Validation and Examination of Upper Extremity Kinematics in Typically Developing Children During the Box and Blocks Functional Test using Marker-based and Markerless Technology

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Abstract

Joint kinematics of upper extremity (UE) impairments in a pediatric population are often difficult to examine using marker-based motion capture. As a result of the cost and availability of tools such as marker-based motion capture in clinical settings, clinicians use functional tasks to examine improvement in movement quality. However, some of these tasks, such as the Box and Block test (BBT), which is examined in this study, rely on scoring to assess motor improvement. This scoring method can be misleading due to the possibility of movement compensation to improve scores. Therefore, finding kinematic correlations that can lead to improved BBT scores could improve the quality of functional assessments by providing discrete measures for clinicians. Understanding human motion using marker-based motion capture has been the accepted standard in biomechanics. However, it is not without its drawbacks, especially in upper extremity examination due to complex anatomical positioning. The introduction of markerless motion capture software could drastically alter how human biomechanics is analyzed in various settings. Additionally, avoiding possible errors due to clothing and skin movement could greatly improve reported results. Therefore, examining similarities in UE joint kinematics between accepted marker-based and markerless software could introduce markerless motion capture as a method for examining complex kinematics. This study aims to examine UE joint kinematics in a typically developing pediatric population while they complete the BBT, as well as validate *Theia3D* (Theia Markerless Inc., Kingston, ON, Canada). Marker-based motion capture was used to capture UE kinematics during the BBT. This study was performed on typically developing children aged 7, 9, and 11. Average and peak joint angles were determined, as well as hand segment velocity and path length. Significant correlations to BBT scores were found in peak shoulder flexion (FLEX) angle ($r = -0.556$, p-value = 0.009), peak ($r = -0.479$, p-value = 0.028), and average ($\rho = -0.535$, p-value = 0.012) wrist extension (EXT) angle, average mediolateral (ML) hand segment velocity ($r = 0.494$, p-value = 0.023), and path length ($r = -0.522$, p-value = 0.015). Additionally, significant differences between BBT scores (p-value = 0.005), peak shoulder FLEX (p-value = 0.024), and peak shoulder abduction (ABD) angle (p-value = 0.022) were found between the 7- and 11-year-old age groups. Peak elbow FLEX angle was significantly different (p-value = 0.049) between 9- and 11-year-old age groups. These results show that the BBT score could be related to the shoulder and wrist angle, as well as hand segment velocity and path length for typically developing children. Furthermore, root mean square deviation (RMSD) values less than 6° existed in all joint angles. Intraclass correlation coefficients (ICCs) greater than 0.75 were found in shoulder ABD (ICC = 0.79), forearm pronation (ICC = 0.81), wrist EXT (ICC = 0.75), and radial deviation (ICC = 0.87). Additionally, validation results between the marker-based and markerless systems show that there are differences in pose estimations and joint calculations based on rotation sequences. Overall, UE joint kinematics are shown to have correlations to BBT scores, so scores alone may not be indicative of movement quality in other patient populations. Markerless motion capture shows many benefits, however, it should be noted that, due to the complexity of upper extremity motion analysis, understanding what joint rotation sequences align the best with task-specific motions is important.

Validation and Examination of Upper Extremity Kinematics in Typically Developing Children During the Box and Blocks Functional Test using Marker-based and Markerless Technology

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General Audience Abstract

Human motion is commonly analyzed using marker-based motion capture, which consists of fitting participants with retroreflective markers that can be seen by specialized cameras. However, due to equipment costs, difficult implementation, and the occurrence of markers shifting on skin or being concealed by clothing, markerless motion capture is beginning to be introduced into biomechanics research and could be used in hospitals, clinical settings, and for outdoor examination due to its versatility. The software uses machine learning software that can determine skin landmarks in videos from several cameras to develop a 3D skeleton. Markerless motion capture could be beneficial in examining patients with neuromotor disorders or injuries due to being able to capture abnormal or quick movement which often accompanies many neurological disorders that affect motor function. Additionally, observing movement in children is a challenge due to markers being too close together on smaller limbs. Due to cost and obtainability, clinicians tend to use functional tests to examine improvements in motor function by a scoring system relevant to the specific test, such as the Box and Block test (BBT) which will be used in this study. However, there is the possibility of the patient's ability to adapt to the test to improve their score without improving general motor function. Therefore, it is important to find a relationship between upper limb movement and BBT scores. This study aims to find correlations between upper limb movement and Box and Block test scores as well as differences between 7-, 9-, and 11-year-old age groups and compare marker-based motion capture and the *Theia3D* (Theia Markerless Inc., Kingston, ON, Canada) markerless motion capture software. Joint assessment is completed with motion capture, which uses reflective markers on specific landmarks on the skin surface. Markerless motion capture is collected simultaneously with marker-based motion capture to assess similarities. The entire procedure was also completed 2 times within 1 visit. The results showed meaningful comparisons between the BBT scores and shoulder and wrist angle, and hand velocity. BBT scores and shoulder angles were shown to be different between the 7- and 11-year-old age groups. Elbow angles were shown to be different between the 9- and 11-year-old age groups. Additionally, comparisons between the marker-based and markerless results showed that all resulting joint angle data captured by each system were similar. Markerless measurement comparisons showed similarities between both sessions as well. These results show that there are ways to provide discrete measurements in clinical settings to examine movement quality. Comparisons between both motion analysis systems show the need to determine task-specific analyses to obtain meaningful results concerning the upper limbs, due to the inherent joint complexity and differing methods of completing the same task.

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Table of Contents

List of Abbreviations

BBT	Box and Blocks Test
TDC	Typically Developing Children
ADL	Activities of Daily Living
UE	Upper Extremity
MEMS	Microelectromechanical System
RMSD	Root Mean Square Deviation
3D	Three-Dimensional
2D	Two-Dimensional
ICC	Intraclass Correlation Coefficient
IMU	Inertial Measurement Unit
EXT	Extension
FLEX	Flexion
IR	Internal Rotation
ER	External Rotation
ABD	Abduction
PRO	Pronation
RD	Radial Deviation

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Ch. 1 Introduction

Motivation, Purpose, and Aims

Functional tests and classification systems are widely used within the clinical setting for assessing movement because it allows clinicians to objectively measure the movement abilities and performance of patients, which would be difficult to quantify otherwise. Therefore, functional tests that are related to the individual's rehabilitation goals are carefully chosen to ensure it is appropriate for the patient.[1] While validity and reliability research behind functional tests and classification systems have been done, there is little known about the association between the functional tests and the kinematic measures of the intended movement. Specifically, the Box and Block test (BBT) is a commonly used functional test to measure unilateral gross manual dexterity and demonstrate rehabilitation effectiveness in patients with upper limb impairments. The BBT is a standardized assessment that is inexpensive, portable, easy to obtain, simple to implement, and quick to administer.[2] It is particularly beneficial for a pediatric population due to its short testing period and being able to complete the test using simple directions. For clinicians, an improved BBT score implies improvement in manual dexterity. As such, previous literature has demonstrated how manual dexterity improves throughout childhood and has shown BBT to increase with age.[3,4,5] However, there is no kinematic evidence to show what movement differences allow for the improved BBT score. Previous studies have explored upper limb kinematics in a pediatric population; however, few studies explore the association between functional testing scores (BBT) and upper extremity kinematic measures obtained during the functional assessment. Such work with typically developing children could provide critical information for future pediatric research

Significant challenges exist in the assessment of upper extremity kinematics due to measurement systems and the complexity of upper extremity physiology. Understanding the mechanics of the shoulder, elbow, and wrist movement is a crucial insight into the cause of injury or monitoring rehabilitation techniques. While the current gold-standard three-dimensional marker-based motion capture system can be used to examine upper extremity joint motion, there are limitations. These limitations include patients being uncooperative due to the use of markers taped to the skin and having to keep the markers in specified positions. Additionally, marker-based motion capture is expensive, not portable, and not easily accessible, particularly in the clinical or at-home setting. Inertial Measurement Units (IMUs), which are small, wearable accelerometers have also been used to analyze upper extremity joint motion. However, similar to marker-based motion capture, errors exist in kinematic results from IMU data due to motion artifact, random noise, and complex algorithms. Some of the challenges may be mitigated by using a markerless motion capture system. Currently, the *Theia3D* (Theia Markerless, Inc., Ontario, CA) markerless system has only been validated for the lower limb of healthy adults during gait.[6]

<u>**Specific Aim 1:**</u> **Determine the association between the BBT score and upper extremity joint kinematics (peak angle, average angle, and path length) of the shoulder, elbow, and wrist and determine the differences in the BBT and joint kinematics across three age groups (7, 9, and 11 years)**

<u>Hypothesis 1a:</u> Shoulder, elbow, and wrist kinematics as well as path length will be correlation of BBT scores.

<u>Hypothesis 1b:</u> Significant differences in BBT score and upper extremity kinematics will exist between all age groups.

<u>**Specific Aim 2:**</u> **Examine the validity of the Theia3D Markerless motion capture system to assess upper limb joint kinematics in a typically developing pediatric population.**

<u>Hypothesis 2a:</u> The root mean square deviation (RMSD) of demeaned angular measurements are expected to be as accurate (within 6 degrees) as those from the marker-based 3D motion capture system.

<u>Hypothesis 2b:</u> The Markerless results will demonstrate good to excellent between session repeatability (ICC > 0.75).

