2024 IEEE 15th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON) | 979-8-3315-4090-6/24/$31.00 ©2024 IEEE | DOI: 10.1109/UEMCON62879.2024.10754723

Virtual Reality on Assessing the Motor Skills of Individuals with Autism Spectrum Disorder

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Abstract*—Children with Autism Spectrum Disorder (ASD) often experience delays in motor skills, which can substantially affect their future motor function. The Movement Assessment Battery for Children - Second Edition (MABC-2) is a widely used tool in evaluating children's motor skills across different age bands, specifically assessing children ages 3 to 16. It includes eight unique tasks per age band that measure fine and gross motor skills and balance, which explains a child's motor abilities and classifies them by groups. This study extends previous research by exploring the potential of Virtual Reality (VR) to make the MABC-2 tasks more engaging and interactive for children, which could lead to better outcomes. The previous research created the balance and gross motor tasks of the MABC-2 in VR. We refined those tasks and completed the remaining ones. The VR tool was tested on seven individuals aged 19 to 21. Pre- and post-VR MABC-2 scores were collected and analyzed. Most tasks were accurately replicated in VR; however, significant statistical differences were found in the Threading Lace (p= 0.003) and Catching Ball (p = 0.007) tasks, indicating further refinement. Machine learning analysis was also conducted on data from 268 previous MABC-2 scores of children diagnosed with autism to classify them into motor skill proficiency zones based on their scores and to determine the most influential features for accurate prediction. The analysis revealed that balance scores were particularly influential in determining motor proficiency. This indicates the importance of balance in interventions to improve overall motor proficiency.

Keywords*—*autism spectrum disorder, motor skills, virtual reality, movement assessment battery for children, machine learning

I. Introduction

As defined by the National Institute of Mental Health, autism spectrum disorder (ASD) is "a neurological and developmental disorder that affects how people interact with others, communicate, learn, and behave" [1]. Individuals with ASD typically develop social skills at a different pace than their peers, struggle to communicate and interact with others, have specific repetitive interests and behaviors, and exhibit impaired or irregular movement [1]. ASD is described as a spectrum because not all individuals experience the symptoms in the same way or to the same degree. Because of the differences in the way ASD is expressed, three levels of severity described as "requiring support," "requiring substantial support," and "requiring very substantial support" have been defined by the American Psychiatric Association in their Diagnostic and Statistical Manual of Mental Disorders, fifth edition (DSM-5) [2].

A lesser-studied aspect of ASD is its impact on movement. Almost all individuals with ASD experience some degree of motor impairment or irregularity. It has been found that 86% of children diagnosed with ASD are at risk of motor impairment [3]. Despite this high prevalence, the effects of ASD on motor performance are still poorly understood and are not a factor taken into account for diagnosis [4]. Numerous studies have shown disrupted lateralization and a higher rate of left-handed individuals in people with ASD, along with clumsiness, postural instability, and altered motor coordination. Additionally, children with ASD tend to have more unstable balance, which leads to problems in muscle balance and posture later in life [4]. Comparative studies of the motor symptoms of children with ASD and children with other afflictions such as attention deficit hyperactivity disorder (ADHD) and developmental coordination disorder (DCD) have revealed ASD-specific effects and symptoms that suggest children with ASD have poorer motor skills in comparison [4].

A. *The Movement Assessment Battery for Children - Second Edition (MABC-2)*

The Movement Assessment Battery for Children—Second Edition (MABC-2) [5], a revised version of the Movement

This work was funded by the National Science Foundation – Research Experiences for Undergraduates (NSF-REU) under Grant #2150135.

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Assessment Battery for Children (MABC) [6], is an assessment tool used to evaluate the motor skills of children ages 3 to 16. It identifies the risk of motor impairments and assists in planning interventions. It is widely accepted by occupational therapists, physiotherapists, psychologists, and educational professionals [7].

The assessment is divided into three age groups, each with tasks specific to the developmental stages of the children: Age Band 1 (3 to 6 years), Age Band 2 (7 to 10 years), and Age Band 3 (11 to 16 years). Each age band consists of eight tasks that measure motor skills in three main areas: manual dexterity, aiming and catching, and balance. Manual Dexterity tasks involve fine motor skills such as precise hand and finger movements, aiming and catching tasks assessing the child's ability to throw and catch objects, and balance tasks evaluating static and dynamic balance.

Task performance is graded as per the guidelines in the official MABC-2 manual. After completing all tasks, each score is converted to standardized scores based on age group norms. Scores are averaged for tasks with multiple versions (preferred and non-preferred hands or legs) to create an item standard score. Item standard scores for tasks in the same core area (manual dexterity, aiming and catching, balance) are combined to get a three-point score. This sum is then used to find a three-component standardized score and percentile rank. The overall test score is the sum of the standardized scores from all eight tasks. Based on their overall score, participants are classified into one of three groups: Red Zone (≤ 5th percentile, significant difficulties, needs immediate intervention), Amber Zone (5th-15th percentile, at risk, needs monitoring), and Green Zone (> 15th percentile, no detected movement difficulties).

Our study enhances this process by recreating the MABC-2 exam in a virtual environment. This fun and interactive tool may also help improve the children's results by replacing the examiner with avatar demonstrations for each task during practice sessions.

