
Master thesis : Kinematic Profiling of Motor Patterns Using Body-Worn Sensors in Typically Developing Children and Adults: Establishing a Reference Framework for Future Assessment in Children with Neurodevelopmental Disorders (including introduction to research methodology)

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Kinematic Profiling of Motor Patterns Using Body-Worn Sensors in Typically Developing Children and Adults: Establishing a Reference Framework for Future Assessment in Children with Neurodevelopmental Disorders.

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Abstract

Motor development involves substantial changes in movement organization, coordination and control throughout childhood. Objective quantification of these changes could complement conventional clinical assessments and provide a basis for the future characterization of motor alterations associated with neurodevelopmental disorders. This study aimed to develop and evaluate a functional motor assessment protocol combining three-dimensional (3D) optoelectronic motion capture and wearable inertial measurement units (IMUs), and to investigate the potential of IMU-derived parameters for distinguishing typically developing children from adults.

A group of typically developing children aged 6-12 years and a group of adults were recruited to establish and compare their kinematic profiles. Participants performed eight experimental tasks assessing different aspects of motor function, including gait, postural control, fine upper-limb motor function, social interaction, and object affordance. 3D reflective markers and IMUs were positioned at C7, the pelvis and the dominant wrist. A broad set of movement features was extracted and classified into six categories: *Speed and Acceleration*, *Movement Smoothness*, *Efficiency*, *Control Strategy*, *Signal Complexity*, and *Inter-segmental Coordination*. Statistical comparisons were then performed between the two groups.

Significant differences between typically developing children and adults were identified across all eight tasks, although their magnitude and nature were strongly task- and parameter-dependent. The two-leg standing task yielded the largest proportion of significant parameters, while the drinking and pegboard tasks were also particularly discriminative. Overall, *Speed and Acceleration* and *Movement Smoothness* provided the largest number of significant differences, whereas *Signal Complexity* and *Inter-segmental Coordination* measures provided complementary information on motor organization. Importantly, approximately half of the significant parameters across tasks were derived from IMU measurements, demonstrating their substantial contribution to group discrimination.

These findings demonstrate that typically developing children and adults exhibit distinct quantitative kinematic profiles across a range of functional motor tasks. They support the ability of the proposed protocol to characterize developmental motor differences and highlight the potential of wearable IMUs to simplify quantitative motor assessment. This work provides an encouraging methodological basis for future application of the protocol to children with neurodevelopmental disorders and for the development of more accessible instrumented motor assessment approaches.

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Introduction

Motor development is a continuous process through which motor abilities progressively evolve from childhood to adulthood. Throughout childhood, the interaction between neurological maturation, physical growth, experience, and motor learning progressively refines the way movements are planned, coordinated, and adapted to the constraints of the task and the environment [2, 3]. During this process, motor behaviour gradually becomes more stable, coordinated, and efficient, eventually approaching the more mature patterns observed in adulthood. Comparing motor behaviour across different stages of development can therefore provide valuable information about the progressive maturation of motor control and help establish reference patterns of typical motor development. Understanding typical motor development is also important in the context of neurodevelopmental disorders (NDDs), in which motor difficulties are frequently reported [4–6]. These difficulties may affect different dimensions of motor function and can interfere with everyday activities and autonomy. Characterizing typical developmental motor patterns therefore provides an important reference for the subsequent investigation of atypical motor development.

Recent developments in motion capture and wearable sensing technologies have made it possible to investigate human movement with increasing precision while also opening perspectives for more accessible assessment protocols. In particular, three-dimensional optoelectronic motion capture and wearable inertial measurement units (IMUs) provide complementary information about movement and represent promising tools for the quantitative characterization of motor behaviour. Their use could contribute to a better understanding of developmental motor differences and, in the longer term, support the development of objective approaches complementary to conventional clinical assessment. In this context, this study investigates the use of instrumented movement analysis to characterize motor development through a standardized multi-task protocol combining three-dimensional motion capture and wearable IMUs.

To address these objectives, this study is organized into six chapters. Chapter 1 presents the *State of the Art*, covering motor development and motor patterns across populations, standardized clinical motor assessments, task selection, and technologies used for quantitative movement analysis, with particular attention to optoelectronic systems and wearable IMUs. Chapter 2 defines the main objectives of this study. Chapter 3 describes the *Materials and Methods*, including the study population, experimental equipment, motor-task protocol, extracted movement parameters, parameter-reduction procedure, and statistical analysis. Chapter 4 presents and discusses the results obtained from the comparison between children and adults across the different experimental tasks. The findings are interpreted in relation to motor development, while the contribution and potential of IMU-based assessment are also evaluated. Chapter 5 discusses the main limitations of the study and the perspectives for future work, particularly regarding the improvement and simplification of the protocol and its future application to neurodevelopmental populations. Finally, Chapter 6 presents the general conclusion of this study.

Chapter 1

State of the Art

This chapter presents the theoretical and technological background underlying this study. Section 1.1 first describes motor development across populations, from typical development in childhood to adulthood, before addressing atypical motor development in children with neurodevelopmental disorders. Section 1.2 presents the main standardized clinical assessments currently used to evaluate motor function, with their relevance and limitations for the identification of motor difficulties. Then, Section 1.3 discusses the rationale behind the selection of the motor tasks considered in this study. Finally, Section 1.4 focuses on the use of technology for objective motor assessment. It introduces optoelectronic motion capture systems and inertial measurement units (IMUs), describes the main movement features that can be extracted from body-worn sensors. Together, these sections provide the theoretical basis for the development of the motor assessment protocol investigated in this study.

1.1 Motor Development and Patterns Across Populations

Motor development can be considered as a continuous process that evolves from childhood into adulthood. Motor performance changes progressively through the interaction between biological maturation, accumulated motor experience, practice and the constraints imposed by the body, the task, and the environment [2]. Consequently, motor development should not be considered as a simple linear consequence of physical growth. Instead, individuals progressively acquire a broader and more efficient repertoire of motor solutions that can be selected and adapted according to the situation. This evolution remains observable beyond early childhood. Indeed, motor performance has been shown to improve from childhood to young adulthood across both fine and gross motor tasks [3]. Motor performance should therefore be considered as a dynamic characteristic that changes throughout development, supporting the relevance of comparing motor behaviour at different stages of maturation.

1.1.1 Typical Motor Development of the Child

During school age, motor development is characterized by the progressive refinement and consolidation of previously acquired motor skills. Between childhood and adulthood, motor performance improves across a variety of tasks, including both fine and gross motor activities [3]. However, these changes cannot be attributed solely to increases in body size or age. Motor behaviour emerges from the interaction between the individual's current physical capacities, previous experience, and the specific constraints imposed by the task and the environment [2]. Repeated practice and exploration therefore contribute to the progressive development of more appropriate motor solutions.

These behavioural changes occur in parallel with the progressive maturation and reorganization of the neural systems involved in sensorimotor control. Motor behaviour does not depend on a single brain structure but rather on interconnected cortical and subcortical networks involving, among others, the motor

cortex, the basal ganglia and the cerebellum [7, 8]. These structures contribute complementary functions to movement control. The motor cortical areas are strongly involved in the planning and execution of voluntary movements, whereas the basal ganglia contribute to action selection, motor learning, and the progressive organization of appropriate motor responses. The cerebellum plays a major role in sensorimotor integration, movement coordination, error-based correction, and the prediction of the sensory consequences of an action [7]. Importantly, these structures should not be considered as independent systems, as the cerebral cortex, basal ganglia, and cerebellum interact through interconnected neural networks supporting motor control and learning [7]. These neural systems continue to undergo developmental changes throughout childhood and adolescence. Structural neuroimaging studies have demonstrated age-related changes in both the basal ganglia and cerebellum between childhood and early adulthood, with different structures following distinct developmental trajectories [8]. Such prolonged maturation provides a neural basis for the progressive refinement of motor control observed during childhood. In particular, the balance between feedback and feedforward-based control changes with age [9]. Younger children rely more strongly on sensory feedback to correct their movements during execution, whereas the ability to anticipate movement consequences based on previous experience and adapt actions through feedforward mechanisms progressively develops throughout childhood [9]. This transition remains particularly relevant during the age range investigated in this study, as developmental differences in motor adaptation remain observable between school-age children and adults [9]. Consequently, differences in movement smoothness, variability, coordination and temporal organization between children and adults may partly reflect the ongoing maturation of the neural networks underlying sensorimotor control.

An important aspect of motor development is the management of motor variability. Variability should not systematically be interpreted as poor motor control, particularly during development. The availability of multiple movement solutions provides opportunities for exploration and contributes to motor learning. With increasing experience, the developing nervous system becomes progressively better able to select motor solutions that are appropriate for the specific context. *Hadders-Algra* describes motor development as involving a progression from abundant motor variation toward an increasing ability to vary and adapt movement according to environmental and task demands [10]. Motor maturation should therefore not necessarily lead to the disappearance of variability but rather to a more functional organization of this variability.

This progressive refinement can be observed through several characteristics of motor performance. With development, motor actions become increasingly adapted to the objective of the task, while the organization of different components of movement is progressively refined. Importantly, the developmental trajectory is task-dependent. Indeed, performance in one motor task does not necessarily represent an individual's performance in another. Studies examining several fine and gross motor tasks across age groups have demonstrated both age-related improvements and task-specific differences in motor performance [3]. This supports the use of multiple complementary motor tasks when characterizing developmental motor patterns rather than relying on a single movement.

Motor development is also strongly influenced by the opportunities for action provided by the environment. As motor abilities evolve, children continuously learn to adapt their movements to changes in their body, objects, environmental constraints, and previous experience [2]. Consequently, developmental differences may become more or less apparent depending on the requirements of a particular task. Tasks involving postural control, locomotion, reaching, object manipulation, or interpersonal interaction may therefore reveal different aspects of motor development.

Overall, school-age motor development can be viewed as a progressive reorganization and refinement of motor behaviour rather than as the simple acquisition of new movements. Children become increasingly capable of selecting and adapting motor solutions to the requirements of the task, while their motor

performance progressively approaches adult patterns. Nevertheless, substantial developmental differences remain observable between childhood and young adulthood [3]. For this reason, the 6-12-year age range investigated in this study represents a relevant developmental period for identifying kinematic and inertial markers associated with motor maturation.

1.1.2 Typical Motor Development of the Adult

Young adulthood is generally associated with a high level of motor performance and represents a period during which motor behaviour has reached a relatively mature organization. Across different fine and gross motor tasks, motor performance improves from childhood to young adulthood, reflecting the progressive refinement of motor abilities throughout development [3]. This maturation does not imply that the adult motor system becomes fixed. Rather, mature motor control remains highly adaptable, allowing movements to be continuously adjusted to changes in the body, the task and the environment [11].

An important characteristic of mature motor control is the ability to combine predictive and reactive mechanisms. Sensory feedback provides information about the current state of the body and allows errors to be corrected during movement, whereas predictive mechanisms use previous experience to anticipate the consequences of motor commands and adapt subsequent actions [11]. Recent developmental evidence shows that the relative contribution of these mechanisms evolves throughout childhood, with younger children relying more strongly on feedback-based corrections and feed-forward adaptation progressively approaching adult-like levels during adolescence [9]. Adults can therefore be considered an appropriate reference for a more mature balance between predictive adaptation and online feedback control.

At the neural level, mature motor control relies on the coordinated interaction of cortical and subcortical sensorimotor networks. The motor and premotor cortical areas contribute to the preparation and execution of voluntary actions, while the basal ganglia participate in action selection and the organization of learned motor behaviours. The cerebellum plays an important role in sensorimotor prediction, error-based learning, and the fine adjustment of ongoing movements. Importantly, these structures do not operate independently but interact through interconnected cortico-basal ganglia and cortico-cerebellar networks supporting motor control and learning [7]. Compared with childhood, adulthood is characterized by a more mature organization of these sensorimotor networks and by a more established integration of predictive and feedback-based mechanisms. This mature neural organization contributes to the ability to generate well-adapted motor commands while continuously integrating sensory information and correcting errors when required [9, 11]. Thus, the differences observed between children and adults at the kinematic level can be considered, at least partly, as behavioural manifestations of the ongoing maturation of the sensorimotor system during childhood.

This mature organization is particularly relevant for the kinematic characteristics investigated in this study. Skilled movements require the nervous system to integrate sensory information, select appropriate actions, and regulate movement according to task-dependent constraints such as accuracy and effort [11]. Consequently, developmental differences between children and adults may be expressed through several dimensions of movement, including its temporal organization, smoothness, variability, and coordination. However, these differences should not be interpreted according to a single universal pattern, as motor performance remains strongly dependent on the characteristics and requirements of each task. Indeed, developmental changes may differ between fine and gross motor activities [3].

In the context of this study, healthy adults therefore provide a reference for mature motor behaviour against which the motor characteristics of typically developing children can be compared. The purpose of this comparison is not to consider adult movement as an "ideal" motor pattern, but rather to identify which kinematic characteristics continue to differ between school-age children and individuals with a more

mature sensorimotor organization. This developmental comparison provides a basis for identifying parameters that are sensitive to motor maturation and that could subsequently be investigated in children with neurodevelopmental disorders.

1.1.3 Atypical Motor Development in Children with Neurodevelopmental Disorders

Neurodevelopmental disorders (NDDs) comprise a group of conditions with onset during the developmental period that affect different aspects of cognitive, behavioural, social and motor functioning [12]. Although NDDs are traditionally defined according to distinct diagnostic categories, they are characterized by substantial heterogeneity within diagnoses and frequent overlap and co-occurrence across diagnostic boundaries [13, 14]. This complexity challenges a strictly categorical interpretation of neurodevelopmental difficulties and supports the relevance of more dimensional and transdiagnostic approaches to characterize developmental profiles [14]. Motor function is particularly relevant within this perspective, as motor difficulties can be observed across several neurodevelopmental conditions, although their nature, severity, and functional consequences may vary considerably between individuals and diagnostic groups [6, 15]. Quantitative characterization of motor behaviour may therefore contribute to identifying both disorder-specific characteristics and motor features shared across neurodevelopmental profiles.

The DSM-5 includes several diagnostic categories within neurodevelopmental disorders, including autism spectrum disorder (ASD), attention-deficit/hyperactivity disorder (ADHD), developmental coordination disorder (DCD), specific learning disorders and communication disorders [12]. Although these conditions are defined by distinct diagnostic criteria, difficulties affecting different functional domains may coexist within the same child. This is particularly relevant for motor function. Indeed, motor impairment is central to the diagnosis of DCD, whereas clinically relevant motor difficulties may also occur in children with ASD or ADHD [4, 6]. Consequently, the presence and severity of motor difficulties cannot necessarily be inferred from the primary diagnostic label alone.

The frequent co-occurrence of neurodevelopmental difficulties has become an important consideration in the understanding of NDDs. Literature notably emphasizes that developmental difficulties involving motor coordination, attention, language, behaviour, cognition, and social interaction frequently overlap during childhood [13]. More recent transdiagnostic approaches similarly highlight that neurodevelopmental characteristics may extend across conventional diagnostic boundaries [14]. This overlap has important implications for motor assessment, since an observed motor difficulty may be associated with the primary diagnosis, a co-occurring condition such as DCD, or a motor dimension shared across several neurodevelopmental profiles [6, 15]. These observations support a more detailed characterization of individual motor profiles rather than relying solely on categorical diagnoses.

ADHD is primarily characterized by developmentally inappropriate levels of inattention and/or hyperactivity [12, 16]. Although motor difficulties are not part of its core diagnostic criteria, children with ADHD may present difficulties in motor coordination, timing, and regulation and co-occurring DCD is frequently observed [6, 16]. The motor phenotype associated with ADHD is therefore heterogeneous and some of the observed motor difficulties may be influenced by co-occurring developmental conditions rather than by ADHD alone. This distinction is particularly important when searching for quantitative motor markers, as motor performance should not be assumed to follow a unique ADHD-specific pattern. Then, from a neurodevelopmental perspective, ADHD has been associated with differences in the development and functioning of distributed brain networks involved in attention, executive control and behavioural regulation [16]. These functions interact with the processes required for the preparation and regulation of motor behaviour. Consequently, motor difficulties observed in some children with ADHD may reflect interactions between motor control, attention, inhibition, and executive processes rather than an isolated impairment of the motor system. Such interactions may contribute to the increased variability and difficulties in motor regulation reported in some children with ADHD [16]. Neuroimaging studies suggest that these

differences are distributed across several cortical and subcortical systems rather than being restricted to a single brain region. In particular, differences have been reported in fronto-striatal, fronto-parietal and fronto-cerebellar networks, involving regions such as the prefrontal cortex, basal ganglia, parietal regions, and cerebellum [17]. These networks contribute to functions such as executive control, inhibition, attention, and temporal processing, which interact with the regulation of motor behaviour.

DCD is the neurodevelopmental disorder in which motor impairment is most directly represented in the diagnostic definition. It is characterized by difficulties in the acquisition and execution of coordinated motor skills that are substantially below those expected for the individual's age and that interfere with activities of daily living, academic achievement, and leisure [4, 12]. Its clinical expression is heterogeneous and may involve difficulties in manual dexterity, balance, gross motor skills, motor learning, postural control, or combinations of these dimensions [4, 18]. Then, from a neurofunctional perspective, neuroimaging studies suggest that DCD is not associated with dysfunction of a single brain region but rather with differences across distributed neural networks involving sensorimotor, parietal, prefrontal, and cerebellar regions, as well as their structural connectivity [18, 19]. These neural systems contribute to several processes involved in motor control, including motor planning, sensorimotor integration, prediction, and motor learning. However, the considerable heterogeneity observed among children with DCD suggests that no single neurofunctional mechanism can explain the complete motor phenotype. This heterogeneity is particularly relevant because DCD frequently co-occurs with other neurodevelopmental conditions, including ADHD and ASD [4, 6]. Consequently, difficulties in prediction, postural control, coordination, or motor learning may vary substantially between children, further supporting the need for a quantitative assessment of multiple dimensions of motor behaviour rather than relying on a single motor outcome.

Motor difficulties are frequently reported in children with ASD, although they are not part of the core diagnostic criteria of autism [5, 12]. These difficulties may involve several aspects of motor function, including fine and gross motor coordination, postural control, gait, upper-limb movements and motor learning. A meta-analysis by *Fournier et al.* [5] identified substantial motor coordination differences between individuals with ASD and typically developing controls, supporting the relevance of motor function as an important dimension of the autistic phenotype. Then, from a neurodevelopmental perspective, motor alterations in ASD have been associated with differences across distributed sensorimotor networks rather than with a single neural structure. Indeed, motor-related neurobiological differences in ASD have been reported at several levels of the motor system, involving cortical motor regions, the striatum, cerebellum and brainstem [20]. The cerebellum has nevertheless received particular attention because of its extensive interactions with cortical sensorimotor regions and its important contribution to motor prediction and adaptation. Research has particularly highlighted the role of cerebellar circuits in feedforward and feedback motor control. Experimental evidence has demonstrated differences in both predictive and feedback-based motor control in individuals with ASD, supporting the involvement of cerebellar mechanisms in some sensorimotor alterations [21]. Neuroimaging studies have additionally identified differences in functional connectivity between the cerebellum and visual and sensorimotor networks in ASD [22]. These neurofunctional differences may contribute to some of the difficulties in motor coordination, sensorimotor integration, and motor adaptation observed in autistic individuals. Nevertheless, the substantial neurobiological and behavioural heterogeneity of ASD prevents the definition of a single ASD-specific motor mechanism. Furthermore, motor difficulties observed in ASD should not automatically be interpreted as specific to autism. Considerable overlap exists with the motor difficulties observed in DCD, and co-occurring DCD may contribute to the motor phenotype of some autistic children [6]. This overlap reinforces the importance of characterizing individual motor profiles independently of the primary diagnostic label.

Mixed learning profiles, referred to here as *multidys* profiles, correspond to the co-occurrence of several specific developmental or learning disorders within the same child. These profiles may combine difficulties

affecting reading, written expression, spelling, mathematics, language or other learning-related functions, depending on the individual combination of disorders [12]. Such profiles are therefore highly heterogeneous and should not be considered as a single homogeneous disorder. The frequent co-occurrence of different specific learning difficulties further supports the need to consider these profiles beyond isolated diagnostic categories [23]. Then, from a neurodevelopmental perspective, it would be inappropriate to associate *multidys* profiles with one specific neural alteration. Different learning difficulties are associated with partly distinct neurocognitive systems. For example, reading difficulties have been related to language and phonological processing networks, whereas mathematical difficulties involve systems supporting number and visuospatial processing [23, 24]. Consequently, the neurofunctional characteristics of a *multidys* profile are likely to depend on the particular combination of difficulties present in each child. Although specific learning disorders are primarily defined by difficulties in academic skills, motor difficulties may also be observed in some children. In developmental dyslexia, for example, a recent meta-analysis reported differences across several motor skills and capacities compared with typically developing children [25]. Graphomotor difficulties have also been investigated, with evidence that some children with dyslexia experience difficulties in the motor processes involved in handwriting [26]. These findings suggest that motor assessment may provide complementary information in children presenting complex learning profiles. However, such motor difficulties should not be considered a universal characteristic of *multidys* profiles, as their presence and severity are likely to depend on the specific combination of developmental difficulties.

Overall, the literature highlights both shared and heterogeneous motor difficulties across neurodevelopmental disorders. Difficulties in motor coordination, postural control and other dimensions of motor performance may occur across diagnostic groups, while their severity and expression vary considerably between individuals [6, 15]. Recent transdiagnostic studies further suggest that motor profiles do not necessarily align with conventional diagnostic boundaries, supporting the characterization of motor function as a dimension that can be investigated across neurodevelopmental conditions [14, 15]. Consequently, rather than searching exclusively for a disorder-specific motor signature, quantitative motor assessment may help identify both shared and profile-dependent characteristics of movement. This perspective supports the use of a common instrumented protocol across different neurodevelopmental populations and emphasizes the importance of first establishing a reference of typical motor development against which future clinical populations can be compared.

1.2 Standardized Clinical Assessments

To assess neurodevelopment, many different methods already exist. The main standardized clinical assessment methods are motor assessments, cognitive assessments, and behavioural assessments. The MABC-2 [27], the BOT-2 [28] and the Purdue Pegboard Test [29] are examples of standardized clinical assessment methods. These are motor assessments that require the child to perform standardized motor tasks under controlled conditions, such as inserting pegs into a board, catching a beanbag, or maintaining balance. In this type of test, the clinician measures an objective outcome like an execution time, a number of successes, or an error score. These results are then converted into standardized scores allowing comparison against developmental norms stratified by age and sex [4]. The NEPSY-II [30] is another example of a standardized clinical assessment, notably used in cognitive assessment. This test consists of a broad neuropsychological battery that includes a sensorimotor domain with subtests such as fingertip tapping, imitation of hand positions, and visuomotor precision, administered within the same session as cognitive, language, and attentional domains. This architecture allows examination of the relationships between motor control and executive functions within an integrated framework, which is particularly relevant for ADHD and DCD. The WISC-V [31] is another example of a standardized clinical assessment for cognitive assessment. It provides an evaluation of the intelligence quotient in children aged 6 to 16 years. Although it does not directly measure motor function, it is systematically administered in NDD assessments to rule

out intellectual disability as the primary explanation for the observed difficulties, and to identify potential discrepancies between indices of verbal comprehension, visuospatial reasoning, working memory, and processing speed. Finally, the Conners-3 [32], the BRIEF-2 [33], and the SRS-2 [34] are also examples of standardized clinical assessments, notably used in behavioural assessment. These tests are quite particular in that it is not the clinician who directly applies the test. Indeed, they consist of evaluations by parents and teachers of the frequency of occurrence of behaviours in daily life, converted into T-scores allowing normative comparison. Diagnostic tools such as the ADOS-2 [35], reserved for ASD, function through direct structured observation during a session of standardized interactions with the clinician, whose scoring is then converted into calibrated severity scores.

These standardized assessments have been extensively developed and validated and remain essential components of clinical neurodevelopmental assessment. Nevertheless, they provide a different level of information from instrumented movement analysis. In particular, performance-based motor tests such as the MABC-2 primarily quantify the functional outcome of a task rather than the detailed kinematic strategy used to achieve it [4]. Consequently, two individuals may achieve similar functional outcomes while using different movement strategies, differences that cannot necessarily be identified from the final clinical score alone. Moreover, performance may be influenced by factors such as attention, repeated testing, and the conditions under which the assessment is performed [4]. Finally, instrumented measures may help address some of the limitations associated with conventional clinical rating scales, such as non-linearity and floor or ceiling effects, by providing continuous and objective quantitative measures of motor performance [36].

Another important consideration is the overlap of motor difficulties across neurodevelopmental conditions. Traditional assessment frameworks are often organized according to specific functional domains or diagnostic categories, whereas similar movement difficulties can occur across different neurodevelopmental profiles. Recent work has therefore emphasized the potential value of considering motor difficulties from a transdiagnostic perspective rather than interpreting them exclusively within individual diagnostic categories [15]. Such an approach may facilitate the identification of shared and distinct motor characteristics across neurodevelopmental conditions.

Consequently, in view of the different limitations observed, it is interesting to move towards instrumented approaches capable of objectively capturing movement kinematics, applying identically to several profiles within a common protocol and providing comparable data between children and adults.

1.3 Task Selection

An important step in the design of the protocol was the choice of the different tasks performed by the participants. The tasks had to be as generic as possible and had to be feasible for all participants. In addition, it was important to consider that the time participants had to spend in the lab should not be too long. Indeed, one of the perspectives of this study was to validate the protocol for application to children with neurodevelopmental disorders. Consequently, the time spent in the lab should not be too long. Ideally, the intended time per participant was 30 minutes.

In motor assessment, the choice between analytical and ecological tasks is complex. Analytical tasks offer high experimental control, excellent reproducibility, and sensitivity to subtle motor disorders. However, they are often far removed from activities of daily living, which limits their ecological validity. Indeed, a child may perform well on an isolated laboratory task while still experiencing difficulties in real functional situations [37, 38]. Ecological tasks, by contrast, are designed to imitate everyday activities such as drinking, writing, or manipulating objects. They capture the complexity of natural movement and are more meaningful for patients and clinicians. Their main drawback is that they are more difficult to standardize and more sensitive to contextual variability, which can reduce reproducibility across participants [38, 39].

In this protocol, it was decided to combine both approaches in order to benefit from both the sensitivity of analytical tasks and the ecological relevance of everyday tasks. Eight tasks were selected in this study, which makes it possible to have a sufficiently comprehensive protocol for assessing different factors while also limiting laboratory time to around 30-40 minutes. The variety of tasks covers different dimensions such as fine motor skills, gross motor skills, postural control, social interaction, and the concept of affordance. First, there is a task that assesses postural control in a static condition, since the participant must remain standing still on both legs. There are four tasks involving targeted upper-limb movements commonly encountered in daily life, such as drinking a glass of water, reaching and placing an object, the pegboard game, and toasting with someone, which provides ecological validity while remaining sufficiently structured for kinematic analysis. One task assesses gross motor skills through natural walking, which is the most studied motor behaviour in the literature on NDDs [40]. Finally, there is a special task that makes it possible to assess affordance perception, an aspect rarely addressed in existing assessment protocols. This task consists of manipulating an affordance object. The concept of affordance was introduced by the perception psychologist James Gibson in 1979, who defined it as *"the possibilities for action that an environment or object offers to an individual"* [41]. The same object can offer different possibilities for action to different individuals depending on their physical and cognitive abilities. This exploratory learning is thought to be impaired in children with NDDs, who may present atypical strategies for object manipulation. This affordance task, therefore, allows for the assessment of how a child and an adult spontaneously interact with a novel object of unknown function.

1.4 Technologies in Motor Assessment

Over the past several years, numerous technologies have emerged for the assessment of human movement. These include laboratory based systems, wearable technologies, systems requiring specialized equipment and more accessible approaches based on software using conventional cameras, such as those integrated into tablets (e.g., OpenCap). In this study, two different but complementary technologies are used. The first is an optoelectronic motion capture system based on three-dimensional reflective markers, while the second consists of wearable inertial measurement units (IMUs). This combination provides the accuracy of optoelectronic motion capture, which is widely considered a reference method for laboratory based movement analysis, together with the greater flexibility, portability, and potential for ecological assessment offered by wearable IMUs. However, one of the objectives of this study is also to investigate how the proposed protocol could be simplified to facilitate its future application to children with neurodevelopmental disorders. In particular, the study explores whether sufficient information could be obtained using a single technology, with particular attention to the possibility of relying on wearable IMUs alone. This section therefore establishes the theoretical background required to understand the different technologies used in this study.

1.4.1 Optoelectronic System and Inertial Measurement Units

Marker-based optoelectronic motion capture systems have been widely used for several years as a reference method for kinematic analysis in biomechanics and rehabilitation. These systems use multiple infrared cameras positioned around a calibrated capture volume to detect passive reflective markers attached to the participant. By combining observations of the same markers from multiple cameras, their three-dimensional trajectories can be reconstructed with high spatial accuracy under controlled laboratory conditions [42]. Several optoelectronic motion capture systems are commercially available, including Qualisys and Vicon. In this study, a Qualisys system available in the laboratory was used, consisting of ten infrared cameras positioned around a predefined capture volume. The systematic review by Schwarz *et al.* [43], which included 225 studies investigating upper-limb kinematics after stroke, illustrates the widespread use of optoelectronic motion capture systems in clinical kinematic research.

Despite their high accuracy, optoelectronic systems present several constraints that may limit their applicability, particularly in paediatric populations and in multi-task protocols involving a broad range of motor behaviours. Measurements are restricted to a calibrated capture volume in which the markers must remain visible to a sufficient number of cameras. Marker placement and system preparation may also increase the preparation time and may be constraining for children, particularly in neurodevelopmental populations in which sensory or attentional difficulties can interfere with the experimental procedure. Furthermore, laboratory-based motion capture provides a highly controlled environment, which may differ from the conditions in which movements are naturally performed. The laboratory environment and experimental equipment may therefore influence participants' behaviour and should be considered when interpreting the ecological validity of the recorded movements.

Inertial Measurement Units (IMUs), in contrast, are miniature wearable sensors that typically combine several sensing components. A tri-axial accelerometer measures specific force along three orthogonal axes and is therefore influenced by both sensor motion and gravity. A tri-axial gyroscope measures angular velocity around the same axes. Then, many inertial measurement systems additionally incorporate a magnetometer, which measures the local magnetic field. In this study, magnetometer measurements were not included in the parameters extracted for the analysis. Compared with optoelectronic systems, IMUs offer several practical advantages for clinical and paediatric movement assessment. They are small, lightweight, wearable and do not require a fixed multi-camera infrastructure. Consequently, measurements are not restricted to a laboratory capture volume, making it possible to investigate movement over larger spaces and potentially in environments that are closer to everyday conditions. These characteristics make IMUs particularly interesting for the development of more accessible and wearable approaches to quantitative motor assessment.

The choice of sensor placement is an important methodological consideration for both IMU and optoelectronic measurements. In the protocol, the placement strategy was designed to minimize the number of sensors worn by participants and to reduce preparation time. This consideration is particularly relevant because one of the perspectives of this study is the future application of the protocol to children with neurodevelopmental disorders, for whom prolonged preparation procedures or multiple body-mounted sensors may be difficult to tolerate. Sensor placement was also selected according to the motor domains targeted by the protocol. Three anatomical locations were therefore selected, with an IMU and reflective markers positioned at each location. The dominant wrist was selected to capture distal upper-limb motion during the different manipulation and functional tasks. A second measurement location was positioned on the upper trunk around C7 to characterize upper-trunk motion and to investigate its coordination with the other measured body segments. Finally, a third location was positioned at the pelvis to characterize pelvic motion during tasks involving gait and postural control. Together, these three locations provide complementary information about distal upper-limb movement, trunk motion, postural behaviour and inter-segmental coordination.

An important limitation of both skin-mounted reflective markers and IMUs is soft tissue artefact (STA). Because markers and sensors are attached to the skin rather than directly to the underlying bone, motion of the skin and other soft tissues relative to the skeleton can introduce differences between the measured signal and the actual motion of the underlying body segment [44]. The magnitude of this artefact depends on several factors, including the anatomical location, sensor attachment, surrounding soft tissues and characteristics of the movement. Sensor placement should therefore aim to limit relative motion between the sensor and the underlying segment whenever possible. Nevertheless, STA cannot be completely eliminated and should be considered when interpreting segmental kinematic measurements.

In conclusion, the combination of these three measurement locations provides complementary coverage of the motor dimensions. The combination of these locations also limits the number of measurement

units required, thereby reducing preparation time and participant burden. This configuration is therefore compatible with the objective of developing a protocol that remains sufficiently comprehensive for quantitative motor assessment while being as practical and tolerable as possible for future use in paediatric neurodevelopmental populations.

1.4.2 Features Extracted from Body-Worn Sensors

One of the main differences between instrumented assessment and conventional clinical tools lies in the wide range of kinematic parameters that can be extracted from sensor data. Moreover, these parameters do not only characterize the observed outcome of a task but also the way in which the task was performed, thereby providing information about the underlying motor process [1, 43]. A systematic review [43] highlights that kinematic metrics can provide valuable complementary information to conventional clinical scales, particularly for identifying compensatory strategies and quantifying movement quality. The different parameters that can be derived from instrumented assessments can be classified into several categories [1, 43]. Figure 1.1 shows an example of the classification of these parameters proposed by *de los Reyes-Guzmán* [1]

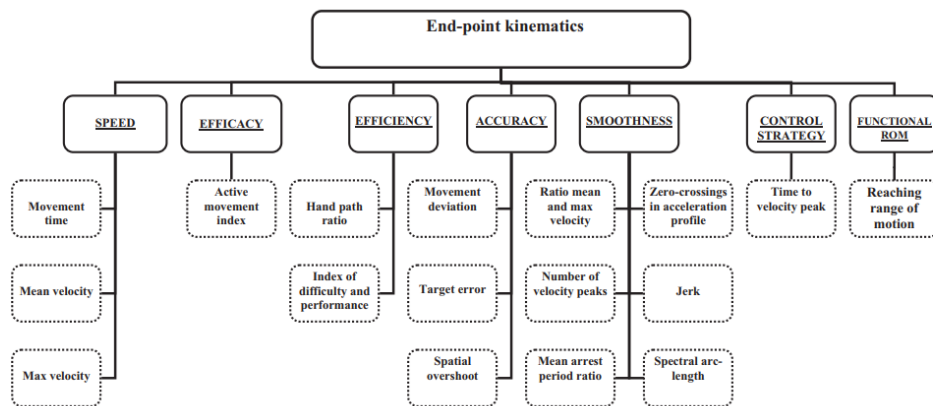


Figure 1.1: Example of the classification of the different parameters calculated using an instrumented assessment, as proposed by *de los Reyes-Guzmán* [1]

In this study, the extracted parameters were selected to be applicable across all tasks and to span several categories, enabling discussion at the level of parameter families rather than individual metrics. The parameters were therefore grouped into six categories, which are described below. The detailed definitions and formulas used to compute each parameter are provided in the *Materials and Methods* section.

The first category is *Speed and Acceleration*. This category quantifies the kinematic properties of movement through velocity magnitude derived from 3D markers and acceleration derived from the IMU norm. Velocity metrics are among the best-validated clinical kinematic parameters, with peak velocity showing good test-retest reliability, with intraclass correlation coefficients ranging from 0.74 to 0.95 [43].

The second category is *Movement Smoothness*. Smoothness reflects the quality of motor planning and neuromuscular control and is one of the most extensively studied kinematic features in motor assessment. The Log Dimensionless Jerk from Acceleration (LDLJ-A) is one important parameter within this category. LDLJ-A is computed directly from the IMU acceleration norm, avoiding the cumulative drift associated with velocity and position signals [45]. Jerk corresponds to the time derivative of acceleration and therefore quantifies rapid changes in the acceleration profile. The Spectral Arc Length (SPARC) provides another measure of movement smoothness based on the frequency-domain representation of the

movement signal. A smoother movement is associated with a less complex frequency spectrum, whereas fragmented movements involving multiple corrections result in greater spectral complexity and more negative SPARC values [46]. SPARC was retained because it is dimensionless and relatively robust to changes in movement duration and amplitude. Additional smoothness descriptors considered in this study include the mean/max ratio, the median/Q3 ratio, the Movement Arrest Period Ratio (MAPR), and the number of zero crossings of the centred acceleration signal.

The third category is *Movement Efficiency*. For this category, the selected parameter was adapted from the concepts described in the literature [1]. Determining an ideal trajectory for each of the different tasks included in the protocol would be complex and highly task-dependent. Therefore, trajectory length was retained as a simpler descriptor of movement efficiency. This parameter quantifies the cumulative distance travelled during the movement and can be used to compare how directly or economically a task is performed between groups.

The fourth category is *Control Strategy*. This category characterizes how movement is organized over time. The dominant frequency of the velocity or acceleration signal reflects the predominant oscillatory component of the movement, whereas the Position of Peak Velocity (PPV) describes the temporal position of the velocity peak within the movement. A PPV close to 50% corresponds to a relatively symmetric velocity profile, whereas values below or above 50% indicate that peak velocity occurs respectively earlier or later in the movement [1]. These parameters therefore provide information on differences in the temporal organization of movement between populations.

The fifth category is *Signal Complexity*. Approximate Entropy (ApEn) quantifies the regularity and predictability of a time series signal [47]. Lower ApEn values indicate a more regular and predictable signal, whereas higher values indicate greater temporal complexity and variability. Complexity-based metrics have previously been used to characterize changes in motor behaviour during development [48]. However, the interpretation of ApEn must remain task dependent. Indeed, greater complexity should not systematically be interpreted as either better or poorer motor performance, since the functional meaning of signal variability depends on the motor demands of the task.

Finally, the sixth category is *Inter-segmental Coordination*. Correlation coefficients calculated between signals from different body locations (wrist-C7, wrist-pelvis and C7-pelvis) quantify the degree and direction of coupling between segments during a task. When applied to normalized signals for which the direction of motion is preserved, a positive correlation indicates predominantly in-phase behaviour, whereas a negative correlation indicates predominantly anti-phase behaviour. These measures can therefore provide information on whether body segments tend to move together or dissociate during movement. The development of such inter-segmental organization is an important component of postural and motor maturation, with progressive changes in segmental stabilization and coordination occurring throughout childhood [49, 50].

In conclusion, this set of parameters was selected to cover several major dimensions of movement identified in the literature on instrumented motor assessment [1, 43]. Their relevance for the assessment of children with neurodevelopmental disorders remains to be established. However, their selection is motivated by the motor characteristics associated with the different neurodevelopmental profiles described in the previous sections. The comparison between typically developing children and healthy adults performed in this study therefore represents a first step toward evaluating the feasibility and sensitivity of the proposed protocol before its future application to children with neurodevelopmental disorders.

Chapter 2

Objectives

The previous sections highlighted the importance of objectively characterizing motor development and the limitations of conventional clinical assessments for capturing detailed movement characteristics. However, before investigating atypical motor patterns in children with neurodevelopmental disorders (NDDs), it is important to characterize how these parameters differ during typical development. Comparing typically developing school-age children with healthy adults provides a first developmental reference, with the adult group representing a mature motor profile against which the motor behaviour of children can be compared. This study therefore investigates motor differences between typically developing children aged 6-12 years and healthy adults using a multi-task protocol combining three-dimensional optoelectronic motion capture and wearable inertial measurement units (IMUs). More specifically, the study addresses three main objectives.

The first objective is to characterize the motor profiles of typically developing children and healthy adults across eight experimental tasks covering different dimensions of motor function, including gait, static postural control, fine upper-limb motor function, social interaction, and object affordance. Movement is characterized using both 3D kinematic and inertial measurements collected at the wrist, C7, and pelvis. This first objective aims to establish a quantitative description of typical motor behaviour for children and adults.

The second objective is to determine which tasks and movement parameters are most sensitive to developmental differences between children and adults. The analysis aims to identify which dimensions of movement quality, such as speed, smoothness, complexity, postural control, and coordination, provide the most relevant information regarding motor maturation. In addition, the comparison of the eight tasks aims to determine whether they provide redundant or complementary information and, consequently, which tasks may be the most relevant for a future simplified assessment protocol.

The third objective is to evaluate whether the proposed experimental protocol provides a suitable methodological basis for future application to children with neurodevelopmental disorders (NDDs), while also identifying potential ways to improve and simplify its implementation. The ability of the protocol to detect consistent developmental differences between typically developing children and adults represents an important first step before investigating its sensitivity to atypical motor development. In parallel, the respective contributions of the optoelectronic system and wearable IMUs are examined to determine whether a simplified protocol could retain sufficient discriminative information. In particular, this study investigates whether IMU-derived parameters alone could distinguish children from adults across the different tasks and parameter categories, and identifies situations in which the absence of 3D kinematic measurements may remain a limitation. Ultimately, reducing the dependence on laboratory-based optoelectronic motion capture could simplify the protocol, facilitate its implementation, and support the future development of a more accessible assessment approach for children with NDDs.

Chapter 3

Materials and Methods

This chapter describes the methodological framework used for this study. Section 3.1 presents the study population, including the children and adult control groups as well as the eligibility, inclusion and exclusion criteria applied throughout recruitment. Section 3.2 details the systems, equipment and setup used for data acquisition. Section 3.3 describes the standardized battery of experimental tasks administered to each participant, covering gross motor function, postural control, fine motor function, social interaction and affordance perception. Section 3.4 outlines the movement features extracted from the recorded data, classified into different categories, along with the parameter reduction procedure based on Spearman correlation analysis. Finally, Section 3.5 presents the statistical methods used to analyse the extracted features and compare the study groups.

3.1 Study Population

It is important to note that before any tests on the participants, this study had to be approved by the Hospital-Faculty Ethics Committee of the University of Liège. This study included two control groups. The first one is a group of typically developing children, the control group of children (G1). All participants of this group are listed in Table 3.1. The second one is a group of healthy adults (G2). All participants of this group are also listed in Table 3.1. For both groups, participants were required to be French-speaking and before starting any tests, all the protocol and exercises that participants had to perform were explained to them. All participants and their legal guardians, for minors, had to provide informed consent to take part in the study. There were some common exclusion criteria applied to all participants. Participants presenting a progressive neurological or somatic pathology, or any condition interfering with motor function (e.g., neuromuscular disease, cerebellar disease), were excluded from the study. Control participants were not required to undergo a prior cognitive or psychomotor assessment within the Child and Adolescent Psychiatry Department, as their inclusion was based on the absence of any known developmental, learning, or motor concern.