Background

Functional tests are commonly used to examine movement performance and capability in clinical settings due to the capacity of these tests to provide objective and quantitative results without much difficulty.[1] Functional tests can be used for a variety of purposes like examining injury risks for athletes as well as analyzing rehabilitation improvement for a patient with a neuromotor impairment. The basis of the test depends on related activities to their rehabilitation goal. For example, patients with stroke will complete functional tests that are more related to daily activities to provide a quantitative measure of improvement. Additionally, functional tests to measure motor function are commonly administered for children to examine improvement in gross and fine motor skills related to rehabilitation or examine general motor function improvement. Functional tasks can include drawing, reaching, grasping, throwing, etc. The Box and Block test (BBT) is a standardized functional test that measures an individual's manual dexterity.[7] The BBT is simple, portable, quick to administer, and easily obtained, which makes it ideal to use with children. The test consists of a 53.7 cm by 25.4 cm wooden box that is divided into two equal compartments by a 15.2 cm high partition, as seen in Figure 1.

Figure 1. Box and Blocks test contents with example of how the test is performed. (https://airgovie.com/boutique/materiel-devaluation/bilans-mesures/box-and-block-test/)

One compartment is filled with one hundred and fifty, 2.5 cm cubes that the participant is instructed to move one at a time as quickly as possible over the partition into the opposite compartment within a 60-second session.[7] The resulting score would be how many blocks are moved to the opposite compartment in the allotted time. Generally, the understanding is that as the score for the BBT improves, manual dexterity is improving. Early examination of BBT test-retest reliability was performed by Cromwell in 1976, which resulted in a ρ coefficient value ranging from 0.78 to 0.92.[8] More recent exploration into the BBT in 2013 by Jongbloed-Pereboom et al. reported a test-retest ICC of 0.85 for typically developing children between 3 and 10.[4] Currently, there exist BBT normative scores for 3-year-olds to adults. [9,7,10,4]

While functional tests and assessments were developed to provide standardization and simple administration and analysis, they are not necessarily indicative of the strategies used by the patient to accomplish the task. As previously mentioned, UE movements are highly dependent on the task being performed and general movement variability still exists due to the complex nature of the shoulder, unless the task itself is constrained.[11] Therefore, the use of kinematic data could elucidate the methods that are being used to accomplish the tasks and if the methods are comparative to standardized data. Since the 1900s, movement analysis has been the primary method to further the understanding of movement biomechanics.[12] However, the focus has been on the lower extremity and gait. Understanding the biomechanics of upper extremity motion has become more common; however, there are challenges due to the complex nature of the shoulder and lack of cyclic patterns of movement as is seen in the lower extremity during gait. Specifically, techniques that are used for gait analysis cannot be reproduced for upper limb movement analysis due to the variability of upper-extremity movements, which even for cyclic movements are not as repeatable as a gait pattern. Additionally, three-dimensional (3D) rotations occurring at the shoulder make it difficult to examine major movements in specific planes, increasing the variability of joint rotation orders specific to each movement. There is also more soft tissue artifact due to larger movements, and task variability and complexity have made it difficult to provide standardized methods in measuring upper extremity movements.[12]

These difficulties extend to the examination of upper limb movement in typically developing children. It is well known that movement control improves in typically developing children as they age. Previous studies exploring the improvement of upper limb movement have shown improved smoothness and trajectory straightness, as well as increased maturity in coordination between arm and trunk movements.[13] It is accepted that motor control and performance continue to increase until young adulthood; therefore, motor control is still a concern in a population of typically developing children.[14]

There have been some studies exploring UE kinematics in children during activities of daily living (ADLs), which helps with the introduction of 3D motion analysis into functional tests to characterize UE movements. Petuskey et al. explored the differences in upper extremity joint kinematics between age groups for a pediatric population, reporting the measures for common ADLs.[15] These ADLs include hand-to-back pocket, hand-to-top of head, high reach above head, forward reach to receive change, and wave with arm at side. The point of task achievement (PTA) was used to define when kinematics was examined. [15] Additionally, Reid et. al. examined the repeatability of UE kinematics for a typically developing pediatric population during tasks similar to ADLs adopted from the Melbourne Assessment and reported the joint kinematics during these tasks [16]. Similarly, Jaspers et. al. explores tasks within the Melbourne Assessment with several measures of control, by developing a custom device to adhere to their height and reaching distance and reporting the average joint angles at PTA. [17] The tasks used to characterize UE kinematics are designed to be controlled and lack the possibility of movement variability, which begins to reduce clinical relevance. Consequently, there is a lack of data in literature allowing researchers to examine motor development patterns in movements that allow for variation, which relate to tasks performed in clinical settings.

An IMU is a microelectromechanical system (MEMS) that uses inertial measurement to determine kinematic data. The measurement system commonly consists of an accelerometer and a gyroscope used to measure inertial acceleration and angular rotation, respectively. There could also be the addition of a magnetometer that measures the bearing magnetic direction, which, in turn, improves the gyroscope accuracy. The sensors that make up the IMU all have three degrees of freedom.[18] IMUs are an attractive option for motion analysis due to their small size and portability. This allows them to be used in a clinical setting for rehabilitation or used for full-speed sports injury analysis. However, IMUs reduce data accuracy after extended periods of use due to errors based on biases, scale factor imperfections, drifts, misalignments, or random noise. Additionally, IMUs rely on complex algorithms that require specific and extensive knowledge in that area, which leaves room for excess error.[19]

Examining upper extremity kinematics is crucial in understanding injury mechanisms and rehabilitation techniques. Previous studies have used marker-based motion capture with different marker set techniques to accurately measure joint kinematics in pediatric populations.[15,16,20,21] While marker-based motion capture is considered the "gold standard" in capturing kinematic data, there are limitations, such as soft tissue artifact, the time needed for marker placement, repeatability in marker placement, using possibly irritating adhesive, and ensuring the markers cannot fall off. The researcher is expected to be fully trained in palpating bony landmarks to accurately place markers; this is learned through long-term experience and training. Lack of knowledge of anatomical landmarks and experience in marker placement leads to measurement errors within the data, along with any error caused by skin movement. [22,23] Marker-based systems are also expensive and not portable, which makes them difficult to implement in a home or clinical setting. Therefore, several systems have been implemented to avoid limitations with data collection, like Inertial Measurement Units (IMU) and markerless motion capture.

Markerless motion capture systems analyze standard videos of movement or images of humans in various settings and use machine learning algorithms to estimate human pose during physical tasks. While marker-based motion capture relies on the hardware, like reflective markers placed on the skin, to extract movement data, markerless motion capture relies heavily on software to accurately track human motion in videos. Markerless motion capture software can use a single camera, which is commonly prone to errors due to self-occlusion, or multiple cameras to reduce this type of error and produce more accurate biomechanics data.[24] *OpenCap* is an emerging markerless motion capture software that is an open-access, web-based software, that requires at least two iOS device cameras set up on tripods to capture 2D videos to be processed. This software uses 2D pose estimation algorithms: OpenPose[25] and HRNet[26], as well as their 2D key point processing to improve the fidelity of the processed data. The OpenCap website provides detailed instructions for set-up and data collection. Set-up, camera calibration, and data collection and processing all consist of a simple, thoroughly explained process. However, the use of only two cameras limits the movements that can be captured due to the lack of viewing angles and the participant cannot exit and re-enter the capture volume. More than two cameras can be used, but they all cameras must be able to capture the calibration checkerboard. The checkerboard is expected to be standing perpendicular to the ground, which means you cannot have cameras from all angles. There exists an option to orient the calibration checkerboard flat on the ground, but the calibration identification struggles in this position. Additionally, if using two cameras, they must be placed at about a 45-degree angle off the front facing line to produce the most accurate results.[27] The validation that has been performed on this software consists of examining similarities between this system and marker-based kinematic data for walking, a sit-to-stand task, and a squatting task. However, there were no upper extremity-specific tasks performed and only low extremity joints were examined. Overall, OpenCap is a promising software that is simple to access and implement; however, it lacks task variety due to the lack of viewing angles and there is limited research supporting the validity of this emerging software.

The Markerless motion capture system being explored in this study is *Theia3D* (Theia Markerless Inc., Kingston, ON, Canada), which uses a deep learning algorithm for human feature recognition within two-dimensional (2D) camera views. Deep convolutional neural networks are used for object recognition, which was trained on over 500,000 images of humans in different settings. Highly trained annotators manually labeled 51 noticeable points on the human body in the images, including various joint locations and other identifiable surface features, and were controlled for quality by an additional expert feature labeler. The algorithms can estimate joint centers using predetermined points on the human body, which, overall, eliminates errors associated with marker placement repeatability and soft tissue artifact.[28] *Theia3D* has been validated using the gait of healthy young adults, which resulted in an average root mean square distance (RMSD) of less than 3 cm for all joints except for the hip at an RMSD of 4.1 cm. Additionally, an RMSD of less than 6^{o} was observed for all lower limb segment angles, except those that represent rotations about the long axis of the segment.[6] A study exploring the possibility of clothing conditions affecting the validity of the system determined that clothing would negligibly alter clinically relevant results.[29] The kinematic comparison between Markerless and marker-based only had a focus on the lower extremity; only joint position comparisons were reported for all upper extremity segments. Nonetheless, these findings are the only published validation work for *Theia3D*, therefore, future researchers need to explore kinematic comparisons for the upper extremity, as well as participant populations, such as children. Markerless motion capture shows promise due to avoiding the limitations that currently exist in marker-based motion capture.