B. Virtual Reality Tools for Intervention

Numerous studies have been conducted involving ASD and VR tools, each employing different environments and VR devices tailored to specific applications.

Many technologies can deliver highly immersive experiences with advanced motion tracking, olfactory stimulation, and more. Still, their prohibitive cost often leads to using head-mounted displays (HMD) in most studies. HMDs offer superior immersion, completely blocking the real-world and enveloping the user in the virtual environment. They provide an enhanced sense of presence, with more accurate head and hand tracking. Moreover, software development for such systems is well established, offering precise control over environment creation, extensive documentation, and numerous large communities dedicated to support. HMD systems also support a variety of accessories that can even be custom-built, enabling greater control over the experience delivered to users and enhancing immersion.

With recent campaigns from companies like Meta to make VR technologies more accessible, HMDs have become affordable and consumer-friendly. As such, HMD implementations are typically more accessible and practical for conducting a wide range of research relating to ASD. Studies have shown that both VR and AR can effectively address developmental coordination disorder (DCD) and enhance coordination skills in children [8]. For example, Avila Pesantez [9] looked at the impact of an AR training tool, Athynos, designed to improve hand-eye coordination through interactive and problem-solving activities. Another study from 2020 [10] used a serious VR game to boost motor control in children with DCD, which led to significant improvements in motor imagery and action-planning skills.

VR has also been explored as a tool for social skill intervention in children with ASD. Research by Yuan and Ip [11] shows that VR can train emotional and social skills by offering children a safe and controlled environment to practice and develop these social skills.

Despite these advancements, there is a notable gap in the literature on using VR to help assess task-specific motor movements in children with ASD. Previously, studies have evaluated differences in full-body motor skills and the impact of goal-directed movements in virtual environments [10]. However, the literature on comprehensive investigations focusing on VR to directly improve specific motor tasks in children with ASD is primitive. Our study addresses this gap by using VR to specifically facilitate children with ASD's understanding and replication of precise motor movements.

II. Methodology

A. Selecting a Template (Heading 2)

Participants in the study were college students (ages 19- 21; N = 7, M = 2, F = 5) from the Research Experience for Undergraduates (REU) program at Texas State University. Inclusion criteria for participation required 1) willingness and ability to perform all movement tasks and 2) providing informed consent.

B. Development of Virtual Reality Tool

Creating a virtual environment was necessary to gather data in VR, as shown in Fig. 1 [12]. The Unity game engine was chosen for this task because it is one of the most popular 3D development programs available, with extensive documentation, an active community, and robust support of VR applications. Unity provides users with rich tools that can be used to set up detailed environments and have complex procedures and events take place through scripts written in the C# programming language. A VR headset is required to interact with this environment, the Meta Quest 2 developed by Meta. The Quest 2 connects to a computer via a cable, enabling the user to see the environment in an immersive, life-like manner.