The control children group (G1) comprised 12 participants aged between 6 and 12 years with a mean age of 8.3 ± 2.0 years including both male and female participants. It should be noted that data from several children could not be included in the analysis due to recording issues encountered during laboratory testing. The large majority were right-hand dominant, with only one left-handed participant identified. Mean height was 131.7 ± 14.6 cm, consistent with expected values for this age range. To be eligible, children had to be free of any grade repetition, reasonable accommodations, or enrolment in a specialized class, ensuring a sample representative of typical developmental trajectories rather than children with unidentified learning or motor difficulties.

The adult control group (G2) comprised 10 participants aged between 23 and 56 years with a mean age 38.8 ± 15.0 years, also comprising both sexes. All participants were right-hand dominant. Mean

height was 164.6 ± 9.1 cm. This group was included to provide an adult reference profile against which age-related differences in motor performance could be characterized.

Children (G1, $n = 12$)					Adults (G2, $n = 10$)				
ID	Age (years)	Sex	Dom. hand	Height (cm)	ID	Age (years)	Sex	Dom. hand	Height (cm)
S004	9	M	Right	138	S018	54	F	Right	160
S005	10	M	Right	145	S019	51	M	Right	183
S006	6	F	Right	110	S020	25	F	Right	156
S007	8	F	Right	128	S021	27	M	Right	170
S008	9	F	Right	137	S022	48	F	Right	155
S009	6	M	Right	122	S023	23	M	Right	171
S011	10	F	Right	131	S024	56	F	Right	160
S012	12	F	Right	163	S025	55	M	Right	170
S013	6	F	Right	116	S026	25	F	Right	155
S014	8	M	Right	133	S027	24	M	Right	166
S015	6	F	Right	117					
S016	10	F	Left	140					
Mean $\pm$ SD	8.3 $\pm$ 2.0	–	–	131.7 $\pm$ 14.6	Mean $\pm$ SD	38.8 $\pm$ 15.0	–	–	164.6 $\pm$ 9.1

Table 3.1: Individual demographic characteristics of the participants in the two study groups. Participants were divided into a group of typically developing children (G1, $n = 12$) and a group of healthy adults (G2, $n = 10$). Age, sex, dominant hand, and height are reported for each participant. Continuous variables are expressed as mean $\pm$ standard deviation (SD).

3.2 Systems, Equipments and Setup

All equipment, systems, experimental setups, and experimental tasks used in this study were implemented and conducted at the Laboratory of Human Motion Analysis at the University of Liège, on the Sart-Tilman campus. Kinematic data were acquired using two complementary measurement systems. The first one is a three-dimensional optoelectronic motion capture system (Qualisys) and the second one is wearable inertial measurement units (Delsys). The optoelectronic system provided three-dimensional position data from reflective markers, whereas the inertial sensors recorded segmental linear acceleration and angular velocity. The simultaneous use of both modalities therefore enabled complementary characterization of segmental motion throughout the different motor tasks. The laboratory was equipped with ten infrared Qualisys cameras positioned around the experimental area to cover the volume in which the tasks were performed. The system recorded the trajectories of passive reflective markers at a sampling frequency of 200 Hz. Following calibration, the three-dimensional position of each marker was reconstructed within the laboratory coordinate system. In addition, a conventional video camera was used to record the different experimental tasks. These recordings allowed the experimenters to verify that each task was performed correctly and provided complementary visual information to facilitate the interpretation of specific results when necessary. Inertial data were simultaneously recorded using Delsys wearable sensors. Each sensor included a tri-axial accelerometer and a tri-axial gyroscope, providing measurements of linear acceleration and angular velocity, respectively. IMU data were acquired at a sampling frequency of 2000 Hz. The inertial sensors provided information complementary to the optical measurements by characterizing the local dynamics of each instrumented body segment.

As explained in the *State of the Art* section, the 3D markers and IMU sensors were positioned at three anatomical locations: C7, the pelvis, and the wrist of the dominant hand. Figure 3.1 illustrates the sensor placement used throughout the experimental protocol. The sensors were attached to the skin using dedicated double-sided adhesive tape. When necessary, the skin was cleaned before sensor placement to

ensure adequate adhesion throughout the experiments. At each anatomical location, one 3D reflective marker and one IMU sensor were used. To facilitate sensor placement and ensure that both measurement systems recorded motion from approximately the same location, the 3D reflective marker was directly attached on top of the IMU sensor, as illustrated in Figure 3.2. Participants were asked to wear a tee-shirt to ensure that the wrist sensor remained uncovered. Participants with long hair were also asked to tie their hair back to prevent it from covering the C7 marker. In addition, the tee-shirt was secured at the waist to prevent the clothing from covering the pelvis marker during movement. It was essential that the 3D reflective markers remained visible to the optoelectronic cameras throughout data acquisition. Indeed, the markers reflect the infrared light emitted by the cameras, allowing their three-dimensional positions to be tracked within the calibrated capture volume. Consequently, obstruction or occlusion of a marker could result in missing or incomplete trajectory data. This configuration was maintained across all tasks of the experimental protocol and enabled the simultaneous acquisition of 3D kinematic data, including position and derived velocity, together with inertial data, including tri-axial acceleration and angular velocity measured by the IMUs.

Prior to data acquisition, the Qualisys capture volume was calibrated using the standard wand calibration procedure. A reference frame was used to define the laboratory coordinate system, while the calibration wand was moved throughout the acquisition volume to determine the position and orientation of the cameras. Data collection was initiated only after a satisfactory calibration of the experimental volume had been obtained.

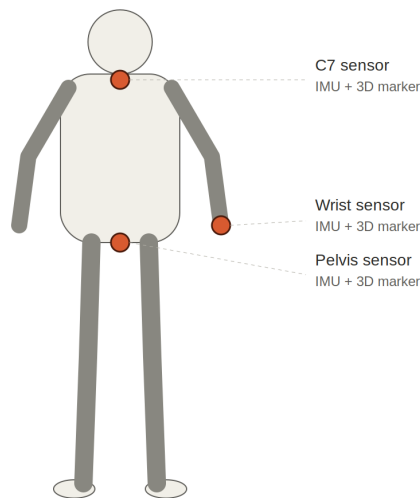


Figure 3.1: Schematic representation of sensor placement on the participant. An inertial measurement unit (IMU) and a 3D reflective marker were placed together at three anatomical locations: C7 (seventh cervical vertebra, upper trunk), pelvis and the wrist of the dominant hand.



Figure 3.2: Sensors used during data acquisition. (A) IMU combined with a 3D reflective marker attached on top, as used at the three anatomical locations (C7, pelvis, and wrist). (B) Delsys IMU sensor.

3.3 Experimental Tasks

During data acquisition in the laboratory, each participant performed 8 tasks assessing different functions, as explained in the *State of the Art* section. Each task was performed a minimum of once. A task was repeated only when it had not been correctly executed according to the given instructions, or in case of an issue during data acquisition, such as a 3D marker not being visible. As explained previously, for each task, each participant was equipped in the manner described in Section 3.2. In addition, a 3D marker was placed at all times on the left corner of the table, in order to always have a fixed reference point in Qualisys.

3.3.1 Gross Motor Function

To assess gross motor skills across participants, as described in the *State of the Art* section, participants were asked to walk over a distance of 15m. A mark is placed on the floor to indicate the start of the walk, and another mark is placed to indicate the end of the task. These marks ensure that exactly the same walking distance is performed by every participant. They are instructed to walk naturally, looking straight ahead at their own comfortable pace. The parameters for the walking task are computed over the 4 central steps only for each participant. This approach avoids artefacts caused by the acceleration and deceleration phases at the beginning and end of the walk.

3.3.2 Postural Control

To assess postural control in the different participants, as explained in the *State of the Art* section, the participants were asked to remain static for 30 seconds. The participant stands on both legs with the feet slightly apart (hip-width stance) on a flat surface, with the arms alongside the body and the eyes open, looking straight ahead. The task was recorded for 30 seconds, and the parameters were analysed over the entire recording.

3.3.3 Fine Motor Function

To assess fine motor skills, each participant is asked to perform three different tasks.

Pouring Water and Drinking Task The first task to assess fine motor skills consists of pouring a glass of water and drinking it. Figure 3.3 shows the experimental set-up for this task. Each participant sits

on a chair and positions themselves correctly close to the table with their feet under it. A 3D marker is placed on the bottle as well as on the glass. In addition, markings are placed on the table to reposition the bottle and glass at the same location between each trial, thereby ensuring reproducibility across trials. Each participant must open the bottle cap with their dominant hand, then pour a small amount of water using their dominant hand, and finally close the bottle again with their dominant hand. They then drink the water from the glass using their dominant hand. It is important that all actions are performed with the dominant hand, as the sensors are placed on that hand. The left hand may only be used to hold the object in place to prevent it from moving, but no action should be performed with it.

The onset is defined by the common wrist displacement criterion ($\delta_{\text{start}} = 15$ mm). The offset corresponds to the moment the glass is brought to the mouth detected by the simultaneous satisfaction of two conditions after the onset:

1. The height of the glass relative to its initial position exceeds the threshold: $\Delta z_{\text{cup}}(t) = z_{\text{cup}}(t) - z_{\text{cup}}(0) > 50$ mm (CUP_HEIGHT_THRESHOLD).
2. The wrist gyroscope norm exceeds the threshold: $\|\omega_{\text{Wrist}}(t)\|_2 > \overline{\|\omega\|_2} + k_{\text{gyro}} \cdot \sigma_{\|\omega\|_2}$, with $k_{\text{gyro}} = 3.0$.

This double condition prevents false positives caused by a simple upward glass movement without the pronation rotation of the wrist that characterises actual drinking. Two fallback mechanisms are implemented. If condition 1 alone is satisfied, it is sufficient to define the offset. If neither condition is met, the last active gyroscope frame is used.

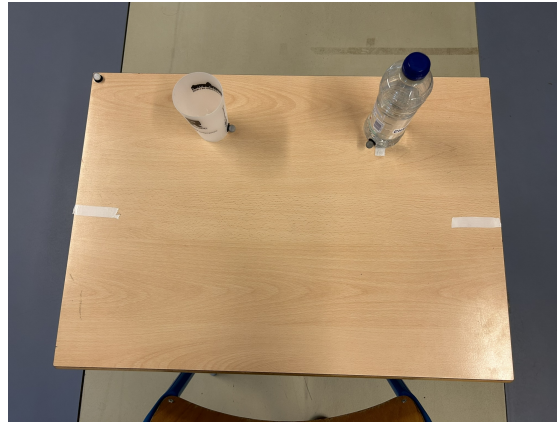


Figure 3.3: Set-up for the pouring water and drinking task.

Reach and Drop Task The second task used to assess fine motor skills is the reach and drop task. This task consists of picking up a tennis ball and placing it into a box. Figure 3.4 shows how the two objects are positioned. The ball is always placed on the side of the dominant hand and the box on the opposite side of the table. Marks are placed on the table so that the two objects (the ball and the box) can be repositioned exactly in the same place each time, thereby ensuring reproducibility. A 3D marker is also placed on the tennis ball as well as at the center of the box. Each participant is seated at the table during the execution of the task and must use their dominant hand to perform the task. The parameters are calculated within the window between the start and the end. The start is defined by the simultaneous satisfaction of two criteria:

1. The wrist velocity or acceleration exceeds the movement threshold: $\|\mathbf{v}_{\text{Wrist}}(t)\|_2 > 20$ mm/s (VEL_THRESHOLD).
2. The displacement of the wrist from its initial position exceeds $\delta_{\text{start}} = 15$ mm.

The end corresponds to the frame where the distance between the ball and the box is minimal after the start, marking the instant of the drop:

$$\text{End} = \arg \min_{t > \text{Start}} \|\mathbf{p}_{\text{ball}}(t) - \mathbf{p}_{\text{box}}(t)\|_2. \quad (3.1)$$

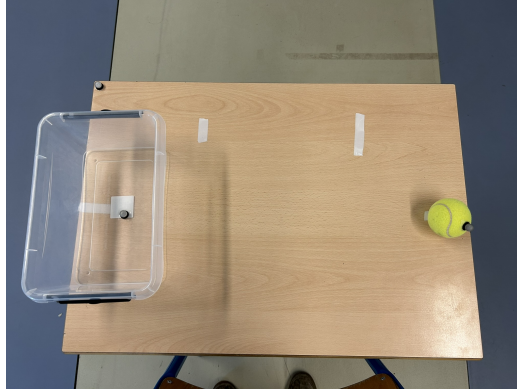


Figure 3.4: Setup for the reach and drop task.

Pegboard Task The third task used to assess fine motor skills is the pegboard task. This task consists of placing each wooden peg into a hole in the board and then, once all 16 pegs have been placed without regard to colour, removing them all. The participant must perform the task with their dominant hand, while seated at the table, and pick up only one peg at a time. The participant is instructed to perform the task as quickly as possible. The 16 pegs are all positioned on the dominant-hand side, and a 3D marker is placed on the wooden board in the upper-left corner to provide a reference in Qualisys. Figure 3.5 shows the setup for this task. The parameters are analyzed over the time window defined by the start and the end. The start is defined by the common wrist displacement criterion ($\delta_{\text{start}} = 15 \text{ mm}$). The end is defined after the final peg insertion. The wrist–pegboard distance signal exhibits a local minimum at each target approach (peg insertion or removal); $N_{\text{pegs}} \times 2 = 32$ minima are expected (16 insertions + 16 removals). The end corresponds to the first frame after the last detected minimum where the distance rises above the 50th percentile of the wrist–pegboard distance ($\text{DIST_PCT_THRESHOLD} = 50$):

$$\text{End} = \min \{ t > t_{32}^{\min} \mid d_{\text{Wrist-peg}}(t) > P_{50}(d_{\text{Wrist-peg}}) \}, \quad (3.2)$$

where $t_{32}^{\min}$ is the frame of the 32nd wrist–pegboard distance minimum. A fallback mechanism is provided in case 32 minima are not detected, in that case, the last available minimum is used.

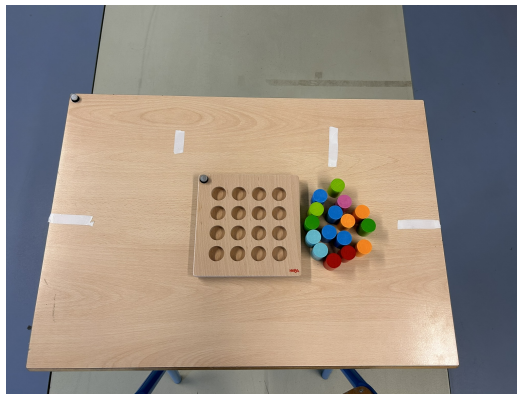


Figure 3.5: Setup for the pegboard task.

3.3.4 Social Interaction

To assess the participants' behaviour during social interaction, they were asked to perform two tasks.

Glass Clinking Task The first task is an everyday activity consisting of clinking glasses to cheers. In this task, the participant sits at a table facing another person, and each person holds a glass and taps it against the other's glass to cheers. Figure 3.7 shows the setup for this task. The participant must perform the action with their dominant hand. A 3D marker is placed on each glass. The parameters are calculated over the time window defined by the start and the end. The start is defined by the wrist displacement criterion ($\delta_{\text{start}} = 15$ mm). The end corresponds to the frame where the distance between the two glasses is minimal after the start, marking the cheers:

$$\text{End} = \arg \min_{t > \text{Start}} \|\mathbf{p}_{\text{cup1}}(t) - \mathbf{p}_{\text{cup2}}(t)\|_2. \quad (3.3)$$

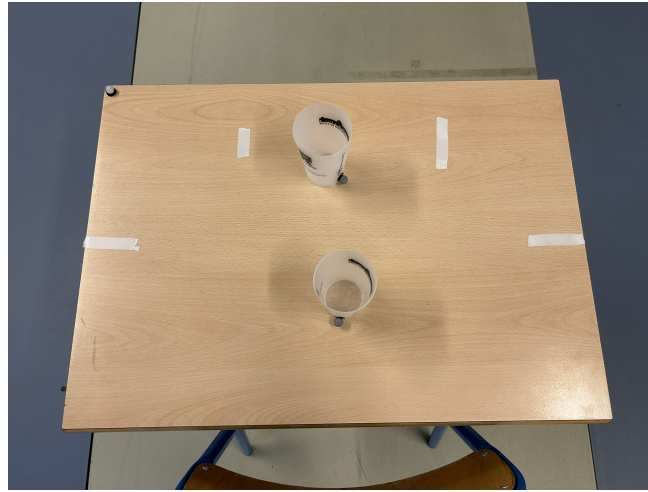


Figure 3.6: Setup for the glass clinking task.

Ball Throwing Task The second task to assess movement during social interactions consists of throwing a ball to someone else. The participant is seated facing another person and must pass the ball (by throwing it in the air) to them. Six passes must be made in total (three each). It is always the participant who starts, and for this task the participant may use both hands to perform the action. Figure 3.7 shows the setup for this task. A handball-style ball is used to avoid it being too large for the children. A 3D marker is placed on this ball. The parameters for this task are studied over the window defined by the start and the end. The onset is defined by the wrist displacement criterion ($\delta_{\text{start}} = 15$ mm). The offset is detected after the 3rd throw, identified by the peaks of the ball-to-wrist distance signal (the ball moves away from and returns to the wrist at each throw). The offset corresponds to the first frame after the 3rd ball-to-wrist distance peak at which this distance falls back below an adaptive threshold:

$$\text{End} = \min \left\{ t > t_3^{\text{peak}} \mid d_{\text{ball-Wrist}}(t) < P_{70}(d_{\text{ball-Wrist}}) \right\}, \quad (3.4)$$

where t_3^{peak} is the frame of the 3rd ball-to-wrist distance peak and P_{70} its 70th percentile ($\text{DIST_PCT_THRESHOLD} = 70$), ensuring that the ball has returned close to the wrist after the last throw.

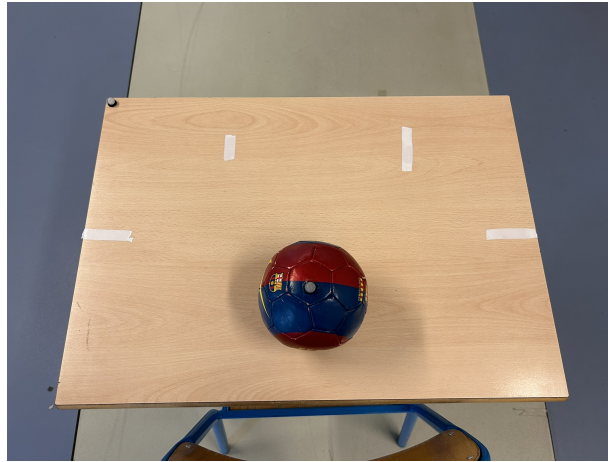


Figure 3.7: Setup for the ball throwing task.

3.3.5 Affordance Perception

To assess affordance perception in participants, they are confronted with an affordance object for 30 seconds. This affordance object was designed from scratch using Fusion 360 software and then 3D printed. This object has no specific utility, as described in the *State of the Art* section. The participant is seated at the table as shown in Figure 3.8. For this task, the participant is first asked to close their eyes, then the object is placed in front of them and the start is defined when the participant opens their eyes and discovers the object. The task is recorded for 30 seconds, during which the participant is free to do whatever they want with the object, no specific instructions are given. They are free to manipulate it however they wish. At the end of the task, the participant is asked what the object reminds them of. It is important to note that this task is performed only once, even if the participant does not complete it correctly. If this is the case, this participant will not be taken into account in the calculation of the parameters. Indeed, the purpose of this task is to observe each participant's reaction to an unknown object, consequently, once the object has been seen for the first time, repeating the task could bias the results.

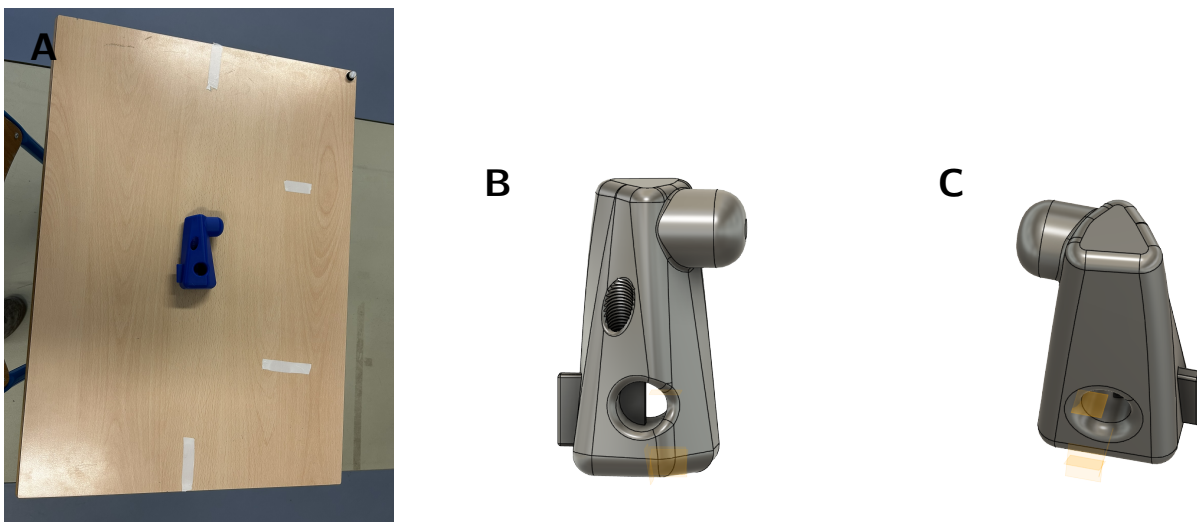


Figure 3.8: (A) Experimental setup for the affordance task. (B) and (C) Two different views of the 3D-printed affordance object.

3.4 Extracted Movement Features

Before detailing each parameter, it is important to clarify the coordinate system and preprocessing pipeline applied to both data sources. The Qualisys motion capture system uses the following convention: X = antero-posterior (AP), Y = medio-lateral (ML, positive toward the left), Z = vertical (upward). This convention differs from the IMU axes and must be taken into account when interpreting directional parameters such as `vel_Q3_AP`.

Raw 3D positions are filtered using a fourth order zero phase Butterworth low-pass filter at 12 Hz prior to any computation. This cut-off frequency is standard for human motion analysis and removes high-frequency noise while preserving the physiologically relevant movement content. For some tasks, certain 3D markers were not continuously visible throughout the entire analysis window. Therefore, to address this issue, the *Gap Filling Trajectory* function was used. This function performs polynomial or linear interpolation to fill in missing portions of the trajectories. Then, IMU signals are first decimated from 2000 Hz to 200 Hz to match the marker sampling rate. No additional filter is applied to the IMU signals. For the accelerometer, gravity is deliberately retained in the signal. Since all subjects are recorded in the same gravitational field, the resting norm ($\approx 9.81 \text{ m/s}^2$) is identical across participants and does not affect inter-participant comparisons. For the gyroscope, the raw signal is used directly without filtering.

To compare the two groups, different parameters will be extracted from each task. For each task, the extracted parameters will be the same in order to be able to compare which type of parameter is of interest for a given task. The parameters were grouped into different categories based on the classification found in the literature. [1, 43] Furthermore, the following parameters are extracted for each of the three instrumented segments: wrist (dominant hand), C7 (seventh cervical vertebra, approximating trunk motion) and pelvis (approximating the body centre of mass). Each parameter is therefore computed three times, once per segment, yielding a comprehensive characterisation of whole-body kinematics during each task.

3.4.1 Speed and Acceleration

Movement duration (`movement_time_s`) Total duration of the analysed time window, expressed in seconds. For segmented tasks, this duration corresponds to the interval between the automatically detected movement onset and offset. For static tasks (two leg standing task and affordance task), it corresponds to the fixed 30 second analysis window.

Scalar speed The scalar speed is the Euclidean norm $\|\mathbf{v}(t)\|_2 = \sqrt{v_x^2 + v_y^2 + v_z^2}$.

Third-quartile antero-posterior and medio-lateral speed (`vel_Q3_AP`, `vel_Q3_ML`)

$$\text{vel_Q3_AP} = Q_{75}(|v_x(t)|), \quad \text{vel_Q3_ML} = Q_{75}(|v_y(t)|), \quad (3.5)$$

where x denotes the antero-posterior axis and y the medio-lateral axis in the Qualisys coordinate system (X = AP, Y = ML, Z = vertical). The third quartile is preferred over the maximum value as it is robust to transient peaks. These two parameters are computed separately for static task in order to distinguish the antero-posterior and medio-lateral components. For all other tasks, the scalar 3D speed norm $\|\mathbf{v}(t)\|_2$ is used instead.

Maximum, mean and median speed (`vel_max`, `vel_mean`, `vel_median`) Summary statistics of the scalar speed $\|\mathbf{v}(t)\|_2$ computed over the entire analysis window, expressed in mm/s or m/s (depending on the task and the literature).

Third-quartile and median acceleration (`acc_Q3`, `acc_median`) The Euclidean norm of the IMU acceleration vector:

$$\|\mathbf{a}(t)\|_2 = \sqrt{a_x^2 + a_y^2 + a_z^2}, \quad (3.6)$$

expressed in m/s^2 . Gravity remains included in this signal (resting norm $\approx 9.81 \text{ m/s}^2$), which is acceptable for inter-participant comparisons as it is identical for all subjects. The Q3 and median of this signal are reported.

3.4.2 Movement Smoothness

Log Dimensionless Jerk from Acceleration - LDLJ-A (`LDLJ_A_imu`) Jerk is the time derivative of acceleration. Let $a(t) = \|\mathbf{a}(t)\|_2$ be the acceleration norm signal. Its time derivative $\dot{a}(t)$ is computed numerically, and the LDLJ-A is evaluated over the entire analysis window [51]:

$$\text{LDLJ-A} = -\log\left(\frac{T}{A_p^2} \int_0^T \dot{a}(t)^2 dt + \varepsilon\right), \quad (3.7)$$

where T is the duration of the analysis window, A_p the peak acceleration norm, and $\varepsilon = 10^{-9}$ a regularisation term. Normalisation by T/A_p^2 makes the result dimensionless and comparable across movements of different durations and amplitudes. A value close to zero indicates a smooth movement but a highly negative value indicates a jerky movement. This parameter is computed from the IMU acceleration norm only, as using 3D marker positions would require an additional derivative, increasing some potential errors (noise).

Zero crossings (`zero_crossings_acc`) The acceleration norm signal is median centred: $\tilde{a}(t) = \|\mathbf{a}(t)\|_2 - \text{median}(\|\mathbf{a}\|_2)$. The number of sign changes of $\tilde{a}(t)$ is counted on this scalar centred-norm signal over the entire window. A smooth signal produces few zero crossings but a jerky signal produces many [52].

Mean Arrest Period Ratio - MAPR (`MAPR_3D`, `MAPR_imu`) The proportion of time during which the signal falls below 20% of its mean value [53]:

$$\text{MAPR} = \frac{1}{N} \sum_{t=1}^N \mathbf{1}[s(t) < 0.20 \cdot \bar{s}], \quad (3.8)$$

where $s(t)$ denotes either $\|\mathbf{v}(t)\|_2$ (3D version) or $\|\mathbf{a}(t)\|_2$ (IMU version). A high MAPR indicates a fragmented movement with numerous near-arrest phases.

Spectral Arc Length - SPARC (`SPARC_3D`, `SPARC_acc`, `SPARC_gyr`) The signal spectrum is normalised by its DC component: $\hat{V}(f) = |\mathcal{F}\{s\}(f)| / |\mathcal{F}\{s\}(0)|$. The arc length of this normalised spectrum is then computed [46]:

$$\text{SPARC} = -\int_0^{f_c} \sqrt{\left(\frac{df}{f_c}\right)^2 + \left(\frac{d\hat{V}}{df}\right)^2} df, \quad f_c = 10 \text{ Hz}. \quad (3.9)$$

A smooth movement concentrates its energy on few frequencies (short arc, SPARC close to zero), a jerky movement spreads it over a wide spectrum (long arc, very negative SPARC). Three versions are computed: from the scalar 3D speed (`SPARC_3D`), from the accelerometer norm (`SPARC_acc`), and from the gyroscope norm (`SPARC_gyr`). For `SPARC_3D`, the input signal is the scalar 3D speed $\|\mathbf{v}(t)\|_2$ derived from the Qualisys marker positions. For `SPARC_acc`, it is the Euclidean norm of the raw IMU acceleration vector $\|\mathbf{a}(t)\|_2$, which includes the gravitational component (approximately 9.81 m/s^2). For `SPARC_gyr`, it is the Euclidean norm of the gyroscope signal $\|\boldsymbol{\omega}(t)\|_2$.

Mean-to-maximum ratio (ratio_mean_max)

$$r = \frac{\bar{s}}{\max(s)}, \quad (3.10)$$

where $s(t)$ denotes the signal (scalar 3D speed or IMU acceleration norm) over the analysis window. A ratio close to 1 indicates a flat and homogeneous temporal profile but a low ratio indicates a signal dominated by a few high peaks. The ratio is computed once over the entire analysis window (the detected movement segment $[start, end]$ for some tasks, or the fixed 30 seconds window for others tasks).

Median-to-third-quartile ratio (ratio_median_Q3) Computed over the entire window, this ratio is defined as:

$$\rho = \frac{Q_{50}(s)}{Q_{75}(s)}, \quad (3.11)$$

where s denotes either the scalar 3D speed $\|\mathbf{v}(t)\|_2$ or the mean-centred acceleration norm $\tilde{a}(t) = \|\mathbf{a}(t)\|_2 - \|\bar{\mathbf{a}}\|_2$, the latter removing the gravitational component prior to computation. A value close to 1 indicates a compressed distribution with no dominant peaks. A lower value indicates a more skewed distribution driven by occasional large excursions.

3.4.3 Efficiency

Trajectory length (length_traj) Sum of Euclidean distances between consecutive 3D positions, expressed in mm or m, over the entire analysis window [1]:

$$L = \sum_{t=1}^{N-1} \|\mathbf{p}(t+1) - \mathbf{p}(t)\|_2. \quad (3.12)$$

3.4.4 Control Strategy

Peak velocity position - PPV (PPV_pct) Temporal position of the speed (or acceleration) peak expressed as a percentage of the total duration [1]:

$$\text{PPV} = \frac{\arg \max_t s(t)}{N} \times 100 [\%]. \quad (3.13)$$

An early PPV (low value) indicates rapid acceleration followed by a long deceleration phase, a late PPV reflects a progressive speed build-up (ballistic or disturbed profile). An optimal movement presents a centred peak ($\approx 50\%$) with an approximately symmetric velocity profile.

Dominant frequency (f_dom_Hz) Frequency at which the FFT spectrum of the speed (3D) or acceleration norm (IMU) signal is maximal within a task-specific analysis band $[f_{min}; f_{max}]$. For gait task, the band is set to $[0.5; 2.5]$ Hz to capture the dominant stepping cadence. For static task, the band is set to $[0.1; 3.0]$ Hz, targeting postural sway oscillations, which typically occur below 0.5 Hz [40]. For affordance task, the band is widened to $[0.1; 10.0]$ Hz. For the others tasks, the band is set to $[0.5; 10.0]$ Hz to capture faster, goal-directed upper-limb movements. For the ball throwing task, the lower bound is extended down to 0.1 Hz to avoid missing the overall repetition frequency of the cycle.

3.4.5 Signal Complexity (Data-Driven)

Approximate Entropy - ApEn (ApEn_3D, ApEn_imu) Approximate Entropy quantifies the regularity and complexity of a time series [54]. It is computed with embedding dimension $m = 2$ and tolerance $r = 0.2\sigma$, in accordance with standard recommendations:

$$\text{ApEn}(m, r, N) = \phi^m(r) - \phi^{m+1}(r), \quad (3.14)$$

where $\phi^m(r) = \frac{1}{N-m+1} \sum_{i=1}^{N-m+1} \ln C_i^m(r)$ and $C_i^m(r)$ is the proportion of subsequences of length m that are similar to the i -th subsequence (within tolerance r). A high entropy indicates an irregular and unpredictable signal but a low entropy indicates a repetitive and regular signal. Two versions are computed: from the scalar 3D speed (ApEn_3D) and from the IMU accelerometer norm (ApEn_imu).

3.4.6 Inter-segmental Coordination

Coordination coefficient (coord_r) The Pearson correlation coefficient is computed between the signals of two body segments over the entire analysis window [1]. Three signal sources are used: the scalar 3D speed norm (suffix _3D), the gyroscope norm (_gyr), and the accelerometer norm (_acc):

$$r_{AB} = \frac{\sum_t (s_A(t) - \bar{s}_A)(s_B(t) - \bar{s}_B)}{\sqrt{\sum_t (s_A(t) - \bar{s}_A)^2} \sqrt{\sum_t (s_B(t) - \bar{s}_B)^2}}. \quad (3.15)$$

Three segment pairs are analysed: Wrist–C7, Wrist–Pelvis, and C7–Pelvis, yielding a total of 9 coordination coefficients per task (3 pairs $\times$ 3 signals). A value $r \approx +1$ indicates that the two segments move in a coupled and synchronous fashion. A value $r \approx 0$ indicates independent movements between segments.

3.4.7 Parameter Reduction via Spearman Correlation Analysis

Each of the eight tasks yields a large set of computed movement parameters, up to 80 per task across the three instrumented segments (wrist, C7, pelvis) and both data sources (3D markers and IMUs). This results in a large number of parameters to analyse, which can lead to a loss of visibility and a loss of relevance in the discussion section. To avoid this, a preliminary step is therefore required to identify and remove redundant parameters. A redundant parameter is one of a pair of variables that carry essentially the same information about the participant population. To this end, the principle of correlation between two parameters was used. More precisely, the Spearman rank correlation coefficient was used to quantify the degree of redundancy between all pairs of parameters within each task.

Let X and Y be two parameters measured on N participants. Denote by R_i^X the rank of participant i for parameter X , and by R_i^Y their rank for parameter Y , with ranks assigned in ascending order from 1 to N . The Spearman rank correlation coefficient is defined as [55]:

$$r_s = \frac{\sum_{i=1}^N (R_i^X - \bar{R}^X)(R_i^Y - \bar{R}^Y)}{\sqrt{\sum_{i=1}^N (R_i^X - \bar{R}^X)^2 \cdot \sum_{i=1}^N (R_i^Y - \bar{R}^Y)^2}}, \quad (3.16)$$

where $\bar{R}^X = \bar{R}^Y = (N + 1)/2$ is the mean rank, identical for both variables since ranks range from 1 to N . In the absence of tied ranks, equation (3.16) simplifies to:

$$r_s = 1 - \frac{6 \sum_{i=1}^N d_i^2}{N(N^2 - 1)}, \quad (3.17)$$

where $d_i = R_i^X - R_i^Y$ is the rank difference for participant i . The coefficient r_s takes values in $[-1, +1]$:

- $r_s = +1$: perfect positive monotonic relationship, participants ranked highest on X are also ranked highest on Y .
- $r_s = -1$: perfect negative monotonic relationship, participants ranked highest on X are ranked lowest on Y .
- $r_s = 0$: no monotonic relationship between X and Y .

Crucially, both $r_s = +0.9$ and $r_s = -0.9$ indicate a strong redundancy between the two parameters. Indeed, whether two variables evolve in the same or opposite directions across participants, they convey the same underlying information. The absolute value $|r_s|$ is therefore used as the redundancy criterion throughout this analysis. A threshold of $|r_s| \geq 0.8$ was applied to identify redundant parameter pairs, consistent with recommendations for feature reduction in biomechanical research [56]. This threshold corresponds to a very strong association, meaning that the two parameters share at least 64% of their variance ($r_s^2 \geq 0.64$), which is considered sufficient to justify the removal of one. For each identified redundant pair, the parameter to be retained was selected according to the following hierarchy:

1. **Significant difference**: the parameter shows a significant difference between the two groups was retained.
2. **Clinical relevance**: the parameter with the clearest and most established clinical interpretation was preferred.
3. **Established reference**: the parameter supported by the strongest evidence in the literature was preferred
4. **Data completeness**: in case of equal clinical relevance, the parameter with fewer outliers values was retained.

The correlation matrix was computed independently for each of the eight tasks, using the `DataFrame.corr_(method='spearman')` function from the `pandas` library, which implements equation (3.16).

The Pearson correlation coefficient is one of the most commonly used measure of linear association but was not selected for this analysis for three reasons. First, the sample size is small ($N \leq 22$), which makes Pearson's r sensitive to outliers. Indeed, a single extreme value can substantially distort the estimated correlation, leading to either inflated or deflated coefficients [57]. Second, not all parameters follow a normal distribution, as confirmed by Shapiro-Wilk normality tests (see Section 3.5). Pearson's r assumes that both variables are jointly normally distributed, an assumption frequently violated by biomechanical parameters such as spectral features (SPARC) or entropy measures. Third, the relationship between parameters is not necessarily linear. Spearman's r_s measures monotonic association, whether one variable tends to increase when the other increases, regardless of the functional form of the relationship. This makes it appropriate for detecting redundancy even between parameters with non-linear relationships [58]. To conclude, by working on the ranks of observations rather than their raw values, Spearman's coefficient is robust to outliers, distribution-free and sensitive to any monotonic association, making it the method of choice for redundancy analysis with small, heterogeneous clinical datasets.

3.5 Statistical analysis

For each of the eight tasks, statistical analyses were performed independently on every parameter. The analysis pipeline comprises three sequential steps applied to each parameter:

1. Descriptive statistics computed on the full cohort and on each group separately
2. Normality testing
3. Comparison between group

All analyses were performed in Python using the `scipy.stats` and `pandas` libraries. The significance level was set at $\alpha = 0.05$ throughout. As explained previously, two different groups are analysed. G1 is the group composed of 12 children and G2 is the group composed of 10 adults.

For each parameter and each group, the following descriptive statistics were computed:

- **Sample size N**
- **Central tendency:** mean ($\bar{x}$), median, first quartile (Q_1), third quartile (Q_3), minimum and maximum.
- **Dispersion:** standard deviation (σ), standard error of the mean ($SE = \sigma/\sqrt{N}$), 95% confidence interval of the mean ($\bar{x} \pm 1.96 SE$), interquartile range ($IQR = Q_3 - Q_1$), range ($\max - \min$).
- **Coefficient of variation** ($CV = \sigma/\bar{x} \times 100$, in %), reflecting the relative dispersion of the parameter.
- **Shape:** skewness and excess kurtosis to characterise the asymmetry and tail heaviness of the distribution.

These statistics were computed at two levels: on G1 alone and on G2 alone, yielding a comprehensive overview of the parameter distribution within and between groups.

Prior to between-group comparisons, the normality of each parameter distribution was assessed independently within each group using the Shapiro-Wilk test [59]. This test was preferred over alternatives such as the Kolmogorov-Smirnov or Anderson-Darling tests because it has been shown to be the most powerful normality test for small sample sizes ($N < 50$) [60], which is the case here given the group sizes of 10 to 12 participants. The Shapiro-Wilk test statistic W is defined as:

$$W = \frac{\left(\sum_{i=1}^N a_i x_{(i)} \right)^2}{\sum_{i=1}^N (x_i - \bar{x})^2}, \quad (3.18)$$

where $x_{(i)}$ are the order statistics (sorted values), $\bar{x}$ is the sample mean, and a_i are constants derived from the expected values and covariance matrix of the order statistics of a standard normal distribution [59]. W ranges from 0 to 1, with values close to 1 indicating normality. The null hypothesis (H_0 : the data are normally distributed) is rejected when the associated p -value is below $\alpha = 0.05$. A parameter is considered normally distributed in a group if and only if the Shapiro-Wilk test fails to reject normality ($p > 0.05$) in that group.

Then, once normality has been assessed, the comparison between the groups must be performed. To do this, two different tests will be used. Indeed, the choice of statistical test for between group comparison

was determined by the normality results. Figure 3.2 shows the test selection procedure applied to each parameter.

Table 3.2: Selection of the statistical test for between-group comparison based on the normality of data in G1 and G2.

G1 normal?	G2 normal?	Test applied
Yes	Yes	Welch's t -test
Yes	No	Mann-Whitney U
No	Yes	Mann-Whitney U
No	No	Mann-Whitney U

When both groups follow a normal distribution for the parameter under consideration, Welch's independent samples t -test was applied [61]:

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}, \quad (3.19)$$

where $\bar{x}_k$, s_k^2 and n_k are the mean, variance and sample size of group k , respectively. The degrees of freedom are approximated using the Welch-Satterthwaite equation [62]:

$$\nu = \frac{\left(\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}\right)^2}{\frac{(s_1^2/n_1)^2}{n_1 - 1} + \frac{(s_2^2/n_2)^2}{n_2 - 1}}. \quad (3.20)$$

Welch's t -test was preferred over Student's t -test because it does not assume equal variances between groups (homoscedasticity), an assumption that cannot be guaranteed in clinical data with unequal group sizes [63]. Once the t -statistic and the corresponding degrees of freedom were obtained, the p -value was computed.

When at least one group does not follow a normal distribution, the Mann-Whitney U test was applied as a non-parametric alternative [64]. This test evaluates whether the distributions of the two groups are stochastically equal, without assuming any particular distributional form. The test statistic is:

$$U_1 = R_1 - \frac{n_1(n_1 + 1)}{2} \quad (3.21)$$

where R_1 is the sum of ranks assigned to G1 observations when all $n_1 + n_2$ values are ranked jointly. The null hypothesis (H_0 : the two groups are drawn from the same distribution) is rejected when $p < \alpha = 0.05$. The Mann-Whitney U test is equivalent to testing whether the probability that a randomly selected value from G1 exceeds a randomly selected value from G2 is different from 0.5 [65]. The p -value was computed using the asymptotic normal approximation with continuity correction, as implemented by default in `scipy.stats.mannwhitneyu`.

For each task, the statistical results were exported to a structured Excel file containing five sheets:

1. *Stats_Global*: descriptive statistics on the full cohort.
2. *Stats_Groupe1*: descriptive statistics on G1.
3. *Stats_Groupe2*: descriptive statistics on G2.