Research has been performed to examine abnormal biomechanical movement using markerless motion capture due to errors associated with marker-based motion capture, different body types, or atypical motion. Therefore, validating *Theia3D* for use in pediatric populations to examine UE kinematics could be beneficial in avoiding limitations that come along with marker-based motion capture use on children.

Ch. 2 Characterizing Upper Extremity Kinematics in Typically Developing Children during Box and Blocks Functional Test

Abstract

Movement analysis in the upper extremity is important in understanding functional ability as well as improved performance. Clinicians often use functional tasks to analyze movements similar to drills performed in sports, or activities of daily living. The Box and Blocks test is an example of a standardized functional test used to measure manual dexterity, which is commonly used for children or patients with stroke. This allows clinicians to provide quantitative insight into the functional performance of a patient. However, important kinematic parameters could be overlooked, and compensation methods could be used to complete a task. Therefore, this study proposed an examination of correlations between upper extremity kinematics and box and blocks test scores. Age group differences for box and blocks test scores and upper extremity kinematics for 7-, 9-, and 11-year-olds were examined. The participants completed 2 sessions of the functional test and test scores and kinematic measures were determined. Kinematic measures were only determined for selected block movements that existed during the middle of each trial to consider consistency in movements. Pearson's Correlation Coefficients were determined for each kinematic measure, which resulted in significant correlations in the shoulder, wrist, hand segment velocity, and path length. A mixed-effects model was used with an ANOVA to identify differences between age groups. Significant differences in test scores and kinematic measures were seen between the 7-year-old age group and the 11-year-old age group and the 9-year-old and the 11-year-old age groups.

Introduction

Functional tests are commonly used by clinicians to examine the movement performance of a patient by obtaining objective and quantitative results with simple approaches. They can also be used to examine the functional capability of a patient by having them perform simple tests, in which the outcome measures are provided through tests related to activities of daily living (ADL), athletic drills for return to sport, isolated joint movements, or general motor function tests. [1] Many functional tests are performed on children to examine gross motor performance and movement disorders caused by neuromotor diseases[30], as well as patients with stroke to evaluate the severity of motor function deficit due to stroke and examine improvement throughout rehabilitation.[31]

Specifically for assessing the function of the upper limbs, pediatric functional tests are more commonly comprised of tasks that involve ADL, upper extremity (UE) range of motion (ROM) as seen in the Fugl Meyer Assessment[32] and tasks that require the patient to reach, grasp, transport, and release objects, showing coordination and dexterity similar to the Action Research Test (ARAT).[33] It is well known that motor function improves significantly in early childhood until young adulthood and then begins to decline.[14] Therefore, movement variability is more likely in younger age groups.

One of the most commonly used functional tests is the Box and Blocks test (BBT).[10] The BBT, developed in 1957 by Aryes and Holser is a standardized functional test that examines manual dexterity.[7] It is commonly used in children due to the simple directions that accompany the test, its portability, quick testing time, and the ability to obtain the test. As pictured in Figure 1, the BBT is made up of a 53.7 cm by 25.4 cm wooden box, having two divided compartments with a 15.2 cm high partition. The instructions consist of moving as many of the one hundred and fifty, 2.5 cm cubes that fill one compartment to the other in 60 seconds. The clinical score used is how many blocks are moved with each arm. An increase in score indicates manual dexterity improvement. Various studies have shown the validity and reliability of this functional test, as early as 1976, when Cromwell reported a test-retest reliability range of r = 0.78 to r = 0.92.[34] There was additional exploration completed by Jongbloed-Pereboom in 2013, who examined BBT scores in children between 3 and 10, resulting in a test-retest intraclass correlation coefficient (ICC) of 0.85. However, there is limited information on normative BBT scores for typically developing children. There are currently normative scores for 3-year-olds to adults.[9,7,10,35] The most recent publication of normative BBT scores for a pediatric population was in 2013 by Jongbloed-Pereboom.

The standardization and simple quantitative analysis of functional tests provide clinical insight into movement ability. However, many functional test results cannot measure strategies used to complete the task, which can show musculoskeletal improvement or deterioration. Currently, many clinicians use subjective methods to examine movement in their patients during functional tasks to evaluate movement and rehabilitation progress. However, slight movement impairments can be missed if the motion analysis is being performed using scoring methods, especially in upper extremity movement due to its non-cyclic nature. Connecting clinical analysis of movement to specific kinematic measures of movement could improve the ability to observe motor function impairments during functional tasks.

To avoid general movement variability, the task would have to be constrained, which would still not eliminate all movement variability. Biomechanical analysis of the upper extremity has recently become a larger topic of exploration, due to expanded work in understanding the complex motion in the shoulder and movement constraints. There has been success in developing repeatable procedures to examine pediatric upper extremity movement in literature, with Jaspers et al. showing intraclass correlation coefficients (ICCs) greater than 0.60 for all joint angles except the wrist in their custom measurement procedure.[17] Nonetheless, the increase in movement constraint begins to reduce the clinical relevance, due to the lack of realistic movements during tasks.

Therefore, this study proposes to explore the correlation between upper extremity joint kinematics, as well as path length and BBT scores to provide objective movement metrics related to the BBT. Additionally, this study aims to provide a way for clinicians to examine movement quality with age. BBT scores and UE kinematics between age groups will be examined. There is expected to be a correlation between BBT scores and shoulder, elbow, and wrist joint angles and path length. Additionally, BBT scores and joint kinematics are expected to be significantly different between age groups. Therefore, our results will also further our understanding of kinematic change with age.

Methods

Participants

Twenty-one typically developing children were recruited to participate in this institutional review board-approved study (IRB #22-662). The inclusion criteria consisted of the participants being 7-, 9-, or 11 years old, having full-upper limb mobility, being able to complete activities without continuous assistance, being able to follow verbal and visual directions, having functional vision and hearing, having no medical conditions that could inhibit full participation and being able to understand English. The participants were excluded if they had any injuries or neuromotor disorders that affected the upper limbs. The age groups were determined based on age bands used in the Movement Assessment Battery for Children.[36]

Previously reported BBT normative scores from Mathiowetz et al. were used to determine the sample size needed to detect a difference between the three age groups. [7] A power analysis was performed in JMP Version 16 (SAS Institute Inc., Cary, NC) with the *k* sample means calculator. The sample means for the age groups of interest were used as well as the pooled SD with a statistical power of 0.8 to obtain an ideal sample size of 21 participants, with 7 participants per group.

Testing Procedure

Consent was given by each participant and their parent or guardian by signing an institutional review board-approved assent form and parent permission form before completing the procedure. The participant's age, sex assigned at birth, height, weight, and upper limb dominance were collected and organized using REDCap, a secure web platform for databases. Upper limb dominance was determined by asking the participant which hand they write with. Immediately following the demographic data collection, the participant was fitted with 26 retroreflective markers as well as two 4-marker clusters. The marker set used for this study consisted of a combined method from the c-motion Plug-In Gait Full-Body[37] and the Rab Upper Extremity Model.[38,15] As shown in Figure 2, the markers are placed at the following anatomical bony landmarks: left and right iliac crest, left and right anterior superior iliac spines, left and right posterior superior iliac spines, sacral, 7th cervical vertebrae, xiphoid process of the sternum, the suprasternal notch, the 10th thoracic vertebrae, an offset marker placed on the right scapula, left and right acromioclavicular joint, the medial and lateral epicondyle of each humerus, the left and right olecranon, the distal radius and ulna of each wrist, and on the distal end of the third metacarpal bone on each hand. As well as two, 4-marker rigid clusters placed laterally on each humerus, secured by a non-adhesive elastic bandage.

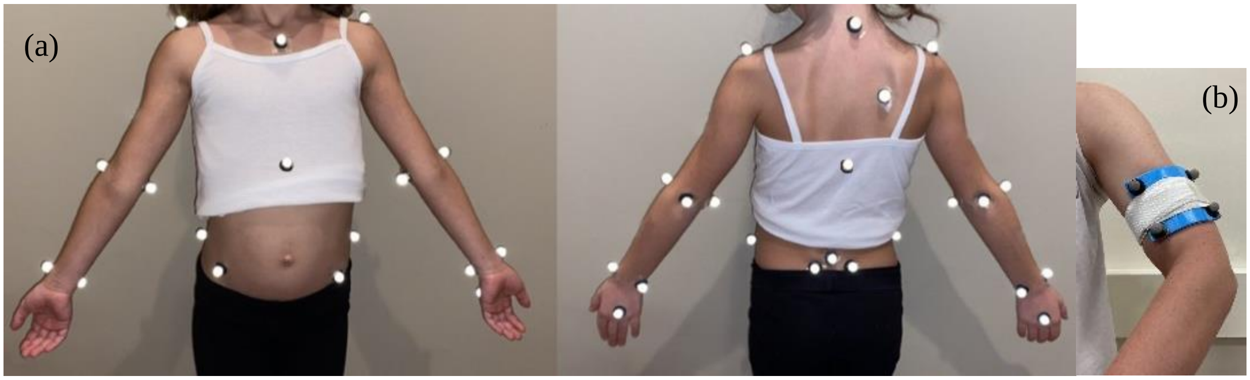

Figure 2. Retroreflective marker set (a) used in the study, with a 4-marker rigid cluster (b) placed on each humerus.

