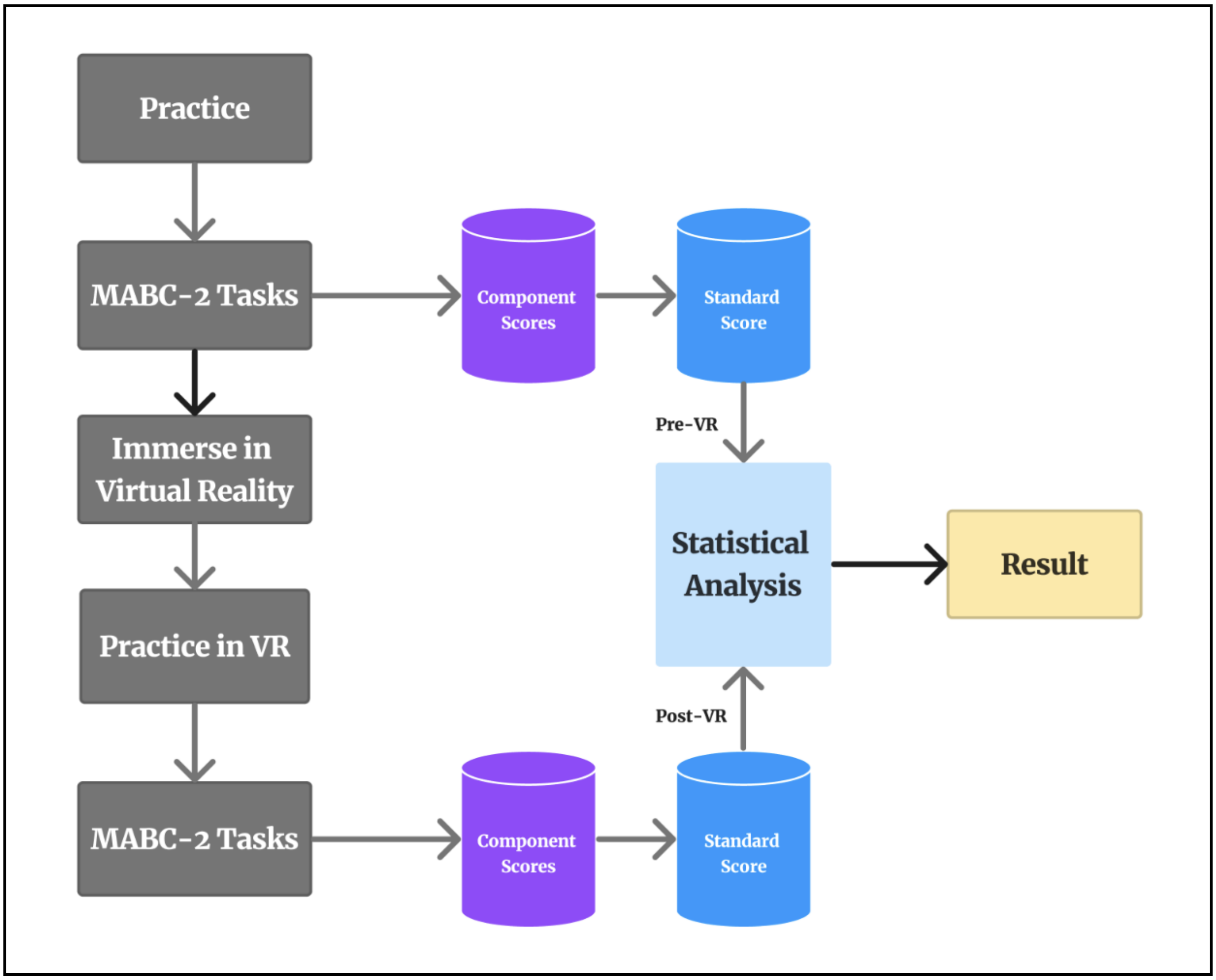

Fig. 5. The procedures of MABC-2 data collecting pre- and post-VR.