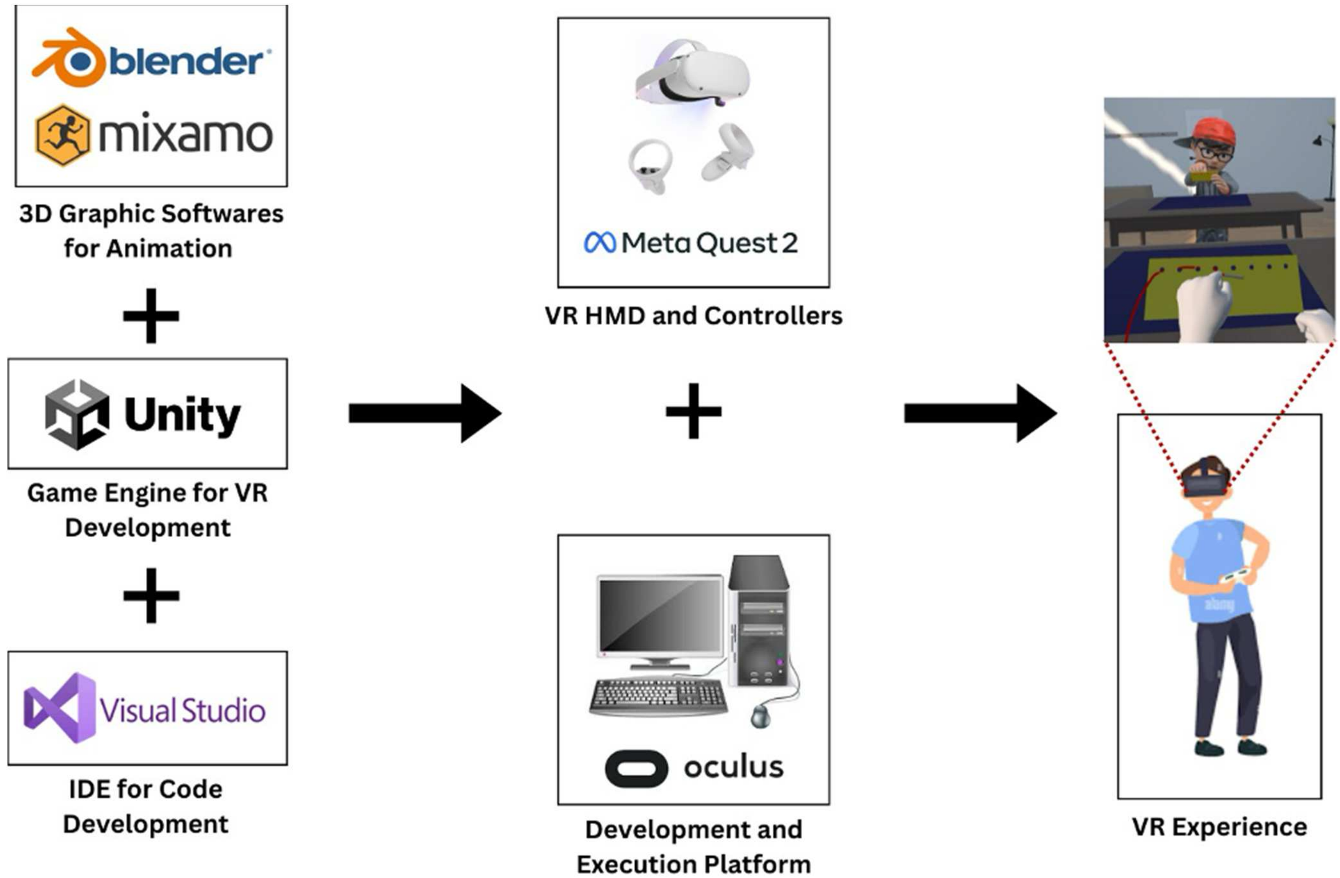

Fig. 1. Elements of the VR development [12].

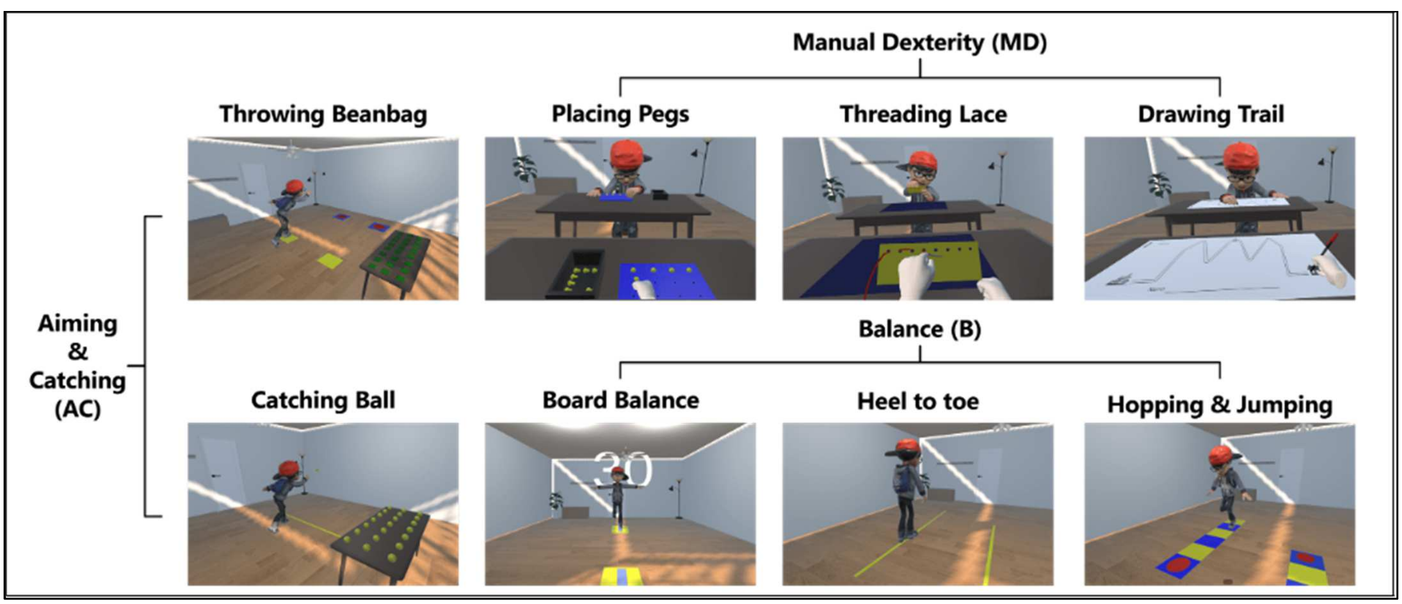

Fig. 2. MABC-2 age band 2 tasks in the VR environment [12]

The Quest 2 also comes with two hand controllers, allowing users to interact with objects in their surroundings.

To enable the environment to run in VR, the OpenXR plugin was installed in Unity to ensure that the headset and controllers would properly function and interact with the environment. Numerous assets, from simple objects such as tennis balls and beanbags to buildings, furniture, and decorations, were imported into the scene to develop a cohesive and immersive environment. These assets were brought together to create a spacious room with a large window where participants could complete the MABC-2 tasks.