4. *Comparison_G1_vs_G2*: test results (test type, statistic, p -value, normality conclusion).
5. *Raw_data*: raw parameter values for all participants, with outliers highlighted in orange (values outside $[Q_1 - 1.5 \text{IQR} ; Q_3 + 1.5 \text{IQR}]$).

Boxplots were generated for each parameter, displaying the full distribution alongside individual G1 and G2 data points. Kernel Density Estimation (KDE) curves were additionally generated to visualise the distribution shape of each group independently.

Chapter 4

Results and Discussions

This chapter presents the results of the analysis performed on the eight tasks of the protocol, comparing group G1 to group G2. For each task, a correlation based reduction (Spearman, $|r_s| \geq 0.8$) was applied to eliminate redundant parameters. The parameters were compared between the two groups using either Welch's t -test or the Mann-Whitney U test, depending on the normality of the distributions (Shapiro-Wilk). The significance threshold was set at $\alpha = 0.05$.

Results are presented task by task. For each task, a section reports the statistical results and discusses them in linked of the literature. Selected figures (box plots and distribution plots) illustrate the most discriminating or clinically relevant parameters. Tables containing all retained parameters after the correlation-based reduction are presented in this section, while the full unreduced tables are available in Appendix. For clarity throughout the discussion, C7 and the pelvis are referred to as proximal segments, whereas the wrist is referred to as a distal segment. Finally, a general discussion is provided to address the different objectives of this study.

4.1 Gross Motor Function: Gait Task

After collecting the data for the gait task for each participant, the calculation of each parameter described in the Materials and Methods section was then performed. Next, a correlation analysis between parameters was carried out in order to reduce the number of parameters to be presented and discussed. This correlation-based reduction made it possible to eliminate redundant parameters by identifying pairs with an absolute Spearman correlation coefficient of $|r_s| \geq 0.8$. For this task, all participants in each group successfully completed the task. Consequently, all participants were retained in the analysis. As described in the Materials and Methods section 3.3, the kinematic parameters for this task are computed over 4 consecutive steps. In total, several correlated pairs were identified among the all tested pairs. Table 4.1 shows the results obtained after parameter reduction using correlation and Table A.1 in the appendix contains all the parameters.

In the *Speed and Acceleration* category, `movement_time`, `step_duration_mean` and `f_dom_3D_Wrist` were perfectly correlated with `cadence` ($r_s = 1.00$). Consequently, `movement_time` and `f_dom_3D_Wrist` were removed, whereas `cadence` and `step_duration_mean` were retained because they provide complementary clinical information, reflecting step frequency and absolute step duration, respectively. Furthermore, the mean, median, and maximum scalar velocities of the three body segments were highly intercorrelated ($r_s \geq 0.85$), therefore, only `vel_Q3_Pelvis` was retained as a robust representative parameter. Similarly, `acc_Q3_C7` and `acc_Q3_Wrist` were excluded due to their high correlation with `acc_Q3_Pelvis` ($r_s \geq 0.83$). Within the *Movement Smoothness* category, `SPARC_acc_C7` and `SPARC_acc_Wrist` were removed because they were highly correlated with `SPARC_acc_Pelvis` ($r_s = 0.91$). Likewise, `ratio_median_Q3_3D_Wrist` was excluded because of its strong correlation with `ratio_mean_max_3D_`

Wrist ($r_s = 0.82$). Finally, all other statistically significant were retained. Then, all parameters in the *Efficiency* category were non-significant. Only the pelvis path length was retained for descriptive purposes. In the *Control Strategy* category, the dominant IMU frequencies measured at the wrist, C7, and pelvis ($f_{\text{dom_imu_Wrist}}$, $f_{\text{dom_imu_C7}}$, and $f_{\text{dom_imu_Pelvis}}$) were perfectly correlated ($r_s = 1.00$). Consequently, only $f_{\text{dom_imu_Pelvis}}$ was retained. PPV_imu_Pelvis was retained due to its statistical significance. Finally, in the *Signal Complexity* and *Coordination* categories, all statistically significant parameters were retained.

Speed and Acceleration Cadence is significantly higher in children (131.4 ± 17.3 steps/min vs 107.7 ± 8.2 steps/min, $p = 0.001$), and step duration is significantly shorter (0.46 ± 0.06 s vs 0.56 ± 0.05 s, $p = 0.001$). Step duration variability is not significantly different ($p = 0.428$). However, it is interesting to note that in this task, one participant in the adult group performed the task very slowly, with a movement time of 2.7 seconds, whereas the mean of the nine other participants was 2.19 seconds. As a result, this may affect some of the speed parameters in the results. It is therefore important to interpret the results obtained for this parameter category with caution. Then, Q3 velocity at the pelvis is significantly higher in children (1.48 ± 0.25 m/s vs 1.23 ± 0.15 m/s, $p = 0.005$). Q3 acceleration at the pelvis is significantly higher in children (12.76 ± 1.77 vs 11.44 ± 0.61 m/s², $p = 0.030$).

The significantly higher cadence in children (131.4 vs 107.7 steps/min) and the shorter step duration (0.46 vs 0.56 s) are consistent with the literature on gait development. Indeed, the literature [66, 67] shows values between 120 and 148 steps/min for children between 6 and 12 years old and values around 110 steps/min for adults aged 18 to 30 years old. Various parameters such as walking speed and stride (2 steps) length increase with age, whereas cadence decreases [66, 67]. Actually, this pattern is explained by the difference in body size between the groups, adults, being taller, produce longer but less frequent strides [66, 67]. Normative studies using inertial sensors have confirmed that both absolute and normalized cadence decrease with age in typically developing children, whereas walking speed and stride length increase [66, 67]. Figure 4.1 A shows the cadence, with a clear separation between the two groups and a much greater inter-individual variability in G1 compared to G2, reflecting the developmental heterogeneity within the 6-12 year age range. This heterogeneity within the children's group is also consistent with the literature. Indeed, the literature [66] shows that the difference in walking strategy varies enormously between 6 and 12 years old. Then, the absence of a significant difference in step duration variability ($p = 0.428$) suggests that the two groups have comparable temporal regularity.

The higher Q3 velocity and Q3 acceleration at the pelvis in children are consistent with a higher cadence gait. Indeed, more frequent strides generate greater inertial forces as well as a higher velocity. The acceleration values notably higher than 9.81 m/s^2 reflect the dynamic contribution of the walking movement to the IMU signal. The large intra-group variability of G1 for Q3 Pelvis velocity (± 0.249 m/s) is consistent with the data from Voss *et al.* [67], who report a notably higher inter-individual variability in children aged 5-13 years than in adults for some kinematic gait parameters.

Movement Smoothness 3D SPARC is significantly more negative in children at the pelvis (-0.55 ± 0.03 vs -0.52 ± 0.02 , $p = 0.001$) and at C7 (-0.49 ± 0.04 vs -0.44 ± 0.02 , $p = 0.005$). SPARC ACC at the pelvis is significantly more negative in children (-0.86 ± 0.19 vs -0.71 ± 0.11 , $p = 0.037$). Gyroscopic SPARC at the wrist is significantly more negative in adults (-1.19 ± 0.23 vs -0.93 ± 0.14 , $p = 0.006$). The IMU median/Q3 ratio at C7 is lower in children (0.81 ± 0.10 vs 0.88 ± 0.04 , $p = 0.005$). Mean/max ratios are significantly higher in children for 3D wrist (0.70 vs 0.63 , $p = 0.040$) but lower for IMU C7 (0.56 vs 0.65 , $p = 0.012$), and IMU pelvis (0.53 vs 0.64 , $p = 0.029$).

The significantly more negative 3D SPARC in children at the pelvis and C7 indicates less smooth segmental velocity profiles during gait. This result is consistent with the progressive maturation of dynamic

postural control and trunk-pelvis coordination throughout childhood. Indeed, literature [68] showed that dynamic postural stability is not fully mature by 10 years of age and that trunk and pelvis coordination continues to evolve during childhood [68]. The more negative Pelvis SPARC ACC in children further suggests that this developmental difference is also present in the acceleration signal. Figure 4.1B shows the 3D SPARC at the pelvis, where both groups present compact distributions with limited overlap. The particularly low intra-group variability in G2 makes this parameter highly discriminative between children and adults.

Gyroscopic SPARC at the wrist is a smoothness parameter showing the opposite pattern, with significantly more negative values in adults (-1.19 vs. -0.93). This result suggests greater spectral complexity of wrist rotational velocity during adult arm swing. Importantly, arm-swing characteristics continue to develop throughout childhood. Literature [69] reported age-related changes in upper-limb kinematics during gait, with movement patterns becoming more consistent with age and adult participants showing a larger range of shoulder axial rotation than younger groups [69]. The opposite SPARC pattern observed at the wrist may therefore reflect developmental differences in arm-swing dynamics. However, since SPARC characterizes spectral smoothness rather than movement amplitude, the more negative value in adults cannot be directly attributed to a larger arm-swing amplitude.

The significantly lower IMU mean/max ratios at C7 and the pelvis in children indicate that maximum acceleration values are more pronounced relative to the mean signal amplitude. Similarly, the lower median/Q3 ratio at C7 indicates a greater separation between the typical acceleration level and the upper part of its distribution. Together, these parameters suggest a less homogeneous distribution of proximal acceleration amplitudes in children. In contrast, the higher 3D mean/max ratio at the wrist in children (0.70 vs. 0.63 , $p = 0.040$) reveals an opposite distal pattern, further suggesting that developmental differences during gait are segment-specific.

Efficiency Pelvis trajectory length is not significantly different between the two groups ($2.512 \text{ m} \pm 0.350$ vs $2.532 \text{ m} \pm 0.225$, $p = 0.877$). It is interesting to note that none of the parameters in this category show significant differences. Although adults would be expected to exhibit a greater trajectory length per step because of their larger body dimensions, the higher cadence observed in children likely compensates for their shorter step length. As a result, the trajectory length over the walking task remains comparable between groups.

Data Driven and Control Strategy ApEn 3D is significantly higher in children for the wrist (0.12 ± 0.03 vs 0.09 ± 0.02 , $p = 0.003$) and the pelvis (0.30 ± 0.05 vs 0.25 ± 0.03 , $p = 0.015$). ApEn IMU is significantly higher in children for the wrist (0.44 ± 0.06 vs 0.36 ± 0.05 , $p = 0.002$) and C7 (0.41 ± 0.06 vs 0.33 ± 0.04 , $p = 0.001$). IMU dominant frequency at the pelvis is significantly higher in children ($1.96 \pm 0.45 \text{ Hz}$ vs $1.79 \pm 0.14 \text{ Hz}$, $p = 0.019$). IMU PPV at the pelvis is significantly higher in children ($72.3 \pm 25.4\%$ vs $47.5 \pm 29.8\%$, $p = 0.032$).

The consistently higher ApEn observed in children across several segments indicates less regular and less predictable locomotor signals. In the context of gait, this higher complexity may reflect a less consolidated locomotor organization rather than greater adaptive control. Indeed, recent studies have shown that intra-individual variability of several spatiotemporal gait parameters decreases with age in typically developing children, reflecting the progressive stabilization of gait during development [70]. Moreover, dynamic postural stability and trunk-pelvis coordination continue to develop throughout childhood and may not yet be fully mature at 10 years of age [68]. These developmental changes may therefore contribute to the higher signal complexity observed in G1.

The higher IMU dominant frequency at the pelvis in children (1.96 vs. 1.79 Hz , $p = 0.019$) is consistent

with their higher cadence, indicating a faster dominant periodic component of pelvis motion. Finally, the higher IMU PPV at the pelvis in children (72.3% vs. 47.5%, $p = 0.032$) indicates that the peak of the analysed pelvis signal occurs later within the gait cycle. This difference suggests a distinct temporal organization of pelvis motion between children and adults, potentially reflecting the ongoing maturation of postural and segmental coordination during gait.

Inter-segmental Coordination Gyroscopic Wrist-C7 correlation is negative in children (-0.19 ± 0.16) and positive in adults (0.22 ± 0.16 , $p < 0.001$). 3D C7-Pelvis correlation is significantly higher in adults (0.87 ± 0.06 vs 0.69 ± 0.11 , $p < 0.001$).

The opposite sign of the Wrist-C7 gyroscopic correlation between children and adults (-0.19 vs. 0.22) represents a marked developmental difference in upper-body coordination during gait. This result suggests that the temporal coupling between wrist rotation and C7 motion is organized differently in children and adults. Arm swing is known to undergo substantial developmental changes during childhood, with movement patterns becoming progressively more consistent and adult-like with age [69]. This finding may therefore reflect the progressive reorganization of arm-trunk coordination during gait. The negative Wrist-C7 gyroscopic correlation in children and the positive correlation in adults indicate a different temporal coupling of rotational activity between the wrist and C7. In children, periods of greater wrist rotational activity tend to coincide with lower C7 rotational activity, whereas in adults both segments tend to increase or decrease their rotational activity together. Figure 4.1 D illustrates the strong discrimination provided by this parameter, with very limited overlap between the two groups.

The significantly higher 3D C7-Pelvis correlation in adults (0.87 vs. 0.69) indicates a stronger coupling between the spatial movements of these two proximal segments during walking. This result is consistent with the progressive development of torso coordination during childhood. Previous studies have shown that dynamic balance and trunk-pelvis coordination continue to mature throughout childhood [68]. The higher and less dispersed C7-Pelvis correlations observed in adults may therefore reflect a more consistent and reproducible organization of proximal segmental motion during gait. Figure 4.1C illustrates this difference, with G2 showing higher and more concentrated correlation values than G1.

Conclusion To conclude, the gait task yielded several interesting findings. The *Speed and Acceleration* category confirms expected developmental differences, with a higher cadence and greater pelvis motion in children, consistent with the literature on gait maturation. The *Smoothness* category is particularly informative, with 3D SPARC discriminating both proximal segments and gyroscopic SPARC at the wrist showing an opposite pattern, highlighting the importance of interpreting smoothness metrics in a segment and task-specific context. The *Complexity* category (ApEn) consistently shows higher values in children across several segments, indicating more complex and less predictable locomotor signals. The *Coordination* category provides the two most discriminative results of the task, revealing marked developmental differences in Wrist-C7 and C7-Pelvis coupling. No significant difference is observed in the *Efficiency* category. Finally, it should be noted that the analysis is based on only four steps, which may limit the characterization of intra-individual gait variability.

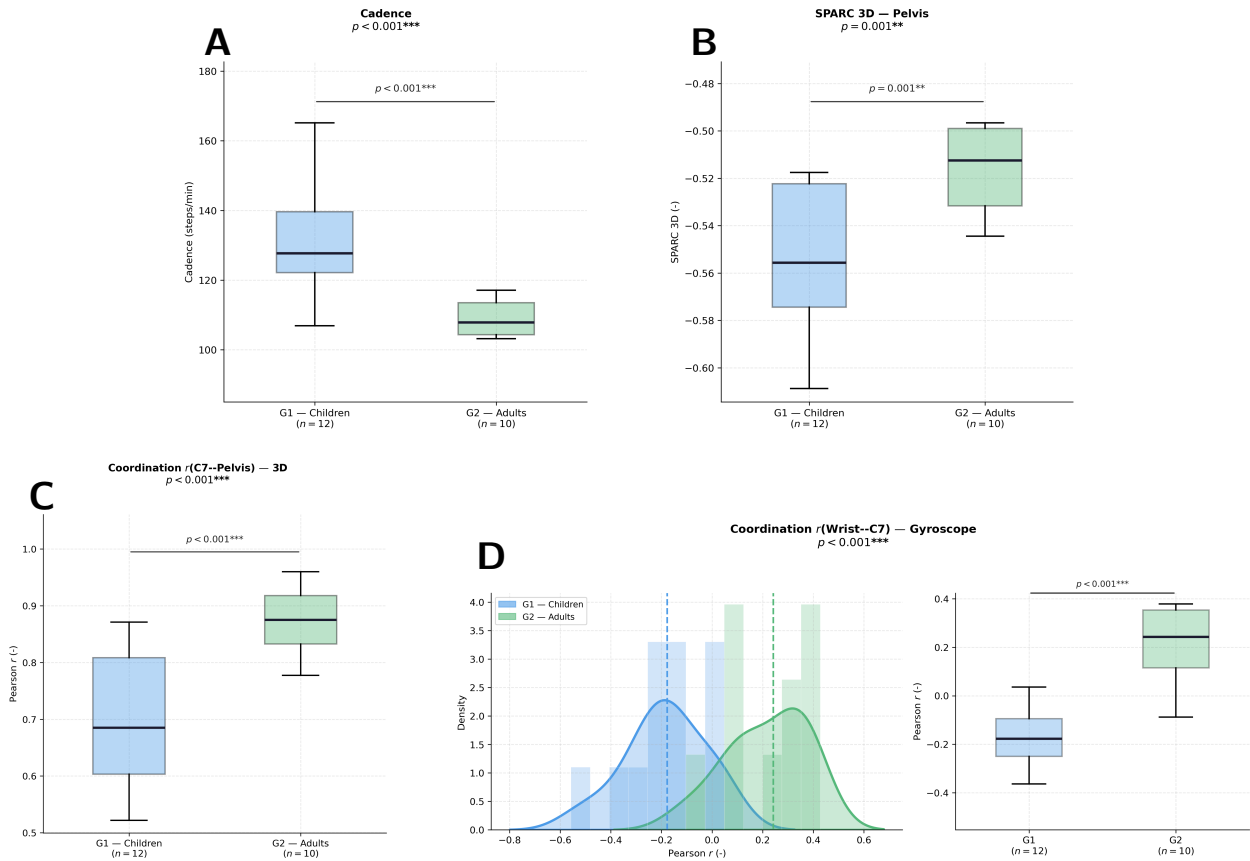


Figure 4.1: Comparison of parameters between children (G1, $n = 12$) and adults (G2, $n = 10$) during the gait task. (A) Cadence. (B) SPARC 3D measured at the pelvis. (C) Coordination coefficient between C7 and pelvis computed from the 3D kinematic signal. (D) Distribution (left) and boxplot (right) of the coordination coefficient between the wrist and C7 computed from the gyroscope signal. Boxplots display the median, interquartile range (IQR), and whiskers extending to $1.5 \times \text{IQR}$.

Table 4.1: Comparison between G1 (children, $n = 12$) and G2 (adults, $n = 10$) for the retained parameters of gait task after correlation-based reduction ($|r_s| \geq 0.8$, Spearman, $N = 22$). Values are mean $\pm$ SD. *Normal*: normality assessment per group via Shapiro-Wilk ($\alpha = 0.05$): Y = normal, N = non-normal. Statistical test: Welch's t -test (both normal) or Mann-Whitney U (at least one non-normal). * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$. Rows highlighted in green indicate a significant difference ($p < 0.05$).

Parameter	G1 - Children (<i>n</i> = 12)		G2 - Adults (<i>n</i> = 10)		<i>p</i> -value
	Mean ± SD	Norm.	Mean ± SD	Norm.	
Speed and Acceleration					
Cadence (steps/min)	131.4 ± 17.3	Y	107.7 ± 8.2	Y	0.001**
Step duration mean (s)	0.46 ± 0.06	Y	0.56 ± 0.05	N	0.001**
Step duration SD (s)	0.01 ± 0.01	N	0.01 ± 0.01	N	0.428
Velocity Q3 - Pelvis (m/s)	1.478 ± 0.249	Y	1.233 ± 0.147	N	0.005**
Acceleration Q3 - Pelvis (m/s ²)	12.76 ± 1.77	Y	11.44 ± 0.61	Y	0.030*
Movement Smoothness					
SPARC 3D - Pelvis	−0.55 ± 0.03	Y	−0.52 ± 0.02	Y	0.001**

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Parameter	G1 - Children ($n = 12$)		G2 - Adults ($n = 10$)		p -value
	Mean $\pm$ SD	Norm.	Mean $\pm$ SD	Norm.	
SPARC 3D - C7	-0.49 ± 0.04	Y	-0.44 ± 0.02	Y	0.005**
SPARC ACC - Pelvis	-0.86 ± 0.19	Y	-0.71 ± 0.11	Y	0.037*
SPARC Gyroscope - Wrist	-0.93 ± 0.14	Y	-1.19 ± 0.23	Y	0.006**
Median/Q3 ratio IMU - C7	0.81 ± 0.10	N	0.88 ± 0.04	Y	0.005**
Mean/max ratio 3D - Wrist	0.70 ± 0.06	Y	0.63 ± 0.07	Y	0.040*
Mean/max ratio IMU - C7	0.56 ± 0.10	Y	0.65 ± 0.05	Y	0.012*
Mean/max ratio IMU - Pelvis	0.53 ± 0.13	Y	0.64 ± 0.08	Y	0.029*
Efficiency					
Trajectory length - Pelvis (m)	2.512 ± 0.350	Y	2.532 ± 0.225	Y	0.877
Control Strategy					
Dominant frequency IMU - Pelvis (Hz)	1.96 ± 0.45	N	1.79 ± 0.14	Y	0.019*
PPV IMU - Pelvis (%)	72.3 ± 25.4	N	47.5 ± 29.8	N	0.032*
Signal Complexity (Data-Driven)					
ApEn 3D - Wrist	0.12 ± 0.03	N	0.09 ± 0.02	N	0.003**
ApEn 3D - Pelvis	0.30 ± 0.05	Y	0.25 ± 0.03	Y	0.015*
ApEn IMU - Wrist	0.44 ± 0.06	Y	0.36 ± 0.05	Y	0.002**
ApEn IMU - C7	0.41 ± 0.06	Y	0.33 ± 0.04	Y	0.001**
Inter-segmental Coordination					
$r(\text{Wrist-C7})$ gyroscope	-0.19 ± 0.16	Y	0.22 ± 0.16	Y	$< 0.001^{***}$
$r(\text{C7-Pelvis})$ 3D	0.69 ± 0.11	Y	0.87 ± 0.06	Y	$< 0.001^{***}$

4.2 Postural Control: Two-Leg Standing Task

After collecting the data for the two-leg standing task for 30 seconds for each participant, the calculation of each parameter described in the Materials and Methods section was then performed. Next, a correlation analysis between parameters was carried out in order to reduce the number of parameters to be presented and discussed. This correlation-based reduction made it possible to eliminate redundant parameters by identifying pairs with an absolute Spearman correlation coefficient of $|r_s| \geq 0.8$. For this task, all participants in each group successfully completed the task. Consequently, all participants were retained in the analysis. In total, several correlated pairs were identified among the all tested pairs. For this task, an additional parameter specific to two-leg standing is computed to characterize postural sway. Postural sway amplitude is quantified separately along the antero-posterior (AP) and medio-lateral (ML) axes using the range Q3. This parameter is defined as the 75th percentile of the absolute mean-centred displacement signal along each axis, providing a robust estimate of the typical sway excursion while limiting the influence of extreme values. This directional decomposition into AP and ML components is specific to the two-leg standing task. Table 4.2 shows the results obtained after parameter reduction using correlation and Table A.2 in the appendix contains all the parameters.

In the *Speed and Acceleration* category, the scalar velocity parameters (`vel_mean`, `vel_median`, and `vel_max`) were excluded because they were highly correlated with `vel_Q3`. Given the static nature of the task, only the directional Q3 velocity parameters along the antero-posterior (AP) and medio-lateral

(ML) axes were retained for the three measurement points. For acceleration, `acc_Q3` was retained instead of `acc_median`, as both parameters were highly correlated ($r_s \geq 0.94$). Among the parameters specifically describing postural sway amplitude, only statistically significant `range_Q3` parameters were retained. Within the *Movement Smoothness* category, `LDLJ_A_imu` was retained for all three measurement positions. Several additional smoothness parameters were excluded because of strong correlations with other retained parameters. At the wrist, `SPARC_acc_Wrist` was removed because of its strong correlations with `ApEn_imu_Wrist` ($r_s = 0.99$) and `zero_crossings_acc_Wrist` ($r_s = 0.94$). `zero_crossings_acc_Wrist` was also strongly correlated with `ApEn_imu_Wrist` ($r_s = 0.92$) and was therefore excluded. Similarly, `ratio_mean_max_imu_Wrist` was removed because of its strong correlations with `ApEn_imu_Wrist` ($r_s = 0.93$) and `SPARC_acc_Wrist` ($r_s = 0.91$). A similar pattern was observed at C7. `SPARC_acc_C7`, `zero_crossings_acc_C7`, and `ratio_mean_max_imu_C7` were excluded because they were strongly correlated with `ApEn_imu_C7` ($r_s = 0.88, 0.90, \text{ and } 0.92$, respectively). At the pelvis, `SPARC_acc_Pelvis` was removed because of its strong correlation with `ApEn_imu_Pelvis` ($r_s = 0.93$), while `zero_crossings_acc_Pelvis` was excluded because of its correlation with `SPARC_acc_Pelvis` ($r_s = 0.83$). Finally, `ratio_mean_max_imu_Pelvis` was removed because it was strongly correlated with `ApEn_imu_Pelvis` ($r_s = 0.86$). Within the *Efficiency* category, `length_traj_C7` was discarded because it was strongly correlated with both `length_traj_Wrist` and `length_traj_Pelvis` ($r_s = 0.97$). Wrist and pelvis trajectory lengths were retained as complementary descriptors of distal and proximal movement, respectively. Within the *Signal Complexity* and *Inter-segmental Coordination* categories, only statistically significant parameters were retained. Finally, the entire *Control Strategy* category, including `f_dom` and `PPV`, was discarded. None of the parameters in this category differed significantly between groups. Moreover, these parameters have limited physiological interpretability in a static task without a goal-directed movement.

Speed and Acceleration and Efficiency The children (group 1) showed significantly greater medio-lateral sway than the adults (group 2) at the wrist level (Range Q3 ML-wrist: 4.9 ± 2.9 mm vs 2.8 ± 1.1 mm, $p = 0.036$). Q3 AP velocities were significantly higher in group 1 than in group 2 for all three 3D sensor positions (wrist, C7, and pelvis). Regarding IMU acceleration, Q3 values differed significantly between the two groups for C7 ($p = 0.038$) and the pelvis ($p = 0.023$). Indeed, children showed higher C7 acceleration (9.71 vs 9.57 m/s²) but lower pelvis acceleration (9.70 vs 9.83 m/s²) than adults. It is also useful to group the *Speed and Acceleration* and *Efficiency* categories together for the discussion, as they are strongly related. Table 4.2 shows that trajectory length for the three positions was significantly greater in children than in adults for all three positions (see Appendix Table A.2 for the C7 trajectory length values).

The differences observed in sway and trajectory length are expected for this type of task. Indeed, previous studies have shown that trajectory length, sway area, and sway velocity decrease with age [71–74]. However, it is important to note that the standard deviations for these parameters are relatively large, which is consistent with the literature. Indeed, studies have shown that adult-like sway values may be reached around the age of 12, and that a transition in postural control occurs around 6–7 years of age [49, 71–73, 75]. Since group 1 includes children aged 6 to 12 years, this likely explains the relatively large standard deviations. It is also noteworthy that, among the different Q3 sway range parameters, only *range Q3 ML-wrist* was significantly different (see Appendix Table A.2). A difference could also have been expected along the AP axis. However, the literature shows that the postural mechanisms controlling the anteroposterior axis mature earlier than those involved in mediolateral control, which may explain the different results observed across the two axes [75]. In contrast to the Q3 sway range, for which only the ML axis at the wrist was significant, Q3 velocity significantly discriminated the two groups along both AP and ML axes at the wrist and C7. This suggests that velocity may be a more sensitive parameter than amplitude for detecting developmental differences in postural control.

Furthermore, the lack of significance for C7 and pelvis sway in the ML direction, despite similar trends, may be explained by the lower sensitivity of these segments to lateral oscillations, unlike the wrist, which is

the most distal and most mobile segment and may therefore better capture these variations. In addition, children showed higher C7 acceleration but lower pelvis acceleration than adults. This result suggests that each group adopts a different segmental organization. Adults appear to concentrate postural corrections more at the pelvis level while maintaining a more stable head and upper trunk, which is consistent with the literature [49]. According to this view, the mature nervous system organizes postural control in a top-down manner, prioritizing head stabilization in space.

Figure 4.2 B shows the trajectory length at the wrist, with G1 showing a very large inter-individual variability (range ≈ 130 -600 mm, IQR ≈ 200 mm) compared to G2 which is tightly concentrated between 130 and 200 mm (IQR < 50 mm). This contrast illustrates the developmental heterogeneity within the 6-12 year age range. Some children already approach adult levels of wrist displacement, while others show markedly greater postural sway, likely linked to differences in postural maturity across this wide age range.

Movement Smoothness The table 4.2 shows that IMU LDLJ-A is significantly more negative in children (group 1) for the wrist (-11.84 ± 0.51 vs -10.92 ± 0.22 , $p < 0.001$) and the pelvis (-11.07 ± 0.39 vs -10.72 ± 0.38 , $p = 0.049$). IMU LDLJ-A is also significantly more negative in children for C7 (-11.40 ± 0.45 vs -10.70 ± 0.15 , $p < 0.001$). 3D SPARC is also more negative in children for the wrist (-3.11 vs -2.48 , $p = 0.001$) and the pelvis (-2.58 vs -2.23 , $p = 0.020$). Gyroscopic SPARC shows the strongest effects, with highly significant differences for the wrist (-1.16 ± 0.80 vs -0.28 ± 0.04 , $p < 0.001$) and the pelvis (-0.65 ± 0.33 vs -0.19 ± 0.04 , $p < 0.001$). The 3D mean/max ratio at the pelvis is significantly lower in children (0.22 vs 0.31 , $p = 0.001$) and the IMU median/Q3 ratios are significantly lower in children for C7 (0.56 ± 0.02 vs 0.58 ± 0.01 , $p = 0.002$) and the pelvis (0.57 ± 0.01 vs 0.59 ± 0.01 , $p < 0.001$).

The more negative IMU LDLJ-A values observed in children indicate less smooth acceleration profiles at the three measurement positions. This is particularly interesting in the context of a static task, where the recorded movements mainly reflect low-amplitude postural oscillations and adjustments. The consistency of this result across the wrist, C7, and pelvis suggests that developmental differences in movement smoothness are not restricted to a single segment but can be observed at both distal and proximal levels.

Gyroscopic SPARC is a highly discriminative parameter for this task, with highly significant differences ($p < 0.001$) at both the pelvis and the wrist. At the wrist, gyroscopic SPARC is substantially more negative in children (-1.16) than in adults (-0.28), indicating lower rotational movement smoothness in children. Together with the LDLJ-A results, these findings suggest that the small postural adjustments recorded during static standing are less smooth in children than in adults. The higher 3D mean/max ratio at the pelvis in adults further suggests a more homogeneous movement profile at this proximal level, consistent with less intermittent postural adjustments.

Figure 4.2 C shows the LDLJ-A IMU at the wrist, with G1 distributed between -12.5 and -10.5 (median ≈ -11.5) and G2 concentrated between -11.3 and -10.6 (median ≈ -11.0), showing limited but consistent overlap. Despite the relatively small absolute difference (≈ 0.5 units), the low intra-group variability in G2 contributes to the strong discrimination between groups and indicates greater homogeneity of wrist LDLJ-A values among adults during 30 seconds of static standing.

Figure 4.2 D shows the distribution and boxplot of gyroscopic SPARC at the wrist, one of the most visually striking results of this task. The distribution of G2 is extremely narrow and concentrated near zero (peak density ≈ 10 , with nearly all adults between -0.5 and 0), whereas G1 is broadly distributed from approximately -4 to 0 with a lower peak density (≈ 1.0). This pattern indicates both lower rotational movement smoothness and greater inter-individual variability in children, whereas adults exhibit less negative and more homogeneous gyroscopic SPARC values during static standing.

Data-Driven Pelvis 3D ApEn was significantly higher in adults than in children (0.33 ± 0.12 vs. 0.22 ± 0.08 , $p = 0.023$), as was wrist IMU ApEn (1.48 ± 0.09 vs. 1.05 ± 0.24 , $p < 0.001$). IMU ApEn at C7 was also significantly higher in adults (1.78 ± 0.07 vs 1.46 ± 0.23 , $p < 0.001$).

The significantly higher 3D and IMU ApEn values observed in adults indicate that their postural signals are more complex and less regular than those of children. This finding is consistent with the concept that the temporal organization of postural sway evolves with the development and maturation of postural control. Previous studies have shown that greater regularity of postural sway may be associated with a more constrained and attention-dependent control strategy, whereas greater irregularity can, under certain conditions, accompany more automatic postural control [76]. Entropy-based analyses have also demonstrated that differences in postural signal complexity can reflect differences in the developmental organization of motor control [48]. However, higher entropy should not systematically be interpreted as better postural control, and this interpretation should therefore remain cautious.

Figure 4.2A shows the ApEn IMU at the wrist, with G2 concentrated between 1.3 and 1.6 (IQR ≈ 0.15), while G1 is more dispersed between 0.7 and 1.5 (IQR ≈ 0.35). The limited overlap between the group medians illustrates the higher wrist signal complexity observed in adults. Interestingly, children also show greater inter-individual variability, suggesting substantial heterogeneity in the organization of postural control within the children group.

Inter-segmental Coordination The correlation between wrist and C7 accelerations is positive in children (0.12 ± 0.11) and negative in adults (-0.06 ± 0.13 , $p = 0.003$). The 3D C7-Pelvis correlation is significantly higher in adults (0.70 ± 0.15 vs 0.53 ± 0.12 , $p = 0.007$), whereas the gyroscopic C7-Pelvis correlation is positive in children (0.11 ± 0.33) and negative in adults (-0.32 ± 0.17 , $p = 0.001$).

The Wrist-C7 acceleration correlation shows different patterns between groups, being positive in children (0.12 ± 0.11) and slightly negative in adults (-0.06 ± 0.13). This difference suggests a developmental change in the relationship between distal and proximal segment movements during postural adjustments. Differences in inter-segmental organization were also observed between C7 and the pelvis. The 3D signals showed a stronger positive correlation in adults than in children, whereas the gyroscopic signals showed different correlation patterns between groups, with a positive correlation in children and a negative correlation in adults. These findings indicate that developmental differences in inter-segmental coordination depend on both the segments and the type of signal considered, rather than reflecting a uniform increase or decrease in coupling. This result suggests greater flexibility in motor control in adults, who are able to adapt inter-segmental coordination to task demands. During static standing, they may stabilize the body by adopting a more rigid trunk organization, whereas during fine motor tasks, they are able to dissociate the different segments to allow more independent movements.

Conclusion The static task yielded several significant parameters. *Speed and Acceleration*, *Efficiency*, and *Movement Smoothness* emerged as the most informative categories for distinguishing between children and adults in this task. *Signal Complexity*, assessed using ApEn, revealed more complex and less regular postural signals in adults. The *Coordination* category showed fewer significant differences, but the observed correlation patterns suggest developmental differences in inter-segmental organization and may reflect a greater ability in adults to adapt segmental coordination to the specific postural demands of the task. Finally, the *Control Strategy* category did not discriminate between the two groups under this static condition.

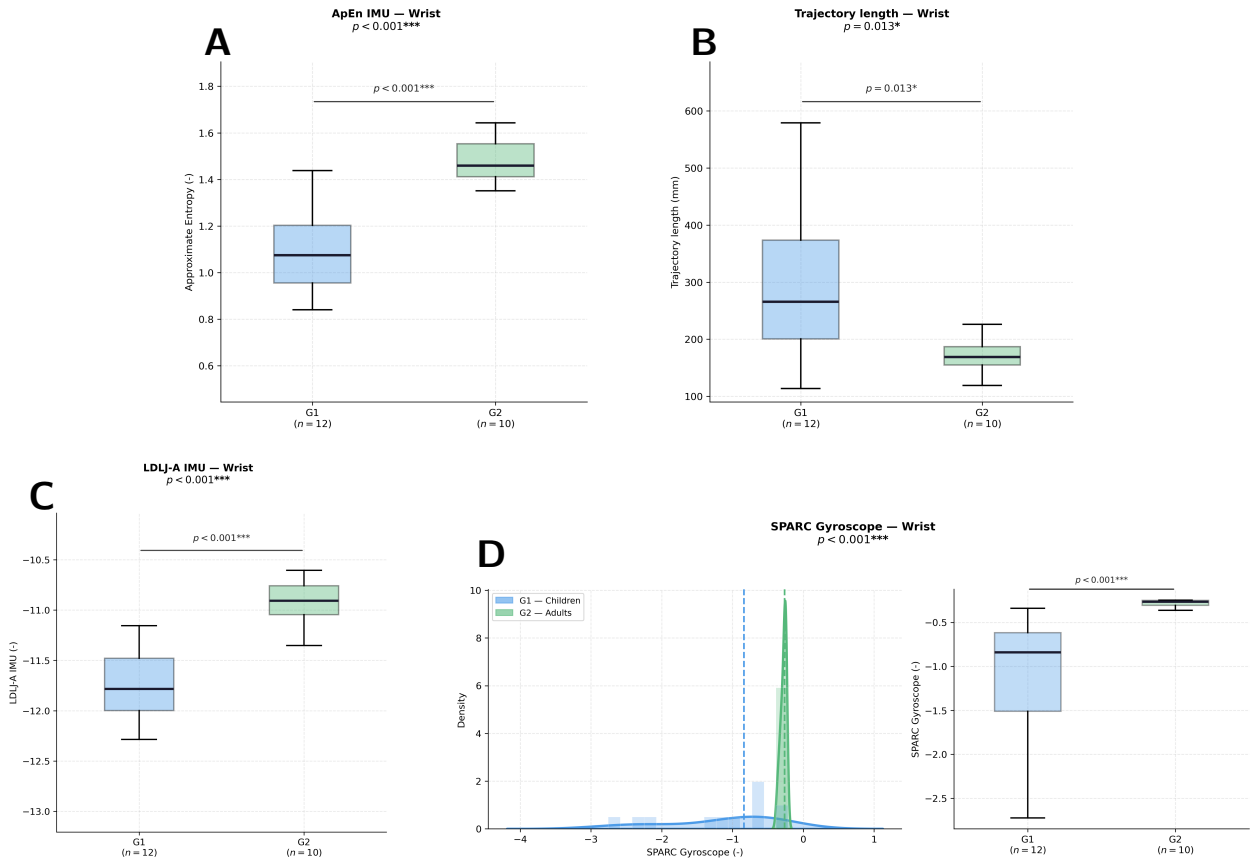


Figure 4.2: Comparison of parameters between children (G1, $n = 12$) and adults (G2, $n = 10$) during the two-leg standing task with eyes open. (A) Approximate Entropy (ApEn) computed from the wrist IMU signal. (B) Trajectory length measured at the wrist. (C) LDLJ-A IMU signal measured at the wrist. (D) Distribution (left) and boxplot (right) of the SPARC gyroscope signal measured at the wrist. Boxplots display the median, interquartile range (IQR), and whiskers extending to $1.5 \times \text{IQR}$.

Table 4.2: Comparison between G1 (children, $n = 12$) and G2 (adults, $n = 10$) for the retained parameters after correlation-based reduction ($|r_s| \geq 0.8$, Spearman) for two-leg standing task. Values are mean $\pm$ SD. *Normal*: normality assessment per group via Shapiro-Wilk ($\alpha = 0.05$): Y = normal, N = non-normal. Statistical test: Welch's t -test (both normal) or Mann-Whitney U (at least one non-normal). * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$. Rows highlighted in green indicate a significant difference ($p < 0.05$).

Parameter	G1 - Children ($n = 12$)		G2 - Adults ($n = 10$)		p -value
	Mean $\pm$ SD	Norm.	Mean $\pm$ SD	Norm.	
Speed and Acceleration					
Range Q3 sway ML - Wrist (mm)	4.9 $\pm$ 2.9	Y	2.8 $\pm$ 1.1	Y	0.036*
AP velocity Q3 - Wrist (mm/s)	9.0 $\pm$ 4.2	Y	5.6 $\pm$ 1.2	Y	0.019*
AP velocity Q3 - C7 (mm/s)	8.1 $\pm$ 2.4	Y	6.2 $\pm$ 1.1	Y	0.024*
AP velocity Q3 - Pelvis (mm/s)	6.2 $\pm$ 2.3	Y	4.5 $\pm$ 0.8	Y	0.034*

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Parameter	G1 - Children ($n = 12$)		G2 - Adults ($n = 10$)		p -value
	Mean $\pm$ SD	Norm.	Mean $\pm$ SD	Norm.	
ML velocity Q3 - Wrist (mm/s)	6.1 $\pm$ 3.3	Y	3.7 $\pm$ 1.1	Y	0.037*
ML velocity Q3 - C7 (mm/s)	5.2 $\pm$ 2.2	Y	3.5 $\pm$ 1.7	N	0.038*
ML velocity Q3 - Pelvis (mm/s)	4.2 $\pm$ 2.3	Y	2.8 $\pm$ 1.2	N	0.12
Acceleration Q3 - C7 (m/s ²)	9.71 $\pm$ 0.10	Y	9.57 $\pm$ 0.15	N	0.038*
Acceleration Q3 - Pelvis (m/s ²)	9.70 $\pm$ 0.16	Y	9.83 $\pm$ 0.06	Y	0.023*
Movement Smoothness					
LDLJ-A IMU - Wrist	-11.84 $\pm$ 0.51	Y	-10.92 $\pm$ 0.22	Y	< 0.001***
LDLJ-A IMU - C7	-11.40 $\pm$ 0.45	Y	-10.70 $\pm$ 0.15	Y	< 0.001***
LDLJ-A IMU - Pelvis	-11.07 $\pm$ 0.39	Y	-10.72 $\pm$ 0.38	Y	0.049*
SPARC 3D - Wrist	-3.11 $\pm$ 0.32	Y	-2.48 $\pm$ 0.37	Y	0.001**
SPARC 3D - Pelvis	-2.58 $\pm$ 0.32	Y	-2.23 $\pm$ 0.32	Y	0.020*
SPARC Gyroscope - Wrist	-1.16 $\pm$ 0.80	N	-0.28 $\pm$ 0.04	Y	< 0.001***
SPARC Gyroscope - Pelvis	-0.65 $\pm$ 0.33	Y	-0.19 $\pm$ 0.04	Y	< 0.001***
Mean/max ratio 3D - Pelvis	0.22 $\pm$ 0.06	Y	0.31 $\pm$ 0.06	Y	0.001**
Median/Q3 ratio IMU - C7	0.56 $\pm$ 0.02	Y	0.58 $\pm$ 0.01	Y	0.002**
Median/Q3 ratio IMU - Pelvis	0.57 $\pm$ 0.01	Y	0.59 $\pm$ 0.01	N	< 0.001***
Efficiency					
Trajectory length - Wrist (mm)	292.4 $\pm$ 141.1	Y	170.5 $\pm$ 35.3	Y	0.013*
Trajectory length - Pelvis (mm)	186.4 $\pm$ 78.4	Y	127.8 $\pm$ 24.1	Y	0.029*
Signal Complexity (Data-Driven)					
ApEn 3D - Pelvis	0.22 $\pm$ 0.08	Y	0.33 $\pm$ 0.12	Y	0.023*
ApEn IMU - C7	1.46 $\pm$ 0.23	Y	1.78 $\pm$ 0.07	Y	< 0.001***
ApEn IMU - Wrist	1.05 $\pm$ 0.24	Y	1.48 $\pm$ 0.09	Y	< 0.001***
Inter-segmental Coordination					
r (Wrist-C7) acc	0.12 $\pm$ 0.11	Y	-0.06 $\pm$ 0.13	Y	0.003**
r (C7-Pelvis) 3D	0.53 $\pm$ 0.12	Y	0.70 $\pm$ 0.15	Y	0.007**
r (C7-Pelvis) gyroscope	0.11 $\pm$ 0.33	Y	-0.32 $\pm$ 0.17	Y	0.001**

4.3 Fine Motor Function

4.3.1 Pouring Water and Drinking Task

After collecting the data for the pouring water and drinking task for each participant, the calculation of each parameter described in the Materials and Methods section was then performed. Next, a correlation analysis between parameters was carried out in order to reduce the number of parameters to be presented and discussed. This correlation-based reduction made it possible to eliminate redundant parameters by identifying pairs with an absolute Spearman correlation coefficient of $|r_s| \geq 0.8$. In total, several correlated pairs were identified among the all tested pairs. It is interesting to note that, during the laboratory sessions, children generally appeared to experience some difficulty when pouring themselves a drink, and

the task often had to be repeated. Moreover, for both groups, it was not natural to do everything with the same hand. This remark is logical since when pouring water, both hands are typically used simultaneously without necessarily doing everything with the dominant hand. During this task, one participant in the children group was excluded from the parameter calculations because the task was not performed exactly as expected. As a result, this created unintended outliers. Therefore, the discussion for this task is based on a group of 11 children for the group 1. Table 4.3 shows the results obtained after parameter reduction using correlation and Table A.3 in the appendix contains all the parameters.