Once the marker set was applied, the participant was able to move their arms around however they wanted until they were comfortable. A 10-second static trial of the participant in an anatomical position was collected using a 10-camera 3D motion capture system (Qualisys, Gothernburg, Sweden) recorded at 170 Hz in the Kevin P. Granata Biomechanics Lab on the Virginia Tech campus. When a successful static trial was collected, the participant could complete the Box and Blocks test (BBT). The BBT involves the use of a 53.7 cm by 25.4 cm wooden box that was divided into two compartments with a 15.2 cm high partition.[7] One compartment was filled with one hundred and fifty, 2.5 cm cubes. A form of targeted BBT was used similar to studies completed by Herbert et al. in 2014 and Kontson et al. in 2017 to control general movement variability, as seen in Figure 3.[11,39] The table and stool were set at a standard height of 51.6" and 20.2" respectively, for all participants. Additionally, the BBT was placed 1" away from the edge of the table and the table was moved to where the participant could touch the back edge of the box with their arms fully extended, as seen in Figure 4. Two reflective markers were placed on the front and back edge of the middle of the box to assist with successful cycle determination in data processing.

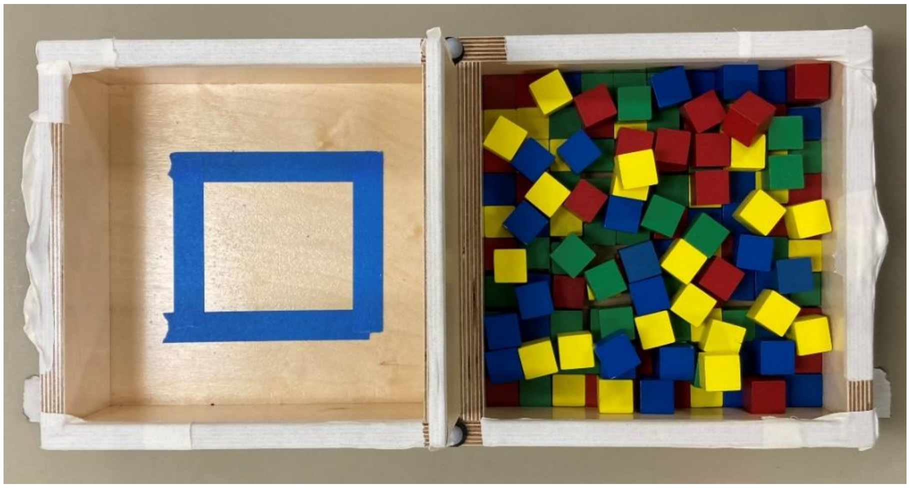

Figure 3. Overhead view of the modified BBT

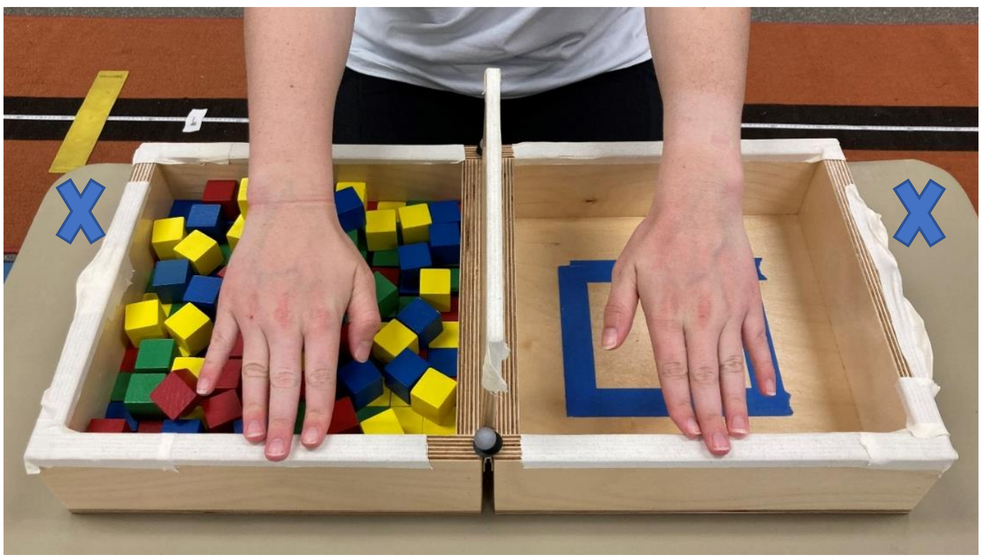

Figure 4. A representation of how the BBT was lined up in reference to the participant. The table was moved toward them until their fingertips could touch the back edge of the box. The blue x's indicate the starting position of the participant's hands before the test began.

Once the participant was sitting comfortably on the stool, the instructions for the BBT were explained. The participants were told that they would move one block at a time from one side of the box to the other over the divider as fast as they could for 60 seconds. Due to the addition of the modified version of the BBT, they were also told that they were trying to "aim for the square" when the block was dropped on the opposite side and that their entire hand must pass the divider, as shown in Figure 4. They were given a practice round to become comfortable with the movement with the markers attached. When they stated that they felt comfortable with the movement, the first trial began for the limb of their choosing. As shown in Figure 5, the participants started each trial with their hands flat on the table beside the box until they were counted down verbally. The researcher would say “ready, set, go” to inform the participant that they can begin the test, only using the limb that is indicated for that trial, and then saying “stop” once the timer had reached 60 seconds. The number of blocks successfully moved was counted between each trial. A successful block movement consisted of the participant only moving one block at a time and their entire hand passing the divider before releasing the block. The limb used for the test would then be switched to avoid possible fatigue between trials. Additionally, they were offered breaks between trials if they were needed. Three trials for each limb were collected, for a total of 6 trials per participant.

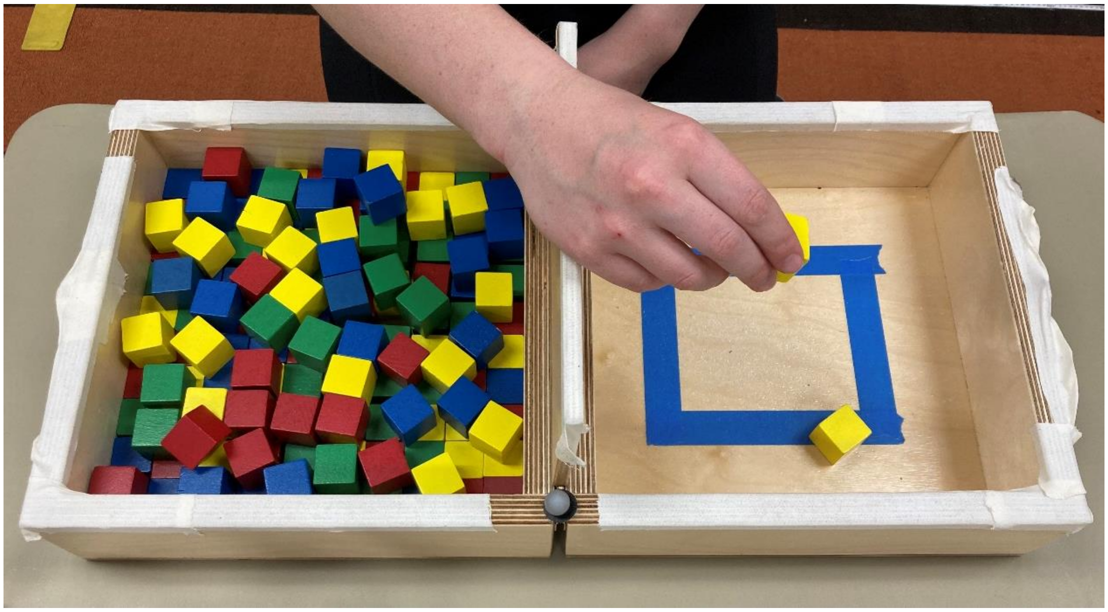

Figure 5. Example of the minimum distance over the divider the participant can release the block.

Data Processing and Analysis

The three-dimensional motion capture marker data was collected and processed using Qualisys Track Manager (Qualisys, Gothenburg, Sweden), and then exported and analyzed using Visual3D. Marker data are filtered using a low-pass Butterworth filter with a cutoff-frequency of 7 Hz. The markers on the medial epicondyle and olecranon of each elbow were used for calibration. For example, due to the marker occlusion for the medial epicondyle of the elbow and the olecranon, the medial elbow marker was used to determine a calibration-only elbow joint center landmark, and the lateral epicondyle elbow marker was used as the tracking marker. This method is described in c-motion's Plug-in Gait Full Body model.[37] The methods for determining the remaining joint landmarks were based on the Rab Upper Extremity model.[38] The segment coordinate systems followed the lab coordinate system orientation. Therefore, for each joint, X represented flexion and extension, Y represented abduction and adduction, and Z represented internal and external rotation. An XYZ rotation order was used for all joints. Upper extremity joint angles and angular velocities were calculated in Visual3D and exported. The joint angles included shoulder flexion (FLEX), abduction (ABD), and internal/external rotation (IR/ER), elbow FLEX and forearm pronation (PRO) and wrist FLEX/EXT and radial deviation (RD). Forearm PRO was calculated from the Z coordinate for the elbow joint center. Hand segment position and velocity were also extracted from Visual3D. The exported text files were analyzed using a custom MATLAB (MathWorks, Natick, MA) script, which determined the dependent measures from the middle 15 successful block movements, or cycles, for each trial. A cycle was determined using each participant's hand position relative to the box, with cycle start time defined as when the participant's hand retrieves a block and cycle end time defined as when the participant's hand crosses the divider and releases the block. Average and peak joint angles were determined as well as hand segment velocity and path length based on hand position in the x, y, and z coordinates.