Following the initial assessments to establish a control (pre-VR) MABC-2 score, participants were immersed in a virtual environment using the Meta Quest 2. In this virtual environment, they could observe the avatars and interact with the virtual objects within a virtual room, thus allowing them to practice the performance tasks while wearing the headset, as seen in Fig. 6. In addition, a timer was displayed for the static One-Board Balance task. The researchers accessed the casting mode on the Meta Quest 2 through a computer to observe the children in virtual reality. Participants were asked to perform the required movement task for both left and right conditions if necessary. Finally, participants were scored again post-VR on the tasks they practiced in the real world. The pre-VR and post-VR MABC-2 data collection process is illustrated in Fig. 5.

Fig. 6. Children with ASD performing MABC-2 tasks in VR.

Data Analysis

The sum of the pre-VR item standard scores for the Manual Dexterity, Aiming & Catching, and Balancing components of the MABC-2 were standardized for each component, yielding a component score for each domain. Additionally, the total sum of all item standard scores, the total test score, was converted into an overall standard score used to determine the extent of motor delay.

Descriptive data were used for children's pre-VR total standard scores and previous MABC-2 data (ages 5-16, Age Bands 1-3, n = 250) collected from children attending the Autism Summer Camp from 2010-2019 and 2022. All outliers were removed from previous MABC-2 data; none were present in pre-VR MABC-2 data. Post-VR MABC-2 data were obtained from 6 children in Age Band 2 who completed MABC-2 practice in VR. Notably, the VR intervention lacked the Threading Lace task, a component of Manual Dexterity for Age Band 2, resulting in the absence of data for this category; however, Aiming & Catching and Balancing tasks were fully implemented in VR. Consequently, a paired t-test was only conducted on pre- and post-VR

Aiming & Catching and Balance standard scores (n = 6), and an independent 2 sample t-test was only performed on post-VR (2023) and (2010-2019, 2022) Aiming & Catching and Balance standard score data. An additional single sample t-test was performed upon pre-VR MABC-2 and norm MABC-2 data across all Manual Dexterity, Aiming & Catching, and Balance components. For all t-tests, results were considered significant if p-values were less than 0.05.

Feature analysis using the Random Forest machine learning model was executed upon a combined dataset of current control (2023) and previous MABC-2 data (2010-2019, 2022), for a total of (n = 268) data points classified into red, amber, and green zones. This analytic process to determine the most significant feature is demonstrated in Fig. 7. Combining multiple decision trees and the Random Forest model offered improved predictive performance and robustness to overfitting. Moreover, the importance score in the Random Forest model was calculated based on the frequency with which each feature was used for splitting the data across all trees, with higher scores indicating a more significant contribution to predictive accuracy.