In the *Speed and Acceleration* category, the scalar velocity parameters measured at the pelvis (`vel_mean`, `vel_median`, and `vel_max`) were excluded because they were highly correlated with `vel_Q3_Pelvis` ($r_s \geq 0.85$). The scalar velocity parameters measured at C7 were highly correlated with the pelvis and were thus excluded. At the wrist, `vel_Q3_Wrist` was retained because it was statistically significant ($p = 0.028$). The parameter `acc_Q3_C7` was retained instead of `acc_median_C7`, as both parameters were highly correlated ($r_s = 0.96$) and equally significant ($p = 0.001$). Similarly, `acc_median_Pelvis` was retained instead of `acc_Q3_Pelvis` because of their strong correlation ($r_s = 0.94$). Within the *Movement Smoothness* category, the cluster centred on `LDLJ_A_imu_Wrist`, which was strongly correlated with `movement_time` ($r_s = -0.92$) and `zero_crossings_acc_Wrist` ($r_s = -0.93$), was entirely discarded but `LDLJ_A_imu_C7` and `LDLJ_A_imu_Pelvis` were retained. The parameter `MAPR_3D_Pelv` was also discarded because it was strongly correlated with both `ApEn_imu_Pelvis` ($r_s = -0.90$) and `ratio_mean_max_imu_Pelvis` ($r_s = -0.86$). In addition, `ratio_median_Q3_imu_Pelvis` was removed because of its correlation with `ratio_median_Q3_3D_Pelvis` ($r_s = 0.80$), whereas `ratio_mean_max_imu_C7` was retained. Within the *Efficiency* category, `length_traj_C7` was retained despite its correlations with `LDLJ_A_imu_Pelvis` ($r_s = -0.83$) and `SPARC_gyr_Pelvis` ($r_s = -0.85$), as it provides complementary information on cumulative displacement rather than movement smoothness. `length_traj_Pelvis` was removed because of its strong correlation with `vel_Q3_Pelvis` ($r_s = 0.90$). Then, within the *Control Strategy* and *Data-Driven* categories, only statistically significant parameters were retained. Finally, within the *Inter-segmental Coordination* category, `coord_r_C7_Pelvis_3D` was retained despite its correlations with `MAPR_3D_Pelvis` ($r_s = 0.85$), since this parameter was excluded. The parameter `coord_r_C7_Pelvis_gyr` was also retained because it was not correlated with `coord_r_C7_Pelvis_3D` and statistically significant.

Speed and Acceleration Movement duration is not significantly different between groups (14.9 ± 4.7 s vs 11.3 ± 3.4 s, $p = 0.057$). Q3 velocity at the pelvis is significantly higher in children (19.4 ± 9.7 mm/s vs 5.4 ± 2.3 mm/s, $p = 0.001$). In contrast, Q3 velocity at the wrist is significantly lower in children (293.2 ± 48.4 mm/s vs 362.7 ± 77.9 mm/s, $p = 0.028$). Median pelvis acceleration is significantly lower in children (9.74 ± 0.18 vs 9.99 ± 0.08 m/s², $p = 0.001$) but Q3 acceleration at C7 is higher in children (9.78 ± 0.10 vs 9.57 ± 0.16 m/s², $p = 0.001$). Median wrist acceleration is significantly lower in adults (9.39 ± 0.09 vs 9.59 ± 0.11 m/s², $p < 0.001$).

Although movement duration is not significantly different between groups ($p = 0.057$), children performed the task more slowly on average. Q3 wrist velocity is significantly lower in children (293.2 vs 362.7 mm/s, $p = 0.028$), whereas pelvic velocity is markedly higher (19.42 vs 5.35 mm/s, $p = 0.001$). This dissociation, characterized by lower wrist velocity but greater pelvic motion in children, is consistent with developmental differences reported for functional upper-limb movements. Literature [77] showed that reach-to-drink movements in typically developing school-aged children are characterized by age-related differences in movement speed and smoothness, reflecting the progressive maturation of upper-limb motor control. Three-dimensional studies have also shown that upper-limb movement characteristics progressively mature throughout childhood, with several spatiotemporal parameters approaching adult-like patterns during late childhood [78]. Adults tend to perform reaching movements with more organized velocity profiles, approaching the bell-shaped profile associated with efficient point-to-point movements [79]. The

greater pelvic motion observed in children may reflect less developed trunk-arm segmental dissociation and a greater contribution of proximal body segments to task execution. Moreover, this result may also be influenced by compensatory strategies related to differences in body size, as all participants performed the task while seated at the same table. Figure 4.3 C shows the velocity Q3 at the pelvis, with a clear and almost complete separation between groups. All adults cluster below 10 mm/s while most children range between 10 and 35 mm/s, with one outlier reaching 40 mm/s. This confirms that children generate substantially greater pelvic oscillations to support the functional arm movement, while adults maintain a near stationary trunk. This also highlights the considerable heterogeneity within the group of children.

Movement Smoothness IMU LDLJ-A is significantly more negative in children at the pelvis (-9.75 ± 1.46 vs -7.15 ± 1.02 , $p < 0.001$) and C7 (-10.64 ± 1.25 vs -8.81 ± 1.07 , $p = 0.002$). 3D SPARC at the pelvis ($p = 0.038$) and gyroscopic SPARC at the pelvis ($p < 0.001$) and C7 ($p = 0.010$) are all significantly more negative in children. IMU mean/max ratios are significantly lower in children at the pelvis (0.91 vs 0.97 , $p < 0.001$), at C7 (0.89 vs 0.95 , $p = 0.022$), and at the wrist (0.43 vs 0.53 , $p = 0.017$). The 3D mean/max ratio at the wrist (0.21 vs 0.26 , $p = 0.016$), the 3D median/Q3 ratio at the pelvis (0.49 vs 0.59 , $p = 0.032$), and ACC zero crossings at the wrist (259.4 vs 167.7 , $p = 0.016$) are also significant.

IMU LDLJ-A is significant at the pelvis and C7, gyroscopic SPARC is significant at the pelvis and C7, and IMU mean/max ratios are significant at all three segments. This pattern suggests that the drinking task, which lasts approximately 15 s and includes several sub-phases, reveals immaturity of smoothness at all levels of the kinematic chain, not only at the proximal postural level as observed in shorter tasks. Figure 4.3 B shows the SPARC gyroscope at the pelvis, with G1 widely dispersed between -2.0 and -0.5 (median ≈ -1.4) and G2 concentrated between -0.6 and -0.3 (median ≈ -0.4). The large intra-group variability in G1 reflects heterogeneous postural strategies among children of different developmental levels when performing the drinking task. Figure 4.3 D shows the distribution and boxplot of the LDLJ-A IMU at the pelvis. The two distributions partially overlap but are clearly shifted. G1 is broadly distributed between -14 and -6 with a median around -9.5 , while G2 is more concentrated between -10 and -5 with a median around -7.2 . The wider distribution of G1 again reflects developmental heterogeneity, with some children producing postural acceleration profiles as smooth as the least smooth adults, while others show markedly more abrupt corrections.

ACC zero crossings at the wrist are significantly higher in children (259.4 vs 167.7 , $p = 0.016$), indicating more wrist oscillations during the task. Combined with the lower wrist IMU mean/max ratio in children (0.43 vs 0.53), this result suggests that the effector arm movement is also more irregular and less homogeneous in children during this multi-phase task.

Efficiency C7 trajectory length is significantly greater in children (739.1 ± 357.1 mm vs 313.1 ± 100.5 mm, $p = 0.003$). This greater C7 trajectory length indicates increased upper-trunk movement throughout the task, which may reflect a greater contribution of proximal segments to movement execution (in addition, pelvic trajectory length is also significantly greater in children (see Appendix)).

Control Strategy IMU dominant frequency at the wrist is significantly higher in children (2.38 ± 0.92 Hz vs 1.40 ± 0.52 Hz, $p = 0.004$) but 3D PPV at the wrist is significantly lower in children ($26.7 \pm 32.1\%$ vs $85.2 \pm 28.5\%$, $p = 0.004$).

The 3D PPV at the wrist is one of the most striking results of this task. Indeed, the maximum wrist velocity occurs considerably earlier in the overall task in children (26.7% of total duration) than in adults (85.2%, $p = 0.004$). Given that PPV was calculated over the entire drinking task, which consists of several successive movement phases, this result should not be interpreted as a simple difference in

acceleration or deceleration strategy. Instead, it indicates that the largest wrist velocity peak occurs at a markedly different temporal position within the overall movement sequence in the two groups. In children, this peak tends to occur during the early part of the task, particularly during the pouring phase, whereas in adults it tends to occur later, during the drinking phase. This suggests a difference in the temporal organization and relative contribution of the different phases of the task between the two groups. The higher IMU dominant frequency at the wrist in children (2.38 vs 1.40 Hz, $p = 0.004$) additionally indicates a higher dominant oscillatory frequency of wrist movement during the task. Together, these findings suggest differences in the temporal organization of wrist movement between children and adults during the complete drinking sequence. Figure 4.3A shows the PPV 3D at the wrist, the most discriminating control strategy parameter of this task. G1 is broadly distributed between 0 and 40%, with a median around 15%, whereas G2 is concentrated between 80 and 100%, with very small intra-group variability (IQR < 10%). The limited overlap between the two groups further highlights the marked difference in the temporal position of maximum wrist velocity within the complete drinking sequence.

Data-Driven ApEn 3D and IMU at the pelvis are significantly higher in adults ($p = 0.005$ for both). ApEn 3D at the wrist is significantly higher in children (0.20 ± 0.04 vs 0.15 ± 0.03 , $p = 0.005$). ApEn 3D at the wrist is significantly higher in children (0.20 vs 0.15 , $p = 0.005$).

ApEn values measured at the pelvis, both from the 3D kinematics and the IMU signals, were significantly higher in adults, indicating a more complex and less predictable pelvic movement pattern during the drinking task. This finding may be related to developmental differences in the organization of upper-body movement, as previous studies have shown that reaching and reach-to-grasp strategies progressively change throughout childhood [80, 81]. However, higher movement complexity should not necessarily be interpreted as better motor performance, particularly in a multi-phase functional task such as drinking. Interestingly, the opposite pattern was observed at the wrist, where 3D ApEn was significantly higher in children. This suggests that the developmental difference in signal complexity is segment-dependent rather than uniform across the kinematic chain. Moreover, this result may partly be explained by the fact that some children were less familiar with the different actions required to pour themselves a glass of water, including opening and handling the bottle. This may be particularly relevant for the youngest participants, aged 6–7 years, who may have had less experience performing such actions independently in daily life. This lower familiarity with the task could have resulted in a more variable and complex movement pattern.

Inter-segmental Coordination The C7-Pelvis correlations in 3D ($p = 0.003$) and gyroscope ($p < 0.001$) are significantly higher in children.

The significantly higher C7-Pelvis correlations in 3D ($p = 0.003$) and gyroscopic signals ($p < 0.001$), with higher values in children ($r = 0.74$ and 0.45 , respectively) than in adults ($r = 0.46$ and -0.08), indicate stronger coupling between upper-trunk and pelvic motion in children during the task. This pattern may reflect a less differentiated organization of proximal segments, with C7 and the pelvis tending to vary more closely together. In adults, the lower correlations suggest greater independence between these segments. Such developmental differences are consistent with the progressive refinement of segmental stabilization and postural organization described throughout childhood [49].

Conclusion To conclude, the drinking task yielded several interesting findings. The *Speed* category reveals a dissociation between the pelvis (more agitated in children) and the wrist (slower in children), a pattern consistent across all functional tasks. *Smoothness* category is informative at all three segments, unlike shorter tasks where only proximal segments discriminated. The *Control Strategy* category (3D PPV at the wrist) is the most original result of this task, revealing an early velocity peak in children. *Signal complexity* shows an atypical inversion at the wrist (higher ApEn in children). *Coordination* parameters characterize the immature grasping strategy of children. In addition, the lack of phase segmentation

(reaching, transport, drinking, return) does not allow us to determine at which stage the differences are most pronounced [82]. Finally, the protocol for this task should be revised because it is not sufficiently uniform across participants. Indeed, participants are asked to open a bottle, which is not always easy for a 6 year-old child but poses no difficulty for a 10 year-old child, yet this pattern is not related to the development of childrens movements. The amount of water to be poured should also be defined, because asking participants to pour water into a glass is not precise enough. As a result, a timing pattern may simply be related to the amount of water each participant pours into the glass.

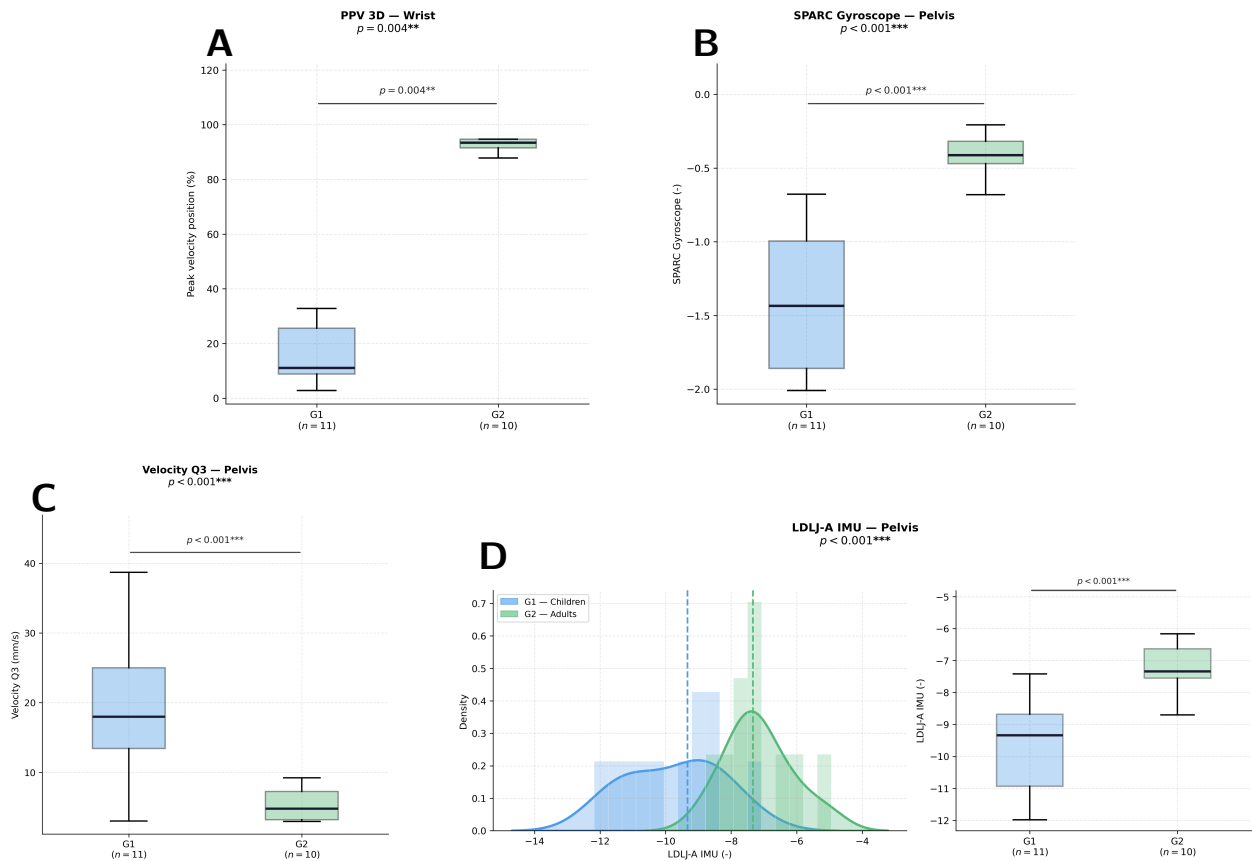


Figure 4.3: Comparison of parameters between children (G1, $n = 11$) and adults (G2, $n = 10$) during the drinking task. (A) Peak velocity position (PPV) measured at the wrist from the 3D kinematic signal. (B) SPARC gyroscope measured at the pelvis. (C) Third quartile (Q3) of pelvis velocity. (D) Distribution (left) and boxplot (right) of the LDLJ-A IMU signal measured at the pelvis. Boxplots display the median, interquartile range (IQR), and whiskers extending to $1.5 \times \text{IQR}$.

Table 4.3: Comparison between G1 (children, $n = 11$) and G2 (adults, $n = 10$) for the retained parameters of the drinking task after correlation-based reduction ($|r_s| \geq 0.8$, Spearman, $N = 21$). Values are mean $\pm$ SD. *Normal*: normality assessment per group via Shapiro-Wilk ($\alpha = 0.05$): Y = normal, N = non-normal. Statistical test: Welch's t -test (both normal) or Mann-Whitney U (at least one non-normal). * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$. Rows highlighted in green indicate a significant difference ($p < 0.05$).

Parameter	G1 - Children (<i>n</i> = 11)		G2 - Adults (<i>n</i> = 10)		<i>p</i> -value
	Mean ± SD	Norm.	Mean ± SD	Norm.	
Speed and Acceleration					
Movement time (s)	14.9 ± 4.7	Y	11.3 ± 3.4	Y	0.057
Velocity Q3 - Pelvis (mm/s)	19.4 ± 9.7	Y	5.4 ± 2.3	Y	0.001***
Acceleration median - Pelvis (m/s ²)	9.74 ± 0.18	Y	9.99 ± 0.08	Y	0.001**
Velocity Q3 - Wrist (mm/s)	293.2 ± 48.4	Y	362.7 ± 77.9	Y	0.028*
Acceleration Q3 - C7 (m/s ²)	9.78 ± 0.10	Y	9.57 ± 0.16	N	0.001**
Acceleration median - Wrist (m/s ²)	9.59 ± 0.11	Y	9.39 ± 0.09	Y	< 0.001***
Movement Smoothness					
LDLJ-A IMU - Pelvis	−9.75 ± 1.46	Y	−7.15 ± 1.02	Y	< 0.001***
LDLJ-A IMU - C7	−10.64 ± 1.25	Y	−8.81 ± 1.07	Y	0.002**
SPARC 3D - Pelvis	−2.58 ± 0.51	Y	−2.11 ± 0.66	N	0.038*
SPARC Gyroscope - Pelvis	−1.41 ± 0.49	Y	−0.42 ± 0.15	Y	< 0.001***
SPARC Gyroscope - C7	−1.83 ± 0.57	Y	−1.21 ± 0.40	Y	0.010*
Mean/max ratio IMU - Pelvis	0.91 ± 0.05	Y	0.97 ± 0.02	N	< 0.001***
Mean/max ratio IMU - C7	0.89 ± 0.07	N	0.95 ± 0.03	N	0.022*
Mean/max ratio 3D - Wrist	0.21 ± 0.03	Y	0.26 ± 0.05	Y	0.016*
Mean/max ratio IMU - Wrist	0.43 ± 0.09	Y	0.53 ± 0.08	Y	0.017*
Median/Q3 ratio 3D - Pelvis	0.49 ± 0.08	N	0.59 ± 0.10	Y	0.032*
Zero crossings ACC - Wrist	259.4 ± 96.2	Y	167.7 ± 57.4	Y	0.016*
Efficiency					
Trajectory length - C7 (mm)	739.1 ± 357.1	Y	313.1 ± 100.5	Y	0.003**
Control Strategy					
PPV 3D - Wrist (%)	26.7 ± 32.1	N	85.2 ± 28.5	N	0.004**
Dominant frequency IMU - Wrist (Hz)	2.38 ± 0.92	Y	1.40 ± 0.52	N	0.004**
Signal Complexity (Data-Driven)					
ApEn 3D - Pelvis	0.20 ± 0.07	Y	0.41 ± 0.18	Y	0.005**
ApEn IMU - Pelvis	0.73 ± 0.19	N	1.16 ± 0.30	Y	0.005**
ApEn 3D - Wrist	0.20 ± 0.04	Y	0.15 ± 0.03	Y	0.005**

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Parameter	G1 - Children (<i>n</i> = 11)		G2 - Adults (<i>n</i> = 10)		<i>p</i> -value
	Mean ± SD	Norm.	Mean ± SD	Norm.	
Inter-segmental Coordination					
<i>r</i> (C7-Pelvis) 3D	0.74 ± 0.09	Y	0.45 ± 0.23	Y	0.003**
<i>r</i> (C7-Pelvis) gyroscope	0.46 ± 0.16	Y	−0.08 ± 0.19	Y	< 0.001***

4.3.2 Reach and Drop Task

After collecting the data for the reach and drop task for each participant, the calculation of each parameter described in the Materials and Methods section was then performed. Next, a correlation analysis between parameters was carried out in order to reduce the number of parameters to be presented and discussed. This correlation-based reduction made it possible to eliminate redundant parameters by identifying pairs with an absolute Spearman correlation coefficient of $|r_s| \geq 0.8$. However, after analysing the results, it was noted that one participant produced surprising results for the 3D marker at the wrist level. It was therefore decided to remove this participant from the analysis of this task, so group 1 of children consists of 11 participants. The surprising results obtained for this participant are due to the fact that the 3D marker was barely visible during the task. In total, several correlated pairs were identified among the all tested pairs. Table 4.4 shows the results obtained after parameter reduction using correlation and Table A.4 in the appendix contains all the parameters.

In the *Speed and Acceleration* category, several redundant parameters were excluded based on their strong correlations. At the pelvis, vel_mean_Pelvis , vel_median_Pelvis , and vel_max_Pelvis were removed in favour of vel_Q3_Pelvis ($r_s \geq 0.91$). Similarly, at C7, vel_mean_C7 , vel_median_C7 were removed in favour of vel_max_C7 ($r_s \geq 0.91$). However, vel_Q3_C7 was retained to provide additional information for the discussion. Regarding acceleration, acc_median_Pelvis , acc_Q3_C7 and acc_Q3_wrist were retained. In the *Movement Smoothness* category, all significant parameters were retained, while the non-significant ones were excluded. In the *Efficiency* category, $\text{length_traj_Pelvis}$ and length_traj_C7 have a strong correlation with velocity parameters but $\text{length_traj_Pelvis}$ was retained for the discussion. In the *Control Strategy* category, as none of the parameters were statistically significant, no parameters were retained. For the *Data-Driven* parameters, all significant parameters were retained. Indeed, ApEn_imu_Pelvis was retained despite its correlations with vel_max_Pelvis ($r_s = -0.90$) and $\text{ratio_mean_max_imu_Pelvis}$ ($r_s = 0.87$), as it captures a distinct dimension related to signal complexity. Finally, in the *Coordination* category, all significant parameters were retained, while the non-significant ones were excluded.

Speed and Acceleration No significant difference in movement duration is observed between the groups (2.51 ± 1.03 s vs 2.10 ± 0.53 s, $p = 0.246$), although children are slightly slower and show greater within-group variability. It is somewhat surprising not to observe a significant difference in task execution time, since it would naturally be expected that adults would perform the task faster than children. However, because the task is very short, this explains why no significant difference is observed.

Q3 velocity at the pelvis is significantly higher in children (32.9 ± 19.8 mm/s vs 8.9 ± 6.6 mm/s, $p = 0.004$). In addition, max C7 velocity is significantly higher in children, whereas Q3 C7 velocity is also higher in children but not significantly so. Median pelvis acceleration is significantly lower in children (9.86 ± 0.13 m/s² vs 9.97 ± 0.08 m/s², $p = 0.023$) but Q3 acceleration at C7 (9.75 ± 0.14 vs 9.59 ± 0.14 m/s², $p = 0.005$) and at the wrist (10.90 ± 0.86 vs 10.40 ± 0.37 m/s², $p = 0.032$) are higher in children. The wrist shows acceleration values above 9.81 m/s², reflecting the dynamic acceleration

added by arm movement during grasping and transport of the ball.

The significantly higher pelvic Q3 velocity in children, with the greater pelvic trajectory length (50.1 vs 12.5 mm, $p = 0.004$), confirms that children generate greater postural oscillations of the trunk during the task. This result is consistent with the literature [78, 83], which showed that typically developing children use the trunk more as a compensatory strategy during reach-to-grasp tasks, due to a lower ability to dissociate arm and trunk movements. This result could also be explained by the fact that children are smaller and therefore, when performing the task while seated, they compensate by combining pelvis and arm movement. The IMU acceleration differences follow an interesting segmental pattern. At the wrist, values exceed 9.81 m/s^2 (≈ 10.9 for G1, 10.4 for G2), reflecting the dynamic contribution of grasping and transport. Values at C7 are closer to 9.81 m/s^2 with an opposite pattern between groups. Indeed, children show higher C7 acceleration than adults, consistent with poorer cervical stabilization during the task [49]. Moreover, this observation is also consistent with the hypothesis that children compensate for their smaller body size relative to adults. However, median pelvis acceleration is higher in adults, suggesting that compensation occurs at the C7 level. Finally, it is interesting to note that maximum C7 velocity is significantly higher in children than in adults, whereas Q3 C7 velocity is not significant even though it is also higher. This shows that Q3 velocity is more robust to outliers and that the two parameters are complementary.

Movement Smoothness IMU LDLJ-A is significantly more negative in children for the pelvis (-2.53 ± 1.69 vs -0.69 ± 1.27 , $p = 0.011$) and C7 (-3.29 ± 1.91 vs -1.80 ± 1.10 , $p = 0.041$). Gyroscopic SPARC is significantly more negative in children for two segments: wrist (-0.91 vs -0.70 , $p = 0.003$) and pelvis (-0.72 vs -0.51 , $p = 0.014$). IMU mean/max ratios are significantly lower in children for the pelvis (0.94 vs 0.98 , $p = 0.002$) and C7 (0.93 vs 0.97 , $p = 0.001$), as is the 3D mean/max ratio at C7 (0.35 vs 0.42 , $p = 0.026$).

As observed in the drinking task, the discriminative smoothness parameters mainly involved the proximal segments, particularly the pelvis and C7. IMU LDLJ-A did not significantly differ between groups at the wrist ($p = 0.128$), whereas significant differences were observed at both proximal segments. This suggests that developmental differences during the reach-and-drop task may be particularly related to the control and stabilization of the trunk rather than exclusively to the distal movement of the upper limb. This interpretation is consistent with previous studies investigating the development of reaching and grasping movements. The literature [84] reported that younger children exhibited more variable and less smooth hand trajectories, together with greater trunk displacement and variability. With increasing age, hand trajectories became smoother and trunk involvement progressively decreased. It is also worth noting that the literature has shown substantial changes in motor strategies throughout childhood, particularly between the ages of 6, 8, 10, and 12 years, which may partly explain the variability observed within the children group [80, 85]. The more negative LDLJ-A values observed at the pelvis and C7 in children may reflect less smooth proximal control during task execution. In contrast, the absence of a significant difference in wrist LDLJ-A suggests that developmental differences in this metric were more pronounced proximally than distally. Nevertheless, gyroscope-based SPARC was significantly more negative at the wrist and pelvis in children, indicating that differences in movement smoothness were also present in the rotational component of the distal movement.

Figure 4.4 B shows the SPARC gyroscope at the wrist, with G1 broadly distributed between -1.2 and -0.7 and G2 more concentrated between -0.8 and -0.6 . The limited overlap between the two distributions confirms that the rotational irregularity of the wrist during grasping and transporting the ball is significantly greater in children. Figure 4.4 C shows the distribution and boxplot of the LDLJ-A IMU at the pelvis. The two distributions overlap partially but are clearly shifted. This clearly shows that the distribution in adults is shifted toward less negative values, indicating smoother movements.

The lower IMU mean/max ratios in children for C7 and the pelvis (0.93 vs 0.97 and 0.94 vs 0.98) reflect a more heterogeneous acceleration profile, dominated by abrupt postural correction episodes. These values, very close to 1 in adults, indicate near-constant acceleration, which in a short functional task reflects a highly controlled and homogeneous movement. Figure 4.4 A allows this result to be seen visually. Indeed, this figure shows the IMU mean/max ratio at C7 with a very homogeneous distribution in adults (narrow whiskers), in contrast with the large inter-individual dispersion in children, illustrating the heterogeneity within G1.

Efficiency Trajectory length of pelvis is significantly higher in children than in adults (50.1 mm vs 12.5 mm). This result highlights differences in segmental involvement, with children relying more on pelvic movements during task execution. However, it is important to consider that the experimental setup was identical for all participants, meaning that this result may also have been influenced by differences in body size between children and adults. Since all participants were seated at the same table, smaller children may have compensated for their shorter stature by increasing pelvic or trunk movements to reach and manipulate the objects. Therefore, the greater involvement of the pelvis observed in children may reflect not only differences in motor control strategies but also an adaptation to the experimental setup.

Control Strategy It is interesting to note that for this reach-and-drop task, no parameter in this category is significant. In this type of task, a significant difference in PPV parameters might have been expected, which would have shown different speed profiles. However, this lack of significance may be explained by the duration of the task. Indeed, this task is quite short and it may therefore be difficult to obtain significantly different velocity profiles.

Data-Driven and Inter-segmental Coordination IMU ApEn is significantly higher in adults for the pelvis (0.99 ± 0.15 vs 0.68 ± 0.23 , $p = 0.002$) and C7 (0.88 ± 0.13 vs 0.73 ± 0.11 , $p = 0.008$). Then, gyroscopic C7-Pelvis correlation is positive in children (0.62 ± 0.31) and negative in adults (-0.15 ± 0.54 , $p = 0.004$). ACC C7-Pelvis correlation is significantly higher in children (0.53 ± 0.18 vs 0.17 ± 0.23 , $p = 0.001$) as for 3D Wrist-C7 correlation (0.40 ± 0.23 vs 0.17 ± 0.22 , $p = 0.032$)

The higher IMU ApEn observed in adults at C7 and the pelvis indicates a more complex and less predictable proximal movement pattern during the task. In parallel, the significantly higher C7-Pelvis correlations observed in children with both gyroscopic and acceleration signals suggest stronger coupling between these two proximal segments. The higher 3D Wrist-C7 correlation in children further supports the presence of greater inter-segmental coupling along the kinematic chain. Together, these results may indicate a less differentiated organization of segmental movement in children, whereas the lower correlations observed in adults suggest greater independence between segments. This interpretation is consistent with the progressive development of segmental coordination and postural organization described during childhood [49, 84].

Conclusion To conclude, the reach-and-drop task yielded several relevant findings. The *Movement Smoothness* category was particularly informative, with gyroscope-based SPARC at the pelvis and wrist and LDLJ-A at the pelvis and C7 significantly discriminating between children and adults. Wrist LDLJ-A was not significant, whereas gyroscopic SPARC was, suggesting that rotational differences at the wrist were better captured by the gyroscope signal. Then, higher pelvis velocity and trajectory length in children further indicated greater proximal involvement during task execution. *Signal Complexity* (ApEn IMU) and *Inter-segmental Coordination* (C7-Pelvis) also revealed developmental differences, reinforcing the presence of a less mature proximal control strategy in children. Interestingly, these kinematic differences were observed despite similar *movement times* and no significant differences in *Control Strategy*.

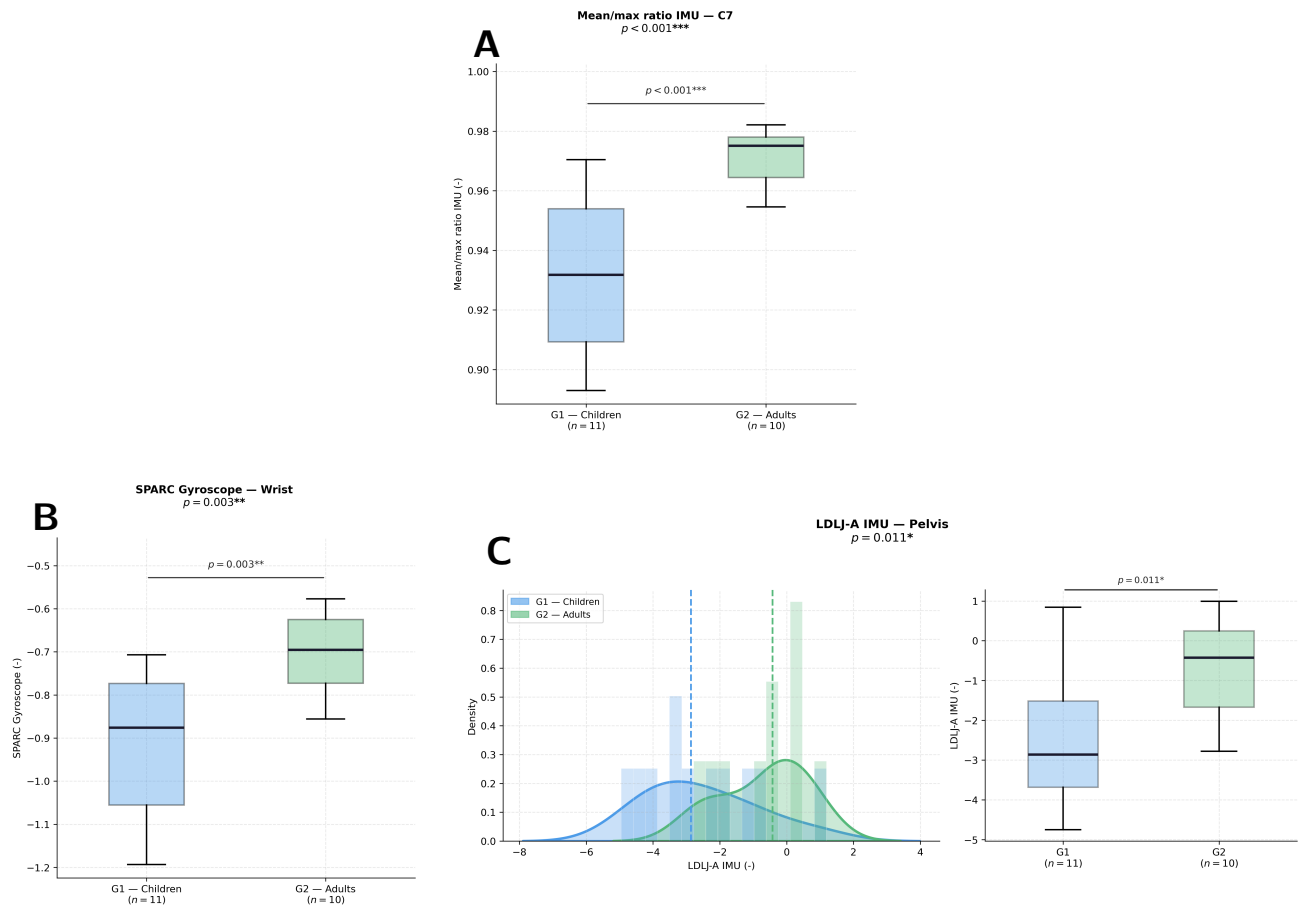


Figure 4.4: Comparison of parameters between children (G1, $n = 11$) and adults (G2, $n = 10$) during the reach and drop task. (A) Mean-to-maximum IMU ratio measured at C7. (B) SPARC gyroscope measured at the wrist. (C) Distribution (left) and boxplot (right) of the LDLJ-A IMU signal measured at the pelvis. Boxplots display the median, interquartile range (IQR), and whiskers extending to $1.5 \times \text{IQR}$.

Table 4.4: Comparison between G1 (children, $n = 11$) and G2 (adults, $n = 10$) for the retained parameters of reach and drop task after correlation based reduction ($|r_s| \geq 0.8$, Spearman). Values are mean $\pm$ SD. *Normal*: normality assessment per group via Shapiro-Wilk ($\alpha = 0.05$): Y = normal, N = non-normal. Statistical test: Welch's t -test (both normal) or Mann-Whitney U (at least one non-normal). * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$. Rows highlighted in green indicate a significant difference ($p < 0.05$).

Parameter	G1 - Children (<i>n</i> = 11)		G2 - Adults (<i>n</i> = 10)		<i>p</i> -value
	Mean ± SD	Norm.	Mean ± SD	Norm.	
Speed and Acceleration					
Movement time (s)	2.51 ± 1.03	Y	2.10 ± 0.53	Y	0.246
Velocity Q3 - Pelvis (mm/s)	32.9 ± 19.8	Y	8.9 ± 6.6	N	0.004**
Velocity Q3 - C7 (mm/s)	89.3 ± 45.1	Y	62.6 ± 37.0	Y	0.153
Max velocity - C7 (mm/s)	172.3 ± 83.9	Y	96.4 ± 50.4	Y	0.0215*
Acceleration median - Pelvis (m/s ²)	9.86 ± 0.13	Y	9.97 ± 0.08	Y	0.023*
Acceleration Q3 - C7 (m/s ²)	9.75 ± 0.14	Y	9.59 ± 0.14	N	0.005**
Acceleration Q3 - Wrist (m/s ²)	10.90 ± 0.86	Y	10.40 ± 0.37	N	0.032*

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Parameter	G1 - Children ($n = 11$)		G2 - Adults ($n = 10$)		p -value
	Mean $\pm$ SD	Norm.	Mean $\pm$ SD	Norm.	
Movement Smoothness					
LDLJ-A IMU - Pelvis	-2.53 ± 1.69	Y	-0.69 ± 1.27	Y	0.011*
LDLJ-A IMU - C7	-3.29 ± 1.91	Y	-1.80 ± 1.10	Y	0.041*
SPARC Gyroscope - Pelvis	-0.72 ± 0.23	Y	-0.51 ± 0.09	Y	0.014*
SPARC Gyroscope - Wrist	-0.91 ± 0.17	Y	-0.70 ± 0.09	Y	0.003**
Mean/max ratio IMU - Pelvis	0.94 ± 0.03	Y	0.98 ± 0.01	Y	0.002**
Mean/max ratio 3D - C7	0.35 ± 0.08	Y	0.42 ± 0.09	Y	0.049*
Mean/max ratio IMU - C7	0.93 ± 0.03	Y	0.97 ± 0.01	Y	0.001**
Efficiency					
Trajectory length - Pelvis (mm)	50.1 ± 36.7	Y	12.5 ± 7.2	N	0.004**
Signal Complexity (Data-Driven)					
ApEn IMU - Pelvis	0.68 ± 0.23	N	0.99 ± 0.15	Y	0.002**
ApEn IMU - C7	0.73 ± 0.11	Y	0.88 ± 0.13	Y	0.008**
Inter-segmental Coordination					
$r(\text{Wrist-C7})$ 3D	0.40 ± 0.23	Y	0.17 ± 0.22	Y	0.032*
$r(\text{C7-Pelvis})$ gyroscope	0.62 ± 0.31	N	-0.15 ± 0.54	Y	0.004**
$r(\text{C7-Pelvis})$ ACC	0.53 ± 0.18	Y	0.17 ± 0.23	Y	0.001**

4.3.3 Pegboard Task

After collecting the data for the pegboard task for each participant, the calculation of each parameter described in the Materials and Methods section was then performed. Next, a correlation analysis between parameters was carried out in order to reduce the number of parameters to be presented and discussed. This correlation-based reduction made it possible to eliminate redundant parameters by identifying pairs with an absolute Spearman correlation coefficient of $|r_s| \geq 0.8$. During this task, one participant was excluded from the computation and analysis of the parameters because it was observed that the participant had not completed the task correctly in accordance with the instructions. Group 1 of children therefore consists of 11 participants for this task. In total, several correlated pairs were identified among all tested pairs. Table 4.5 shows the results obtained after parameter reduction using correlation and Table A.5 in the appendix contains all the parameters.