Statistical Analysis

JMP Version 16 (SAS Institute Inc., Cary, NC) was used to complete all statistical analyses examining the correlation between joint kinematics and BBT scores as well as the differences in BBT scores and kinematics between each group. The joint angles, path length, and BBT scores were checked for normality. For the normally distributed variables, the Pearson Correlation coefficient will be examined between the average BBT scores and kinematic measures and path length for all participants and then each participant within each age group, with significance determined by a p-value less than 0.05. A non-parametric, Spearman's ρ was performed on the remaining, non-normal variables. Following this analysis, the normality of the residuals of the variables of interest was examined. Any non-normal variable was ranked for the analysis. The data were fit to a linear mixed effects model, with participants set as a random dependent variable and age as a fixed effect. An ANOVA was used to determine if there are significant differences between age and BBT scores with an α of 0.05. Significant differences between each age group were determined using Tukey's Honestly Significant Difference (HSD).

Results

Population

Eight 7-year-olds, six 9-year-olds, and seven 11-year-olds participated in the study. Overall, there were 8 females and 12 males, detailed demographics are presented in Table 1.

Table 1. Mean (SD) participant demographics for each age group

Age [years]	7		9		11	
	Male	Female	Male	Female	Male	Female
	4	4	3	3	6	1
Height [cm]	128.22 (4.34)		140.87 (3.21)		149.1 (5.65)	
Mass [kg]	25.85 (3.79)		32.35 (4.39)		41.42 (12.62)	

Correlations

The correlation test for all age groups resulted in peak shoulder flexion (FLEX) angle (r = -0.556, p-value = 0.009), peak wrist extension (EXT) angle (r = -0.479, p-value = 0.028), average mediolateral (ML) hand segment velocity (r = 0.494, p-value = 0.023), and path length (r = -0.522, p-value = 0.015) having statistically significant correlations with the average BBT, as shown in Table 2. Peak shoulder FLEX angle shows a moderately strong negative correlation, peak wrist EXT angle shows a negative correlation as well, but it is a moderately strong relationship. Average ML hand velocity showed a moderately strong positive correlation. Average wrist EXT angle (ρ = -0.535, p-value = 0.012) also showed a significant negative correlation.

Table 2. Significant correlations between measures of interest and BBT score across all age groups.

	Pearson's Correlation		Spearman's ρ	
Kinematic and Spatial Measures	*r*	*p-value*	*ρ*	*p-value*
Peak Sho FLEX	-0.556	0.009		
Avg Wrist EXT			-0.535	0.012
Peak Wrist EXT	-0.479	0.028		
Avg ML Hand Velocity	0.494	0.023		
Path Length	-0.522	0.015		

A seen in Table 3, correlations performed on only the 7-year-old age group resulted in significant correlations between average BBT score and average wrist radial deviation (RD) angle ($r = -0.744$, p-value = 0.034), average anterior-posterior (AP) hand segment velocity ($r = 0.812$, p-value = 0.014), average ML hand segment velocity ($r = 0.715$, p-value = 0.046), and average wrist EXT angle ($\rho = -0.833$, p-value = 0.010).

Table 3. Significant correlations between measures of interest and BBT score within the 7-year-old age group.

	Pearson's Correlation		Spearman's ρ	
Kinematic and Spatial Measures	*r*	*p-value*	*ρ*	*p-value*
Avg Wrist RD	-0.744	0.034		
Avg Wrist EXT			-0.833	0.010
Avg AP Hand Velocity	0.812	0.014		
Avg ML Hand Velocity	0.715	0.046		

The results for the 9-year-olds consisted of the average shoulder abduction (ABD) angle ($r = 0.871$, p-value = 0.024), peak shoulder ABD angle ($r = 0.876$, p-value = 0.022), and peak wrist EXT angle ($r = -0.813$, p-value = 0.049) being significantly correlated with average blocks moved, reported in Table 4. The Spearman's ρ non-parametric test showed correlations between average wrist EXT angle (ρ = -0.886, p-value = 0.019), average wrist FLEX angle (ρ = 0.943, p-value = 0.005), and peak wrist FLEX angle (ρ = 0.886, p-value = 0.019) and average BBT score.

Table 4. Significant correlations between measures of interest and BBT score within the 9-year-old age group.

	Pearson's Correlation		**Spearman's ρ**	
Kinematic and Spatial Measures	*r*	*p-value*	*ρ*	*p-value*
Avg Shoulder ABD	0.871	0.024		
Peak Sho ABD	0.876	0.022		
Avg Wrist EXT			-0.886	0.019
Peak Wrist EXT	-0.814	0.049		
Avg Wrist FLEX			0.943	0.005
Peak Wrist FLEX			0.886	0.019

Pearson's correlation test showed that average elbow pronation (PRO) angle (r = 0.761, p-value = 0.047) and average wrist RD angle (r = 0.896, p-value = 0.006) were all significantly correlated with average BBT score for the 11-year-old age group, as seen in Table 5.

Table 5. Significant correlations between measures of interest and BBT score within the 11-year-old age group.

	Pearson's Correlation	
Kinematic and Spatial Measures	*r*	*p-value*
Avg Elbow PRO	0.761	0.047
Avg Wrist RD	0.896	0.006

The results of examining significant differences between average BBT scores for each age group showed that significant differences (p-value = 0.005) were observed between the 7-year-old and the 11-year-old age group, as shown in Table 6. Peak shoulder FLEX (p-value = 0.024) and ABD (p-value = 0.022) angles were significantly different between the 7- and 11-year-old age groups.

Peak elbow FLEX was found to be significantly different (p-value = 0.049) between the 9- and 11-year-old age groups. Averages for hand segment velocity and path length are listed in Table 7.

Table 6. Resulting BBT scores and average and peak kinematics for the 7-, 9-, and 11-year-old age groups.

	Mean (SD)		
	7-year-olds	*9-year-olds*	*11-year-olds*
BBT Score [Blocks]	44.88 (6.03)	52.44 (3.77)	56.95 (8.37)*
Joint Angles [degrees]			
Avg Sho FLEX	56.04 (11.07)	49.60 (8.82)	46.58 (16.18)
Avg Sho ABD	47.56 (8.87)	45.25 (10.10)	36.91 (7.34)
Avg Sho IR	30.79 (12.17)	27.36 (3.65)	25.64 (8.43)
Avg Sho ER	6.30 (7.91)	1.90 (2.74)	2.08 (2.32)
Peak Sho FLEX	79.32 (11.95)	70.27 (7.79)	61.25 (14.68)*
Peak Sho ABD	55.52 (8.42)	52.22 (9.65)	43.16 (6.09)*
Peak Sho IR	48.43 (17.62)	48.41 (4.73)	40.99 (8.43)
Peak Sho ER	9.08 (11.27)	2.93 (4.23)	3.14 (3.55)
Avg Elbow FLEX	90.17 (12.57)	97.84 (9.89)	94.67 (6.32)
Avg Forearm PRO	98.50 (14.00)	94.81 (17.01)	109.98 (10.05)
Peak Elbow FLEX	98.88 (11.67)	107.27 (6.48)	94.67 (6.34)**
Peak Forearm PRO	114.00 (15.53)	108.32 (18.39)	122.41 (8.91)
Avg Wrist FLEX	1.56 (1.66)	1.77 (2.14)	1.56 (2.22)
Avg Wrist EXT	22.71 (10.04)	18.97 (10.87)	17.25 (5.44)
Avg Wrist RD	10.34 (5.49)	16.00 (5.71)	13.64 (3.72)
Peak Wrist FLEX	2.13 (2.19)	2.76 (3.37)	2.33 (3.28)
Peak Wrist EXT	33.89 (10.22)	26.91 (11.74)	28.46 (5.81)
Peak Wrist RD	14.24 (5.47)	19.44 (5.45)	17.61 (3.03)

* p-value < 0.05, difference between 7-year-old age group

** p-value = 0.049, difference between 9-year-old age group

Table 7. Resulting hand segment velocities and path length for 7-, 9-, and 11-year-old age groups.

	Mean (SD)		
Hand Segment Velocity [cm/s]	*7-year-olds*	*9-year-olds*	*11-year-olds*
Avg ML	51.48 (10.95)	56.81 (8.24)	56.93 (5.59)
Avg AP	13.21 (3.55)	14.86 (1.94)	14.54 (3.36)
Avg SI	48.49 (12.79)	58.63 (7.90)	54.31 (6.81)
Peak ML	104.76 (21.22)	114.82 (18.65)	115.04 (14.35)
Peak AP	32.04 (8.63)	32.71 (5.00)	31.98 (7.63)
Peak SI	123.54 (24.89)	139.78 (15.93)	129.14 (21.14)
Path Length [cm]			
Avg Path Length	20.26 (2.24)	18.83 (3.25)	18.50 (2.82)

* p-value < 0.05, difference between 7-year-old age group

SI = Superior-Inferior

Discussion

Understanding kinematic correlations between BBT scores in a pediatric population as well as examining kinematic and BBT score differences between age groups were the two goals for this study. Standardized, functional movement assessments are clinically beneficial due to the ease of administration and simple understanding of the outcome measures. However, there is the possibility of kinematic data being overlooked, which could show signs of functional impairment or compensation methods. Additionally, there is a need for normalized BBT scores for a pediatric population in literature, which allows an examination of the score differences between age groups as well as kinematic differences. The resulting kinematic correlations for all participants between BBT scores and shoulder and wrist kinematics, as well as hand segment velocity and path length, were found to be significant which agrees with the hypothesis stated for this study. Significant differences in BBT scores and kinematics were found between the 7- and 11-year-old group and the 9- and 11-year-old group, which partly agrees with the hypothesis.