Since the project had been ongoing for two years prior, some aspects, such as the room and some tasks, had already been implemented. The main goal was to recreate the remaining MABC-2 tasks within VR, as the room had already been completed, as shown in Fig. 2 [12]. Eight tasks for age band two needed to be replicated in VR. Aside from the tasks, animations had to be created to demonstrate how to perform each task to the children in VR. These animations were created in Blender, an open-source 3D modeling and animation software, and then imported into Unity. Each animation was created for a male avatar only.

The environment layout was also adjusted to allow participants to complete all the tasks from the same starting point. Some tasks involve traveling, such as hopping and heel-to-toe walking, requiring movement in one direction until completion, after which participants return to the starting position.

Manual Dexterity 1: Placing Pegs

The participant takes twelve small plastic pegs from a box and places them all in holes on a board one at a time as quickly as possible. The participant completes the task with their preferred hand first and then the other. Both hands are tested and timed with a stopwatch.

In the VR environment, the table, pegs, peg board, and basket were previously set up and interactive but had bugs, such as the pegs not properly interacting and stretching and distortion occurring when moving around. The original pegs were imported assets resembling Nerf darts, which did not look appropriate, so they were replaced with realistic peg models modeled in Blender.

A management panel was added in the Unity Inspector for the game object associated with this task to control relevant configurations. This included two check boxes for left—and right-hand setups that moved the box containing the pegs and the peg board according to the manual setup instructions. After each attempted trial, these also cleared the peg board and returned pegs to the box.

The animation for this task had yet to be created and done from scratch. The character was animated, moving each peg from the basket to the board, with the pegs being controlled by constraints to make them appear as if they were moving with the avatar's hands. These constraints could not be directly imported into Unity; they had to be baked into the animations of each peg and then imported into Unity.

Manual Dexterity 2: Threading Lace

The participant picks up a lace and a threading board with eight holes, inserts the lace fully through the first hole, and threads it back and forth through the remaining holes. The child may choose which hand to hold the objects in. The table and threading board assets were present for this scene.

The existing threading board was remodeled in Blender to resemble its real-world counterpart in the MABC-2 testing kit more closely, and colliders were added in Unity to ensure proper lace threading. The lace was created using a series of character joints configured for optimal thread-like behavior. Then, a C# script was used to render a line on top of the joints, and a mesh collider was added to the thread to allow for realistic interaction with the environment. The script dynamically updates the joint positions of each frame to enable the line to be followed by the renderer and mesh collider.

An additional script was written and added to the main game object for the threading task. Its main functionality is to reset the threading board and lace it back to its original position on the table in case either is dropped. This animation also had to be created from scratch. The character was animated to hold the threading board in place with his right hand and thread the lace through with his left hand. The lace in this animation is a thin red cylinder that contains a series of bones within, allowing it to bend. The effect of the lace threading through the board was achieved by appropriately bending the cylinder when the avatar's hand moved.

Manual Dexterity 3: Drawing Trail

The participants are given a pen and instructed to draw a single continuous line following a trail on paper without crossing its boundaries. This task is only done with the participant's dominant hand.

This task already had a table with a piece of paper containing an enlarged version of the trail and pens beside it. The trail did not render correctly in VR, so that was fixed by altering the associated C# script to render the trail texture on runtime. The pens could write on paper but had extreme latency errors and erratic lines that did not follow exactly where the pen moved. The line drawn by the pens was improved to be smoother by optimizing the associated script to make half as many Lerp calls and using an enumerator to implement a co-routine to update the pen position on paper rather than relying solely on the built-in Unity update function. The pens initially had a basic model, but they were replaced with a higher fidelity version from the Unity Asset store that more closely resembled an actual pen.

A management panel was also added to the game object of the drawing task, which cleared the whiteboard between trials and replaced the pens to their original position if they were dropped. This animation also only existed initially. The avatar was animated, moving his hand along the trail on the paper with a red pen attached to it. As the avatar moves the pen, a red trail appears behind it. This effect was created similarly to the lace, with a thin, long cylinder containing a series of bones hidden under the page and bending into place when the pen moved.

Aiming & Catching 1: Catch with Two Hands

The participant stands behind a line two meters from the wall before them and throws a tennis ball against it, catching it with two hands. For ages 7 and 8, the ball may bounce once off the ground before catching. At ages 9 and 10, the ball must be caught on return without bouncing off the floor. In previous years, the line had been placed on the floor, and numerous tennis balls had been placed on a table next to the line, but the tennis balls were not interactive. As such, the balls were made interactive by adding an "XR Grab Interactable" component.

Significant effort on this task was spent perfecting the physics of the ball by balancing different properties such as the drag and physics material bounciness on the rigid body component, as well as increasing the catch radius collider to make it easier to grab the ball in VR. A management panel in the game object for the catching ball task was also added to control left- and right-hand configurations. This reset the balls on the table and adjusted the table position to either the participant's left or right side, depending on hand dexterity. This animation was already present, with the avatar holding a tennis ball, tossing it to the wall, and then catching it (with one or two hands, depending on the version) after it bounced off the wall and floor.

Aiming & Catching 2: Throwing Beanbag onto Mat

The participants must stand on a yellow mat and toss a beanbag onto a target 1.8 meters before them. The mats and beanbags for this task were already imported, but the beanbags needed to be more interactive.