In the *Speed and Acceleration* category, the parameter `acc_median_Pelvis` was retained instead of `acc_Q3_Pelvis`, as both were highly correlated ($r_s = 0.975$) and equally significant ($p = 0.001$). Similarly, `acc_median_C7` was retained instead of `acc_Q3_C7` ($r_s = 0.975$, $p = 0.002$ vs. $p = 0.004$). For wrist velocity, `vel_median_Wrist` was retained. Within the *Movement Smoothness* category, `SPARC_gyr_Pelvis` was excluded because of its high correlation with `MAPR_3D_Pelvis` ($r_s = -0.86$). Likewise, `ratio_median_Q3_3D_Pelvis` was removed due to its strong correlation with `MAPR_3D_Pelvis` ($r_s = -0.94$). In addition, `ratio_mean_max_imu_Pelvis` was removed because of its correlation with `MAPR_3D_Pelvis` ($r_s = -0.83$), and `ratio_median_Q3_imu_Wrist` was excluded due to its correlation with `SPARC_gyr_Wrist` ($r_s = 0.83$). For *Efficiency* category, both `length_traj_Pelvis` and `length_traj_Wrist` were retained as interesting parameters. In the *Control Strategy* category, both `f_dom_3D_Wrist` and `f_dom_imu_Wrist` showed significant differences between groups. Since the correlation between these two parameters remained below the defined threshold, both were retained to represent the dominant

frequency derived from the 3D and IMU signals, respectively. For *Signal Complexity* category, only *ApEn_3D_C7*, *ApEn_3D_Wrist* and *ApEn_IMU_Wrist* were retained. Finally, for *Inter-segmental Coordination*, the *coord_r_Wrist_Pelvis_gyr* coefficient was close to, but did not reach, statistical significance ($p = 0.065$) and was therefore excluded, together with the other non-significant coefficients. Six parameters were ultimately retained. As none of these parameters showed correlations above the threshold of 0.8, they were all retained to represent distinct segmental relationships and measurement modalities.

Speed and Acceleration Children take significantly longer time to complete the task (44.08 ± 7.77 s vs 33.17 ± 4.25 s, $p = 0.002$). Median wrist velocity is significantly lower in children (198.8 ± 52.3 mm/s vs 256.9 ± 43.4 mm/s, $p = 0.012$). Median pelvis acceleration is significantly lower in children (9.76 ± 0.18 vs 9.98 ± 0.08 m/s², $p = 0.001$) but median C7 acceleration is significantly higher in children (9.66 ± 0.13 vs 9.50 ± 0.16 m/s², $p = 0.002$).

The significant difference in duration (44.08 vs 33.17 s, $p = 0.002$) is consistent with the literature on fine motor tasks. [80] Kinematic studies of peg-moving tasks have shown that adults perform reaching-to-grasp movements in a better organized way than children with shorter durations and with differences being larger between adults and 6-year-old children than between adults and 10-year-old children. [85,86] The significantly lower wrist median velocity in children (198.8 vs 256.9 mm/s, $p = 0.012$) illustrates this functional immaturity. Adults complete each insertion more quickly, in line with the mature velocity profile. [87] The absence of a difference in scalar pelvis velocity (not significant) is an interesting result. Unlike in the other tasks for the fine motor function, both groups show similar pelvic oscillation amplitudes, suggesting that the longer task duration leads to a homogenization of global sway between groups.

Movement Smoothness IMU LDLJ-A is significantly more negative in children for all three segments: pelvis (-13.32 ± 0.65 vs -11.69 ± 0.71 , $p < 0.001$), C7 (-13.93 ± 0.62 vs -12.82 ± 0.52 , $p < 0.001$), and wrist (-17.64 ± 0.61 vs -17.04 ± 0.48 , $p = 0.020$). 3D MAPR is significantly higher in children for the pelvis (0.049 vs 0.028 , $p = 0.025$) and C7 (0.041 vs 0.030 , $p = 0.008$). 3D SPARC is more negative in children for all three segments ($p \leq 0.001$), and gyroscopic SPARC is more negative for C7 ($p = 0.010$) and wrist ($p < 0.001$). ACC zero crossings at the wrist are significantly higher in children (496.1 ± 68.5 vs 400.5 ± 45.8 , $p = 0.001$). Mean/max 3D ratios are significantly lower in children for all three segments ($p \leq 0.019$), as are median/Q3 3D ratios for C7 ($p < 0.001$) and wrist ($p = 0.038$).

This task shows that IMU LDLJ-A is significant for all three segments simultaneously. In contrast to others tasks for the fine motor function, where only proximal segments discriminated between groups, distal smoothness (wrist, $p = 0.020$) is also significant here. This result suggests that the repetitive and precise nature of the pegboard task reveals immaturity at all levels of the kinematic chain. The literature confirms that the development of hand trajectory smoothness and stability continues until 8-10 years of age in typically developing children, with a maturation plateau around 11-12 years [78,83,86]. The cyclical nature of the task amplifies inter-group differences because irregularities can be accumulated over the full duration.

Figure 4.5 D shows the distribution and boxplot of IMU LDLJ-A at the pelvis. The two distributions partially overlap but are clearly shifted with G1 centered around -13.5 and G2 around -12.0 . Figure 4.5 A shows gyroscopic SPARC at the wrist, with an almost complete separation between the two groups. All G1 values are below -3.4 , whereas G2 values range from -3.5 to -2.5 , illustrating the difference in rotational regularity of the wrist during repetitive insertions.

The significantly higher 3D MAPR in children for the pelvis and C7 indicates more quasi-static phases, corresponding to the pauses between two successive insertions. Children stop more between movements, which is a sign of more serial and less fluid motor planning than in adults, who chain movements more

continuously [86]. However, given the values obtained, it is important to remain cautious when interpreting this result. Then, the higher ACC zero crossings at the wrist in children (496.1 vs 400.5, $p = 0.001$) can be explained by the repetitive nature of the task. Indeed, children produce more low-amplitude oscillations, reflecting more frequent but less organized micro-corrections during successive insertions. [86]

Efficiency Trajectory length of pelvis is significantly higher in children than in adults and is twice as large (0.40 m vs 0.20 m) in children. This result highlights differences in segmental involvement, with children relying more on pelvic movements during task execution. However, it is important to consider that the experimental setup was identical for all participants, meaning that this result may also have been influenced by differences in body size between children and adults. Since all participants were seated at the same table, smaller children may have compensated for their shorter stature by increasing pelvic or trunk movements to reach and manipulate the objects. Therefore, the greater involvement of the pelvis observed in children may reflect not only differences in motor control strategies but also an adaptation to the experimental setup. In contrast, wrist trajectory is not significantly different. It is interesting to note that this parameter is not significant, one might have expected wrist trajectory length to be significantly greater in children. Indeed, in a long precision task, children may take longer paths and less direct routes.

Control Strategy Dominant frequency 3D at the wrist is significantly higher in adults (1.92 ± 0.30 Hz vs 1.45 ± 0.30 Hz, $p = 0.002$), as is IMU frequency (2.58 ± 0.47 Hz vs 1.88 ± 0.43 Hz, $p = 0.002$).

The significantly higher wrist dominant frequency in adults for the 3D and IMU marker reflects a faster insertion rhythm. The difference of approximately 0.47 Hz corresponds to nearly one additional dominant movement cycle every 2 s in adults. This higher dominant frequency is consistent with a faster execution of the repetitive wrist movements involved in the pegboard task. Figure 4.5 C shows the 3D dominant frequency at the wrist. Although the distributions partially overlap, the median of G2 is clearly higher than that of G1, corresponding to a faster execution in favour of adults, consistent with the observed total duration difference (44.1 s vs 33.2 s, $p = 0.002$).

Data-Driven ApEn 3D is significantly higher in adults for C7 (0.38 ± 0.08 vs 0.27 ± 0.07 , $p = 0.003$) and wrist (0.29 ± 0.04 vs 0.21 ± 0.03 , $p < 0.001$). Moreover, ApEn IMU at the wrist is also significantly higher in adults (0.67 ± 0.04 vs 0.61 ± 0.06 , $p = 0.013$). The significantly higher ApEn in adults for C7 and wrist (3D and IMU) suggests a more complex and less stereotyped movement signal during the repetitive task.

Inter-segmental Coordination Six coefficients out of nine are significant. Wrist-C7 (3D and gyro) and Wrist-Pelvis 3D correlations are significantly higher in children. The Wrist-C7 ACC correlation is significantly higher in adults. Then, the C7-Pelvis 3D correlation is higher in children (0.54 ± 0.12 vs 0.38 ± 0.13 , $p = 0.018$). The C7-Pelvis gyroscopic correlation is positive in children (0.38 ± 0.21) and negative in adults (-0.31 ± 0.06 , $p < 0.001$).

The pegboard task yields the largest number of significant coordination coefficients (6 out of 9), highlighting the importance of inter-segmental organization during this repetitive fine-motor task. The higher Wrist-C7 and Wrist-Pelvis correlations observed in children suggest stronger coupling between distal and proximal segments during peg insertion, whereas the lower correlations in adults indicate greater independence between segmental movements. This pattern is consistent with the progressive development of segmental dissociation and postural organization described throughout childhood [49].

The C7-Pelvis gyroscopic correlation is positive in children (0.38) and strongly negative in adults (-0.31 , $p < 0.001$). This anti-phase in adults reflects an active dissociation for the rotation between the cervical spine and the pelvis during the task, consistent with the head-stabilization strategy [49] that frees

the head from pelvic oscillations. Figure 4.5 B is particularly striking. Indeed, the two distributions of the C7-Pelvis gyroscopic correlation coefficient do not overlap at all, with G1 entirely positive and G2 entirely negative, visually illustrating the complete dissociation of strategy between block movement for rotation in children and cervico-pelvic anti-phase in adults.

Conclusion To conclude, the pegboard task yielded several interesting findings. For this task, *Smoothness* is a very important category because a lot of parameters are significant. Then, *Smoothness* is significant at all three segments for multiple metrics simultaneously (LDLJ-A, SPARC 3D, SPARC gyro). The *Coordination* category is the richest of all tasks, with 6 out of 9 coefficients significant, reflecting the importance of segmental dissociation in a repetitive precision task. The *Control Strategy* category is significant here, translating the faster insertion rhythm of adults into a measurable frequency shift. For this task, the *Speed* category (scalars) is not really discriminating. Moreover, this task, which is directly inspired by standardized clinical assessments, highlights the added value of combining 3D motion capture and IMU data. As previously discussed, conventional assessments of this type mainly focus on the final outcome, such as task completion time or the number of pegs successfully placed. However, the present findings suggest that analysing the underlying movement provides substantially more information about motor performance, with completion time representing only one aspect of the overall movement strategy.

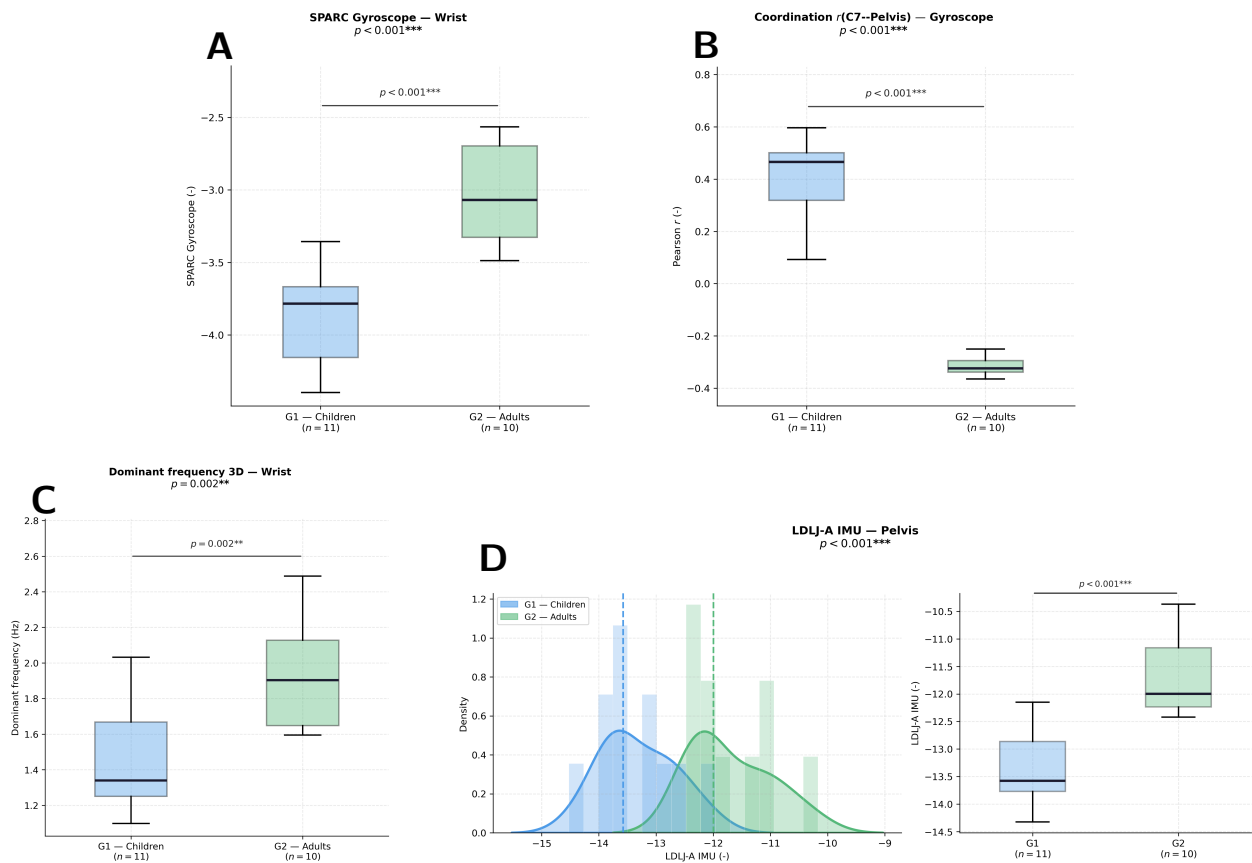


Figure 4.5: Comparison of parameters between children (G1, $n = 11$) and adults (G2, $n = 10$) during the pegboard task. (A) SPARC gyroscope measured at the wrist. (B) Coordination coefficient between C7 and pelvis computed from the gyroscope signal. (C) Dominant frequency measured at the wrist. (D) Distribution (left) and boxplot (right) of the LDLJ-A IMU signal measured at the pelvis. Boxplots display the median, interquartile range (IQR), and whiskers extending to $1.5 \times \text{IQR}$.

Table 4.5: Comparison between G1 (children, $n = 11$) and G2 (adults, $n = 10$) for the retained parameters of pegboard task after correlation-based reduction ($|r_s| \geq 0.8$, Spearman, $N = 21$). Values are mean $\pm$ SD. *Normal*: normality assessment per group via Shapiro-Wilk ($\alpha = 0.05$): Y = normal, N = non-normal. Statistical test: Welch's t -test (both normal) or Mann-Whitney U (at least one non-normal). * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$. Rows highlighted in green indicate a significant difference ($p < 0.05$).

Parameter	G1 - Children (<i>n</i> = 11)		G2 - Adults (<i>n</i> = 10)		<i>p</i> -value
	Mean ± SD	Norm.	Mean ± SD	Norm.	
Speed and Acceleration					
Movement time (s)	44.08 ± 7.77	N	33.17 ± 4.25	Y	0.002**
Acceleration median - Pelvis (m/s ²)	9.76 ± 0.18	N	9.98 ± 0.08	Y	0.001**
Acceleration median - C7 (m/s ²)	9.66 ± 0.13	N	9.50 ± 0.16	N	0.002**
Median velocity - Wrist (mm/s)	198.8 ± 52.3	Y	256.9 ± 43.4	Y	0.012*
Movement Smoothness					
LDLJ-A IMU - Pelvis	−13.32 ± 0.65	Y	−11.69 ± 0.71	Y	< 0.001***
MAPR 3D - Pelvis	0.049 ± 0.026	Y	0.028 ± 0.010	Y	0.025*
SPARC 3D - Pelvis	−4.91 ± 0.66	Y	−3.42 ± 0.60	Y	< 0.001***
SPARC 3D - C7	−3.92 ± 0.44	Y	−2.95 ± 0.24	Y	< 0.001***
SPARC 3D - Wrist	−4.08 ± 0.39	Y	−3.28 ± 0.26	Y	< 0.001***
SPARC Gyroscope - C7	−3.13 ± 0.97	Y	−2.19 ± 0.37	Y	0.010*
SPARC Gyroscope - Wrist	−3.88 ± 0.34	Y	−3.02 ± 0.35	Y	< 0.001***
Mean/max ratio 3D - Pelvis	0.14 ± 0.04	Y	0.21 ± 0.07	Y	0.019*
Mean/max ratio 3D - C7	0.20 ± 0.04	Y	0.26 ± 0.06	Y	0.010*
Mean/max ratio 3D - Wrist	0.23 ± 0.04	Y	0.29 ± 0.03	Y	0.002**
Median/Q3 ratio 3D - C7	0.64 ± 0.02	Y	0.68 ± 0.02	Y	< 0.001***
Median/Q3 ratio 3D - Wrist	0.53 ± 0.05	Y	0.58 ± 0.05	N	0.038*
LDLJ-A IMU - C7	−13.93 ± 0.62	Y	−12.82 ± 0.52	Y	< 0.001***
LDLJ-A IMU - Wrist	−17.64 ± 0.61	Y	−17.04 ± 0.48	Y	0.020*
MAPR 3D - C7	0.041 ± 0.010	Y	0.030 ± 0.008	Y	0.008**
Zero crossings ACC - Wrist	496.1 ± 68.5	Y	400.5 ± 45.8	Y	0.001**
Efficiency					
Trajectory length - Pelvis (m)	0.40 ± 0.29	Y	0.20 ± 0.08	Y	0.0479*
Trajectory length - Wrist (m)	11.19 ± 1.69	Y	10.05 ± 1.41	Y	0.109
Control Strategy					
Dominant frequency 3D - Wrist (Hz)	1.45 ± 0.30	Y	1.92 ± 0.30	Y	0.002**
Dominant frequency IMU - Wrist (Hz)	1.88 ± 0.43	Y	2.58 ± 0.47	Y	0.002**
Signal Complexity (Data-Driven)					
ApEn 3D - C7	0.27 ± 0.07	Y	0.38 ± 0.08	Y	0.003**
ApEn 3D - Wrist	0.21 ± 0.03	Y	0.29 ± 0.04	Y	< 0.001***
ApEn IMU - Wrist	0.61 ± 0.06	Y	0.67 ± 0.04	Y	0.013*

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Parameter	G1 - Children ($n = 11$)		G2 - Adults ($n = 10$)		p -value
	Mean $\pm$ SD	Norm.	Mean $\pm$ SD	Norm.	
Inter-segmental Coordination					
$r(\text{Wrist-C7})$ 3D	0.30 ± 0.16	Y	0.12 ± 0.19	Y	0.031*
$r(\text{Wrist-C7})$ gyroscope	0.28 ± 0.10	Y	0.05 ± 0.12	Y	0.0002***
$r(\text{Wrist-C7})$ ACC	0.08 ± 0.10	Y	0.22 ± 0.10	Y	0.007**
$r(\text{Wrist-Pelvis})$ 3D	0.33 ± 0.11	Y	0.18 ± 0.09	Y	0.003**
$r(\text{C7-Pelvis})$ 3D	0.54 ± 0.12	Y	0.38 ± 0.13	N	0.018*
$r(\text{C7-Pelvis})$ gyroscope	0.38 ± 0.21	N	-0.31 ± 0.06	Y	< 0.001 ***

4.4 Social Interaction

4.4.1 Glass Clinking Task

After collecting the data for the glass clinking task for each participant, the calculation of each parameter described in the Materials and Methods section was then performed. Next, a correlation analysis between parameters was carried out in order to reduce the number of parameters to be presented and discussed. This correlation-based reduction made it possible to eliminate redundant parameters by identifying pairs with an absolute Spearman correlation coefficient of $|r_s| \geq 0.8$. All participants performed the task correctly, and thus all parameters were correctly computed for group 1, consisting of 12 children, and group 2, consisting of 10 adults. However, it is interesting to note that for 2-3 children, the calculation of certain parameters yielded outliers that are not true outliers but rather valid biomechanical results that were correctly computed, which increases the standard deviation for some parameters. In total, several correlated pairs were identified among all tested pairs. It is also interesting to note that this task yielded the lowest number of correlated parameters, which may be related to its short duration and rapid execution. Table 4.6 shows the results obtained after parameter reduction using correlation and Table A.6 in the appendix contains all parameters.

In the *Speed and Acceleration* category, `vel_mean_Pelvis`, `vel_median_Pelvis`, and `vel_max_Pelvis` were excluded because they were highly correlated with `vel_Q3_Pelvis` ($r_s \geq 0.87$). Likewise, `length_traj_Pelvis` was removed due to its strong correlation with `vel_Q3_Pelvis` ($r_s = 0.95$). `vel_mean_C7` and `vel_max_C7` were removed due to their strong correlations with `length_traj_C7` ($r_s \geq 0.84$). The parameter `acc_median_Pelvis` was retained instead of `acc_Q3_Pelvis`, as both were highly correlated ($r_s = 0.97$), while `acc_median_Pelvis` showed stronger statistical significance ($p = 0.009$ vs. $p = 0.022$). In addition, `acc_median_C7` was discarded because of its high correlation with `acc_Q3_C7` ($r_s = 0.97$). At the wrist, `vel_median_Wrist` and `acc_median_Wrist` were retained as the representative velocity and acceleration parameters, respectively, as they were the only significant parameters for these measures at the wrist. Within the *Movement Smoothness* and *Signal Complexity*, only statistically significant parameters were retained. Within the *Efficiency* category, `length_traj_Pelvis` was excluded because of its correlation with the velocity parameters, whereas `length_traj_C7` and `length_traj_Wrist` were retained. Within the *Control Strategy* category, no parameter was retained, as none was statistically significant or clinically relevant for such a short-duration task. Finally, in the *Coordination* category, only two of the nine coordination coefficients reached statistical significance and were therefore retained.

Speed and Acceleration No significant difference in duration is observed (1.36 ± 0.32 s vs 1.28 ± 0.27 s, $p = 0.598$), with both groups completing the task in a comparable amount of time. Because this task

is very short and has a strong social component, this result was expected. Q3 velocity at the pelvis is significantly higher in children (9.9 ± 6.7 mm/s vs 3.1 ± 0.8 mm/s, $p = 0.005$). Median wrist velocity is significantly lower in children (185.4 ± 52.2 mm/s vs 223.1 ± 45.5 mm/s, $p = 0.038$). IMU accelerations differ significantly at the pelvis ($p = 0.009$), at C7 ($p = 0.011$), and at the wrist ($p = 0.001$). Lower pelvis acceleration in children and higher C7 and wrist accelerations.

Developmental differences in upper-limb kinematics are strongly dependent on the characteristics and constraints of the task. Previous studies have shown that the maturation of motor control involves progressive changes in movement organization, inter-segmental coordination and variability during reaching and grasping movements [80, 84–86]. Therefore, the very short duration of the glass clinking task may have limited the expression of some developmental differences compared with longer or more complex functional tasks. In addition, during the laboratory testing sessions, the children were observed to be particularly enthusiastic and engaged during this task, which could explain the higher median wrist acceleration observed in children. Consequently, the social and playful nature of the task may have influenced the children's behaviour and encouraged rapid task execution, potentially reducing between-group differences in conventional performance measures.

As in the drinking and reach-and-drop tasks, pelvis Q3 velocity was significantly higher in children (9.9 vs 3.1 mm/s), whereas median wrist velocity was lower (185.4 vs 223.1 mm/s). This combination of greater proximal involvement and slower distal movement is consistent with developmental changes in segmental organization. Younger children have been reported to exhibit greater trunk displacement and variability during reaching, whereas increasing age is associated with improved inter-joint coordination and reduced trunk involvement [84]. More generally, motor development involves a progressive transition toward more differentiated and independently controlled body segments [49]. The markedly lower variability of pelvis velocity in adults (± 0.8 mm/s vs ± 6.7 mm/s in children) further supports the presence of a more stable proximal strategy during this rapid functional movement.

Movement Smoothness IMU LDLJ-A at the pelvis is significantly more positive in adults (2.16 ± 0.67 vs 0.70 ± 1.40 , $p = 0.006$). Zero crossings at the pelvis are significantly lower in children (36.3 ± 15.7 vs 55.5 ± 13.7 , $p = 0.006$). Gyroscopic SPARC at C7 is significantly more negative in children (-0.79 ± 0.10 vs -0.70 ± 0.05 , $p = 0.008$). The IMU mean/max ratio at the pelvis is significantly lower in children (0.98 ± 0.01 vs 0.99 ± 0.00 , $p = 0.013$).

IMU LDLJ-A at the pelvis is significant ($p = 0.006$) despite the very short task duration. Note that LDLJ-A pelvis values are positive (0.70 for G1, 2.16 for G2), unlike the negative values observed in all other tasks. This is due to the combination of a very short duration and a high peak acceleration during the clinking movement. Indeed, the term in the denominator of the LDLJ-A formula 3.7 is very small, which makes the logarithm positive. This result nevertheless remains consistent. Indeed, adults obtain more positive values and therefore smoother movement than children. Figure 4.6 C shows the distribution and boxplot of the LDLJ-A IMU at the pelvis. The distribution of G1 is broad and flat while G2 is tightly concentrated with a very high peak density. This contrast is particularly informative. Indeed, adults produce a highly homogeneous and reproducible postural acceleration profile during the clinking gesture, while children show highly variable profiles reflecting the developmental heterogeneity of postural control.

The significantly lower number of pelvis zero crossings in children (36.3 vs. 55.5, $p = 0.006$) indicates fewer fluctuations of the acceleration signal around its median value. Interestingly, this occurs despite the greater pelvis trajectory length observed in children, suggesting larger and more sustained proximal movements rather than frequent small fluctuations. However, this parameter should be interpreted with caution, as zero crossings were computed from the acceleration signal and may therefore be sensitive to high-frequency noise. Consequently, the higher number of crossings observed in adults cannot be

attributed exclusively to more frequent postural corrections.

Efficiency C7 trajectory length is significantly higher in children than in adults and is twice as large (40.1 mm vs 22.2 mm) in children. In contrast, wrist trajectory is not significantly different. It is interesting to note that this parameter is not significant. One might have expected wrist trajectory length to be significantly greater in children. This shows that children follow the same wrist trajectory as adults but that compensation occurs at the level of C7 and the pelvis.

Control Strategy It is interesting to note that for this task, no parameter in this category is significant as in the reach-and-drop task. In this type of task, a significant difference in PPV parameters might have been expected, which would have shown different speed profiles. However, this lack of significance may be explained by the duration of the task. Indeed, this task is quite short, and it may therefore be difficult to obtain significantly different velocity profiles.

Data-Driven ApEn 3D and IMU at the pelvis are significantly higher in adults (3D: 0.55 ± 0.11 vs 0.39 ± 0.14 , $p = 0.009$ and IMU: 1.02 ± 0.08 vs 0.83 ± 0.20 , $p = 0.009$). ApEn IMU at the wrist is significantly higher in children (0.55 ± 0.07 vs 0.48 ± 0.07 , $p = 0.030$).

The higher wrist ApEn IMU observed in children differs from the general pattern found in the other tasks, where adults tended to exhibit higher entropy. This task specific result may be related to the constrained and socially oriented nature of the glass clinking movement, which requires the participant to reach a precise spatial target represented by the glass held by another person. In this context, a lower entropy at the wrist in adults may reflect a more regular and predictable movement. Literature has reported that lower entropy during socially oriented actions may result from the additional constraints imposed by social interaction [88]. The task promotes greater motor regularity, predictability and anticipatory control. Conversely, higher entropy was associated with less constrained and more variable motor behaviour. In this task, the higher wrist ApEn IMU observed in children may therefore reflect greater variability in distal motor organization when adapting the movement to the spatial and social constraints of the clinking task. Figure 4.6 B shows the ApEn IMU at the wrist with the atypical result discussed. G1 shows higher entropy than G2 at the inverse of the pattern observed at the pelvis. The limited overlap and relatively compact distributions confirm that this inversion is systematic and not driven by outliers.

Importantly, these findings emphasize that higher entropy should not systematically be interpreted as better motor control or greater adaptability. Its interpretation depends on the requirements of the task and the segment considered. In highly constrained actions, lower entropy may instead reflect a more stable and precisely organized motor strategy. Moreover, pelvis ApEn (3D and IMU) was higher in adults, consistent with the results observed in the other tasks and with what was expected, given that the pelvis is not directly involved in the movement required by this task. This also highlights the need to interpret this parameter with caution depending on the nature of the task and that each segment behaves differently.

Inter-segmental Coordination C7-Pelvis gyroscope is positive in children (0.30 ± 0.41) and negative in adults (-0.19 ± 0.27 , $p = 0.003$). Then, C7-Pelvis ACC is significantly higher in children (0.37 ± 0.23 vs 0.11 ± 0.24 , $p = 0.017$).

The two C7-Pelvis coefficients (gyro and ACC) are significant, reproducing the block pattern observed in all previous tasks. The robustness of this result across all tasks and durations suggests that segmental dissociation is the most stable developmental marker and the least dependent on task nature. Figure 4.6 A shows the C7-Pelvis gyroscopic coordination coefficient. G1 is broadly distributed between -0.50 and 0.80 with a median around 0.45 , while G2 is concentrated between -0.50 and 0.25 with a median around -0.20 . Despite some overlap, the shift between the two distributions is clear and consistent with

the pattern observed across all tasks. The large intra-group variability in G1 reflects the heterogeneity of coordination strategies within the 6-12 year age range.

Conclusion To conclude, the glass clinking task yielded several interesting findings. The *Speed* dissociation (pelvic vs wrist) and *Coordination* (C7-Pelvis) persist even at this timescale, confirming their robustness as developmental markers. Then, *Efficiency* confirms the difference in movement strategy between distal and proximal segments. *Smoothness* is only significant at the pelvis and C7 (LDLJ-A at pelvis and SPARC gyro at C7), with no distal significance. *Signal complexity* produces an atypical inversion at the wrist (higher ApEn in children). Finally, *Control Strategy* is entirely non-significant. It is also important to keep in mind that this task is very short, which may influence the calculation of the parameters.

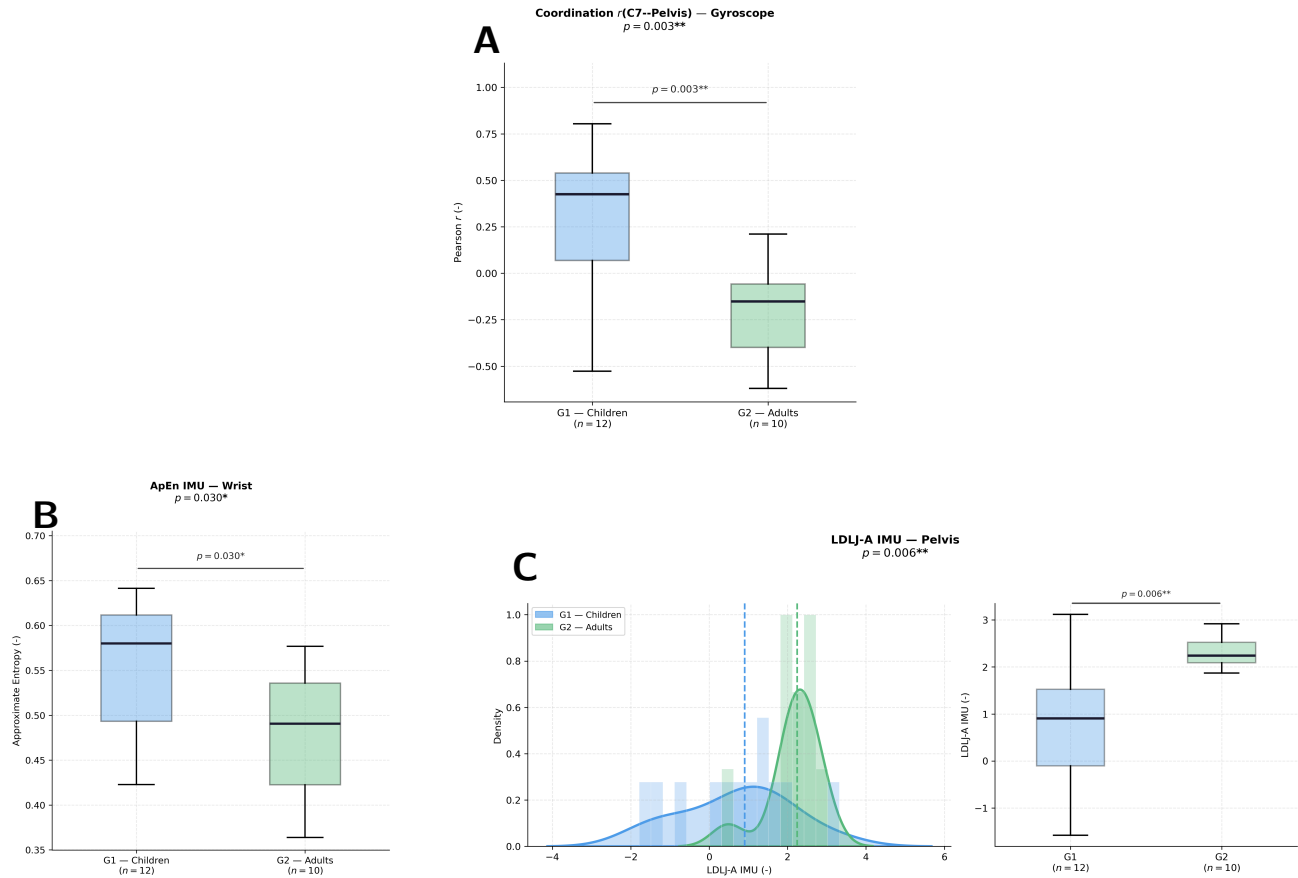


Figure 4.6: Comparison of parameters between children (G1, $n = 12$) and adults (G2, $n = 10$) during the glass clinking task. (A) Coordination coefficient between C7 and pelvis measured from the gyroscope signal. (B) Approximate entropy (ApEn) of the IMU signal measured at the wrist. (C) Distribution (left) and boxplot (right) of the LDLJ-A IMU signal measured at the pelvis. Boxplots display the median, interquartile range (IQR), and whiskers extending to $1.5 \times \text{IQR}$.

Table 4.6: Comparison between G1 (children, $n = 12$) and G2 (adults, $n = 10$) for the retained parameters of glass clinking task after correlation-based reduction ($|r_s| \geq 0.8$, Spearman). Values are mean $\pm$ SD. *Normal*: normality assessment per group via Shapiro-Wilk ($\alpha = 0.05$): Y = normal, N = non-normal. Statistical test: Welch's t -test (both normal) or Mann-Whitney U (at least one non-normal). * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$. Rows highlighted in green indicate a significant difference ($p < 0.05$).

Parameter	G1 - Children (<i>n</i> = 12)		G2 - Adults (<i>n</i> = 10)		<i>p</i> -value
	Mean ± SD	Norm.	Mean ± SD	Norm.	
Speed and Acceleration					
Movement time (s)	1.36 ± 0.32	Y	1.28 ± 0.27	N	0.598
Velocity Q3 - Pelvis (mm/s)	9.9 ± 6.7	Y	3.1 ± 0.8	Y	0.005**
Acceleration median - Pelvis (m/s ²)	9.80 ± 0.20	Y	9.98 ± 0.08	Y	0.009**
Acceleration Q3 - C7 (m/s ²)	9.73 ± 0.11	Y	9.61 ± 0.13	N	0.011*
Acceleration median - Wrist (m/s ²)	9.73 ± 0.25	Y	9.41 ± 0.10	Y	0.001**
Median velocity - Wrist (mm/s)	185.4 ± 52.2	N	223.1 ± 45.5	Y	0.038*
Movement Smoothness					
LDLJ-A IMU - Pelvis	0.70 ± 1.40	Y	2.16 ± 0.67	N	0.006**
Zero crossings ACC - Pelvis	36.3 ± 15.7	Y	55.5 ± 13.7	Y	0.006**
SPARC Gyroscope - C7	−0.79 ± 0.10	Y	−0.70 ± 0.05	Y	0.008**
Mean/max ratio IMU - Pelvis	0.98 ± 0.01	Y	0.99 ± 0.00	N	0.013*
Efficiency					
Trajectory length - C7 (mm)	40.1 ± 26.8	Y	22.2 ± 13.1	N	0.038*
Trajectory length - Wrist (mm)	281 ± 112	Y	285 ± 60.0	Y	0.912
Signal Complexity (Data-Driven)					
ApEn 3D - Pelvis	0.39 ± 0.14	N	0.55 ± 0.11	Y	0.009**
ApEn IMU - Pelvis	0.83 ± 0.20	Y	1.02 ± 0.08	Y	0.009**
ApEn IMU - Wrist	0.55 ± 0.07	Y	0.48 ± 0.07	Y	0.030*
Inter-segmental Coordination					
<i>r</i> (C7-Pelvis) gyroscope	0.30 ± 0.41	Y	−0.19 ± 0.27	Y	0.003**
<i>r</i> (C7-Pelvis) ACC	0.37 ± 0.23	Y	0.11 ± 0.24	Y	0.017*

4.4.2 Ball Throwing Task

After collecting the data for the ball throwing task for each participant, the calculation of each parameter described in the Materials and Methods section was then performed. Next, a correlation analysis between parameters was carried out in order to reduce the number of parameters to be presented and discussed. This correlation-based reduction made it possible to eliminate redundant parameters by identifying pairs with an absolute Spearman correlation coefficient of $|r_s| \geq 0.8$. However, after observing the results following the parameter calculation, some outliers were identified for one participant in group 1 (children). These outliers were due to unintended behaviour during the task. As a result, this participant was excluded from this task in order to avoid biasing the results. Group 1 of children therefore consists of 11 participants for this task. In total, several correlated pairs were identified among the all tested pairs. Table 4.7 shows the results obtained after parameter reduction using correlation and Table A.7 in the appendix contains all the parameters.

In the *Speed and Acceleration* category, `vel_median_Pelvis`, `vel_mean_Pelvis`, and `vel_max_Pelvis` were all highly correlated with `vel_Q3_Pelvis` ($r_s \geq 0.85$). Consequently, `vel_Q3_Pelvis` was retained as the representative velocity parameter, while `vel_max_Pelvis` was also preserved as a complementary indicator of peak velocity. Although `length_traj_Pelvis` was strongly correlated with `vel_mean_Pelvis` ($r_s = 0.92$), it was retained because it provides complementary information on cumulative displacement. For the C7 segment, `vel_mean_C7`, `vel_median_C7`, and `length_traj_C7` were excluded because of their strong correlation with `vel_Q3_C7` ($r_s \geq 0.86$), while `length_traj_C7` was also correlated with `length_traj_Pelvis` ($r_s = 0.83$). The parameter `acc_median_Pelvis` was retained instead of `acc_Q3_Pelvis`, as both were highly correlated ($r_s = 0.97$), while `acc_median_Pelvis` showed stronger statistical significance ($p = 0.008$ vs. $p = 0.031$). Conversely, `acc_Q3_C7` was retained instead of `acc_median_C7` ($r_s = 0.88$, $p = 0.010$ vs. $p = 0.027$). Finally, all wrist velocity parameters were excluded because none reached statistical significance. Within the *Movement Smoothness* category, `ratio_mean_max_imu_Pelvis` was removed because of its strong correlation with `LDLJ_A_imu_Pelvis` ($r_s = 0.89$). Then, only the other statistically significant parameters were retained. Within the *Control Strategy* category, `f_dom_3D_C7` was excluded because of its correlation with `ApEn_3D_Pelvis` ($r_s = 0.80$). The only parameter retained in this category was `PPV_imu_C7`, as it was the sole statistically significant metric. Within the *Signal Complexity* category, `ApEn_3D_C7` was the sole statistically significant metric and thus was retained. Finally, within the *Coordination* category, the two statistically significant parameters were retained.

Speed and Acceleration and Efficiency No significant difference in duration is observed (5.72 ± 1.09 s vs 5.17 ± 1.04 s, $p = 0.251$). Q3 velocity at the pelvis is significantly higher in children (34.8 ± 13.6 mm/s vs 18.5 ± 7.6 mm/s, $p = 0.002$), as are the maximum velocity at the pelvis (139.8 ± 52.4 mm/s vs 81.1 ± 44.4 mm/s, $p = 0.012$) and trajectory length at the pelvis (151.78 ± 60.78 mm vs 76.71 ± 31.69 mm, $p = 0.003$). Q3 velocity at C7 is also significantly higher in children (80.0 ± 25.5 mm/s vs 56.7 ± 24.8 mm/s, $p = 0.047$). Median pelvis acceleration is significantly lower in children (9.80 ± 0.20 vs 10.00 ± 0.09 m/s², $p = 0.008$), and Q3 acceleration at C7 is higher in children (9.90 ± 0.11 vs 9.74 ± 0.15 m/s², $p = 0.010$). Interestingly, no significant differences were observed at the wrist. It might have been expected that children would throw the ball with greater intensity, as they may have more difficulty accurately controlling the distance and velocity required to pass the ball to another person.

These results indicate greater involvement of the proximal segments in children during the repetitive ball throwing task. This finding is consistent with the developmental nature of throwing. However, it is important to keep in mind that, in this task, the ball is not thrown overarm but rather passed forward using a movement similar to a volleyball pass. Therefore, comparisons with the existing literature should be interpreted with caution. Some studies [89] reported age-related changes in whole-body coordination during overarm throwing, particularly in the coupling between the centre of mass and the wrist. Similarly, [90], using IMUs positioned at the wrist, trunk and pelvis in children aged 5-10 years, showed that proximal kinematic and temporal parameters vary with throwing maturity. Thus, the greater pelvis and C7 involvement observed in G1 may reflect a less mature whole-body coordination strategy rather than simply greater postural instability. Moreover, it is interesting to note that wrist trajectory length is similar in both groups, suggesting a similar strategy for throwing and receiving the ball despite differences in body size and strength. In contrast, the differences in trajectory length observed at C7 and the pelvis suggest that compensatory movements occur primarily at these proximal segments.

Pelvis median acceleration was lower in children (9.80 ± 0.20 vs. 10.0 ± 0.09 m/s², $p = 0.008$), whereas C7 Q3 acceleration was higher than in adults (9.90 ± 0.11 vs. 9.74 ± 0.15 m/s², $p = 0.010$). Rather than interpreting these parameters independently, their combination with the 3D results suggests that children and adults organize proximal motion differently during throwing. Importantly, these kinematic differences were detected despite similar total task durations, again highlighting the additional information provided by

multi-segment 3D and IMU analysis compared with completion time alone. Figure 4.7 B shows Q3 velocity at the pelvis, with a clear separation between the groups. G2 is extremely homogeneous (IQR ≈ 4 mm/s, median ≈ 16 mm/s), whereas G1 shows a large dispersion (IQR ≈ 20 mm/s, median ≈ 32 mm/s), illustrating the variability of pelvic postural strategies in children during throwing.