Overall, there exists significant correlations between BBT scores and shoulder and wrist angles as well as hand velocity. Significant elbow joint correlations were only seen in the 11-year-old age group. There were correlations seen for path length, but only across all age groups. It was not correlated within age groups. Additionally, there were only significant differences between the 7-year-old and 11-year-old groups for BBT scores. While significant differences in kinematic measures existed between the 7- and 11-year-old age groups and the 9- and 11-year-old age groups. The significant differences between the two age groups are consistent with findings reported by Mathiowetz et al., who saw an average BBT score difference of 14 blocks between the 7-year-old group and the 11-year-old group.[7] Similarly, the difference between the average BBT scores of the two groups from this study is 12.73 blocks. However, there are discrepancies between the average BBT scores for each group reported by Mathiowetz et al. compared to the results obtained from this study.[7] This can be attributed to the smaller sample size and the addition of the modified BBT, which can lead to a reduction in score.

It was found that the overall kinematic correlations to BBT score didn't match specific age group correlations. Peak shoulder FLEX angle was shown to be significantly correlated to BBT score for the combined age groups, however, this correlation was not seen within each group. This could be due to shoulder stability changes in children, which are related to overall motor function during childhood.[14] Shoulder stability is directly related to resultant kinematic measures.[40] Therefore, shoulder kinematics can be considered age-dependent and may not prove optimized movement performance. Similarly, path length shows significant BBT score correlation across all age groups but is not correlated within each age group. This shows another effect of age rather than score improvement. However, wrist kinematics are seen to be correlated within each age group as well as across the age groups. This shows that wrist kinematics are not age dependent in terms of examining correlation and can be seen as a method for performance optimization. Only the 7-year-old age group showed significant correlations for hand segment velocity, which could lead us to believe that that age group is using speed to improve their score. The 9-year-old age group showed the largest number of significant correlations, which could show that they are trying different methods to complete the task. Finally, the 11-year-old age group had only two significant correlations, which shows possible focus on specific movements that are able to complete the task efficiently.

The correlations reported between BBT scores, and kinematics could not be directly compared to results in literature. However, the results of the average kinematics during the BBT can be compared to results reported by Kontson et al. They presented graphical results for adults performing a standard BBT and the general joint angle ranges are consistent with findings from this study.[39] The BBT scores reported for the age groups in this study are lower than reported scores in other studies. Espinosa et al. reported average BBT scores for 7-, 9-, and 11-year-olds to be 53.66, 63.02, and 70.07, respectively.[41] Additionally, Jongbloed-Pereboom et al. reported scores of 51.1 for a 7-year-old age group and 57.4 for a 9-year-old age group.[35] The published scores are also similar to scores reported by Mathiowetz et al. with reported scores of 54.4, 63.4, and 68.4 for 7-, 9-, and 11-year-old age groups, respectively.[7] The differences in reported scores could be attributed to the modified BBT that was used in this study, with the participants focusing on the general placement of the block. Additionally, all three BBT score publications examined sample sizes of over 100 participants; therefore, sample size differences could be a factor.

Limitations and Future Studies

Upper extremity functional tests are becoming more prevalent due to the ability to quantify an upper limb movement despite the difficulty of inherent movement variability in upper limb tasks.[42] Upper extremity movement tasks are often constrained to reduce the possibility of movement variability affecting kinematic standards.[17] Consequently, within-subject movement variability continues to reduce the ability to standardize upper extremity kinematics, even with the addition of functional tasks related to ADL, which could be the cause of the lack of correlation between some kinematic measures and BBT scores.[42] This could be mitigated by recruiting a larger sample size, which should reduce the movement variability across groups. Additionally, a simpler marker set was used to analyze upper extremity kinematics, which could lead to misrepresented kinematics, so a more complex marker-set with optimized rotation sequence techniques should be adopted for further examination. Future studies could further explore upper extremity kinematics related to the BBT. Trunk kinematics were not collected in this study but would be beneficial in understanding performance optimization during the BBT.[43]

Ch. 3 Validation of Upper Extremity Kinematics in Typically Developing Children using Markerless Motion Capture

Abstract

Movement research has typically been performed using three-dimensional (3D) marker-based motion capture, which is considered the "gold-standard" of biomechanical assessment. However, limitations exist due to the lack of portability, extensive preparation for data collection, and possible skin irritation due to adhesives used to attach markers. Additionally, extensive training is required to accurately place markers on body landmarks in relation to joint centers to produce results that are without error. However, there is inherent error due to motion artifact stemming from skin movement, especially when examining quick movements. *Theia3D* (Theia Markerless Inc., Kingston, ON, Canada), a Markerless motion capture system, is becoming a frequently used method of determining kinematics. It requires little preparation and there is no need to alter participant clothing. It has also been validated for the lower extremity in healthy older adults during gait. However, it has not been validated for other populations such as children or in upper extremity (UE) analysis. Therefore, the purpose of this study is to examine deviations in calculated UE kinematics between marker-based and Theia3D, a markerless motion capture system. Participants attended data collection for 1 visit split into 2 sessions. Marker-based and markerless motion capture data were collected simultaneously while participants completed the Box and Blocks test (BBT). Cycles during the task were determined and applied to the kinematic data from both systems to ensure identical conditions for comparison. A model for marker-based data was developed to closely match the embedded Theia3D reference model, with the same segment coordinate systems and joint rotation sequences in joint angle calculations. Root mean square deviation (RMSD) values were determined between demeaned UE joint angles for the two systems. RMSD values for all UE joint angles were found to be less than 6°. Intraclass Correlation Coefficients (ICC) were determined to examine between session reliability for Theia3D. ICC values between 0.75 and 0.9, showing good to excellent between session reliability, existed for the shoulder, forearm, and wrist.

Introduction

Upper extremity (UE) movement analysis has become an emerging area of exploration due to the introduction of technologies and research that assist with the difficulties that inherently exist in the upper limbs. Measurement devices such as Inertial Measurement Units (IMUs), marker-based motion capture, and newly introduced Markerless motion capture technologies have been used to examine UE kinematics. Upper limb function plays an important role in completing activities of daily living (ADL) with tasks that involve grasping, reaching, transporting, etc. Additionally, several upper extremity tests exist to test motor function in early childhood to determine if there is normal motor function or if interventions must occur due to motor function.[44] Therefore, understanding the motor function of typically developing children can provide insight into the early detection of motor function impairments.

IMUs are commonly used for movement analysis due to their small size and portability. They are microelectromechanical systems (MEMS) that use an embedded accelerometer and gyroscope to determine kinematic.[18] IMUs are ideal for at-home or clinical use as explored by Held et al, where they examined the kinematic improvement of patients with stroke during everyday tasks.[45] This was an ideal application due to the ability to have the patient wear it at home and perform daily activities. However, when IMUs are used in athletic settings, to examine movement in sports, it can lead to error due to the movement of the device on the skin causing significant errors.[46] Due to biases, misalignments, scale factor imperfections, or noise, data accuracy declines over long periods.[47] The algorithms that accompany the determination of joint kinematics allow room for error due to the need for extensive knowledge of the measurement device.[46]

The most common method of capturing joint kinematics in the UE is three-dimensional (3D) marker-based motion capture, which is also considered a gold-standard for all kinematic analysis. The measurement analysis consists of actively tracking retro-reflective markers that are attached to a participant. Then that data can be used to determine joint kinematics and analyze movement. However, some limitations accompany the use of marker-based motion capture, such as motion artifact errors due to skin movement, the possibility of markers falling off or being occluded[48], and the extensive training needed to place markers on bony landmarks to accurately capture joint kinematics, which also leads to error in repeatability. Measurement accuracy is especially affected by motion artifact in upper extremity joints, such as the shoulder, where scapular movement is difficult to examine.[49] There exist several methods of marker placements and model building to reduce errors in kinematic data.[38,50,51] Additionally, there needs to be time allocated to a study procedure to apply the markers and there is the risk of skin irritation due to the adhesive used to attach them. The marker-based systems are not portable and are expensive, which leads to the inability to provide this type of movement assessment in a clinical setting or at home. Therefore, many of these movement measurement devices are application based.

There has been recent advancement into markerless motion capture, which alleviates the limitations that researchers experience using other measurement devices. Markerless motion capture uses machine learning to analyze thousands of photos of different people in various settings, to estimate human poses.[52] This kinematic measurement method relies on software rather than hardware to produce pose estimations of input videos of movement. Similar to marker-based motion capture, more cameras provide increased accuracy in the determination of joint centers based on visual indications of the human body.[24] There is accessible motion capture software such as Microsoft Kinect[53] and *OpenCap*, which is an open-access and web-based software. However, the kinematic processing in both systems experiences significant errors when excessive movement occurs and, in the ankles, and feet.[27,54]

This study explores the reliability and repeatability of the markerless motion capture system *Theia3D* (Theia Markerless Inc., Kingston, ON, Canada). Theia3D uses deep-machine learning that analyzes thousands of images of the human body in different settings and wearing various types of clothing and joint landmarks are marked by highly trained annotators.[28] Due to the software's ability to use surface indicators to determine joint landmarks, participants can wear any clothing.[29] Validation of Theia3D using the gait of healthy adults resulted in an average root mean square distance (RMSD) of less than 3 cm for all joints except for the hip at an RMSD of 4.1 cm. All lower limb segment angles had an RMSD of less than 6°, except for rotations about the long axis of the segment.[6] A more recent validation on upper extremity movement in boxing has been performed, which resulted in larger joint position differences in the elbow at 3cm, than the shoulder and wrist with less than 2.5 cm.[55] However, the validation was performed on a smaller sample size and young adults. Nonetheless, Theia3D validation for joint kinematics has mostly been performed on the lower extremity during gait and on healthy adults.[26] Markerless motion capture would be a beneficial software to be used in a pediatric population due to the speed of collection as well as the reduction of limitations that accompany marker-based motion capture. Therefore, this study aims to validate the Markerless motion capture system, Theia3D, which could provide insight into the ability to capture accurate upper extremity joint kinematics in children. It is hypothesized that the angular measurements from the Markerless motion capture system would have an RMSD value within 6 degrees of the marker-based data, which is based on lower-extremity expectation from Kanko et al.[26] Additionally, the Markerless results are expected to show good to excellent between session repeatability, with intraclass correlation coefficients (ICCs) greater than 0.75.