We imported a higher-fidelity model of a bean bag from the Unity Asset store and made it interactive by adding an "XR Grab Interactable" component. The changes to this scene were similar to those for the catching ball task, including bean bag physics adjustments for optimal interactions and a management panel to reset bean bags and configure the table placement for left—and right-hand users.

There was no animation for this task initially. Since the movement for this task was more involved, a third-party website called Mixamo, owned by Adobe, was used. Mixamo has hundreds of motion-captured animations that can be freely used in 3D software such as Blender. There was an underhand throw animation on Mixamo, which we could use as a base for the animation. The beanbag was animated to follow the same path as the avatar's hand and then move to where it was supposed to land in an arc.

Balance 1 (Static): One-Board Balance

The participants are to stand on one foot on a balance board and maintain their position for thirty seconds. This is done for both legs. The balance board and a 30-second countdown timer had already been placed, but the balance board was resized to match the exact dimensions of the board used in the real-life MABC-2 testing kit. A management panel was added to this task to reset and start the timer at 30 seconds (previously, it was set to loop continuously), as well as buttons to change the avatar demo's feet from left to right. This animation had already been created and found in [12]. It involved the avatar standing on one leg on the balance board for thirty seconds, slightly swaying back and forth.

Balance 2 (Dynamic): Walking Heel-To-Toe Forwards

The participants must walk across a 4.5-meter long line on the floor from beginning to end, ensuring that the toe of their rear foot touches the heel of their front foot when stepping forward. This task was already fully implemented, with the line on the ground. This animation was also present, with the avatar moving across the line, putting his heels to his toes each step until he reached the end.

Balance 3 (Dynamic): Hopping on Mats

The participants are instructed to start on one mat and make five continuous hops on one leg forward, stopping at the last target mat. There are six mats in total. This task is repeated for both legs while keeping their feet within the mats. The mats were already modeled and placed in the environment, but they were resized to match the exact dimensions of the mats in the real-life MABC-2 testing kit.

The animation for this task still needed to be created. The character starts standing on the first mat, raises one leg, and begins to hop forward on each mat. Once the avatar reaches the last mat, he stops and puts down his leg. The character returns to the first mat and performs the task using the non-dominant leg.

C. Procedure

The experiment was conducted in a well-lit, closed lab space with limited distractions to ensure a controlled testing environment. Before the participants arrived, the testing space was already set up with the materials from the real-life MABC-2 testing kit, and the virtual reality environment was set up and configured on the headset.

Pre-Assessment

Upon arrival, each participant was greeted and given a brief study overview. Participants received consent forms detailing the study's purpose, procedures, risks, and benefits. At this time, the examiner recorded the participant's chronological age, which is determined by subtracting the date of birth from the date of testing. A pen was placed directly in front of each participant's dominant hand on the table to determine each participant's dominant hand. Participants were instructed to pick up the pen and write their names. This procedure ensured that the preferred hand, used for tasks requiring uni-manual dexterity, was accurately identified.

Assessment

The assessment process involved three phases: an initial real-world MABC-2 exam to establish a baseline, followed by the same tasks in a VR environment, and concluding with a post-VR real-world MABC-2 exam to evaluate any improvements. Participants first completed the MABC-2 exam in a real-world setting. This was administered and scored according to the MABC-2 Examiner's Manual. Each task was preceded by a verbal explanation and a visual demonstration to ensure participants understood the instructions and goals.

Following the baseline assessment, participants repeated the tasks in the VR environment. In this setting, an animated avatar demonstrated each task in real-time next to the participant. Participants then performed the tasks themselves within the VR environment. After completing the VR tasks, participants were presented with the NASA Task Load Index (NASA-TLX) form to evaluate their perceived workload across six dimensions: mental demand, physical demand, temporal demand, performance, effort, and frustration [13].

Additionally, they were asked an open-ended question ("What parts of the environment did you like and dislike?") to gather qualitative feedback on their experience and any difficulties they encountered. Participants then returned to the real-world setting to perform the MABC-2 tasks again. This assessment was recorded to evaluate any improvements. Specific tasks were timed, such as placing pegs, threading lace, and one-board balance. Participants were asked to repeat the task if they did not complete these tasks within the allotted time frame.

D. Machine Learning for Zone Classification and Feature Analysis

Machine learning data analysis was conducted to classify children with ASD into motor skill proficiency zones based on their performance on three-component scores in each category. The objective was to achieve the highest possible zone classification accuracy and determine which feature combinations are the most influential in predicting the target zone.

The data set comprised 268 children diagnosed with ASD and was collected from a local autism camp in San Marcos, TX, from the years 2010-2019 and 2022-2023. It consisted of 213 children classified in the red zone, thirteen in the amber zone, and 42 in the green zone. Each record included the following features: Age Band (AB), Manual Dexterity Component Score (MD_CS), Aiming and Catching Component Score (AC_CS), Balance Component Score (B_CS), Manual Dexterity Standard Score (MD_SS), Aiming and Catching Standard Score (AC_ SS), Balance Standard Score (B _ SS), Manual Dexterity Percentile Score (MD _PS), Aiming and Catching Percentile Score (AC_PS), and Balance Percentile Score (B_PS).