Movement Smoothness IMU LDLJ-A at the pelvis is significantly more negative in children (-7.84 ± 0.58 vs -6.37 ± 1.71 , $p = 0.025$). Gyroscopic SPARC at the pelvis is significantly more negative in children (-1.28 ± 0.35 vs -0.79 ± 0.70 , $p = 0.002$). Then, ACC zero crossings at the wrist is significantly higher in children (64.8 ± 18.6 vs 50.0 ± 8.6 , $p = 0.032$). Finally, the IMU median/Q3 ratio at the wrist is significantly higher in children (0.57 ± 0.07 vs 0.50 ± 0.07 , $p = 0.032$).

As in glass clinking task, the main differences in smoothness were observed at the proximal level. Both LDLJ-A and gyroscope-based SPARC at the pelvis discriminated between groups, with more negative values in children indicating less smooth pelvis motion. This is consistent with previous IMU-based analyses showing that trunk and pelvis kinematics vary with the developmental level of throwing [90]. More recent work has also shown that throwing development involves a progressive reorganization of whole-body coordination and a more consistent temporal organization of trunk and upper-limb muscle synergies [91]. Figure 4.7 C shows the distribution and boxplot of gyroscopic SPARC at the pelvis. The G2 distribution is spread toward negative values (pronounced left tail down to -2.7 due to one participant), reflecting substantial inter-individual heterogeneity in adults for this parameter during this task, with some adults producing highly irregular pelvic rotation during throwing, whereas G1 shows a more concentrated distribution between -2 and -0.5 , with a median around -1.2 .

The significantly higher number of ACC zero crossings at the wrist in children (64.8 vs. 50.0 , $p = 0.032$) indicates more frequent fluctuations of wrist acceleration around its median value. However, this parameter should be interpreted with caution, as it was computed from the acceleration signal and may therefore be sensitive to high-frequency noise. The higher IMU median/Q3 ratio in children (0.57 vs. 0.50 , $p = 0.032$) further indicates a different distribution of wrist acceleration amplitudes between groups, although this metric alone does not provide information about the ballistic nature of the movement.

Control Strategy IMU PPV at C7 is significantly lower in children ($43.5 \pm 17.7\%$ vs $63.7 \pm 17.4\%$, $p = 0.017$).

The significantly lower IMU PPV at C7 in children is a very interesting result. This difference suggests an age-related change in the organization of C7 segment motion during throwing. It indicates that the peak angular velocity of C7 occurs earlier in the movement cycle in children (at 43.5% of the total duration) than in adults (63.7%). Figure 4.7 A shows IMU PPV at C7. G1 shows a median around 45% with an extended distribution (15-70%), whereas G2 shows a higher median ($\approx 70\%$) but also a very dispersed distribution (40-85%). This result indicates that C7 reaches its angular velocity peak earlier in the throwing cycle in children, reflecting less mature kinetic-chain timing and premature deceleration of the upper-trunk.

Data-Driven ApEn 3D at C7 is significantly higher in adults (0.34 ± 0.05 vs 0.27 ± 0.09 , $p = 0.033$).

This result shows greater complexity and lower predictability of upper-trunk motion in adults. This result may reflect a more flexible organization of proximal control in adults, allowing subtle adaptations of trunk motion across the repeated throwing cycles. Importantly, higher complexity does not imply lower smoothness as these metrics characterize different aspects of movement organization. In this task, adults may combine smoother pelvis motion with more complex and adaptable upper-trunk kinematics.

Inter-segmental Coordination The C7-Pelvis 3D (0.56 ± 0.15 vs 0.28 ± 0.19 , $p = 0.001$) and C7-Pelvis gyroscopic (0.35 ± 0.19 vs 0.16 ± 0.14 , $p = 0.019$) correlations are significantly higher in children.

The higher C7-Pelvis correlations observed in children reproduce the general pattern found across the previous tasks. Despite the whole-body and dynamic nature of throwing, C7 and pelvis movements remain more strongly coupled in children. This finding is consistent with literature [49]. Indeed, motor maturation is associated with a progressive transition from a block-like organization toward more differentiated segmental control. Adults may therefore be able to control C7 and pelvis more independently, whereas children rely on a more synchronized proximal strategy.

Conclusion To conclude, the ball throwing task yielded several interesting findings. The *Speed* and *Efficiency* category are the most informative, with significant differences at both the pelvis and C7, reflecting the involvement of the full trunk in the throwing action. *Smoothness* is significant at the pelvis (LDLJ-A and gyroscopic SPARC), reproducing the distal-proximal dissociation of functional tasks. The *Control Strategy* category (IMU PPV C7) is the most original result, revealing a premature cervical velocity peak in children. *Signal complexity* (ApEn 3D C7) and *Coordination* (C7-Pelvis) are also significant. However, the analysis is performed over the total duration of the six throws without segmentation by individual throw. A phase-based analysis or an analysis by individual throw would probably reveal more inter-group differences.

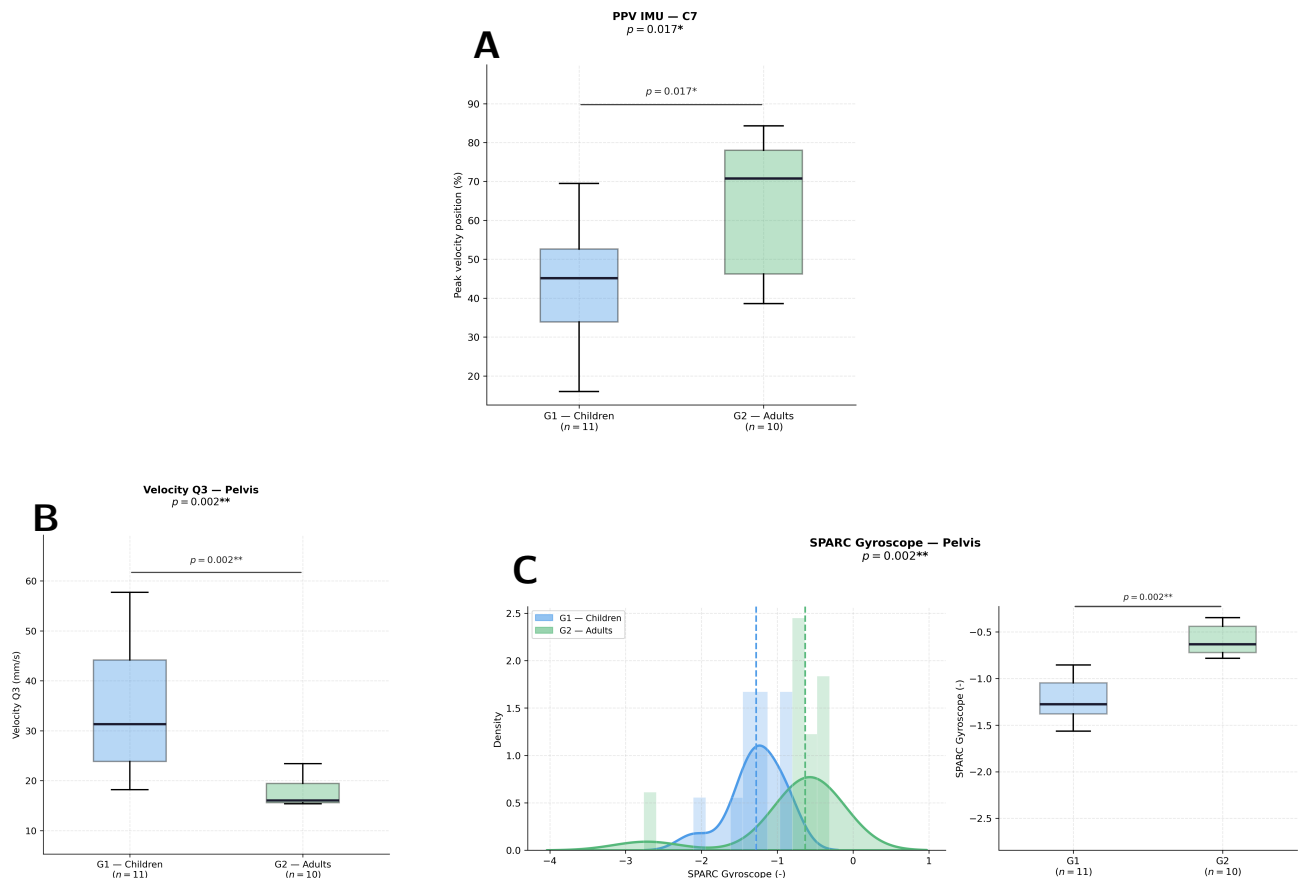


Figure 4.7: Comparison of parameters between children (G1, $n = 11$) and adults (G2, $n = 10$) during the ball throwing task. (A) Peak velocity position (PPV) measured at C7 from the IMU signal. (B) Third quartile (Q3) of pelvis velocity. (C) Distribution (left) and boxplot (right) of the SPARC gyroscope signal measured at the pelvis. Boxplots display the median, interquartile range (IQR), and whiskers extending to $1.5 \times \text{IQR}$.

Table 4.7: Comparison between G1 (children, $n = 11$) and G2 (adults, $n = 10$) for the retained parameters of ball throwing task after correlation-based reduction ($|r_s| \geq 0.8$, Spearman, $N = 21$). Values are mean $\pm$ SD. *Normal*: normality assessment per group via Shapiro-Wilk ($\alpha = 0.05$): Y = normal, N = non-normal. Statistical test: Welch's t -test (both normal) or Mann-Whitney U (at least one non-normal). * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$. Rows highlighted in green indicate a significant difference ($p < 0.05$).

Parameter	G1 - Children (<i>n</i> = 11)		G2 - Adults (<i>n</i> = 10)		<i>p</i> -value
	Mean ± SD	Norm.	Mean ± SD	Norm.	
Speed and Acceleration					
Movement time (s)	5.72 ± 1.09	Y	5.17 ± 1.04	Y	0.251
Velocity Q3 - Pelvis (mm/s)	34.8 ± 13.6	Y	18.5 ± 7.6	N	0.002**
Max velocity - Pelvis (mm/s)	139.8 ± 52.4	Y	81.1 ± 44.4	Y	0.012*
Acceleration median - Pelvis (m/s ²)	9.80 ± 0.20	Y	10.00 ± 0.09	Y	0.008**
Velocity Q3 - C7 (mm/s)	80.0 ± 25.5	Y	56.7 ± 24.8	Y	0.047*
Acceleration Q3 - C7 (m/s ²)	9.90 ± 0.11	Y	9.74 ± 0.15	N	0.010*
Efficiency					
Trajectory length - Pelvis (mm)	151.78 ± 60.78	Y	76.71 ± 31.69	Y	0.003**
Movement Smoothness					
LDLJ-A IMU - Pelvis	−7.84 ± 0.58	Y	−6.37 ± 1.71	Y	0.025*
SPARC Gyroscope - Pelvis	−1.28 ± 0.35	Y	−0.79 ± 0.70	N	0.002**
Zero crossings ACC - Wrist	64.8 ± 18.6	Y	50.0 ± 8.6	Y	0.032*
Median/Q3 ratio IMU - Wrist	0.57 ± 0.07	Y	0.50 ± 0.07	Y	0.032*
Control Strategy					
PPV IMU - C7 (%)	43.5 ± 17.7	Y	63.7 ± 17.4	Y	0.017*
Signal Complexity (Data-Driven)					
ApEn 3D - C7	0.27 ± 0.09	Y	0.34 ± 0.05	Y	0.033*
Inter-segmental Coordination					
<i>r</i> (C7-Pelvis) 3D	0.56 ± 0.15	Y	0.28 ± 0.19	Y	0.001**
<i>r</i> (C7-Pelvis) gyroscope	0.35 ± 0.19	Y	0.16 ± 0.14	Y	0.019*

4.5 Affordance Task

After collecting the data for the affordance task for each participant, the calculation of each parameter described in the Materials and Methods section was then performed. Next, a correlation analysis between parameters was carried out in order to reduce the number of parameters to be presented and discussed. This correlation-based reduction made it possible to eliminate redundant parameters by identifying pairs with an absolute Spearman correlation coefficient of $|r_s| \geq 0.8$. However, after observing the results following the parameter calculation, outliers were identified for two participants in group 1 (children). The first issue was that some sensors were not sufficiently visible, and it was not possible to perform interpolation to compensate for this lack of visibility. The second issue was that one participant in G1 did not perform the task correctly. Group 1 of children therefore consists of 10 participants for this task. In total, several correlated pairs were identified among the all tested pairs. Table 4.8 shows the results obtained after parameter reduction using correlation and Table A.8 in the appendix contains all the parameters.

In the *Speed and Acceleration* category, all scalar velocity parameters measured at the pelvis (vel_median, vel_mean, and vel_max) were highly correlated with vel_Q3_Pelvis ($r_s \geq 0.91$). Consequently, only vel_Q3_Pelvis was retained as the representative pelvis velocity parameter. Similarly, vel_median_Wrist and vel_mean_Wrist were excluded because of their strong correlation with vel_Q3_Wrist ($r_s \geq 0.92$). The parameter length_traj_Pelvis was also removed due to its nearly perfect correlation with the pelvis velocity metrics ($r_s = 0.99$). Finally, acc_median_Pelvis was retained instead of acc_Q3_Pelvis, as both parameters were perfectly correlated ($r_s = 1.00$). acc_Q3_C7 was also retained due to its statistical significance. Within the *Movement Smoothness* category, a large cluster of correlated parameters was identified, including zero_crossings_acc_Pelvis, SPARC_acc_Pelvis, MAPR_3D_Pelvis, ratio_median_Q3_3D_Pelvis. Among these, zero_crossings_acc_Pelvis was retained as the representative parameter because it showed the strongest statistical significance ($p = 0.007$). In addition, ratio_mean_max_imu_Pelvis was excluded because of its strong correlation with LDLJ_A_imu_Pelvis ($r_s = 0.90$). A second correlation cluster was observed for the C7 segment, where SPARC_acc_C7, zero_crossings_C7, ApEn_imu_C7, and SPARC_gyr_C7 were all highly correlated with LDLJ_A_imu_C7 ($r_s \geq 0.83$). Consequently, only LDLJ_A_imu_C7 was retained. The parameter ApEn_imu_Pelvis was preserved within the *Data-Driven* category as a complementary measure of movement complexity. Within the *Efficiency* category, only length_traj_Wrist was retained despite its correlation with other parameters. In the *Control Strategy* category, PPV_3D_Wrist was the only statistically significant and non-redundant parameter and was therefore retained. Finally, in the *Coordination* category, coord_r_C7_Pelvis_gyr was the only statistically significant and was therefore retained.

Speed and Acceleration Q3 velocity at the pelvis is significantly higher in children (5.9 ± 4.5 mm/s vs 2.1 ± 0.9 mm/s, $p = 0.007$). Q3 velocity at the wrist is also significantly higher in children (98.7 ± 45.5 mm/s vs 54.9 ± 29.2 mm/s, $p = 0.021$). Median pelvis acceleration is significantly lower in children (9.75 ± 0.20 vs 9.99 ± 0.07 m/s², $p = 0.005$), and Q3 acceleration at C7 is significantly higher in children (9.71 ± 0.09 vs 9.57 ± 0.12 m/s², $p = 0.014$).

The higher Q3 Wrist velocity observed in children (98.69 vs. 54.86 mm/s) suggests a more dynamic distal exploration of the unfamiliar object. This may reflect developmental differences in the way children explore object properties and adapt their actions to perceived affordances. Moreover, this may also reflect the interest and excitement experienced by children when discovering and interacting with an unfamiliar affordance-based object. At the proximal level, the higher pelvis Q3 velocity in children is consistent with the greater proximal involvement observed in several of the previous functional tasks. Together with the significant differences in pelvis and C7 acceleration, these results suggest that object exploration involves different proximal movement strategies in children and adults. Interestingly, significant velocity differences were observed at both the pelvis and wrist, suggesting that this task captures developmental differences at both proximal and distal levels. Figure 4.8 B shows Q3 velocity at the wrist, with G1 significantly higher (median ≈ 105 mm/s) than G2 (median ≈ 55 mm/s) and substantial within-group variability among children (35 - 175 mm/s), reflecting the heterogeneity of object-exploration strategies.

Movement Smoothness IMU LDLJ-A was significantly more negative in children at the pelvis (-11.64 ± 1.11 vs. -10.68 ± 0.74 , $p = 0.007$) and at C7 (-12.01 ± 0.57 vs. -11.46 ± 0.84 , $p = 0.045$), indicating lower movement smoothness at the proximal segments. Similarly, both 3D SPARC (-3.96 ± 1.56 vs. -2.92 ± 0.63 , $p = 0.045$) and gyroscopic SPARC (-1.09 ± 0.68 vs. -0.25 ± 0.21 , $p = 0.006$) at the pelvis were more negative in children. Together, these metrics consistently suggest less smooth proximal control during object exploration.

ACC zero crossings at the pelvis were significantly lower in children (1091.7 ± 353.5 vs. 1512.7 ± 235.2 , $p = 0.007$), indicating fewer fluctuations of acceleration around its median value. Interestingly, this oc-

curs despite the lower smoothness observed with LDLJ-A and SPARC. This apparent contrast highlights that zero crossings and smoothness metrics capture different characteristics of the signal. Indeed, fewer crossings do not necessarily indicate smoother movement but rather a different temporal organization of pelvis acceleration.

Figure 4.8 D shows the distribution and boxplot of gyroscopic SPARC at the pelvis. The G1 distribution is very spread out ($-3.3:0.0$), whereas G2 is extremely concentrated around -0.2 , with near-zero whiskers, illustrating the very high homogeneity in adults and the marked contrast with the inter-individual variability of children. Figure 4.8 A shows the ACC zero crossings at the pelvis. G1 shows a wide dispersion (600-1800) with a median around 1000, whereas G2 is more homogeneous and concentrated between 1450 and 1750, visually illustrating the paradox that although children sway more, they produce fewer continuous postural micro-corrections than adults.

The lower IMU median/Q3 ratio at the wrist in children (0.49 vs 0.53 , $p = 0.026$) indicates a different distribution of wrist acceleration amplitudes, with the median being relatively lower with respect to the upper quartile in children. In the context of an unfamiliar affordance-based object, this may reflect a different distal exploration strategy between children and adults.

Efficiency Wrist trajectory length is significantly higher in children than in adults ($2.41 \text{ m} \pm 0.99$ vs $1.43 \text{ m} \pm 0.77$, $p = 0.025$). This result is very interesting because it shows that children tend to explore the affordance object much more than adults. The high standard deviation in both groups also shows that each individual within each group has their own exploration strategy.

Control Strategy Wrist 3D PPV is significantly lower in children ($12.7 \pm 28.0\%$ vs $23.6 \pm 19.0\%$, $p = 0.021$).

The significantly lower wrist 3D PPV in children is a very specific result for this task. A lower PPV indicates that the wrist velocity peak occurs very early in the 30-second analysis window. This suggests that children perform a rapid and intense initial exploratory movement at the beginning of the task and then slow down or remain still, whereas adults maintain exploration more evenly over time. Figure 4.8 C is particularly striking. Wrist 3D PPV shows almost all children clustered between 0 and 5% (median $\approx 3\%$), whereas adults show a very broad distribution (0-60%, median $\approx 27\%$), clearly illustrating that children reach their wrist velocity peak very early in the 30-second analysis window, reflecting a brief and intense initial exploratory movement, while adults maintain distributed exploration throughout the task. Adults show a broad heterogeneity.

Data-Driven IMU ApEn at the pelvis is significantly higher in adults (1.58 ± 0.52 vs 1.16 ± 0.41 , $p = 0.038$).

The higher pelvis ApEn observed in adults indicates a more complex and less predictable proximal movement pattern. This result may be particularly relevant in an affordance-based object manipulation task, in which motor behaviour must be adapted to the physical and functional properties of the object. Moreover, it is interesting to note that entropy values are above 1 for both groups for the IMU sensors at the pelvis and C7 (although the latter does not show a significant difference between groups, see Appendix 4.8). This suggests that interaction with an unfamiliar affordance-based object induces more complex body movement patterns, potentially due to the exploratory nature of the task.

Inter-segmental Coordination The gyroscopic C7-Pelvis correlation is positive in children (0.28 ± 0.23) and negative in adults (-0.02 ± 0.20 , $p = 0.003$).

The positive C7-Pelvis gyroscopic correlation in children and negative correlation in adults is the only significant coordination coefficient among the nine computed, and reproduces the pattern observed across the protocol (others tasks). This result definitively confirms that C7-Pelvis dissociation for the rotational motion is the most robust and cross-task developmental marker in the protocol. It is significant in many tasks, whether static or dynamic, short or long, with or without an object.

In addition, at the end of this task, participants were asked about their perception of the affordance object. Children's responses (G1) were characterized by a strong tendency toward functional and playful exploration. Indeed, several children spontaneously tried to insert their fingers into the threaded hole and the associations they evoked (submarine, gun, tree, dog, dragon's head) were mostly related to play and imagination. Adults (G2), in contrast, produced more functional and tool-oriented associations, such as a corkscrew, inhaler, trailer hitch, thermometer, or other tools. Interestingly, adults also showed a tendency to interact with the threaded hole, particularly by considering or attempting to insert something into it. Thus, both groups identified the hole as an important part of the object, although their interpretations differed, with children showing more playful and imaginative associations and adults more tool-oriented ones. These observations may be related to the kinematic results obtained. Indeed, the higher wrist Q3 velocity in children (98.7 vs 54.9 mm/s, $p = 0.021$) and the very early PPV ($\approx 13\%$) suggest a more rapid initial exploration of the object. This behavior may reflect a more spontaneous and playful exploration strategy in children, including direct interaction with the threaded hole, whereas adults appear to adopt a more function-oriented exploration strategy.

Conclusion To conclude, the affordance task yielded several interesting findings and revealed substantial differences between children and adults, particularly at the pelvis and wrist. The *Speed and Acceleration* and *Movement Smoothness* categories were the most informative, with significant differences observed for several parameters, including SPARC gyro, LDLJ-A, zero crossings, and SPARC 3D. In particular, *Velocity Q3 at the wrist* and *Wrist 3D PPV* highlight differences in the temporal organization of object exploration, with children showing faster wrist movements and an earlier velocity peak. The *Coordination* category, particularly the C7-Pelvis gyroscopic correlation, further suggests differences in inter-segmental organization between the two groups. *Control Strategy* and *Efficiency* also highlight different exploration strategies between children and adults. These differences may partly reflect the specific nature of the affordance task, which consisted of holding and exploring an unfamiliar object without explicit instructions regarding how it should be manipulated. Consequently, participants may have adopted different strategies, with some actively exploring the object and its possible functions, while others interacted with it more passively. This behavioural heterogeneity may contribute to the large variability observed for wrist velocity, wrist trajectory length, and PPV, particularly in G1. However, it is important to note that the beginning of this task was defined as the moment when participants opened their eyes. This event was identified manually by selecting the first frame corresponding to eye opening. Consequently, the temporal identification of task onset may lack precision and could have slightly influenced time-dependent parameters.

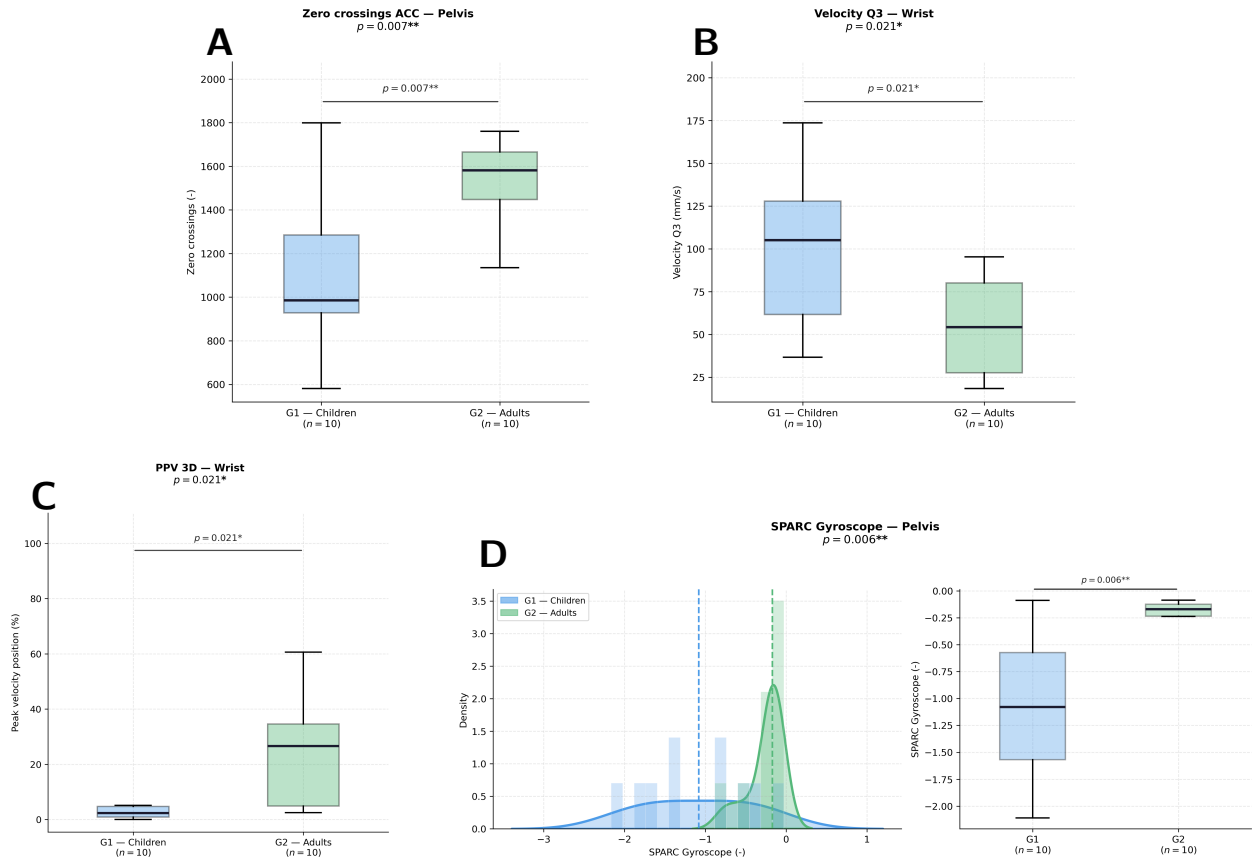


Figure 4.8: Comparison of parameters between children (G1, $n = 10$) and adults (G2, $n = 10$) during the affordance task. (A) Number of acceleration zero crossings measured at the pelvis. (B) Third quartile (Q3) of wrist velocity. (C) Peak velocity position (PPV) measured at the wrist. (D) Distribution (left) and boxplot (right) of the SPARC gyroscope signal measured at the pelvis. Boxplots display the median, interquartile range (IQR), and whiskers extending to $1.5 \times \text{IQR}$.

Table 4.8: Comparison between G1 (children, $n = 10$) and G2 (adults, $n = 10$) for the retained parameters of the affordance task after correlation-based reduction ($|r_s| \geq 0.8$, Spearman, $N = 20$). Values are mean $\pm$ SD. *Normal*: normality assessment per group via Shapiro-Wilk ($\alpha = 0.05$): Y = normal, N = non-normal. Statistical test: Welch's t -test (both normal) or Mann-Whitney U (at least one non-normal). * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$. Rows highlighted in green indicate a significant difference ($p < 0.05$).

Parameter	G1 - Children (<i>n</i> = 10)		G2 - Adults (<i>n</i> = 10)		<i>p</i> -value
	Mean ± SD	Norm.	Mean ± SD	Norm.	
Speed and Acceleration					
Velocity Q3 - Pelvis (mm/s)	5.9 ± 4.5	N	2.1 ± 0.9	N	0.007**
Acceleration median - Pelvis (m/s ²)	9.75 ± 0.20	Y	9.99 ± 0.07	Y	0.005**
Acceleration Q3 - C7 (m/s ²)	9.71 ± 0.09	Y	9.57 ± 0.12	N	0.014*
Velocity Q3 - Wrist (mm/s)	98.7 ± 45.5	Y	54.9 ± 29.2	Y	0.021*
Movement Smoothness					
LDLJ-A IMU - Pelvis	−11.64 ± 1.11	Y	−10.68 ± 0.74	N	0.007**

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Parameter	G1 - Children ($n = 10$)		G2 - Adults ($n = 10$)		p -value
	Mean $\pm$ SD	Norm.	Mean $\pm$ SD	Norm.	
Zero crossings ACC - Pelvis	1091.7 $\pm$ 353.5	Y	1512.7 $\pm$ 235.2	Y	0.007**
SPARC 3D - Pelvis	-3.96 $\pm$ 1.56	Y	-2.92 $\pm$ 0.63	N	0.045*
SPARC Gyroscope - Pelvis	-1.09 $\pm$ 0.68	Y	-0.25 $\pm$ 0.21	N	0.006**
LDLJ-A IMU - C7	-12.01 $\pm$ 0.57	Y	-11.46 $\pm$ 0.84	N	0.045*
Median/Q3 ratio IMU - Wrist	0.49 $\pm$ 0.03	N	0.53 $\pm$ 0.03	Y	0.026*
Efficiency					
Trajectory length - Wrist (m)	2.41 $\pm$ 0.99	Y	1.43 $\pm$ 0.77	Y	0.025*
Control Strategy					
PPV 3D - Wrist (%)	12.7 $\pm$ 28.0	N	23.6 $\pm$ 19.0	Y	0.021*
Signal Complexity (Data-Driven)					
ApEn IMU - Pelvis	1.16 $\pm$ 0.41	Y	1.58 $\pm$ 0.52	N	0.038*
Inter-segmental Coordination					
r (C7-Pelvis) gyroscope	0.28 $\pm$ 0.23	Y	-0.02 $\pm$ 0.20	N	0.003**

4.6 General Discussion

To provide an overall view of the results and address the objectives of this study, it is relevant to conduct a more general discussion without focusing on specific individual parameters.

Among the 85 parameters computed for the gait task, 36 (42.3%) were statistically significant, confirming that developmental maturation strongly affects gait kinematics. The *Speed and Acceleration* category concentrated most of the significant findings (16 of 22), consistent with expected age-related differences in locomotor speed and segmental dynamics. The *Smoothness* category also proved informative, with 9 of 33 parameters significant. Although fewer in number, these indices captured qualitative aspects of movement not reflected by conventional descriptors. In the *Control Strategy* category, 5 of 12 parameters were significant, indicating developmental changes in postural and organizational mechanisms. For *Signal Complexity*, 4 of the 6 approximate entropy measures were significant, suggesting that children's locomotor signals remain more complex and less predictable than those of adults. In contrast, none of the three *Efficiency* parameters reached statistical significance, indicating no detectable group difference in the cumulative distance covered during the four analysed steps. The *Coordination* category showed only 2 significant parameters out of 9. Nevertheless, these were among the most discriminative findings. Notably, 19 of the 36 significant parameters (52.8%) were derived from IMU measurements, demonstrating that wearable sensors detect a substantial share of developmental differences during gait. Although optoelectronic measures provided a greater absolute number of significant results, IMU-derived parameters accounted for more than half of all significant findings, underscoring their strong potential for detecting developmental motor signatures.

Among the 96 parameters computed for the two-leg standing task, 53 (55.2%) were statistically significant, making this the most discriminative task of the protocol. The *Speed and Acceleration* category yielded 21 significant parameters out of 33, indicating marked developmental differences in postural sway dynamics. The *Smoothness* category was the most informative, with 23 of the 33 parameters reaching statistical significance, suggesting that movement smoothness is highly sensitive to age-related changes during static standing. All three *Efficiency* parameters were significant, whereas no significant result was

observed in the *Control Strategy* category. The *Signal Complexity* and *Coordination* categories each yielded three significant parameters, indicating additional differences in postural complexity and inter-segmental coordination. Notably, 24 of the 53 significant parameters (45.3%) were derived from IMU measurements, underscoring the important contribution of wearable sensors to the assessment of developmental differences in static postural control.

Among the 82 parameters computed for the drinking task, 38 (46.3%) were statistically significant, indicating marked developmental differences during this functional upper-limb movement. The *Speed and Acceleration* category provided the largest number of significant findings, 14 of 19, highlighting differences in movement dynamics between children and adults. The *Smoothness* category was particularly informative, with 15 of 33 parameters reaching statistical significance, suggesting that movement smoothness is strongly influenced by motor maturation during the drinking task. The *Efficiency* category showed 2 significant parameters out of 3, while *Control Strategy* and *Coordination* each yielded 2 significant parameters. Similarly, three of the six *Signal Complexity* measures were significant, indicating developmental differences in signal complexity. Notably, 19 of the 38 significant parameters (50.0%) were derived from IMU measurements, further demonstrating the substantial contribution of wearable sensors for characterizing developmental motor differences during functional tasks.

Among the 82 parameters computed for the reach-and-drop task, 22 (26.8%) were statistically significant. The *Speed and Acceleration* category provided the highest number of significant findings, 9 of 19, followed by the *Smoothness* category with 7 of 33 significant parameters. Only 1 parameter reached significance in the *Efficiency* category, whereas no significant parameter was observed for *Control Strategy*. The *Signal Complexity* category yielded 2 significant parameters and the *Coordination* category showed 3 significant results. Notably, 14 of the 22 significant parameters (63.6%) were derived from IMU measurements, emphasizing the prominent role of wearable sensors in detecting developmental differences during this task.

Among the 82 parameters computed for the pegboard task, 38 (46.3%) were statistically significant. The *Speed and Acceleration* category produced 6 significant findings. *Smoothness* category was by far the most informative, with 20 of the 33 parameters reaching significance, indicating that movement smoothness is particularly sensitive to developmental differences during fine manual dexterity tasks. The *Coordination* category produced 6 significant findings, highlighting differences in inter-segmental organization. The *Efficiency*, *Control Strategy* and *Signal Complexity* categories showed 1, 2 and 3 significant parameters, respectively. Consequently, 19 of the 38 significant parameters (50.0%) were derived from IMU measurements, confirming the complementary value of wearable sensors for assessing upper-limb motor performance.

Among the 82 parameters computed for the glass-clinking task, 23 (28.0%) were statistically significant. Most significant findings were observed in the *Speed and Acceleration* category, 12 of 19, whereas the *Smoothness* category yielded only 4 significant parameters, all of which were IMU-derived. The *Efficiency* category showed 2 significant parameters, while no significant result was observed in the *Control Strategy* category. The *Signal Complexity* and *Coordination* categories yielded 3 and 2 significant parameters, respectively. 13 of the 23 significant parameters (56.5%) were derived from IMU measurements, illustrating the ability of wearable sensors to capture developmental differences during this short functional interaction task.

Among the 82 parameters computed for the ball-throwing task, 21 (25.6%) were statistically significant. The *Speed and Acceleration* category accounted for nearly half of these findings, with 10 of the 19 parameters reaching significance. The *Smoothness* category yielded 5 significant parameters, all of which were IMU-derived. The *Efficiency* category showed 2 significant parameters, whereas the *Control Strategy*,

Signal Complexity and *Coordination* categories produced only a limited number of significant findings. So, 11 of the 21 significant parameters (52.4%) originated from IMU measurements, highlighting the contribution of wearable sensors despite the lower overall proportion of significant findings observed for this task.

Among the 82 parameters computed for the affordance task, 27 (32.9%) were statistically significant. The *Speed and Acceleration* and *Smoothness* categories were equally informative, each contributing 11 significant parameters. The *Efficiency* category yielded 2 significant parameters, whereas only one significant parameter was observed for each of the *Control Strategy*, *Signal Complexity* and *Coordination* categories. So, 14 of the 27 significant parameters (51.9%) were derived from IMU measurements, confirming once again that wearable sensors capture a substantial proportion of the developmental differences observed during complex functional movements.

The results (summarized in Table 4.9) obtained across the eight experimental tasks provide several important insights regarding the use of wearable IMUs for developmental motor assessment. First, the discriminative ability of the extracted parameters strongly depended on both the task and the parameter category. The two-leg standing task was the most discriminative, followed by the drinking and peg-board tasks. Across tasks, the *Speed and Acceleration* and *Smoothness* categories consistently contained the largest number of significant parameters, whereas *Efficiency* and *Control Strategy* contributed less to group discrimination. Interestingly, *Signal Complexity* and *Coordination*, although yielding fewer significant parameters, repeatedly identified developmental differences, suggesting that they provide complementary information beyond conventional kinematic descriptors. However, not all parameters within the most informative categories contributed equally. In particular, MAPR in the *Smoothness* category was rarely computable or statistically significant, suggesting that its current definition may not be sufficiently robust for the signals and tasks investigated here. Future work should therefore reconsider this parameter, either by adapting its formulation, replacing it with a more robust alternative, or removing it if it does not provide additional discriminative information. A similar consideration applies to the *Control Strategy* category. Only a limited number of these parameters were significant across the eight tasks despite the number of parameters computed. Their definition and physiological interpretation should therefore be reconsidered, and the relevance of maintaining this category in a simplified assessment protocol should be evaluated.

The comparison between tasks further highlights the importance of maintaining a diversified functional protocol. The drinking, reach-and-drop and pegboard tasks all assess aspects of fine motor control, yet they produced different patterns of significant parameters. Rather than being redundant, these three tasks therefore appear complementary, as they challenge different components of functional motor control and provide distinct information on developmental differences. Nevertheless, as discussed previously, the drinking task itself, as well as the instructions provided to participants, should be revised to ensure greater consistency in task execution and improve reproducibility across participants. A similar complementarity was observed for the two socially interactive tasks, namely the glass-clinking and ball-throwing tasks. Although both involve interaction with another person, they produced different discriminative patterns. The glass-clinking task represents a short and relatively constrained interpersonal action, whereas the ball-throwing task involves repeated object exchange and continuous adaptation to another person's actions. Their combined use may therefore provide a broader characterization of motor behaviour during social interaction than either task considered independently.

Importantly, the findings also suggest that IMUs alone may be sufficient to detect a substantial proportion of developmental differences. Approximately half of all significant parameters across tasks were IMU-derived, with a particularly strong contribution from *Smoothness*, *Signal Complexity* and *Coordination* measures. This suggests that wearable IMUs could potentially be used independently, without the need for an additional 3D motion capture system, thereby simplifying the experimental protocol and facilitating its implementation. However, an important limitation of an IMU-only approach concerns the

Speed and Acceleration category, for which several discriminative parameters in this study were derived from 3D trajectories. Finally, the present protocol, combining 3D motion capture and IMU measurements, proved capable of identifying consistent developmental differences between typically developing children and adults across a wide range of motor tasks. These results therefore support the validity of the proposed protocol and provide an encouraging basis for its future application to children with neurodevelopmental disorders.

Table 4.9: Overview of statistically significant parameters across the eight experimental tasks. Values in parentheses indicate the number of significant parameters derived from IMU measurements.

Category	Gait	Two-Leg Standing	Drinking	Reach-and-Drop	Pegboard	Glass-Clinking	Ball-Throwing	Affordance
Speed & Acceleration	16(6)	21(4)	14(5)	9(4)	6(5)	12(5)	10(4)	11(4)
Smoothness	9(6)	23(16)	15(11)	7(6)	20(9)	4(4)	5(5)	11(8)
Efficiency	0(0)	3(0)	2(0)	1(0)	1(0)	2(0)	2(0)	2(0)
Control Strategy	5(4)	0(0)	2(1)	0(0)	2(1)	0(0)	1(1)	1(0)
Signal Complexity	4(2)	3(2)	3(1)	2(2)	3(1)	3(2)	1(0)	1(1)
Coordination	2(1)	3(2)	2(1)	3(2)	6(3)	2(2)	2(1)	1(1)
Total significant	36/85 (42.3%)	53/96 (55.2%)	38/82 (46.3%)	22/82 (26.8%)	38/82 (46.3%)	23/82 (28.0%)	21/82 (25.6%)	27/82 (32.9%)
IMU contribution	19/36 (52.8%)	24/53 (45.3%)	19/38 (50.0%)	14/22 (63.6%)	19/38 (50.0%)	13/23 (56.5%)	11/21 (52.4%)	14/27 (51.9%)

Chapter 5

Limitations and Perspectives

This chapter discusses the principal limitations of this study. It then presents future research directions and methodological developments that could build upon the findings of this study.

5.1 Limitations

Several limitations were observed throughout this study.

First, the experimental protocol was conducted in a controlled laboratory environment, with participants wearing multiple IMUs and 3D reflective markers. Although this standardized setup ensured high-quality data acquisition, it may have influenced participants' natural behaviour. In particular, younger children may have felt stressed, intimidated, or constrained by the unfamiliar environment and the instrumentation, potentially affecting the way they performed the different motor tasks. As a result, the recorded movements may not fully represent motor behaviour in everyday life, thereby reducing the ecological validity of the protocol.

Second, the requirement for participants to travel to the laboratory represents a practical constraint that may have limited recruitment and reduced the accessibility of the study. Developing portable assessment protocols or adopting markerless motion capture technologies, such as OpenCap, could facilitate data collection in more natural environments while reducing the burden associated with laboratory visits. Such approaches could improve participant recruitment and increase the ecological validity of future studies.

Another limitation is the relatively small sample size. Although several statistically significant differences were identified between children and adults, the limited number of participants reduces the statistical power of the analyses and prevents the establishment of robust normative reference values stratified by age, sex, or body size. Larger cohorts will therefore be necessary to validate the proposed kinematic markers and improve the generalizability of the findings.

Finally, the optical motion capture system is inherently affected by marker occlusion. During some tasks, reflective markers were occasionally hidden from the cameras because of self-occlusion or body positioning, leading to temporary gaps in the reconstructed trajectories. Although these missing data were corrected whenever possible through interpolation and post-processing, they may have introduced small inaccuracies into some kinematic parameters. Future work could reduce this limitation by optimizing marker placement, increasing camera coverage, or adopting markerless motion capture systems.