Methods

Participants

Through an institutional review board-approved research study and consent process with minors (IRB #22-662), 18 typically developing children participated in this study. They were recruited with the inclusion criteria that consisted of the participants being 7, 9, or 11 years old, having full upper limb mobility, being able to complete activities without continuous assistance, having no medical conditions that could inhibit full participation, being able to follow verbal and visual instructions, and having full understanding of English. If the participants had any injuries or neuromotor disorders that directly affect their upper limbs, they were excluded from the study.

Testing Procedure

Demographic information including age, sex assigned at birth, height, weight, and upper limb dominance was collected for each participant. Upper limb dominance was determined by asking the participant which hand they use to write. Following the collection of demographic information, a retroreflective marker set, determined from the c-motion Plug-In Gait Full Body[37] and the Rab Upper Extremity Model[38], was applied to the participant. Markers for pelvis and thorax determination were placed on the left and right iliac crest, left and right anterior superior iliac spines, left and right posterior superior iliac spines, sacral, 7th cervical vertebrae, xiphoid process of the sternum, the suprasternal notch, 10th thoracic vertebrae, right scapula, and left and right acromioclavicular joint. The upper and lower arm and hand creation are driven by the medial and lateral epicondyle of each humerus, left and right olecranon, distal radius and ulna of each wrist, distal end of the third metacarpal bone on each hand. Humeral rotation is tracked by two, 4-marker rigid clusters placed laterally on each humerus, secured by a non-adhesive elastic bandage. Marker-based data were captured using a 10-camera 3D motion capture system (Qualisys, Gothenburg, Sweden) at 170 Hz, while markerless data was simultaneously captured using an 8-camera 3D motion capture system (Theia Markerless Inc., Kingston, ON, Canada) at 85 Hz. The 8-camera Markerless motion capture cameras were organized in a circle that surrounded the testing area.

A static trial was collected for the marker-based motion capture system, following the marker application. The participant stood as still as possible in an anatomical position for 10 seconds to ensure static marker occlusion did not occur. This is a possibility due to children having a small distance between joint landmarks. Once the static trial was completed, a table, stool, and BBT were brought into the testing space. The table had a standard height of 131.1 cm, and the adjustable stool was set at a height of 51.3 cm and was kept at that height for all participants. A modified BBT was implemented, developed based on methods published by Kontson et al., as shown in Figure 6.[39] Once the participant was comfortably seated on the stool, the BBT was placed ~2.5 cm from the edge of the table. Then the participant was asked to extend their arms directly in front of them and the table with the BBT is brought toward them until their fingertips could touch the back edge of the BBT.

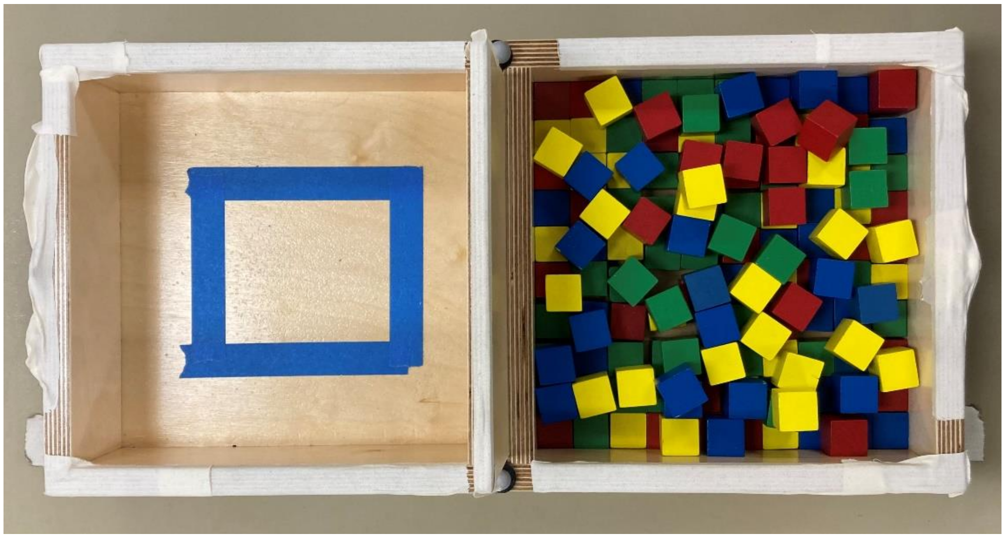

Figure 6. Overhead view of the modified BBT.

The participant was given verbal and physical instructions on how to complete the BBT. The participant was told to move as many blocks, one-by-one, as they can in 60 seconds. They must start with both hands flat on the table until the start of each trial is indicated with a verbal cue: "ready, set, go". The participant then began the trial with the indicated limb. They must have their hand completely over the divider before they can release the block. Additionally, they were encouraged to aim for the smaller taped square within the box, to allow for the possible reduction in movement variability. Each trial would end with the verbal indication: "stop". The participant would not receive encouragement throughout each trial. However, they were told that if they were not following the instructions, they would be corrected during the trial with the ability to continue, or if the correction is too drastic, the trial would have to be redone. The participant switched between arms for each trial to reduce the possibility of fatigue. They were also allowed to rest in between trials if needed. The participant completed 3 trials for each limb. Then the markers were removed, and the participant was given a break of a minimum of 15 minutes before repeating the procedure.

Data Processing and Analysis

The three-dimensional (3D) Markerless motion capture data was collected using Qualisys Track Manager (Qualisys, Gothenburg, Sweden) and processed using the Theia3D markerless motion capture software. The data was then exported, and kinematic analysis was performed in Visual3D. The rotational data exported from the Theia3D software into Visual3D was filtered with a low-pass Butterworth filter at a cutoff frequency of 7 Hz. Marker-based 3D motion capture data was collected and processed using Qualisys Track Manager (Qualysis, Gothernburg, Sweden). Kinematic analysis was performed in Visual3D. Marker data were filtered using a lowpass Butterworth filter at a cutoff of 7 Hz. For both systems, joint angles and joint angular velocities were calculated in Visual3D as well as hand segment velocity and position data. An XYZ rotation sequence was used for all joint kinematics. To ensure the kinematic analysis was performed similarly in both systems, a model in Visual3D was built for the marker-based data with similar joint coordinates as the Theia3D imbedded model. The joint angles analyzed included shoulder flexion (FLEX), abduction (ABD), and internal/external rotation (IR/ER), elbow FLEX and forearm pronation (PRO) and wrist flexion/extension (FLEX/EXT) and radial (RD) deviation. Forearm PRO was calculated from the Z-coordinate for the elbow joint center. A custom

MATLAB code was then used to determine each successful block movement or cycle. The conditions assigned for a cycle consisted of the participant reaching into the box for block pickup to block release. The middle 15 cycles were considered for analysis to ensure a reduction in movement variability by allowing the participant to become consistent with their block transfers. The two systems were synchronized by determining when the participant moved their first block. The moving of the first block was defined as the point when the hand segment position first crossed over the divider. Overall average and peak joint angles and angular velocities were calculated between the 15 cycles and 3 trials for the dominant limb. Hand position data was used to determine the average path length of each cycle. This analysis was performed for both sessions of data collection. Additionally, the average of each joint angle was subtracted from the original data to account for offset bias and the average root mean square deviation (RMSD) was determined for session one between the two systems.

Statistical Analysis

To examine measurement system reliability, Intraclass correlation coefficients (ICCs) were determined between Markerless motion capture sessions for all average joint kinematics using a MATLAB function. An ICC(C,1) model was used based on conditions detailed by McGraw et al.[56] ICC range classifications consist of poor reliability, with ICCs less than 0.5, moderate reliability is represented by ICCs between 0.5 and 0.75, ICCs between 0.75 and 0.9 show good reliability and excellent reliability is represented by ICCs greater than 0.9.[57]

Results

Population

20 participants were included in this study consisting of eight 7-year-olds, six 9-year-olds, and six 11-year-olds. In total, there were 12 males and 8 females. Detailed demographics are reported in Table 8.

Table 8. Mean (SD) of demographics for the participants in the study.

Age [years]	7		9		11	
	Male	Female	Male	Female	Male	Female
	4	4	3	3	6	1
Height [cm]	128.22 (4.34)		140.87 (3.21)		149.1 (5.65)	
Mass [kg]	25.85 (3.79)		32.35 (4.39)		41.42 (12.62)	

Marker-Based vs Markerless

As shown in Table 9, the demeaned joint angles all resulted in RMSD values less than 6°.