TABLE I. BEST HYPERPARAMETERS FOR EACH FEATURE AND MODEL COMBINATION

Model	All features	MD_CS + B_CS + AC_CS	MD_CS + B_CS	AC_CS + B_CS	MD_CS + AC_CS	B_CS	MD_CS	AC_CS
SVM	{'C': 1, 'kernel': 'linear'}	{'C': 10, 'kernel': 'linear'}	{'C': 0.1, 'kernel': 'linear'}	{'C': 1, 'kernel': 'linear'}	{'C': 1, 'kernel': 'linear'}	{'C': 0.1, 'kernel': 'linear'}	{'C': 1, 'kernel': 'linear'}	{'C': 1, 'kernel': 'linear'}
LR	{'C': 100}	{'C': 100}	{'C': 0.1}	{'C': 0.1}	{'C': 10}	{'C': 0.1}	{'C': 10}	{'C': 1}
XGB	{'learning_rate': 0.2, 'max_depth': 3, 'n_estimators': 200}	{'learning_rate': 0.1, 'max_depth': 3, 'n_estimators': 200}	{'learning_rate': 0.2, 'max_depth': 5, 'n_estimators': 200}	{'learning_rate': 0.1, 'max_depth': 3, 'n_estimators': 50}	{'learning_rate': 0.1, 'max_depth': 3, 'n_estimators': 50}	{'learning_rate': 0.1, 'max_depth': 3, 'n_estimators': 50}	{'learning_rate': 0.1, 'max_depth': 3, 'n_estimators': 50}	{'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50}
KNN	{'n_neighbors': 5, 'weights': 'distance'}	{'n_neighbors': 5, 'weights': 'distance'}	{'n_neighbors': 5, 'weights': 'uniform'}	{'n_neighbors': 7, 'weights': 'uniform'}	{'n_neighbors': 7, 'weights': 'uniform'}	{'n_neighbors': 7, 'weights': 'distance'}	{'n_neighbors': 9, 'weights': 'distance'}	{'n_neighbors': 9, 'weights': 'uniform'}
GB	{'learning_rate': 0.2, 'max_depth': 3, 'n_estimators': 100}	{'learning_rate': 0.2, 'max_depth': 3, 'n_estimators': 100}	{'learning_rate': 0.2, 'max_depth': 3, 'n_estimators': 100}	{'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 100}	{'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 50}	{'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 100}	{'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 100}	{'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 100}
RF	{'max_depth': 5, 'n_estimators': 100}	{'max_depth': 5, 'n_estimators': 50}	{'max_depth': 5, 'n_estimators': 200}	{'max_depth': 3, 'n_estimators': 50}	{'max_depth': 5, 'n_estimators': 50}	{'max_depth': 3, 'n_estimators': 100}	{'max_depth': 3, 'n_estimators': 50}	{'max_depth': 5, 'n_estimators': 200}

TABLE II. P-VALUES FROM PAIRED T-TESTS COMPARING AVERAGE REAL-LIFE SCORES TO VR (P > 0.05 = SIGNIFICANT DIFFERENCE INDICATING INACCURATE SIMULATION)

Placing Pegs (Dominant)	Placing Pegs (Non-Dominant)	Threading Lace	Drawing Trail	Catching Ball	Throwing Bean bags	Board Balance (Dominant)	Board Balance (Non-Dominant)	Walking Heel to Toe	Hopping and Jumping
0.168	0.626	0.003	0.172	0.007	0.084	N/A	N/A	N/A	N/A

We trained six different machine learning models: Support Vector Machine (SVM), Logistic Regression (LR), Extreme Gradient Boosting (XGB), K-nearest neighbors (KNN), Gradient Boosting (GB), and Random Forest (RF). Table I shows that hyperparameter tuning was performed for each model to optimize performance.

III. RESULTS

A. Virtual Reality Tool

To validate the accuracy of the VR tasks, we compared participants' VR scores to average real-life scores (pre- and post-VR real-life MABC-2 assessment) using T-tests. This aimed to determine which tasks were accurately replicated in VR and which were not. The T-tests were not performed on balance tasks. This is because the scores for balance (dominant), heel-to-toe, and hopping and jumping were identical across pre-, post-, and VR assessments for every participant, making it insufficient for performing T-tests. For balance (non-dominant), only one participant had a differing post-VR score, which also made statistical comparison unnecessary.

The T-test results for the tasks are highlighted in Table II. A T-test result of $p < 0.05$ suggests that the observed differences between the VR and real-life scores are unlikely due to random chance. The VR simulations for these tasks do not accurately reflect real-life physics. Significant differences were observed for threading lace ($p = 0.003$) and catching the ball ($p = 0.007$), indicating that these tasks need further refinement to replicate the real-life performance better.

Additionally, the NASA Task Load Index (NASA TLX) was given to participants to assess the perceived workload of the VR simulation. Still, the results needed to be more varied to draw any generalized conclusions. We also decided against performing statistical analysis on pre- and post-VR scores as there were no consistent trends; some participants improved post-VR, while some performed worse.

B. Zone Classification and Feature Extraction

Table III's machine learning data analysis revealed that the Support Vector Machine (SVM) model achieved the highest accuracy when trained on all features, with a % accuracy rate of 96%. Logistic Regression also performed well, with an accuracy of 94% when trained on the component scores of manual dexterities, balance, and aiming and catching.