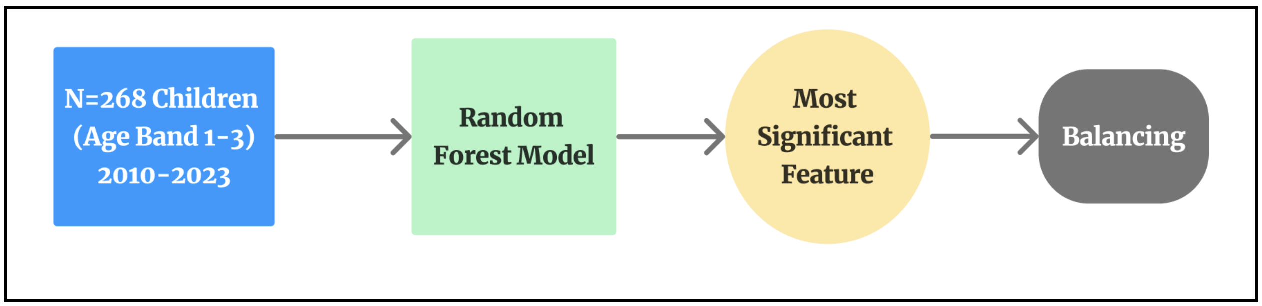

Fig. 7. Machine learning analysis process

Results

Descriptive data of pre-VR scores showed that 88.9% of standard scores for children with ASD were in the red zone, thus demonstrating significant motor delays; only 5.5% of children were in the amber and green zones. Total standard scores for post-VR scores could not be calculated, as only seven of the eight motor tasks in Age Band 2 of the MABC-2 were implemented in VR; only standard scores for the Aiming & Catching and Balance categories were calculated. Descriptive data of previous MABC-2 data (n = 250) revealed that the majority of children with ASD (86.8%) had or were at risk of developing significant motor delays, with 64% and 22.8% of them classified in the red zone and amber zone, respectively. Only 13.2% of the children with ASD were classified in the green zone. Paired t-test results showed that there was no significant difference between the mean Aiming & Catching standard score before and after VR; however, the mean Balance standard score after VR was significantly greater ($p < 0.05$) than before VR, with the absolute value of the t-statistic at 2.076, compared to the left-tailed t critical value of 2.015. These standard scores are displayed in Table 1.

TABLE I
MEAN STANDARD SCORES FROM 2023 DATA

	Movement Tasks	
	Aiming&Catching	***Balancing***
Pre-VR	4	2.3
Post-VR	3.83	3.16

An independent 2-sample t-test conducted on post-VR and previous years' MABC-2 data showed that the mean Aiming & Catching standard score was significantly greater in previous years' data compared to the post-VR data when assuming equal variances as determined by a Two-sample F-test for variance. Further testing demonstrated no significant difference between the mean Balance standard score in the post-VR group and previous years' MABC-2 data, assuming equal variances as determined by a Two-sample F-test for variance. A single-sample t-test on current control MABC-2 standard scores (M = 2.389) compared to the norm MABC-2 data with a mean of ten showed that children with ASD were significantly delayed in all MABC-2 components (Manual Dexterity, Aiming & Catching, Balance). A comparison of norm MABC-2 and pre- and post-VR mean standard scores for Aiming & Catching and Balance is shown in Fig. 8.

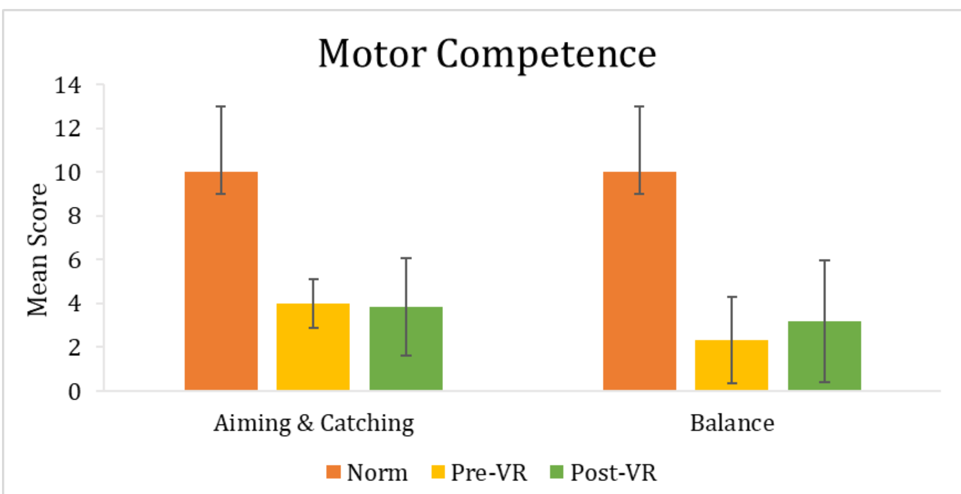

Fig. 8. Mean MABC-2 Aiming & Catching and Balance standard scores for population norms and children with ASD pre- and post-VR.

Random Forest Model

We used a Random Forest machine learning model to analyze the aggregate data from 2010-2019 and 2022-2023 and determine the importance of the features. The results revealed that the

Balance component score (B_CS) attained the highest importance score of 0.195, as demonstrated in Fig. 9. This score was more than and nearly double that of the Aiming & Catching component score (AC_CS) and Manual Dexterity component score (MD_CS), respectively. This implies that B_CS significantly impacts the classification model, suggesting that it plays a crucial role in distinguishing and predicting the target variable (zone code) compared to MD_CS and AC_CS.