5.2 Perspectives

The findings of this study open several ideas for future research, both from methodological and clinical perspectives.

A first perspective, as discussed in the limitations, is to expand the database by increasing the number of participants, particularly within the G1 group. With only 12 children aged between 6 and 12 years, the current sample size limits the statistical power and does not allow the influence of age, sex, and body size on kinematic parameters to be fully investigated. As explained in the previous sections, previous studies have shown that these factors significantly affect movement speed, cadence, and smoothness. A larger cohort would make it possible to establish age-, sex-, and height-specific normative reference values, providing clinically relevant benchmarks and facilitating future clinical applications of the proposed protocol.

A second perspective is to apply the same protocol to children with neurodevelopmental disorders, including autism spectrum disorder (ASD), attention-deficit/hyperactivity disorder (ADHD), developmental coordination disorder (DCD) and *multidys* profiles. The dataset established in this study could serve as a reference for objectively quantifying deviations in motor performance. Several parameters identified as robust across the different tasks may represent sensitive biomarkers capable of distinguishing pathological motor deficits from normal developmental variability. As explained in the previous sections, recent studies have shown that these kinematic metrics can detect subtle motor impairments that are not always captured by conventional clinical assessments.

A third perspective naturally arises from the results obtained in this study and concerns further improvements to the experimental protocol. In particular, the drinking task could be refined in terms of its design and execution, based on the methodological issues identified in this study, while the definition of movement onset should be improved for the affordance task. In addition, the protocol could be simplified by relying exclusively on IMUs, thereby facilitating its implementation.

A fourth perspective would be to use the parameters identified in this study to develop a model capable of predicting whether an individual belongs to the child or adult group based on their kinematic profile. The significant and discriminative parameters retained after the parameter-reduction procedure could be used as input variables, with group membership (child or adult) as the outcome. A multiple logistic regression would represent an appropriate first approach, as it would allow the contribution of the different kinematic parameters to group classification to be quantified while remaining easily interpretable. With a larger dataset, more advanced methods could subsequently be explored, such as decision trees, which could capture more complex relationships between parameters while maintaining relatively straightforward clinical interpretability. Such an approach would provide a first step toward determining whether the quantitative movement parameters identified in this study can collectively characterize a kinematic profile as more child-like or adult-like. This approach is consistent with current trends in clinical biomechanics, where machine learning applied to IMU-derived kinematic data is increasingly being explored for diagnostic and assessment purposes.

Chapter 6

Conclusion

The aim of this study was to develop and evaluate a functional motor assessment protocol combining three-dimensional optoelectronic motion capture and wearable inertial measurement units (IMUs), with the objective of quantitatively characterizing differences in motor behaviour between typically developing children aged 6-12 years and healthy adults. Through a battery of eight motor tasks, different components of motor function were investigated, including locomotion, postural control, fine motor function, social interaction, and affordance-based exploration.

Overall, the results demonstrate that quantitative movement analysis is able to reveal numerous differences between children and adults, even when both groups are able to successfully perform the same functional tasks. These differences were not limited to movement speed or task duration, but involved several dimensions of motor behaviour. In particular, parameters related to movement smoothness, signal complexity, efficiency, postural control and inter-segmental coordination frequently differentiated the two groups. The results therefore highlight that motor development during school age involves not only changes in performance, but also progressive modifications in the way movements are organized and controlled.

An important finding of this study is that developmental differences were observed at both distal and proximal levels. Children generally exhibited greater postural involvement and less smooth movement profiles, particularly at C7 and the pelvis, while differences at the wrist depended more strongly on the nature of the task. Inter-segmental correlations further suggested that the organization of coordination differs between children and adults and varies according to task requirements. Motor maturation should therefore not be considered simply as a transition toward systematically greater segmental dissociation, but rather as the progressive development of the ability to adapt movement organization and inter-segmental coordination to the specific demands of a task.

The comparison of the different parameter categories also demonstrated the complementary information provided by conventional kinematic descriptors and more advanced signal-based measures. Parameters such as SPARC, LDLJ-A, approximate entropy, and inter-segmental correlations revealed differences that would be difficult to identify through task duration or movement velocity alone. Importantly, several discriminative parameters were derived directly from IMU signals. These findings support the potential of wearable sensors as a simpler and more accessible approach for quantitative motor assessment. Although optoelectronic motion capture remains valuable as a reference method for three-dimensional movement analysis, the results suggest that a reduced protocol relying primarily, or potentially exclusively, on IMUs could retain relevant information while considerably facilitating data collection.

Nevertheless, these findings should be interpreted in light of the methodological limitations of the study, particularly the relatively small sample size, the heterogeneity of the child group, and some task-

specific methodological constraints. The results should therefore be regarded as an initial characterization of developmental differences rather than as normative values. A larger and age-stratified population will be necessary to establish robust reference data and to investigate the evolution of the identified parameters throughout childhood.

In conclusion, this study demonstrates the feasibility and relevance of a multi-task quantitative approach for characterizing motor development and provides a first reference framework for distinguishing child and adult kinematic profiles. The identification of a reduced set of informative parameters, together with the promising contribution of IMU-derived measures, provides a methodological basis for future developments of the protocol. Ultimately, its application to children with neurodevelopmental disorders could help determine whether these quantitative movement markers provide complementary information to standardized clinical assessments and contribute to a more objective and detailed characterization of individual motor profiles.

Appendices

Appendix A: Tables with all parameters computed for each task

Table A.1: Comparison between G1 (children, $n = 12$) and G2 (adults, $n = 10$) for all parameters computed in gait task. Values are mean $\pm$ SD. *Norm.*: normality assessment per group via Shapiro-Wilk ($\alpha = 0.05$): Y = normal, N = non-normal. Statistical test: Welch's t -test (both normal) or Mann-Whitney U (at least one non-normal). * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$. Rows highlighted in green indicate a significant difference ($p < 0.05$); N/A indicates the test could not be computed (constant/zero values in both groups).

Parameter	G1 - Children (<i>n</i> = 12)		G2 - Adults (<i>n</i> = 10)		<i>p</i> -value
	Mean ± SD	Norm.	Mean ± SD	Norm.	
Speed and Acceleration					
Movement time (s)	1.85 ± 0.24	Y	2.24 ± 0.19	N	0.001**
Cadence (steps/min)	131 ± 17.3	Y	108 ± 8.23	Y	< 0.001***
Step duration, mean (s)	0.46 ± 0.06	Y	0.56 ± 0.05	N	0.001**
Step duration, SD (s)	0.01 ± 0.01	N	0.01 ± 0.01	N	0.428
Velocity Q3 - Wrist (m/s)	1.766 ± 0.393	Y	1.575 ± 0.327	Y	0.229
Velocity Q3 - C7 (m/s)	1.425 ± 0.262	Y	1.190 ± 0.146	N	0.006**
Velocity Q3 - Pelvis (m/s)	1.478 ± 0.249	Y	1.233 ± 0.147	N	0.005**
Max velocity - Wrist (m/s)	1.995 ± 0.423	Y	1.859 ± 0.406	Y	0.450
Max velocity - C7 (m/s)	1.530 ± 0.272	Y	1.282 ± 0.145	N	0.008**
Max velocity - Pelvis (m/s)	1.698 ± 0.273	Y	1.389 ± 0.158	N	0.002**
Median velocity - Wrist (m/s)	1.379 ± 0.260	Y	1.161 ± 0.159	N	0.009**
Median velocity - C7 (m/s)	1.372 ± 0.259	Y	1.135 ± 0.149	N	0.006**
Median velocity - Pelvis (m/s)	1.345 ± 0.258	Y	1.114 ± 0.145	N	0.008**
Mean velocity - Wrist (m/s)	1.378 ± 0.252	Y	1.155 ± 0.154	N	0.008**
Mean velocity - C7 (m/s)	1.377 ± 0.260	Y	1.141 ± 0.150	N	0.006**
Mean velocity - Pelvis (m/s)	1.376 ± 0.258	Y	1.139 ± 0.149	N	0.005**
Acceleration Q3 - Wrist (m/s ²)	12.30 ± 1.42	N	11.20 ± 0.56	Y	0.027*
Acceleration Q3 - C7 (m/s ²)	12.00 ± 1.41	N	10.60 ± 0.45	Y	0.003**
Acceleration Q3 - Pelvis (m/s ²)	12.80 ± 1.77	Y	11.40 ± 0.61	Y	0.030*
Acceleration median - Wrist (m/s ²)	10.10 ± 0.72	Y	9.71 ± 0.32	Y	0.081
Acceleration median - C7 (m/s ²)	9.59 ± 0.51	Y	9.33 ± 0.27	Y	0.137
Acceleration median - Pelvis (m/s ²)	9.86 ± 0.57	Y	9.59 ± 0.33	Y	0.193
Movement Smoothness					
LDLJ-A IMU - Wrist	−5.29 ± 0.50	Y	−5.15 ± 0.46	Y	0.484
LDLJ-A IMU - C7	−5.68 ± 0.47	Y	−5.46 ± 0.34	Y	0.218
LDLJ-A IMU - Pelvis	−6.35 ± 0.60	Y	−6.34 ± 0.43	Y	0.966
Zero crossings ACC - Wrist	14.1 ± 3.78	Y	13.7 ± 2.50	Y	0.779
Zero crossings ACC - C7	14.3 ± 7.71	N	12.9 ± 5.15	Y	0.640

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Parameter	G1 - Children (n = 12)		G2 - Adults (n = 10)		p-value
	Mean ± SD	Norm.	Mean ± SD	Norm.	
Zero crossings ACC - Pelvis	17.4 ± 7.84	Y	23.6 ± 7.47	Y	0.074
MAPR 3D - Wrist	0.000 ± 0.000	Y	0.012 ± 0.038	N	0.315
MAPR 3D - C7	0.000 ± 0.000	Y	0.000 ± 0.000	Y	N/A
MAPR 3D - Pelvis	0.000 ± 0.000	Y	0.000 ± 0.000	Y	N/A
MAPR IMU - Wrist	0.003 ± 0.012	N	0.000 ± 0.000	Y	0.411
MAPR IMU - C7	0.003 ± 0.009	N	0.000 ± 0.000	Y	0.411
MAPR IMU - Pelvis	0.004 ± 0.011	N	0.000 ± 0.000	Y	0.209
SPARC 3D - Wrist	-0.70 ± 0.15	Y	-0.77 ± 0.16	Y	0.299
SPARC 3D - C7	-0.49 ± 0.04	Y	-0.44 ± 0.02	Y	0.005**
SPARC 3D - Pelvis	-0.55 ± 0.03	Y	-0.52 ± 0.02	Y	0.001**
SPARC Accelerometer - Wrist	-0.76 ± 0.13	Y	-0.69 ± 0.10	Y	0.161
SPARC Accelerometer - C7	-0.80 ± 0.20	Y	-0.66 ± 0.08	Y	0.046*
SPARC Accelerometer - Pelvis	-0.86 ± 0.19	Y	-0.71 ± 0.11	Y	0.036*
SPARC Gyroscope - Wrist	-0.93 ± 0.14	Y	-1.19 ± 0.23	Y	0.006**
SPARC Gyroscope - C7	-0.88 ± 0.24	N	-0.93 ± 0.20	Y	0.307
SPARC Gyroscope - Pelvis	-1.14 ± 0.36	Y	-1.27 ± 0.21	Y	0.288
Median/Q3 ratio 3D - Wrist	0.79 ± 0.09	Y	0.75 ± 0.08	Y	0.266
Median/Q3 ratio 3D - C7	0.96 ± 0.02	Y	0.95 ± 0.02	Y	0.226
Median/Q3 ratio 3D - Pelvis	0.91 ± 0.03	Y	0.90 ± 0.02	Y	0.709
Median/Q3 ratio IMU - Wrist	0.83 ± 0.08	Y	0.87 ± 0.03	Y	0.162
Median/Q3 ratio IMU - C7	0.81 ± 0.09	N	0.88 ± 0.04	Y	0.005**
Median/Q3 ratio IMU - Pelvis	0.79 ± 0.11	Y	0.84 ± 0.05	Y	0.131
Mean/max ratio 3D - Wrist	0.70 ± 0.06	Y	0.63 ± 0.07	Y	0.040*
Mean/max ratio 3D - C7	0.90 ± 0.04	Y	0.89 ± 0.03	Y	0.490
Mean/max ratio 3D - Pelvis	0.81 ± 0.04	Y	0.82 ± 0.02	Y	0.426
Mean/max ratio IMU - Wrist	0.61 ± 0.09	Y	0.66 ± 0.05	Y	0.167
Mean/max ratio IMU - C7	0.56 ± 0.10	Y	0.65 ± 0.05	Y	0.012*
Mean/max ratio IMU - Pelvis	0.53 ± 0.13	Y	0.64 ± 0.08	Y	0.029*
Efficiency					
Trajectory length - Wrist (m)	2.517 ± 0.341	Y	2.566 ± 0.231	Y	0.694
Trajectory length - C7 (m)	2.512 ± 0.352	Y	2.534 ± 0.227	Y	0.863
Trajectory length - Pelvis (m)	2.512 ± 0.350	Y	2.532 ± 0.225	Y	0.877
Control Strategy					
Dominant frequency 3D - Wrist (Hz)	1.09 ± 0.15	Y	0.90 ± 0.07	Y	< 0.001***
Dominant frequency 3D - C7 (Hz)	1.78 ± 0.63	N	1.79 ± 0.14	Y	0.222
Dominant frequency 3D - Pelvis (Hz)	1.96 ± 0.36	Y	1.79 ± 0.14	Y	0.142
Dominant frequency IMU - Wrist (Hz)	2.02 ± 0.28	Y	1.79 ± 0.14	Y	0.026*
Dominant frequency IMU - C7 (Hz)	2.02 ± 0.28	Y	1.79 ± 0.14	Y	0.026*
Dominant frequency IMU - Pelvis (Hz)	1.96 ± 0.45	N	1.79 ± 0.14	Y	0.019*
PPV 3D - Wrist (%)	37.6 ± 32.8	N	60.6 ± 26.9	Y	0.106
PPV 3D - C7 (%)	44.1 ± 30.4	Y	35.2 ± 22.7	Y	0.440
PPV 3D - Pelvis (%)	46.4 ± 30.9	N	56.6 ± 23.3	Y	0.277
PPV IMU - Wrist (%)	46.5 ± 27.4	Y	48.8 ± 28.8	Y	0.854
PPV IMU - C7 (%)	52.3 ± 29.2	Y	47.6 ± 31.9	Y	0.724
PPV IMU - Pelvis (%)	72.3 ± 25.4	N	47.5 ± 29.8	N	0.032*
Signal Complexity (Data-Driven)					

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Parameter	G1 - Children ($n = 12$)		G2 - Adults ($n = 10$)		p-value
	Mean $\pm$ SD	Norm.	Mean $\pm$ SD	Norm.	
ApEn 3D - Wrist	0.12 $\pm$ 0.03	N	0.09 $\pm$ 0.01	N	0.003**
ApEn 3D - C7	0.26 $\pm$ 0.06	Y	0.24 $\pm$ 0.04	Y	0.257
ApEn 3D - Pelvis	0.30 $\pm$ 0.05	Y	0.25 $\pm$ 0.03	Y	0.015*
ApEn IMU - Wrist	0.44 $\pm$ 0.06	Y	0.36 $\pm$ 0.05	Y	0.002**
ApEn IMU - C7	0.41 $\pm$ 0.06	Y	0.33 $\pm$ 0.04	Y	0.001**
ApEn IMU - Pelvis	0.53 $\pm$ 0.06	N	0.49 $\pm$ 0.05	Y	0.176
Inter-segmental Coordination					
r (Wrist-C7) 3D	0.11 $\pm$ 0.19	Y	0.04 $\pm$ 0.17	Y	0.346
r (Wrist-C7) gyroscope	-0.19 $\pm$ 0.16	Y	0.22 $\pm$ 0.16	Y	< 0.001***
r (Wrist-C7) accelerometer	0.71 $\pm$ 0.14	Y	0.69 $\pm$ 0.22	N	0.921
r (Wrist-Pelvis) 3D	0.02 $\pm$ 0.18	Y	-0.01 $\pm$ 0.16	Y	0.666
r (Wrist-Pelvis) gyroscope	-0.05 $\pm$ 0.19	Y	-0.06 $\pm$ 0.11	Y	0.822
r (Wrist-Pelvis) accelerometer	0.65 $\pm$ 0.13	Y	0.60 $\pm$ 0.23	Y	0.559
r (C7-Pelvis) 3D	0.69 $\pm$ 0.11	Y	0.87 $\pm$ 0.06	Y	< 0.001***
r (C7-Pelvis) gyroscope	0.15 $\pm$ 0.21	Y	0.18 $\pm$ 0.25	Y	0.712
r (C7-Pelvis) accelerometer	0.80 $\pm$ 0.12	Y	0.81 $\pm$ 0.08	Y	0.841

Table A.2: Comparison between G1 (children, $n = 12$) and G2 (adults, $n = 10$) for all parameters computed in two-leg standing task. Values are mean $\pm$ SD. *Norm.*: normality assessment per group via Shapiro-Wilk ($\alpha = 0.05$): Y = normal, N = non-normal. Statistical test: Welch's t -test (both normal) or Mann-Whitney U (at least one non-normal). * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$. Rows highlighted in green indicate a significant difference ($p < 0.05$); N/A indicates the test could not be computed (constant/zero values in both groups).

Parameter	G1 - Children (<i>n</i> = 12)		G2 - Adults (<i>n</i> = 10)		<i>p</i> -value
	Mean ± SD	Norm.	Mean ± SD	Norm.	
Speed and Acceleration					
AP range Q3 - Wrist (mm)	8.0 ± 3.3	Y	8.1 ± 2.6	Y	0.987
ML range Q3 - Wrist (mm)	4.9 ± 2.9	Y	2.8 ± 1.1	Y	0.036*
AP range Q3 - C7 (mm)	9.7 ± 2.1	Y	10.3 ± 3.5	Y	0.608
ML range Q3 - C7 (mm)	5.8 ± 5.0	N	3.4 ± 1.9	N	0.223
AP range Q3 - Pelvis (mm)	7.1 ± 2.7	Y	8.1 ± 2.4	N	0.339
ML range Q3 - Pelvis (mm)	4.8 ± 3.8	N	2.7 ± 1.5	N	0.223
AP velocity Q3 - Wrist (mm/s)	9.0 ± 4.2	Y	5.6 ± 1.2	Y	0.018*
AP velocity Q3 - C7 (mm/s)	8.1 ± 2.4	Y	6.2 ± 1.1	Y	0.024*
AP velocity Q3 - Pelvis (mm/s)	6.2 ± 2.3	Y	4.5 ± 0.8	Y	0.034*
ML velocity Q3 - Wrist (mm/s)	6.1 ± 3.3	Y	3.7 ± 1.1	Y	0.037*
ML velocity Q3 - C7 (mm/s)	5.2 ± 2.2	Y	3.5 ± 1.7	N	0.038*
ML velocity Q3 - Pelvis (mm/s)	4.2 ± 2.3	Y	2.8 ± 1.2	N	0.12
Max velocity - Wrist (mm/s)	64.6 ± 64.3	N	20.6 ± 6.0	Y	0.003**
Max velocity - C7 (mm/s)	33.3 ± 17.1	Y	19.2 ± 3.1	Y	0.017*
Max velocity - Pelvis (mm/s)	31.4 ± 16.2	Y	14.1 ± 3.1	Y	0.003**
Median velocity - Wrist (mm/s)	7.9 ± 3.5	Y	5.2 ± 1.2	Y	0.023*
Median velocity - C7 (mm/s)	6.8 ± 2.2	Y	5.0 ± 1.3	Y	0.029*
Median velocity - Pelvis (mm/s)	5.3 ± 2.2	Y	3.8 ± 0.8	N	0.081
Mean velocity - Wrist (mm/s)	9.8 ± 4.7	Y	5.7 ± 1.2	Y	0.013*
Mean velocity - C7 (mm/s)	7.8 ± 2.6	Y	5.4 ± 1.1	Y	0.013*

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Parameter	G1 - Children (n = 12)		G2 - Adults (n = 10)		p-value
	Mean $\pm$ SD	Norm.	Mean $\pm$ SD	Norm.	
Mean velocity - Pelvis (mm/s)	6.2 $\pm$ 2.6	Y	4.3 $\pm$ 0.8	Y	0.029*
AP median velocity - Wrist (mm/s)	5.0 $\pm$ 2.1	Y	3.3 $\pm$ 0.7	Y	0.019*
ML median velocity - Wrist (mm/s)	3.3 $\pm$ 1.8	Y	2.2 $\pm$ 0.6	Y	0.065
AP median velocity - C7 (mm/s)	4.5 $\pm$ 1.3	Y	3.5 $\pm$ 0.7	Y	0.033*
ML median velocity - C7 (mm/s)	3.0 $\pm$ 1.3	Y	2.0 $\pm$ 0.8	N	0.052
AP median velocity - Pelvis (mm/s)	3.5 $\pm$ 1.2	Y	2.6 $\pm$ 0.4	Y	0.026*
ML median velocity - Pelvis (mm/s)	2.3 $\pm$ 1.3	Y	1.6 $\pm$ 0.7	N	0.121
Acceleration Q3 - Wrist (m/s ²)	9.69 $\pm$ 0.11	N	9.59 $\pm$ 0.08	Y	0.070
Acceleration Q3 - C7 (m/s ²)	9.71 $\pm$ 0.10	Y	9.57 $\pm$ 0.15	N	0.038*
Acceleration Q3 - Pelvis (m/s ²)	9.70 $\pm$ 0.16	Y	9.83 $\pm$ 0.06	Y	0.023*
Acceleration median - Wrist (m/s ²)	9.65 $\pm$ 0.11	N	9.57 $\pm$ 0.08	Y	0.199
Acceleration median - C7 (m/s ²)	9.69 $\pm$ 0.10	Y	9.55 $\pm$ 0.15	N	0.038*
Acceleration median - Pelvis (m/s ²)	9.68 $\pm$ 0.17	Y	9.81 $\pm$ 0.06	Y	0.023*
Movement Smoothness					
LDLJ-A IMU - Wrist	-11.80 $\pm$ 0.51	Y	-10.90 $\pm$ 0.22	Y	< 0.001***
LDLJ-A IMU - C7	-11.40 $\pm$ 0.45	Y	-10.70 $\pm$ 0.15	Y	< 0.001***
LDLJ-A IMU - Pelvis	-11.10 $\pm$ 0.39	Y	-10.70 $\pm$ 0.38	Y	0.049*
Zero crossings ACC - Wrist	802 $\pm$ 97.2	Y	991 $\pm$ 104	Y	< 0.001***
Zero crossings ACC - C7	1205 $\pm$ 170	Y	1440 $\pm$ 95.1	Y	< 0.001***
Zero crossings ACC - Pelvis	1198 $\pm$ 182	Y	1177 $\pm$ 281	Y	0.837
MAPR 3D - Wrist	0.026 $\pm$ 0.011	Y	0.016 $\pm$ 0.006	N	0.023*
MAPR 3D - C7	0.027 $\pm$ 0.007	Y	0.031 $\pm$ 0.012	Y	0.404
MAPR 3D - Pelvis	0.031 $\pm$ 0.009	Y	0.021 $\pm$ 0.009	Y	0.024*
MAPR IMU - Wrist	0.000 $\pm$ 0.000	Y	0.000 $\pm$ 0.000	Y	N/A
MAPR IMU - C7	0.000 $\pm$ 0.000	Y	0.000 $\pm$ 0.000	Y	N/A
MAPR IMU - Pelvis	0.000 $\pm$ 0.000	Y	0.000 $\pm$ 0.000	Y	N/A
SPARC 3D - Wrist	-3.11 $\pm$ 0.32	Y	-2.48 $\pm$ 0.37	Y	< 0.001***
SPARC 3D - C7	-2.30 $\pm$ 0.18	Y	-2.24 $\pm$ 0.36	Y	0.631
SPARC 3D - Pelvis	-2.58 $\pm$ 0.32	Y	-2.23 $\pm$ 0.32	Y	0.020*
SPARC Accelerometer - Wrist	-0.05 $\pm$ 0.01	Y	-0.04 $\pm$ 0.00	Y	< 0.001***
SPARC Accelerometer - C7	-0.04 $\pm$ 0.00	Y	-0.03 $\pm$ 0.00	Y	< 0.001***
SPARC Accelerometer - Pelvis	-0.04 $\pm$ 0.00	Y	-0.04 $\pm$ 0.00	Y	0.301
SPARC Gyroscope - Wrist	-1.16 $\pm$ 0.80	N	-0.28 $\pm$ 0.04	Y	< 0.001***
SPARC Gyroscope - C7	-0.77 $\pm$ 0.31	Y	-0.21 $\pm$ 0.07	Y	< 0.001***
SPARC Gyroscope - Pelvis	-0.65 $\pm$ 0.33	Y	-0.19 $\pm$ 0.04	Y	< 0.001***
Mean/max ratio 3D - Wrist	0.20 $\pm$ 0.06	Y	0.30 $\pm$ 0.08	Y	0.008**
Mean/max ratio 3D - C7	0.26 $\pm$ 0.07	Y	0.29 $\pm$ 0.06	Y	0.311
Mean/max ratio 3D - Pelvis	0.22 $\pm$ 0.06	Y	0.31 $\pm$ 0.06	Y	0.001**
Mean/max ratio IMU - Wrist	0.93 $\pm$ 0.09	N	0.99 $\pm$ 0.00	Y	< 0.001***
Mean/max ratio IMU - C7	0.97 $\pm$ 0.02	Y	0.99 $\pm$ 0.00	Y	0.003**
Mean/max ratio IMU - Pelvis	0.98 $\pm$ 0.02	N	0.99 $\pm$ 0.00	N	0.023*
Median/Q3 ratio 3D - Wrist	0.66 $\pm$ 0.05	Y	0.70 $\pm$ 0.02	Y	0.013*
Median/Q3 ratio 3D - C7	0.68 $\pm$ 0.03	Y	0.69 $\pm$ 0.04	N	0.717
Median/Q3 ratio 3D - Pelvis	0.66 $\pm$ 0.05	Y	0.67 $\pm$ 0.04	Y	0.356

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Parameter	G1 - Children (<i>n</i> = 12)		G2 - Adults (<i>n</i> = 10)		<i>p</i> -value
	Mean $\pm$ SD	Norm.	Mean $\pm$ SD	Norm.	
Median/Q3 ratio IMU - Wrist	0.55 $\pm$ 0.03	Y	0.57 $\pm$ 0.02	Y	0.018*
Median/Q3 ratio IMU - C7	0.56 $\pm$ 0.02	Y	0.58 $\pm$ 0.01	Y	0.002**
Median/Q3 ratio IMU - Pelvis	0.57 $\pm$ 0.01	Y	0.59 $\pm$ 0.01	N	< 0.001***
Efficiency					
Trajectory length - Wrist (mm)	292 $\pm$ 141	Y	171 $\pm$ 35.3	Y	0.013*
Trajectory length - C7 (mm)	233 $\pm$ 78.9	Y	163 $\pm$ 32.1	Y	0.013*
Trajectory length - Pelvis (mm)	186 $\pm$ 78.4	Y	128 $\pm$ 24.1	Y	0.029*
Control Strategy					
Dominant frequency 3D - Wrist (Hz)	0.32 $\pm$ 0.28	N	0.45 $\pm$ 0.57	N	0.737
Dominant frequency 3D - C7 (Hz)	0.23 $\pm$ 0.15	N	0.19 $\pm$ 0.12	N	0.459
Dominant frequency 3D - Pelvis (Hz)	0.18 $\pm$ 0.07	N	0.17 $\pm$ 0.12	N	0.537
Dominant frequency IMU - Wrist (Hz)	1.91 $\pm$ 0.63	Y	1.68 $\pm$ 0.81	Y	0.460
Dominant frequency IMU - C7 (Hz)	1.13 $\pm$ 1.01	N	1.93 $\pm$ 0.97	N	0.075
Dominant frequency IMU - Pelvis (Hz)	1.62 $\pm$ 1.18	N	1.75 $\pm$ 1.19	N	0.487
PPV 3D - Wrist (%)	31.9 $\pm$ 36.3	N	24.2 $\pm$ 21.3	Y	0.843
PPV 3D - C7 (%)	54.7 $\pm$ 36.7	N	45.4 $\pm$ 41.3	N	0.668
PPV 3D - Pelvis (%)	35.5 $\pm$ 32.0	Y	42.3 $\pm$ 41.3	N	1.000
PPV IMU - Wrist (%)	38.7 $\pm$ 36.4	Y	52.5 $\pm$ 32.4	Y	0.361
PPV IMU - C7 (%)	39.9 $\pm$ 35.3	N	37.0 $\pm$ 36.5	Y	0.531
PPV IMU - Pelvis (%)	30.4 $\pm$ 31.0	N	33.4 $\pm$ 34.0	Y	0.921
Signal Complexity (Data-Driven)					
ApEn 3D - Wrist	0.28 $\pm$ 0.11	Y	0.28 $\pm$ 0.05	N	0.668
ApEn 3D - C7	0.20 $\pm$ 0.06	Y	0.22 $\pm$ 0.07	Y	0.385
ApEn 3D - Pelvis	0.22 $\pm$ 0.07	Y	0.33 $\pm$ 0.12	Y	0.022*
ApEn IMU - Wrist	1.05 $\pm$ 0.24	Y	1.48 $\pm$ 0.09	Y	< 0.001***
ApEn IMU - C7	1.46 $\pm$ 0.23	Y	1.78 $\pm$ 0.07	Y	< 0.001***
ApEn IMU - Pelvis	1.47 $\pm$ 0.22	Y	1.62 $\pm$ 0.18	Y	0.086
Inter-segmental Coordination					
<i>r</i> (Wrist-C7) 3D	0.31 $\pm$ 0.14	N	0.40 $\pm$ 0.20	Y	0.410
<i>r</i> (Wrist-C7) gyroscope	0.17 $\pm$ 0.33	N	0.22 $\pm$ 0.28	Y	0.767
<i>r</i> (Wrist-C7) accelerometer	0.12 $\pm$ 0.11	Y	-0.06 $\pm$ 0.13	Y	0.003**
<i>r</i> (Wrist-Pelvis) 3D	0.49 $\pm$ 0.11	Y	0.46 $\pm$ 0.23	Y	0.679
<i>r</i> (Wrist-Pelvis) gyroscope	0.06 $\pm$ 0.28	Y	-0.07 $\pm$ 0.18	Y	0.196
<i>r</i> (Wrist-Pelvis) accelerometer	0.13 $\pm$ 0.14	Y	0.06 $\pm$ 0.07	N	0.248
<i>r</i> (C7-Pelvis) 3D	0.53 $\pm$ 0.12	Y	0.70 $\pm$ 0.15	Y	0.007**
<i>r</i> (C7-Pelvis) gyroscope	0.11 $\pm$ 0.33	Y	-0.32 $\pm$ 0.17	Y	0.001**
<i>r</i> (C7-Pelvis) accelerometer	0.05 $\pm$ 0.12	Y	0.08 $\pm$ 0.08	Y	0.514

Table A.3: Comparison between G1 (children, $n = 11$) and G2 (adults, $n = 10$) for all parameters computed in drinking task. Values are mean $\pm$ SD. *Norm.*: normality assessment per group via Shapiro-Wilk ($\alpha = 0.05$): Y = normal, N = non-normal. Statistical test: Welch's t -test (both normal) or Mann-Whitney U (at least one non-normal). * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$. Rows highlighted in green indicate a significant difference ($p < 0.05$); N/A indicates the test could not be computed (constant/zero values in both groups).

Parameter	G1 - Children (<i>n</i> = 11)		G2 - Adults (<i>n</i> = 10)		<i>p</i> -value
	Mean ± SD	Norm.	Mean ± SD	Norm.	
Speed and Acceleration					
Movement time (s)	14.9 ± 4.7	Y	11.3 ± 3.4	Y	0.057
Velocity Q3 - Pelvis (mm/s)	19.4 ± 9.7	Y	5.4 ± 2.3	Y	< 0.001***
Max velocity - Pelvis (mm/s)	112.0 ± 59.1	Y	31.7 ± 37.9	N	0.004**
Median velocity - Pelvis (mm/s)	9.3 ± 4.5	Y	3.0 ± 1.1	Y	< 0.001***
Mean velocity - Pelvis (mm/s)	15.8 ± 7.1	Y	4.8 ± 3.4	N	0.002**
Acceleration Q3 - Pelvis (m/s ²)	9.82 ± 0.18	Y	10.00 ± 0.08	Y	0.005**
Acceleration median - Pelvis (m/s ²)	9.74 ± 0.18	Y	9.99 ± 0.08	Y	< 0.001***
Velocity Q3 - C7 (mm/s)	65.2 ± 27.8	Y	38.7 ± 17.2	N	0.022*
Max velocity - C7 (mm/s)	258.0 ± 124.0	Y	139.0 ± 70.7	Y	0.015*
Median velocity - C7 (mm/s)	32.0 ± 13.7	Y	19.2 ± 7.1	N	0.012*
Mean velocity - C7 (mm/s)	50.1 ± 20.9	Y	29.7 ± 12.6	N	0.026*
Acceleration Q3 - C7 (m/s ²)	9.78 ± 0.10	Y	9.57 ± 0.16	N	0.001**
Acceleration median - C7 (m/s ²)	9.69 ± 0.09	N	9.52 ± 0.16	N	0.001**
Velocity Q3 - Wrist (mm/s)	293.0 ± 48.4	Y	363.0 ± 77.9	Y	0.028*
Max velocity - Wrist (mm/s)	1016.0 ± 200.0	Y	968.0 ± 173.0	Y	0.557
Median velocity - Wrist (mm/s)	154.0 ± 30.9	N	186.0 ± 37.0	Y	0.072
Mean velocity - Wrist (mm/s)	213.0 ± 35.9	Y	251.0 ± 45.4	Y	0.051
Acceleration Q3 - Wrist (m/s ²)	10.50 ± 0.39	Y	10.20 ± 0.34	Y	0.067
Acceleration median - Wrist (m/s ²)	9.59 ± 0.11	Y	9.39 ± 0.09	Y	< 0.001***
Movement Smoothness					
LDLJ-A IMU - Pelvis	−9.75 ± 1.46	Y	−7.15 ± 1.02	Y	< 0.001***
Zero crossings ACC - Pelvis	304 ± 133	Y	403 ± 202	Y	0.207
MAPR 3D - Pelvis	0.163 ± 0.093	N	0.082 ± 0.110	N	0.004**
MAPR IMU - Pelvis	0.000 ± 0.000	Y	0.000 ± 0.000	Y	N/A
SPARC 3D - Pelvis	−2.58 ± 0.51	Y	−2.11 ± 0.66	N	0.038*
SPARC Accelerometer - Pelvis	−0.10 ± 0.03	Y	−0.10 ± 0.03	Y	0.826
SPARC Gyroscope - Pelvis	−1.41 ± 0.49	Y	−0.42 ± 0.15	Y	< 0.001***
Mean/max ratio 3D - Pelvis	0.15 ± 0.05	Y	0.19 ± 0.06	Y	0.096
Mean/max ratio IMU - Pelvis	0.91 ± 0.05	Y	0.97 ± 0.02	N	< 0.001***
Median/Q3 ratio 3D - Pelvis	0.49 ± 0.08	N	0.59 ± 0.10	Y	0.032*
Median/Q3 ratio IMU - Pelvis	0.50 ± 0.04	Y	0.52 ± 0.05	N	0.098
LDLJ-A IMU - C7	−10.60 ± 1.25	Y	−8.81 ± 1.07	Y	0.002**
Zero crossings ACC - C7	374 ± 141	Y	322 ± 122	Y	0.382
MAPR 3D - C7	0.154 ± 0.082	Y	0.142 ± 0.053	N	0.699
MAPR IMU - C7	0.000 ± 0.000	Y	0.000 ± 0.000	Y	N/A
SPARC 3D - C7	−2.12 ± 0.62	Y	−1.70 ± 0.50	Y	0.097
SPARC Accelerometer - C7	−0.10 ± 0.03	N	−0.10 ± 0.03	Y	0.751
SPARC Gyroscope - C7	−1.83 ± 0.57	Y	−1.21 ± 0.40	Y	0.010**
Mean/max ratio 3D - C7	0.20 ± 0.04	Y	0.22 ± 0.05	Y	0.267
Mean/max ratio IMU - C7	0.89 ± 0.07	N	0.95 ± 0.03	N	0.022*
Median/Q3 ratio 3D - C7	0.50 ± 0.08	Y	0.52 ± 0.08	Y	0.579

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Parameter	G1 - Children (<i>n</i> = 11)		G2 - Adults (<i>n</i> = 10)		<i>p</i> -value
	Mean ± SD	Norm.	Mean ± SD	Norm.	
Median/Q3 ratio IMU - C7	0.51 ± 0.06	N	0.52 ± 0.03	Y	0.460
LDLJ-A IMU - Wrist	-13.70 ± 0.96	Y	-12.40 ± 0.96	Y	0.006**
Zero crossings ACC - Wrist	259 ± 96.2	Y	168 ± 57.4	Y	0.016*
MAPR 3D - Wrist	0.106 ± 0.046	Y	0.127 ± 0.036	Y	0.260
MAPR IMU - Wrist	0.000 ± 0.000	N	0.000 ± 0.000	Y	0.045*
SPARC 3D - Wrist	-2.18 ± 0.50	Y	-1.92 ± 0.37	Y	0.182
SPARC Accelerometer - Wrist	-0.65 ± 0.16	Y	-0.56 ± 0.12	Y	0.126
SPARC Gyroscope - Wrist	-3.15 ± 0.63	Y	-2.25 ± 0.47	Y	0.002**
Mean/max ratio 3D - Wrist	0.21 ± 0.03	Y	0.26 ± 0.05	Y	0.016*
Mean/max ratio IMU - Wrist	0.43 ± 0.09	Y	0.53 ± 0.08	Y	0.017*
Median/Q3 ratio 3D - Wrist	0.53 ± 0.06	Y	0.52 ± 0.06	Y	0.703
Median/Q3 ratio IMU - Wrist	0.51 ± 0.04	Y	0.49 ± 0.05	Y	0.230
Efficiency					
Trajectory length - Pelvis (mm)	235 ± 128	Y	49.3 ± 23.7	N	< 0.001***
Trajectory length - C7 (mm)	739 ± 357	Y	313 ± 101	Y	0.003**
Trajectory length - Wrist (mm)	3088 ± 725	Y	2765 ± 721	Y	0.319
Control Strategy					
Dominant frequency 3D - Pelvis (Hz)	0.95 ± 0.40	N	0.99 ± 0.35	Y	0.860
PPV 3D - Pelvis (%)	26.6 ± 28.1	N	10.2 ± 8.70	Y	0.275
Dominant frequency IMU - Pelvis (Hz)	3.59 ± 2.12	Y	3.41 ± 1.85	Y	0.838
PPV IMU - Pelvis (%)	36.8 ± 33.0	Y	21.0 ± 26.7	N	0.307
Dominant frequency 3D - C7 (Hz)	0.94 ± 0.31	Y	0.86 ± 0.24	Y	0.532
PPV 3D - C7 (%)	30.0 ± 32.2	N	20.5 ± 29.5	N	0.549
Dominant frequency IMU - C7 (Hz)	4.71 ± 2.93	Y	4.19 ± 3.88	N	0.647
PPV IMU - C7 (%)	36.4 ± 34.0	N	41.0 ± 38.5	Y	0.699
Dominant frequency 3D - Wrist (Hz)	1.03 ± 0.37	Y	1.05 ± 0.21	Y	0.854
PPV 3D - Wrist (%)	26.7 ± 32.1	N	85.2 ± 28.5	N	0.004**
Dominant frequency IMU - Wrist (Hz)	2.38 ± 0.92	Y	1.40 ± 0.52	N	0.004**
PPV IMU - Wrist (%)	46.2 ± 35.9	N	48.9 ± 37.7	N	0.972
Signal Complexity (Data-Driven)					
ApEn 3D - Pelvis	0.20 ± 0.07	Y	0.41 ± 0.18	Y	0.005**
ApEn IMU - Pelvis	0.73 ± 0.19	N	1.16 ± 0.30	Y	0.005**
ApEn 3D - C7	0.12 ± 0.04	Y	0.15 ± 0.06	N	0.460
ApEn IMU - C7	0.78 ± 0.17	Y	0.95 ± 0.19	N	0.062
ApEn 3D - Wrist	0.20 ± 0.04	Y	0.15 ± 0.03	Y	0.005**
ApEn IMU - Wrist	0.65 ± 0.08	N	0.60 ± 0.05	Y	0.062
Inter-segmental Coordination					
<i>r</i> (Wrist-C7) 3D	0.38 ± 0.18	Y	0.43 ± 0.12	Y	0.490
<i>r</i> (Wrist-C7) gyroscope	0.16 ± 0.13	Y	0.16 ± 0.12	Y	0.930
<i>r</i> (Wrist-C7) accelerometer	0.04 ± 0.06	Y	0.01 ± 0.08	Y	0.334
<i>r</i> (Wrist-Pelvis) 3D	0.34 ± 0.20	Y	0.35 ± 0.14	Y	0.841
<i>r</i> (Wrist-Pelvis) gyroscope	0.13 ± 0.13	Y	0.12 ± 0.11	Y	0.830
<i>r</i> (Wrist-Pelvis) accelerometer	0.02 ± 0.07	Y	-0.03 ± 0.07	Y	0.162
<i>r</i> (C7-Pelvis) 3D	0.74 ± 0.09	Y	0.45 ± 0.23	Y	0.003**
<i>r</i> (C7-Pelvis) gyroscope	0.46 ± 0.16	Y	-0.08 ± 0.19	Y	< 0.001***

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Parameter	G1 - Children ($n = 11$)		G2 - Adults ($n = 10$)		p -value
	Mean $\pm$ SD	Norm.	Mean $\pm$ SD	Norm.	
r (C7-Pelvis) accelerometer	0.30 $\pm$ 0.13	Y	0.23 $\pm$ 0.20	Y	0.374

Table A.4: Comparison between G1 (children, $n = 11$) and G2 (adults, $n = 10$) for all parameters computed in reach and drop task. Values are mean $\pm$ SD. *Norm.*: normality assessment per group via Shapiro-Wilk ($\alpha = 0.05$): Y = normal, N = non-normal. Statistical test: Welch's t -test (both normal) or Mann-Whitney U (at least one non-normal). * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$. Rows highlighted in green indicate a significant difference ($p < 0.05$); N/A indicates the test could not be computed (constant/zero values in both groups).