Among the models that support feature importance for the Random Forest, Gradient Boosting, and XGBoost, shown in Fig. 3, Fig. 4, and Fig. 5. The Balance Component Score (B_CS) was consistently identified as the most essential feature. The importance scores for B_CS were as follows: Random Forest: 25%, Gradient Boosting: 56%, and XGBoost: 35%. This consistent emphasis on the importance of the balance component score across multiple models highlights its critical role in predicting motor skill proficiency zones for children with ASD. This suggests that focusing on balance, specifically in interventions and assessments, could significantly help improve overall motor proficiency.

TABLE III. ZONE CLASSIFICATION ACCURACIES OF VARIOUS MACHINE LEARNING MODELS TRAINED ON DIFFERENT COMBINATIONS OF MOTOR PROFICIENCY FEATURES

Model	All feat.	MD + B + AC	MD + B	AC + B	MD + AC	B	MD	AC
SVM	96	94	89	87	85	85	83	81
LR	93	94	89	87	85	85	83	81
XGB	93	93	91	85	83	87	78	72
KNN	89	91	91	85	85	87	78	72
GB	89	87	87	83	80	87	78	81
RF	85	87	89	81	81	87	78	81

Accurate physics is crucial for the MABC-2 exam because the assessment tests motor skills. If the physics in VR is inaccurate, it can lead to participants learning the tasks incorrectly and, therefore, gaining false expectations of the real-world tasks. Replicating the exact physics of real-world functions in VR is highly challenging. For example, modeling the lace in the Threading Lace task involved using a series of joints linked together to simulate rope-like physics. This is computationally expensive and needs to be fully supported by the Unity stock engine. Most previous applications of rope simulations in Unity involve either static objects meant for decoration or large-scale interactive objects, such as a swinging ball attached to a rope. In our task, the rope needed to be small and flexible enough to thread through a board, pushing the engine's limits. There were moments when the engine updates couldn't keep up, causing the colliders to stretch and the rope to slip through the notches on the threading board. This confused the participants, leading them to take longer to complete the task, which explains the T-test results.

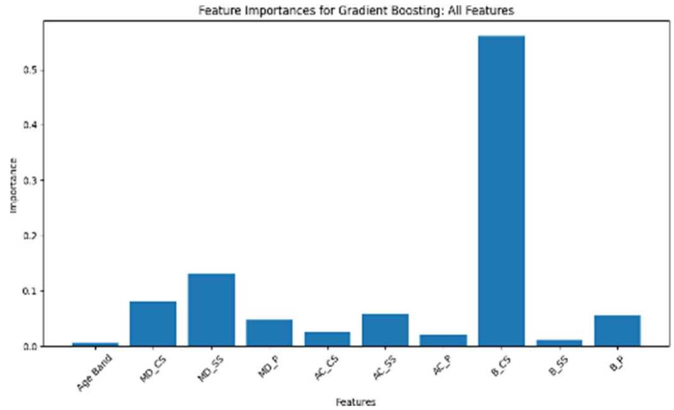

Fig. 3. Feature importances for Gradient Boosting: All Features.

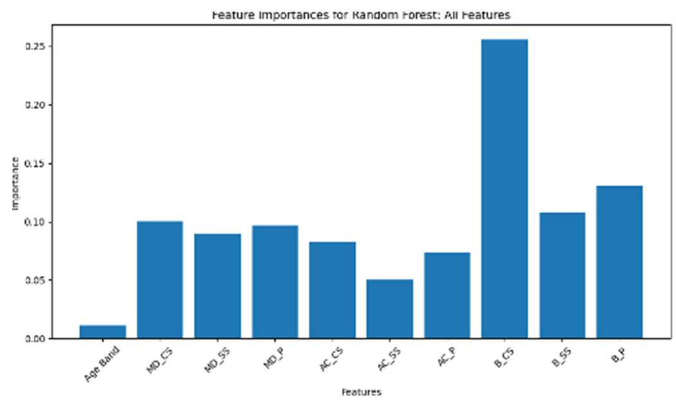

Fig. 4. Feature importances for Random Forest: All Features.

IV. DISCUSSION

A. Limitations

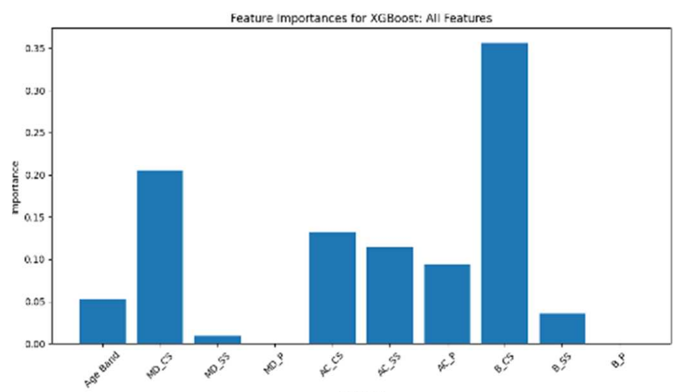

Fig. 5. Feature Importance for XGBoost: All features.