Table 9. Root mean square deviation (RSMD) values between the marker-based and Markerless systems demeaned average joint angles.

	RMSD	**SD**
Sho FLEX	3.45°	2.09°
Sho ABD	2.84°	1.84°
Sho IR/ER	5.02°	2.16°
Elbow FLEX	2.66°	1.38°
Forearm PRO	5.04°	0.92°
Wrist EXT/FLEX	3.01°	0.72°
Wrist RD	2.71°	0.47°

Between Session Reliability

ICC values that show good between session reliability are observed in shoulder ABD angle (ICC = 0.79), forearm pronation (PRO) angle (ICC = 0.81), wrist EXT angle (ICC = 0.75), and wrist RD angle (ICC = 0.87). The remaining measures of interest show moderate reliability, with ICCs between 0.5 and 0.75, seen in Table 10.

Table 10. Average joint angles for both Markerless sessions with corresponding ICCs.

	Mean (SD)		
Joint Angle (degrees)	*Session 1*	*Session 2*	**ICC**
Sho FLEX	68.10 (9.44)	69.51 (9.88)	0.54
Sho ABD	36.22 (6.83)	37.53 (8.30)	0.79*
Sho IR	50.18 (10.19)	51.74 (9.44)	0.74
Sho ER	0.16 (0.44)	0.23 (0.74)	0.59
Elbow FLEX	79.04 (10.55)	76.90 (9.99)	0.69
Forearm PRO	94.05 (6.45)	96.26 (5.79)	0.81*
Wrist EXT	10.85 (3.41)	10.13 (3.40)	0.75*
Wrist FLEX	3.09 (2.51)	3.15 (2.86)	0.68
Wrist RD	9.10 (4.20)	8.47 (4.98)	0.87*

*ICC > 0.75, good to excellent between session reliability

Discussion

This study proposed to examine kinematic comparisons between marker-based and Theia3D Markerless motion capture data, as well as examine between session reliability for the Markerless system. While marker-based motion capture is widely considered the "gold-standard" of movement analysis, there exist limitations that could cause errors within the data. These limitations especially apply to pediatric populations due to their small size, increasing the possibility of marker occlusion, the risk of irritation caused by the adhesive used to attach the markers, and excess movement variability, causing markers to shift on the skin surface. Markerless motion capture is an attractive method for quantitative movement analysis due to the ability to capture motion data without having the participant wear specific clothing or be fitted with retroreflective markers. The results from the upper extremity (UE) kinematic differences between systems showed that the root mean square deviation (RMSD) values for the demeaned shoulder, elbow, and wrist joint angle data were all less than 6°, which supports the first hypothesis. Additionally, between session reliability for the markerless system resulted in ICCs greater than 0.75 for the shoulder and wrist, partially agreeing with the second hypothesis.

These results partly contradict the RMSD values reported by Lahkar et al. who found RMSD values for wrist RD and FLEX angle around 11° and 14°, respectively.[55] However, for this study, offset bias was accounted for by demeaning the data. The results from the study published by Kanko et al. shared similar findings to this study, with slight measurement errors below 4°, except for hip and ankle abduction/adduction and internal/external rotation.[26] Due to the known difficulty of accurately capturing joint kinematics in the shoulder, several methods for marker placement and shoulder joint coordinates and rotation sequences have been proposed, which are a large source of differences in reported kinematics for the UE.[58–60] Additionally, studies have explored UE kinematic analyses that are task-specific, so optimization techniques have been performed to achieve accurate results.[61] Therefore, the marker placement and the model creation for the marker-based data were developed based on optimizing kinematic data accuracy, with only the joint coordinate systems and rotation sequences matching between systems. The model developed by Theia3D involves the clavicle as part of the kinematic chain, which was not developed in the marker-based model.[62] Nonetheless, it should be noted that the hypothesized RMSD value for this study was determined from the study performed by Kanko et al., in which lower-extremity joint angles were explored.

Shoulder abduction (ABD), forearm pronation (PRO), wrist extension (EXT), and wrist RD all showed good between session reliability, with ICCs greater than 0.75. Kanko et al. have been the only reporters of measurement reliability for Theia3D, and it was performed on lower extremity kinematics during gait. Kinematic measures that resulted in ICCs less than 0.75 could have been affected by movement variability involved in completing the task. Although the task is cyclic and general factors were controlled, there exists the possibility of kinematic differences between participants, due to differences in motor function caused by age group differences and compensatory methods to complete the task.

Overall, comparing UE kinematics for the two systems showed close similarities and Theia3D showed good to excellent between session reliability for approximately half of the kinematic measures. The results of this study are beneficial to the introduction of markerless motion capture use in movement analysis by showing that UE movement is inherently complex and that must be considered when analyzing task-specific movements. Therefore, understanding what limitations exist for markerless motion capture assists in further UE research. Additionally, this has proven that movement variability has a large impact on between session reliability. However, further exploration validation of Markerless motion capture using controlled UE movements would further solidify the reliability of Theia3D as an option for 3D movement analysis.

Ch. 4 Conclusions

Correlations between UE kinematics in a pediatric population exist between Box and Blocks test (BBT) scores. There are significant differences between the 7- and 11-year-old age groups and the 9- and 11-year-old age groups for BBT scores and shoulder and elbow kinematics. It is also important to note that peak shoulder flexion correlations that exist across all age groups do not exist within each age group. Therefore, understanding how shoulder kinematics differ between age groups is beneficial for determining accurate kinematic performance metrics.

The first aim sought to understand how performance for a subjective, functional test could be related to UE kinematics as well as explore kinematic and BBT score differences between age groups that are known to have different motor function levels.[36] Marker-based motion capture was used to collect kinematic measures during the BBT in a pediatric population consisting of 7-, 9-, and 11-year-old age groups. The middle 15 successful block movements, or cycles, for the dominant limb, were used to determine average and peak joint angles as well as hand segment velocity and path length. Pearson Correlation Coefficients were found between the normally distributed kinematic measures and BBT score, while non-normal measures were reported using Spearman's ρ. Additionally, kinematic measures and BBT score differences between age groups were examined. The results showed that correlations between BBT scores and UE kinematics exist across age groups and within age groups. It showed slight variation in what was correlated within each group, with a significant correlation found for peak shoulder flexion angle across the groups but was not found within the age groups. This was likely caused by motor function differences between these age groups, meaning this measure should be more correlated with age than BBT score. Similarly, path length and BBT score were correlated across age groups but not within age groups. Nonetheless, wrist kinematics and BBT score were found to be correlated across groups and within groups, which could confirm the wrist joint as an area of performance optimization when completing the BBT.

Significant differences between age groups were shown between 7- and 11-year-olds and 9- and 11-year-olds, which slightly deviates from the hypothesis. BBT scores were only significantly different between the 7- and 11-year-old age groups. However, the age group distinction was determined based on the Movement Assessment Battery[36] and there have been previous studies exploring BBT scores and have found that there are no significant differences between 9- and 11-year-olds.[7] BBT scores between the 7- and 9-year-old age groups were expected to be significantly different due to motor performance increases according to Leversen et al.[14] Additionally, the previously reported BBT scores showed large differences between 7- and 9-year-olds, therefore, it is expected for them to exist in this study. This could be caused by motivation differences between age groups, which have been shown to improve task performance.[63] Additionally, an increase in sample size could result in differing scores.

The second aim proposed to validate Theia3D, a markerless motion capture software, in a pediatric population completing the BBT. Between session reliability was also determined. Marker-based and markerless motion capture data was captured simultaneously over a 2-session testing period. The same method for cycle determination from aim 1 was used but was based on the Theia3D data then carried over to the marker-based data. To ensure data accuracy, the model developed using the marker-based data followed the same coordinate system as the embedded Theia3D model, and joint angles for both systems were calculated using an XYZ rotation sequence. Average and peak joint angles were determined, and the average joint angle was subtracted from each original set of data to reduce offset bias for the two systems. Root mean square deviation (RMSD) values were calculated for each demeaned joint angle. Intraclass correlation coefficients (ICCs) were found for Theia3D between sessions to examine the reliability of the measurement system. The results showed RMSD values below 6° for all joint angles. The largest RMSD values exist in shoulder IR/ER and forearm PRO, which are both z-axis rotation angles. This was also seen by Kanko et al. This shows that there are differences in pose estimations between the systems, in which the error is increased with rotations about the long axis of the segment. This shows that is a possible error in the system set-up for comparison examination, rather than an error in the system. Resulting ICCs that had good to excellent between session reliability, or ICCs > 0.75, were found in the shoulder and wrist. The remaining ICCs showed moderate reliability. This could be due in part to the general movement variability that exists within the task itself, which could show misleading results.

The resulting RMSD values agree with the first hypothesis and the ICC values partially agree with the second hypothesis. The RMSD values reported by Kanko et al. for the lower extremity joint angles were approximately 6° and the values that had larger deviations consisted of axial joint rotations, which was similar to the results from this study. This shows that to report comparisons accurately and meaningfully between marker-based and markerless motion capture, full ROM in upper extremity joints should be examined. Additionally, system comparisons should contain more variables that match between the systems. However, with the complexity of the shoulder, accuracy in determining those joint motions must be explored. Due to the possibility of movement variability within the BBT, a further examination into more controlled movement could be beneficial in determining consistency between session results.

Overall, the 2 aims explored in this study provide insightful data as well as motivation to characterize upper extremity kinematics during functional tasks. Additionally, this could lead to the introduction of markerless motion capture into clinical settings.

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