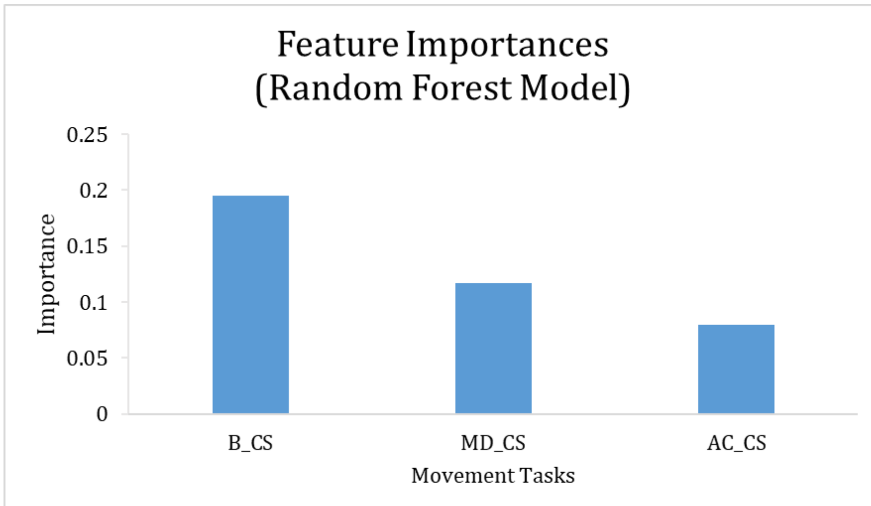

Fig. 9. MABC-2 importance scores using Random Forest machine learning.
Note: B_CS = Balance component score, MD_CS = Manual Dexterity component score, AC_CS = Aiming & Catching component score.

Furthermore, we investigated the potential impact of the Balance component score (B_CS) on classifying children by degree of motor delay. Using Random Forest, we classified children into the three zones of the Traffic Light system: red, amber, and green. Fig. 10 illustrates the initial accuracy rate of 91%, suggesting that focusing solely on the Balancing task could be a promising approach in future research for diagnosing children with ASD. Furthermore, it may guide the development of interventions and targeted activities, as focusing on enhancing or assessing Balancing skills may be more impactful in addressing specific motor challenges.