Although the ball's bounce and speed were accurate for the Catching Ball task, catching it in VR was significantly more complicated than in real-life. To mitigate this, we increased the size of the colliders on the ball so that the "catch radius" is three times the ball's actual radius. This still has not fully resolved the issue. Slowing the ball further would have noticeably compromised its realistic behavior.

The balance board task could not be accurately simulated because participants couldn't see the physical board while wearing VR headsets, which posed a risk of injury. Consequently, we did not use a physical board, which affected the task's fidelity. The Meta Quest 2 does not have foot trackers, which involve dynamic balance tasks like Walking Heel-To-Toe and Hopping on Mats. Some participants mentioned that not being able to see their feet was challenging, although this did not affect their performance.

Furthermore, our study focused only on Age Band 2 (ages 7-10) of the MABC-2. These findings may differ for younger children in Age Band 1 (ages 3-6) or older children in Age Band 3 (ages 11-16). Future research should include these age bands for a more comprehensive evaluation.

Another constraint is the limited dataset. Our data come from young adults (aged 19-21) without ASD, which limits the generalizability of our results to children with ASD. Expanding the sample size and including children with ASD in future studies would help obtain more accurate and generalized results. Lastly, using only male avatars for task demonstrations could introduce gender bias, affecting the comfort and engagement of non-male participants. Future iterations should include avatars of different genders to ensure inclusivity.

B. *Future Work*

Future studies should address VR engine limitations to improve task fidelity. For example, exploring different headsets like the HTC Vive is worthwhile because it supports foot tracking. Adding foot trackers in future studies will help improve immersion for tasks that require feet, such as dynamic balance tasks. Additionally, while this study tested the VR tool on adults, future studies should validate its effectiveness with children with ASD.

REFERENCES

[1] National Institute of Mental Health, "Autism spectrum disorder," https://www.nimh.nih.gov/health/topics/autism-spectrum-disorders- asd, 2024, [Online].

[2] J. N. Constantino and T. Charman, "Diagnosis of autism spectrum disorder: reconciling the syndrome, its diverse origins, and variation in expression," *The Lancet Neurology*, vol. 15, no. 3, pp. 279– 291, Mar. 2016. [Online]. Available: https://doi.org/10.1016/s1474-4422(15)00151-9.

[3] A. N. Bhat, "Is motor impairment in autism spectrum disorder distinct from developmental coordination disorder? a report from the spark study," *Physical Therapy*, vol. 100, no. 4, pp. 633–644, Mar. 2020. [Online]. Available: https://doi.org/10.1093/ptj/pzz190

[4] A. Paquet, B. Olliac, B. Golse, and L. Vaivre-Douret, "Current knowledge on motor disorders in children with autism spectrum disorder (asd)," *Child Neuropsychology*, vol. 22, no. 7, pp. 763–794, Sep. 2015. [Online]. Available: https://doi.org/10.1080/09297049.2015.1085501

[5] S. E. Henderson *et al.*, "Movement assessment battery for children-2a," 2007.

[6] S. E. Henderson and D. A. Sugden, *Movement Assessment Battery for Children*. Kent, UK: The Psychological Corporation, 1992.

[7] A. L. Barnett and S. E. Henderson, *An Annotated Bibliography of Studies Using the TOMI/Movement ABC: 1984–1996*. London, UK: The Psychological Corporation/Harcourt Brace & Company Publishers, 1998.

[8] W. Fu and C. Ji, "Application and effect of virtual reality technology in motor skill intervention for individuals with developmental disabilities: A systematic review," *International Journal of Environmental Research and Public Health*, vol. 20, no. 5, p. 4619, Mar. 2023.

[9] D. Avila Pesantez, L. Vaca-Cardenas, L. Rivera, L. Zuniga, and L. Avila, "Athynos: Helping children with dyspraxia through an augmented reality serious game," 04 2018, pp. 286–290.

[10] S. EbrahimiSani, M. Sohrabi, H. Taheri, M. T. Agdasi, and S. Amiri, "Effects of virtual reality training intervention on predictive motor control of children with dcd - a randomized controlled trial," *Research in Developmental Disabilities*, vol. 107, p. 103768, 2020. [Online]. Available: https://doi.org/10.1016/j.ridd.2020.103768

[11] S. N. V. Yuan and H. H. S. Ip, "Using virtual reality to train emotional and social skills in children with autism spectrum disorder," *London Journal of Primary Care*, vol. 10, no. 4, pp. 110–112, 2018. [Online]. Available: https://doi.org/10.1080/17571472.2018.1483000

[12] N. C. Tran, I. X. Liang, T. A. U. A. Liu, and D. Valles, "Impact of the Virtual Reality on Motor-Skill Performance in Children with Autism Spectrum Disorder," presented at the *2024 ASEE Annual Conference & Exposition*, Portland, Oregon, Jun 2024. Available: https://peer.asee.org/46878.

[13] S. G. Hart and L. E. Staveland, "Development of NASA-tax (task load index): Results of empirical and theoretical research," in *Human Mental Workload*, ser. Advances in Psychology, P. A. Hancock and N. Meshkati, Eds. North-Holland, 1988, vol. 52, pp. 139–183. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0166411508623869