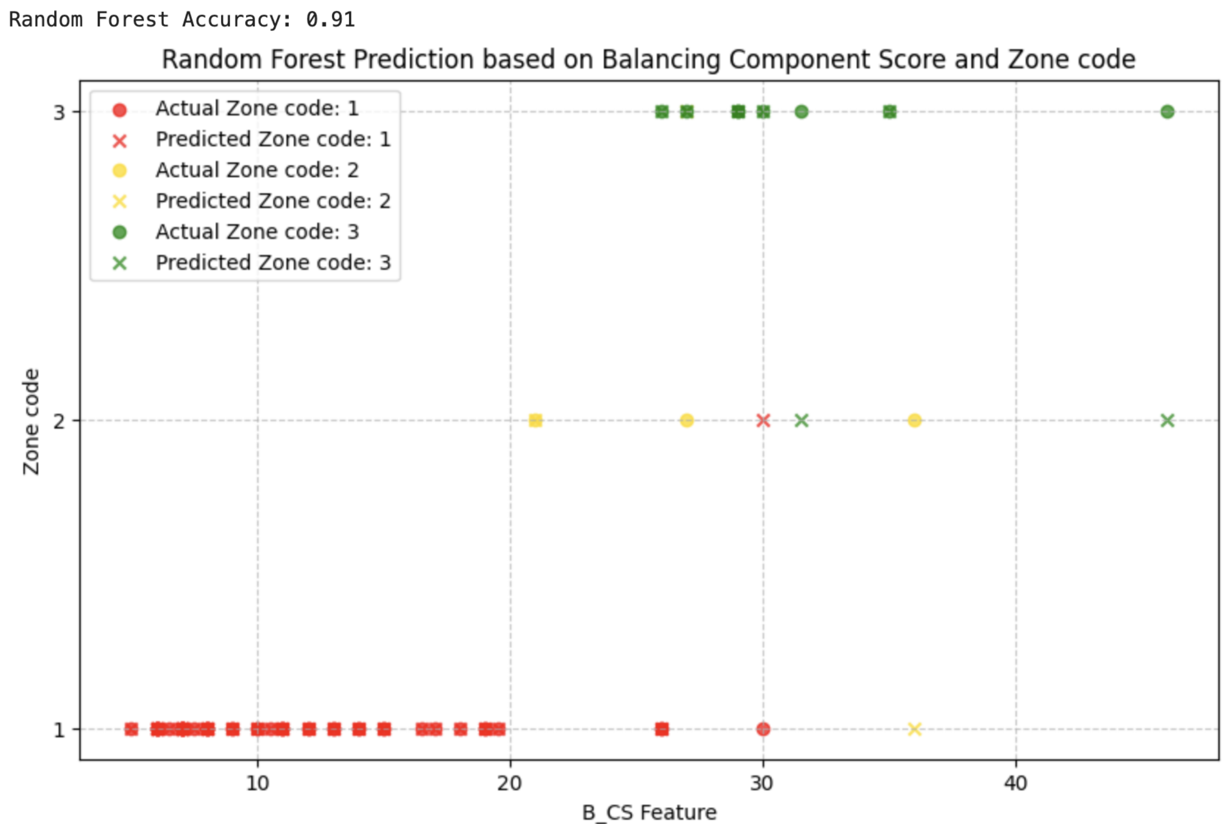

Fig. 10. Classifier-based balance component score (Accuracy: 91%)

Discussion

Our preliminary findings highlight the potential benefits of VR training for improving specific motor skills, particularly balancing, in children with ASD. However, further research is needed to explore the broader implications and potential benefits of VR interventions for motor skill development for this population. In this study, the number of participants who completed the Aiming & Catching, and Balancing tasks was limited to only six children, as only a few were comfortable wearing the VR headset and understood the instructions in the virtual environment. The small sample size and limited geographical spread of our study limits the study's generalizability, as the findings may not represent the broader population of children with ASD. Additionally, during the post-VR MABC-2 assessment, it was observed that the children were more impatient and rushed through the tasks. Individual variability among post-VR scores was high–some children saw a marked increase, whereas others saw a decrease in their MABC-2 score. Furthermore, t-test results may be misleading as assumptions (e.g., independence, random sampling, normality, and equal variance) were not fully met. Due to the missing data for one of the Manual Dexterity tasks (Threading Lace), we specifically focused on analyzing the performance in the Aiming & Catching and Balancing tasks.

Future research with a more prominent and representative, randomized sample with independent data, along with improved data collection strategies, is essential to provide more reliable insights into the effects of VR interventions on motor skills in children with ASD. Non-parametric testing to establish statistical significance may also be necessary. In future studies, we plan to develop an immersive VR system using a Cave Automatic Virtual Environment (CAVE), as executed in [18], that encompasses all motor tasks across age bands 1 and 3 of the MABC-2. By incorporating these tasks into the VR environment, children can interact with virtual objects and avatars while performing motor assessments. To ensure accurate and precise tracking of participants' movements, we intend to integrate sensor cameras into the VR setup [18], enabling us to capture and analyze the whole-body movements in real-time, providing a comprehensive and reliable tool for improving motor competence in children. It may also be particularly beneficial for screening and classifying children with ASD when combined with machine learning techniques. In conclusion, our results display the potential of a VR environment in improving balance skills in children with ASD. Additionally, the significance of balancing tasks and the precision of machine learning analysis in identifying children with ASD using balance performance suggests the potential of machine learning in screening and classifying children with ASD.

Acknowledgments

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