Parameter	G1 - Children (<i>n</i> = 11)		G2 - Adults (<i>n</i> = 10)		<i>p</i> -value
	Mean ± SD	Norm.	Mean ± SD	Norm.	
Speed and Acceleration					
Movement time (s)	2.51 ± 1.03	Y	2.10 ± 0.53	Y	0.261
Velocity Q3 - Pelvis (mm/s)	32.9 ± 19.8	Y	8.9 ± 6.6	N	0.004**
Max velocity - Pelvis (mm/s)	72.9 ± 46.8	Y	20.9 ± 14.2	N	0.004**
Median velocity - Pelvis (mm/s)	13.4 ± 8.0	Y	4.4 ± 1.9	Y	0.004**
Mean velocity - Pelvis (mm/s)	20.8 ± 11.6	Y	6.2 ± 3.8	N	0.004**
Acceleration Q3 - Pelvis (m/s ²)	9.93 ± 0.16	Y	10.00 ± 0.08	Y	0.208
Acceleration median - Pelvis (m/s ²)	9.86 ± 0.13	Y	9.97 ± 0.08	Y	0.023*
Velocity Q3 - C7 (mm/s)	89.4 ± 45.0	Y	62.6 ± 37.0	Y	0.151
Max velocity - C7 (mm/s)	172.0 ± 83.9	Y	96.4 ± 50.4	Y	0.021*
Median velocity - C7 (mm/s)	46.6 ± 29.0	Y	33.7 ± 18.1	Y	0.235
Mean velocity - C7 (mm/s)	59.8 ± 29.0	Y	40.7 ± 22.1	Y	0.104
Acceleration Q3 - C7 (m/s ²)	9.75 ± 0.14	Y	9.59 ± 0.14	N	0.005**
Acceleration median - C7 (m/s ²)	9.65 ± 0.12	N	9.53 ± 0.14	N	0.015*
Velocity Q3 - Wrist (mm/s)	751.0 ± 262.0	Y	739.0 ± 92.4	Y	0.889
Max velocity - Wrist (mm/s)	1227.0 ± 311.0	Y	1157.0 ± 102.0	Y	0.489
Median velocity - Wrist (mm/s)	385.0 ± 163.0	Y	437.0 ± 94.6	Y	0.378
Mean velocity - Wrist (mm/s)	484.0 ± 166.0	Y	496.0 ± 64.0	Y	0.828
Acceleration Q3 - Wrist (m/s ²)	10.90 ± 0.86	Y	10.40 ± 0.37	N	0.032*
Acceleration median - Wrist (m/s ²)	9.62 ± 0.32	Y	9.50 ± 0.30	N	0.379
Movement Smoothness					
LDLJ-A IMU - Pelvis	−2.51 ± 1.71	Y	−0.69 ± 1.27	Y	0.012*
Zero crossings ACC - Pelvis	54.6 ± 41.4	N	71.9 ± 30.8	Y	0.072
MAPR 3D - Pelvis	0.158 ± 0.108	N	0.078 ± 0.103	N	0.085
MAPR IMU - Pelvis	0.000 ± 0.000	Y	0.000 ± 0.000	Y	N/A
SPARC 3D - Pelvis	−1.02 ± 0.22	Y	−0.92 ± 0.20	Y	0.311
SPARC Accelerometer - Pelvis	−0.40 ± 0.15	Y	−0.44 ± 0.09	Y	0.499
SPARC Gyroscope - Pelvis	−0.73 ± 0.22	Y	−0.51 ± 0.09	Y	0.012*
Mean/max ratio 3D - Pelvis	0.29 ± 0.06	Y	0.31 ± 0.09	Y	0.525
Mean/max ratio IMU - Pelvis	0.94 ± 0.03	Y	0.98 ± 0.01	Y	0.002**
Median/Q3 ratio 3D - Pelvis	0.45 ± 0.15	Y	0.59 ± 0.20	Y	0.094
Median/Q3 ratio IMU - Pelvis	0.51 ± 0.09	Y	0.53 ± 0.08	N	0.245
LDLJ-A IMU - C7	−3.28 ± 1.92	Y	−1.80 ± 1.10	Y	0.044*
Zero crossings ACC - C7	58.4 ± 37.4	N	60.1 ± 23.3	Y	0.460
MAPR 3D - C7	0.138 ± 0.101	Y	0.103 ± 0.097	Y	0.427
MAPR IMU - C7	0.000 ± 0.000	Y	0.000 ± 0.000	Y	N/A

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Parameter	G1 - Children (<i>n</i> = 11)		G2 - Adults (<i>n</i> = 10)		<i>p</i> -value
	Mean ± SD	Norm.	Mean ± SD	Norm.	
SPARC 3D - C7	-0.88 ± 0.26	N	-0.75 ± 0.14	Y	0.149
SPARC Accelerometer - C7	-0.40 ± 0.15	Y	-0.44 ± 0.09	Y	0.498
SPARC Gyroscope - C7	-0.83 ± 0.18	Y	-0.70 ± 0.13	Y	0.050
Mean/max ratio 3D - C7	0.35 ± 0.08	Y	0.42 ± 0.09	Y	0.050*
Mean/max ratio IMU - C7	0.93 ± 0.03	Y	0.97 ± 0.01	Y	< 0.001***
Median/Q3 ratio 3D - C7	0.51 ± 0.18	Y	0.58 ± 0.13	Y	0.315
Median/Q3 ratio IMU - C7	0.52 ± 0.08	N	0.54 ± 0.06	Y	0.860
LDLJ-A IMU - Wrist	-6.03 ± 1.40	Y	-5.15 ± 1.13	Y	0.128
Zero crossings ACC - Wrist	25.6 ± 14.2	Y	19.7 ± 10.6	Y	0.289
MAPR 3D - Wrist	0.164 ± 0.119	Y	0.121 ± 0.090	Y	0.356
MAPR IMU - Wrist	0.000 ± 0.000	Y	0.000 ± 0.000	Y	N/A
SPARC 3D - Wrist	-0.87 ± 0.23	N	-0.77 ± 0.06	Y	0.193
SPARC Accelerometer - Wrist	-0.53 ± 0.16	Y	-0.53 ± 0.09	N	0.805
SPARC Gyroscope - Wrist	-0.91 ± 0.17	Y	-0.70 ± 0.09	Y	0.003**
Mean/max ratio 3D - Wrist	0.40 ± 0.09	Y	0.43 ± 0.06	Y	0.303
Mean/max ratio IMU - Wrist	0.56 ± 0.18	Y	0.67 ± 0.05	Y	0.077
Median/Q3 ratio 3D - Wrist	0.51 ± 0.15	Y	0.59 ± 0.12	Y	0.146
Median/Q3 ratio IMU - Wrist	0.50 ± 0.10	Y	0.51 ± 0.12	Y	0.806
Efficiency					
Trajectory length - Pelvis (mm)	50.1 ± 36.8	Y	12.5 ± 7.24	N	0.004**
Trajectory length - C7 (mm)	147 ± 97.1	N	78.6 ± 37.3	Y	0.130
Trajectory length - Wrist (mm)	1081 ± 224	Y	1018 ± 175	Y	0.478
Control Strategy					
Dominant frequency 3D - Pelvis (Hz)	0.89 ± 0.35	Y	1.25 ± 1.07	N	1.000
PPV 3D - Pelvis (%)	61.5 ± 25.5	Y	60.9 ± 21.6	Y	0.955
Dominant frequency IMU - Pelvis (Hz)	2.05 ± 1.75	N	3.75 ± 2.55	Y	0.170
PPV IMU - Pelvis (%)	57.1 ± 25.7	Y	60.4 ± 21.0	Y	0.750
Dominant frequency 3D - C7 (Hz)	0.94 ± 0.51	N	0.93 ± 0.43	N	0.944
PPV 3D - C7 (%)	64.8 ± 26.0	Y	75.1 ± 22.8	Y	0.348
Dominant frequency IMU - C7 (Hz)	3.16 ± 1.69	Y	4.84 ± 3.30	Y	0.170
PPV IMU - C7 (%)	55.2 ± 31.1	Y	70.1 ± 20.9	Y	0.210
Dominant frequency 3D - Wrist (Hz)	0.81 ± 0.30	N	0.99 ± 0.25	Y	0.159
PPV 3D - Wrist (%)	46.8 ± 23.5	Y	50.9 ± 20.7	Y	0.677
Dominant frequency IMU - Wrist (Hz)	1.34 ± 0.55	Y	1.39 ± 0.34	N	0.398
PPV IMU - Wrist (%)	48.9 ± 33.0	Y	48.4 ± 28.6	Y	0.968
Signal Complexity (Data-Driven)					
ApEn 3D - Pelvis	0.20 ± 0.11	N	0.33 ± 0.17	Y	0.098
ApEn IMU - Pelvis	0.68 ± 0.23	N	0.99 ± 0.15	Y	0.002**
ApEn 3D - C7	0.13 ± 0.06	N	0.19 ± 0.12	Y	0.245
ApEn IMU - C7	0.73 ± 0.11	Y	0.88 ± 0.13	Y	0.008**
ApEn 3D - Wrist	0.11 ± 0.03	Y	0.11 ± 0.02	Y	0.852
ApEn IMU - Wrist	0.43 ± 0.09	Y	0.42 ± 0.07	Y	0.829
Inter-segmental Coordination					
<i>r</i> (Wrist-C7) 3D	0.40 ± 0.23	Y	0.17 ± 0.22	Y	0.032*
<i>r</i> (Wrist-C7) gyroscope	0.21 ± 0.19	Y	0.34 ± 0.22	Y	0.164

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Parameter	G1 - Children ($n = 11$)		G2 - Adults ($n = 10$)		p -value
	Mean $\pm$ SD	Norm.	Mean $\pm$ SD	Norm.	
r (Wrist-C7) accelerometer	-0.13 ± 0.17	Y	-0.16 ± 0.16	Y	0.773
r (Wrist-Pelvis) 3D	0.38 ± 0.24	Y	0.24 ± 0.12	Y	0.098
r (Wrist-Pelvis) gyroscope	0.06 ± 0.29	Y	-0.03 ± 0.28	Y	0.503
r (Wrist-Pelvis) accelerometer	-0.12 ± 0.17	Y	-0.10 ± 0.17	Y	0.766
r (C7-Pelvis) 3D	0.69 ± 0.32	N	0.46 ± 0.36	Y	0.098
r (C7-Pelvis) gyroscope	0.62 ± 0.31	N	-0.15 ± 0.54	Y	0.004**
r (C7-Pelvis) accelerometer	0.53 ± 0.18	Y	0.17 ± 0.23	Y	0.001**

Table A.5: Comparison between G1 (children, $n = 11$) and G2 (adults, $n = 10$) for all parameters computed in pegboard task. Values are mean $\pm$ SD. *Norm.*: normality assessment per group via Shapiro-Wilk ($\alpha = 0.05$): Y = normal, N = non-normal. Statistical test: Welch's t -test (both normal) or Mann-Whitney U (at least one non-normal). * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$. Rows highlighted in green indicate a significant difference ($p < 0.05$); N/A indicates the test could not be computed (constant/zero values in both groups).

Parameter	G1 - Children (<i>n</i> = 11)		G2 - Adults (<i>n</i> = 10)		<i>p</i> -value
	Mean ± SD	Norm.	Mean ± SD	Norm.	
Speed and Acceleration					
Movement time (s)	44.10 ± 7.77	N	33.20 ± 4.25	Y	0.002**
Velocity Q3 - Pelvis (mm/s)	12.3 ± 9.9	N	7.9 ± 3.4	Y	0.549
Max velocity - Pelvis (mm/s)	86.7 ± 97.4	N	38.2 ± 30.2	Y	0.149
Median velocity - Pelvis (mm/s)	7.2 ± 5.6	N	5.2 ± 2.1	Y	0.972
Mean velocity - Pelvis (mm/s)	9.9 ± 8.1	N	6.2 ± 2.7	Y	0.549
Acceleration Q3 - Pelvis (m/s ²)	9.82 ± 0.17	N	10.00 ± 0.08	Y	0.001**
Acceleration median - Pelvis (m/s ²)	9.76 ± 0.18	N	9.98 ± 0.08	Y	< 0.001***
Velocity Q3 - C7 (mm/s)	29.5 ± 13.0	Y	29.0 ± 8.7	Y	0.914
Max velocity - C7 (mm/s)	124.0 ± 63.3	Y	91.2 ± 39.6	Y	0.174
Median velocity - C7 (mm/s)	18.8 ± 8.4	Y	19.8 ± 6.3	Y	0.755
Mean velocity - C7 (mm/s)	22.9 ± 10.5	Y	22.2 ± 6.9	Y	0.847
Acceleration Q3 - C7 (m/s ²)	9.72 ± 0.12	Y	9.55 ± 0.16	N	0.004**
Acceleration median - C7 (m/s ²)	9.66 ± 0.13	N	9.50 ± 0.16	N	0.002**
Velocity Q3 - Wrist (mm/s)	375.0 ± 93.5	Y	443.0 ± 57.3	Y	0.057
Max velocity - Wrist (mm/s)	1205.0 ± 504.0	N	1075.0 ± 172.0	Y	0.916
Median velocity - Wrist (mm/s)	199.0 ± 52.3	Y	257.0 ± 43.4	Y	0.012*
Mean velocity - Wrist (mm/s)	262.0 ± 65.6	Y	305.0 ± 39.9	Y	0.086
Acceleration Q3 - Wrist (m/s ²)	11.10 ± 0.80	Y	11.30 ± 0.56	Y	0.519
Acceleration median - Wrist (m/s ²)	9.92 ± 0.34	Y	9.79 ± 0.24	Y	0.347
Movement Smoothness					
LDLJ-A IMU - Pelvis	−13.30 ± 0.65	Y	−11.70 ± 0.71	Y	< 0.001***
Zero crossings ACC - Pelvis	1034 ± 558	Y	855 ± 328	N	0.597
MAPR 3D - Pelvis	0.049 ± 0.026	Y	0.028 ± 0.011	Y	0.025*
MAPR IMU - Pelvis	0.000 ± 0.000	Y	0.000 ± 0.000	Y	N/A
SPARC 3D - Pelvis	−4.91 ± 0.66	Y	−3.42 ± 0.60	Y	< 0.001***
SPARC Accelerometer - Pelvis	−0.08 ± 0.05	N	−0.05 ± 0.01	Y	0.072
SPARC Gyroscope - Pelvis	−2.35 ± 1.52	Y	−1.02 ± 0.44	Y	0.017*
Mean/max ratio 3D - Pelvis	0.14 ± 0.04	Y	0.21 ± 0.07	Y	0.019*
Mean/max ratio IMU - Pelvis	0.92 ± 0.08	N	0.97 ± 0.01	Y	0.038*

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Parameter	G1 - Children (<i>n</i> = 11)		G2 - Adults (<i>n</i> = 10)		<i>p</i> -value
	Mean $\pm$ SD	Norm.	Mean $\pm$ SD	Norm.	
Median/Q3 ratio 3D - Pelvis	0.60 $\pm$ 0.05	Y	0.66 $\pm$ 0.03	Y	0.008**
Median/Q3 ratio IMU - Pelvis	0.55 $\pm$ 0.02	Y	0.56 $\pm$ 0.02	Y	0.687
LDLJ-A IMU - C7	-13.90 $\pm$ 0.62	Y	-12.80 $\pm$ 0.52	Y	< 0.001***
Zero crossings ACC - C7	1105 $\pm$ 398	Y	841 $\pm$ 212	Y	0.074
MAPR 3D - C7	0.041 $\pm$ 0.010	Y	0.030 $\pm$ 0.008	Y	0.008**
MAPR IMU - C7	0.000 $\pm$ 0.000	Y	0.000 $\pm$ 0.000	Y	N/A
SPARC 3D - C7	-3.92 $\pm$ 0.44	Y	-2.95 $\pm$ 0.24	Y	< 0.001***
SPARC Accelerometer - C7	-0.07 $\pm$ 0.03	Y	-0.06 $\pm$ 0.02	Y	0.282
SPARC Gyroscope - C7	-3.13 $\pm$ 0.97	Y	-2.19 $\pm$ 0.37	Y	0.010*
Mean/max ratio 3D - C7	0.20 $\pm$ 0.04	Y	0.26 $\pm$ 0.06	Y	0.010*
Mean/max ratio IMU - C7	0.94 $\pm$ 0.03	Y	0.95 $\pm$ 0.02	Y	0.283
Median/Q3 ratio 3D - C7	0.64 $\pm$ 0.02	Y	0.68 $\pm$ 0.02	Y	< 0.001***
Median/Q3 ratio IMU - C7	0.56 $\pm$ 0.01	Y	0.56 $\pm$ 0.01	Y	0.576
LDLJ-A IMU - Wrist	-17.60 $\pm$ 0.61	Y	-17.00 $\pm$ 0.48	Y	0.020*
Zero crossings ACC - Wrist	496 $\pm$ 68.5	Y	400 $\pm$ 45.8	Y	0.001**
MAPR 3D - Wrist	0.098 $\pm$ 0.026	Y	0.087 $\pm$ 0.018	Y	0.284
MAPR IMU - Wrist	0.000 $\pm$ 0.001	N	0.000 $\pm$ 0.000	N	0.132
SPARC 3D - Wrist	-4.08 $\pm$ 0.39	Y	-3.28 $\pm$ 0.26	Y	< 0.001***
SPARC Accelerometer - Wrist	-1.24 $\pm$ 0.37	Y	-1.17 $\pm$ 0.24	Y	0.612
SPARC Gyroscope - Wrist	-3.88 $\pm$ 0.34	Y	-3.02 $\pm$ 0.35	Y	< 0.001***
Mean/max ratio 3D - Wrist	0.23 $\pm$ 0.04	Y	0.29 $\pm$ 0.03	Y	0.002**
Mean/max ratio IMU - Wrist	0.46 $\pm$ 0.11	Y	0.48 $\pm$ 0.07	Y	0.598
Median/Q3 ratio 3D - Wrist	0.53 $\pm$ 0.05	Y	0.58 $\pm$ 0.05	N	0.038*
Median/Q3 ratio IMU - Wrist	0.54 $\pm$ 0.03	Y	0.57 $\pm$ 0.01	Y	0.010**
Efficiency					
Trajectory length - Pelvis (m)	0.40 $\pm$ 0.29	Y	0.20 $\pm$ 0.08	Y	0.048*
Trajectory length - C7 (m)	0.97 $\pm$ 0.37	Y	0.73 $\pm$ 0.21	Y	0.082
Trajectory length - Wrist (m)	11.19 $\pm$ 1.70	Y	10.05 $\pm$ 1.41	Y	0.109
Control Strategy					
Dominant frequency 3D - Pelvis (Hz)	1.00 $\pm$ 0.39	Y	0.84 $\pm$ 0.34	Y	0.324
PPV 3D - Pelvis (%)	43.9 $\pm$ 38.5	Y	59.3 $\pm$ 36.3	Y	0.357
Dominant frequency IMU - Pelvis (Hz)	3.60 $\pm$ 1.06	Y	3.42 $\pm$ 0.54	Y	0.637
PPV IMU - Pelvis (%)	60.4 $\pm$ 30.9	Y	54.6 $\pm$ 38.6	Y	0.710
Dominant frequency 3D - C7 (Hz)	0.96 $\pm$ 0.37	Y	1.04 $\pm$ 0.31	Y	0.566
PPV 3D - C7 (%)	42.7 $\pm$ 30.0	Y	59.6 $\pm$ 36.2	Y	0.261
Dominant frequency IMU - C7 (Hz)	4.48 $\pm$ 1.89	Y	3.74 $\pm$ 1.74	N	0.379
PPV IMU - C7 (%)	39.8 $\pm$ 29.4	Y	47.5 $\pm$ 36.7	Y	0.605
Dominant frequency 3D - Wrist (Hz)	1.45 $\pm$ 0.30	Y	1.92 $\pm$ 0.30	Y	0.002**
PPV 3D - Wrist (%)	40.1 $\pm$ 38.0	Y	70.9 $\pm$ 33.5	N	0.085
Dominant frequency IMU - Wrist (Hz)	1.88 $\pm$ 0.43	Y	2.58 $\pm$ 0.47	Y	0.002**
PPV IMU - Wrist (%)	50.7 $\pm$ 34.2	Y	67.3 $\pm$ 27.0	Y	0.230
Signal Complexity (Data-Driven)					
ApEn 3D - Pelvis	0.38 $\pm$ 0.13	Y	0.49 $\pm$ 0.11	Y	0.056
ApEn IMU - Pelvis	0.98 $\pm$ 0.37	Y	1.14 $\pm$ 0.31	Y	0.292
ApEn 3D - C7	0.27 $\pm$ 0.07	Y	0.38 $\pm$ 0.08	Y	0.003**

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Parameter	G1 - Children ($n = 11$)		G2 - Adults ($n = 10$)		p -value
	Mean $\pm$ SD	Norm.	Mean $\pm$ SD	Norm.	
ApEn IMU - C7	1.03 $\pm$ 0.22	Y	1.05 $\pm$ 0.15	Y	0.801
ApEn 3D - Wrist	0.21 $\pm$ 0.03	Y	0.29 $\pm$ 0.04	Y	< 0.001***
ApEn IMU - Wrist	0.61 $\pm$ 0.06	Y	0.67 $\pm$ 0.04	Y	0.013*
Inter-segmental Coordination					
r (Wrist-C7) 3D	0.30 $\pm$ 0.16	Y	0.12 $\pm$ 0.19	Y	0.031*
r (Wrist-C7) gyroscope	0.28 $\pm$ 0.10	Y	0.05 $\pm$ 0.12	Y	< 0.001***
r (Wrist-C7) accelerometer	0.08 $\pm$ 0.10	Y	0.22 $\pm$ 0.10	Y	0.006**
r (Wrist-Pelvis) 3D	0.33 $\pm$ 0.11	Y	0.18 $\pm$ 0.09	Y	0.003**
r (Wrist-Pelvis) gyroscope	0.13 $\pm$ 0.13	Y	0.04 $\pm$ 0.06	Y	0.065
r (Wrist-Pelvis) accelerometer	0.08 $\pm$ 0.08	Y	0.06 $\pm$ 0.08	Y	0.691
r (C7-Pelvis) 3D	0.54 $\pm$ 0.12	Y	0.38 $\pm$ 0.13	N	0.018*
r (C7-Pelvis) gyroscope	0.38 $\pm$ 0.21	N	-0.31 $\pm$ 0.06	Y	< 0.001***
r (C7-Pelvis) accelerometer	0.43 $\pm$ 0.17	Y	0.26 $\pm$ 0.20	Y	0.052

Table A.6: Comparison between G1 (children, $n = 12$) and G2 (adults, $n = 10$) for all parameters computed in glass clinking task. Values are mean $\pm$ SD. *Norm.*: normality assessment per group via Shapiro-Wilk ($\alpha = 0.05$): Y = normal, N = non-normal. Statistical test: Welch's t -test (both normal) or Mann-Whitney U (at least one non-normal). * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$. Rows highlighted in green indicate a significant difference ($p < 0.05$); N/A indicates the test could not be computed (constant/zero values in both groups).

Parameter	G1 - Children (<i>n</i> = 12)		G2 - Adults (<i>n</i> = 10)		<i>p</i> -value
	Mean ± SD	Norm.	Mean ± SD	Norm.	
Speed and Acceleration					
Movement time (s)	1.36 ± 0.32	Y	1.28 ± 0.27	N	0.598
Velocity Q3 - Pelvis (mm/s)	9.9 ± 6.7	Y	3.1 ± 0.8	Y	0.004**
Max velocity - Pelvis (mm/s)	23.2 ± 16.9	Y	5.8 ± 2.9	N	< 0.001***
Median velocity - Pelvis (mm/s)	6.5 ± 5.2	N	2.2 ± 0.5	Y	0.011*
Mean velocity - Pelvis (mm/s)	7.9 ± 5.5	Y	2.4 ± 0.6	Y	0.005**
Acceleration Q3 - Pelvis (m/s ²)	9.84 ± 0.19	Y	10.00 ± 0.08	Y	0.022*
Acceleration median - Pelvis (m/s ²)	9.79 ± 0.20	Y	9.98 ± 0.08	Y	0.009**
Velocity Q3 - C7 (mm/s)	38.4 ± 28.6	Y	22.5 ± 9.3	Y	0.091
Max velocity - C7 (mm/s)	71.9 ± 43.6	Y	34.7 ± 16.2	N	0.013*
Median velocity - C7 (mm/s)	26.5 ± 17.9	Y	15.5 ± 5.4	Y	0.064
Mean velocity - C7 (mm/s)	29.7 ± 18.4	Y	16.7 ± 6.1	Y	0.038*
Acceleration Q3 - C7 (m/s ²)	9.73 ± 0.11	Y	9.61 ± 0.13	N	0.011*
Acceleration median - C7 (m/s ²)	9.68 ± 0.09	Y	9.57 ± 0.13	N	0.027*
Velocity Q3 - Wrist (mm/s)	285.0 ± 96.3	N	300.0 ± 50.9	Y	0.339
Max velocity - Wrist (mm/s)	421.0 ± 189.0	Y	391.0 ± 65.5	Y	0.618
Median velocity - Wrist (mm/s)	185.0 ± 52.2	N	223.0 ± 45.5	Y	0.038*
Mean velocity - Wrist (mm/s)	204.0 ± 59.1	Y	224.0 ± 34.8	Y	0.327
Acceleration Q3 - Wrist (m/s ²)	10.30 ± 0.40	Y	10.00 ± 0.14	N	0.081
Acceleration median - Wrist (m/s ²)	9.73 ± 0.25	Y	9.41 ± 0.10	Y	0.001**
Movement Smoothness					
LDLJ-A IMU - Pelvis	0.70 ± 1.40	Y	2.16 ± 0.67	N	0.006**
Zero crossings ACC - Pelvis	36.2 ± 15.7	Y	55.5 ± 13.7	Y	0.006**
MAPR 3D - Pelvis	0.035 ± 0.055	N	0.016 ± 0.012	Y	0.868

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Parameter	G1 - Children (<i>n</i> = 12)		G2 - Adults (<i>n</i> = 10)		<i>p</i> -value
	Mean ± SD	Norm.	Mean ± SD	Norm.	
MAPR IMU - Pelvis	0.000 ± 0.000	Y	0.000 ± 0.000	Y	N/A
SPARC 3D - Pelvis	−0.87 ± 0.13	Y	−0.82 ± 0.10	Y	0.376
SPARC Accelerometer - Pelvis	−0.62 ± 0.12	Y	−0.64 ± 0.08	Y	0.652
SPARC Gyroscope - Pelvis	−0.71 ± 0.08	Y	−0.65 ± 0.08	Y	0.073
Mean/max ratio 3D - Pelvis	0.36 ± 0.10	Y	0.44 ± 0.08	N	0.093
Mean/max ratio IMU - Pelvis	0.98 ± 0.01	Y	0.99 ± 0.00	N	0.013*
Median/Q3 ratio 3D - Pelvis	0.65 ± 0.14	Y	0.73 ± 0.06	Y	0.121
Median/Q3 ratio IMU - Pelvis	0.57 ± 0.08	Y	0.57 ± 0.05	Y	0.949
LDLJ-A IMU - C7	0.04 ± 1.52	Y	0.93 ± 1.01	Y	0.117
Zero crossings ACC - C7	38.5 ± 11.1	Y	38.7 ± 6.5	N	0.668
MAPR 3D - C7	0.037 ± 0.037	Y	0.029 ± 0.044	N	0.531
MAPR IMU - C7	0.000 ± 0.000	Y	0.000 ± 0.000	Y	N/A
SPARC 3D - C7	−0.85 ± 0.16	N	−0.82 ± 0.11	Y	0.717
SPARC Accelerometer - C7	−0.62 ± 0.12	Y	−0.64 ± 0.08	Y	0.653
SPARC Gyroscope - C7	−0.79 ± 0.10	Y	−0.70 ± 0.05	Y	0.008**
Mean/max ratio 3D - C7	0.43 ± 0.13	Y	0.50 ± 0.07	Y	0.121
Mean/max ratio IMU - C7	0.97 ± 0.02	Y	0.98 ± 0.01	Y	0.062
Median/Q3 ratio 3D - C7	0.71 ± 0.13	Y	0.71 ± 0.11	Y	0.950
Median/Q3 ratio IMU - C7	0.55 ± 0.07	Y	0.57 ± 0.06	Y	0.556
LDLJ-A IMU - Wrist	−3.94 ± 1.24	Y	−3.79 ± 0.67	Y	0.712
Zero crossings ACC - Wrist	22.5 ± 7.7	Y	18.9 ± 4.6	Y	0.194
MAPR 3D - Wrist	0.045 ± 0.075	N	0.029 ± 0.059	N	0.437
MAPR IMU - Wrist	0.000 ± 0.000	Y	0.000 ± 0.000	Y	N/A
SPARC 3D - Wrist	−0.80 ± 0.13	Y	−0.82 ± 0.10	Y	0.703
SPARC Accelerometer - Wrist	−0.64 ± 0.11	Y	−0.65 ± 0.07	Y	0.749
SPARC Gyroscope - Wrist	−0.87 ± 0.11	Y	−0.90 ± 0.13	Y	0.538
Mean/max ratio 3D - Wrist	0.52 ± 0.10	Y	0.58 ± 0.09	Y	0.155
Mean/max ratio IMU - Wrist	0.72 ± 0.12	Y	0.72 ± 0.10	Y	0.898
Median/Q3 ratio 3D - Wrist	0.67 ± 0.13	Y	0.75 ± 0.13	Y	0.184
Median/Q3 ratio IMU - Wrist	0.54 ± 0.07	Y	0.54 ± 0.08	Y	0.915
Efficiency					
Trajectory length - Pelvis (mm)	10.8 ± 9.03	N	3.13 ± 1.51	N	0.008**
Trajectory length - C7 (mm)	40.1 ± 26.8	Y	22.2 ± 13.1	N	0.038*
Trajectory length - Wrist (mm)	281 ± 112	Y	285 ± 60.0	Y	0.912
Control Strategy					
Dominant frequency 3D - Pelvis (Hz)	2.01 ± 1.75	N	1.92 ± 2.08	N	0.818
PPV 3D - Pelvis (%)	56.0 ± 33.5	Y	43.1 ± 30.6	Y	0.358
Dominant frequency IMU - Pelvis (Hz)	4.64 ± 1.99	N	3.31 ± 1.29	Y	0.121
PPV IMU - Pelvis (%)	44.4 ± 38.4	N	61.6 ± 19.6	Y	0.307
Dominant frequency 3D - C7 (Hz)	1.15 ± 0.68	N	1.20 ± 0.75	N	1.000
PPV 3D - C7 (%)	60.2 ± 35.7	Y	44.4 ± 20.5	Y	0.213
Dominant frequency IMU - C7 (Hz)	4.25 ± 3.00	Y	4.22 ± 1.82	Y	0.974
PPV IMU - C7 (%)	67.1 ± 28.2	Y	64.0 ± 32.3	Y	0.816
Dominant frequency 3D - Wrist (Hz)	0.98 ± 0.49	N	1.40 ± 0.67	Y	0.121
PPV 3D - Wrist (%)	51.8 ± 29.8	Y	30.7 ± 29.0	Y	0.109
Dominant frequency IMU - Wrist (Hz)	1.76 ± 0.98	Y	1.97 ± 1.65	N	0.921
PPV IMU - Wrist (%)	67.4 ± 32.7	Y	73.8 ± 26.5	Y	0.622
Signal Complexity (Data-Driven)					

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Parameter	G1 - Children ($n = 12$)		G2 - Adults ($n = 10$)		p -value
	Mean $\pm$ SD	Norm.	Mean $\pm$ SD	Norm.	
ApEn 3D - Pelvis	0.39 $\pm$ 0.14	N	0.55 $\pm$ 0.11	Y	0.009**
ApEn IMU - Pelvis	0.83 $\pm$ 0.20	Y	1.02 $\pm$ 0.08	Y	0.009**
ApEn 3D - C7	0.22 $\pm$ 0.12	Y	0.26 $\pm$ 0.11	Y	0.442
ApEn IMU - C7	0.83 $\pm$ 0.14	Y	0.89 $\pm$ 0.08	Y	0.223
ApEn 3D - Wrist	0.23 $\pm$ 0.05	Y	0.19 $\pm$ 0.04	Y	0.053
ApEn IMU - Wrist	0.55 $\pm$ 0.07	Y	0.48 $\pm$ 0.07	Y	0.030*
Inter-segmental Coordination					
r (Wrist-C7) 3D	0.30 $\pm$ 0.44	Y	0.02 $\pm$ 0.29	Y	0.091
r (Wrist-C7) gyroscope	0.24 $\pm$ 0.31	Y	0.10 $\pm$ 0.36	Y	0.341
r (Wrist-C7) accelerometer	-0.05 $\pm$ 0.21	Y	0.06 $\pm$ 0.33	Y	0.395
r (Wrist-Pelvis) 3D	0.28 $\pm$ 0.27	Y	0.06 $\pm$ 0.35	Y	0.121
r (Wrist-Pelvis) gyroscope	0.14 $\pm$ 0.28	Y	0.10 $\pm$ 0.25	Y	0.708
r (Wrist-Pelvis) accelerometer	0.04 $\pm$ 0.19	Y	0.03 $\pm$ 0.17	Y	0.901
r (C7-Pelvis) 3D	0.37 $\pm$ 0.41	Y	0.16 $\pm$ 0.26	Y	0.164
r (C7-Pelvis) gyroscope	0.30 $\pm$ 0.41	Y	-0.19 $\pm$ 0.27	Y	0.003**
r (C7-Pelvis) accelerometer	0.37 $\pm$ 0.23	Y	0.11 $\pm$ 0.24	Y	0.017*

Table A.7: Comparison between G1 (children, $n = 11$) and G2 (adults, $n = 10$) for all parameters computed in ball throwing task. Values are mean $\pm$ SD. *Norm.*: normality assessment per group via Shapiro-Wilk ($\alpha = 0.05$): Y = normal, N = non-normal. Statistical test: Welch's t -test (both normal) or Mann-Whitney U (at least one non-normal). * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$. Rows highlighted in green indicate a significant difference ($p < 0.05$); N/A indicates the test could not be computed (constant/zero values in both groups).

Parameter	G1 - Children (<i>n</i> = 11)		G2 - Adults (<i>n</i> = 10)		<i>p</i> -value
	Mean ± SD	Norm.	Mean ± SD	Norm.	
Speed and Acceleration					
Movement time (s)	5.72 ± 1.09	Y	5.17 ± 1.04	Y	0.251
Velocity Q3 - Pelvis (mm/s)	34.8 ± 13.6	Y	18.5 ± 7.6	N	0.002**
Max velocity - Pelvis (mm/s)	140.0 ± 52.4	Y	81.1 ± 44.4	Y	0.012*
Median velocity - Pelvis (mm/s)	16.5 ± 7.6	Y	8.4 ± 3.6	N	0.002**
Mean velocity - Pelvis (mm/s)	26.2 ± 9.2	Y	14.7 ± 5.2	Y	0.003**
Acceleration Q3 - Pelvis (m/s ²)	9.94 ± 0.18	Y	10.10 ± 0.10	Y	0.031*
Acceleration median - Pelvis (m/s ²)	9.80 ± 0.20	Y	10.00 ± 0.09	Y	0.008**
Velocity Q3 - C7 (mm/s)	80.0 ± 25.4	Y	56.7 ± 24.7	Y	0.046*
Max velocity - C7 (mm/s)	247.0 ± 99.7	Y	178.0 ± 51.8	Y	0.063
Median velocity - C7 (mm/s)	41.6 ± 11.2	Y	31.5 ± 14.1	Y	0.089
Mean velocity - C7 (mm/s)	58.6 ± 17.8	Y	41.5 ± 15.3	Y	0.029*
Acceleration Q3 - C7 (m/s ²)	9.90 ± 0.11	Y	9.73 ± 0.15	N	0.010*
Acceleration median - C7 (m/s ²)	9.71 ± 0.07	Y	9.58 ± 0.13	N	0.026*
Velocity Q3 - Wrist (mm/s)	540.0 ± 145.0	Y	603.0 ± 157.0	Y	0.351
Max velocity - Wrist (mm/s)	1370.0 ± 314.0	Y	1489.0 ± 300.0	Y	0.383
Median velocity - Wrist (mm/s)	322.0 ± 78.5	Y	362.0 ± 120.0	Y	0.384
Mean velocity - Wrist (mm/s)	393.0 ± 87.0	Y	439.0 ± 114.0	Y	0.319
Acceleration Q3 - Wrist (m/s ²)	12.30 ± 0.98	Y	12.40 ± 0.95	Y	0.852
Acceleration median - Wrist (m/s ²)	10.50 ± 0.47	Y	10.70 ± 0.64	Y	0.589
Movement Smoothness					

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Parameter	G1 - Children (<i>n</i> = 11)		G2 - Adults (<i>n</i> = 10)		<i>p</i> -value
	Mean ± SD	Norm.	Mean ± SD	Norm.	
LDLJ-A IMU - Pelvis	-7.84 ± 0.58	Y	-6.37 ± 1.71	Y	0.025*
Zero crossings ACC - Pelvis	91.2 ± 20.3	Y	91.4 ± 26.7	Y	0.984
MAPR 3D - Pelvis	0.148 ± 0.043	Y	0.159 ± 0.086	Y	0.721
MAPR IMU - Pelvis	0.000 ± 0.000	Y	0.000 ± 0.000	Y	N/A
SPARC 3D - Pelvis	-2.19 ± 0.53	Y	-2.48 ± 0.73	Y	0.323
SPARC Accelerometer - Pelvis	-0.21 ± 0.03	Y	-0.21 ± 0.03	Y	0.734
SPARC Gyroscope - Pelvis	-1.28 ± 0.35	Y	-0.79 ± 0.70	N	0.002**
Mean/max ratio 3D - Pelvis	0.20 ± 0.04	Y	0.20 ± 0.06	Y	0.878
Mean/max ratio IMU - Pelvis	0.81 ± 0.05	Y	0.89 ± 0.07	Y	0.016*
Median/Q3 ratio 3D - Pelvis	0.47 ± 0.06	Y	0.46 ± 0.08	Y	0.742
Median/Q3 ratio IMU - Pelvis	0.41 ± 0.06	N	0.40 ± 0.04	Y	0.379
LDLJ-A IMU - C7	-8.78 ± 1.13	Y	-7.85 ± 1.02	Y	0.063
Zero crossings ACC - C7	113.0 ± 25.8	Y	97.2 ± 25.2	Y	0.165
MAPR 3D - C7	0.088 ± 0.037	Y	0.074 ± 0.035	Y	0.394
MAPR IMU - C7	0.000 ± 0.000	Y	0.000 ± 0.000	Y	N/A
SPARC 3D - C7	-1.60 ± 0.29	Y	-1.80 ± 0.45	Y	0.229
SPARC Accelerometer - C7	-0.22 ± 0.04	Y	-0.23 ± 0.04	Y	0.781
SPARC Gyroscope - C7	-1.43 ± 0.39	Y	-1.16 ± 0.23	Y	0.067
Mean/max ratio 3D - C7	0.25 ± 0.05	Y	0.24 ± 0.08	Y	0.743
Mean/max ratio IMU - C7	0.76 ± 0.10	Y	0.79 ± 0.09	Y	0.467
Median/Q3 ratio 3D - C7	0.53 ± 0.08	Y	0.56 ± 0.06	Y	0.449
Median/Q3 ratio IMU - C7	0.43 ± 0.05	Y	0.47 ± 0.05	Y	0.183
LDLJ-A IMU - Wrist	-10.20 ± 0.70	Y	-9.99 ± 0.51	Y	0.476
Zero crossings ACC - Wrist	64.8 ± 18.6	Y	50.0 ± 8.6	Y	0.032*
MAPR 3D - Wrist	0.090 ± 0.057	Y	0.084 ± 0.057	Y	0.816
MAPR IMU - Wrist	0.002 ± 0.003	N	0.005 ± 0.009	N	0.311
SPARC 3D - Wrist	-1.66 ± 0.50	Y	-1.79 ± 0.45	Y	0.517
SPARC Accelerometer - Wrist	-0.87 ± 0.19	N	-0.88 ± 0.17	Y	0.916
SPARC Gyroscope - Wrist	-1.70 ± 0.34	Y	-1.57 ± 0.45	Y	0.482
Mean/max ratio 3D - Wrist	0.29 ± 0.04	Y	0.30 ± 0.06	Y	0.794
Mean/max ratio IMU - Wrist	0.21 ± 0.06	Y	0.28 ± 0.12	Y	0.097
Median/Q3 ratio 3D - Wrist	0.60 ± 0.07	Y	0.59 ± 0.06	Y	0.784
Median/Q3 ratio IMU - Wrist	0.57 ± 0.07	Y	0.50 ± 0.07	Y	0.032*
Efficiency					
Trajectory length - Pelvis (mm)	152 ± 60.8	Y	76.7 ± 31.7	Y	0.003**
Trajectory length - C7 (mm)	343 ± 139	Y	210 ± 79.7	Y	0.015*
Trajectory length - Wrist (mm)	2227 ± 588	Y	2245 ± 621	Y	0.945
Control Strategy					
Dominant frequency 3D - Pelvis (Hz)	0.68 ± 0.48	Y	0.68 ± 0.28	Y	1.000
PPV 3D - Pelvis (%)	38.8 ± 19.4	Y	50.1 ± 18.1	Y	0.184
Dominant frequency IMU - Pelvis (Hz)	3.94 ± 1.50	Y	3.94 ± 0.41	Y	0.990
PPV IMU - Pelvis (%)	41.8 ± 18.9	Y	50.3 ± 18.0	Y	0.307
Dominant frequency 3D - C7 (Hz)	0.55 ± 0.45	N	0.64 ± 0.33	Y	0.418
PPV 3D - C7 (%)	36.7 ± 25.5	N	48.8 ± 29.1	Y	0.307
Dominant frequency IMU - C7 (Hz)	4.36 ± 2.36	Y	5.04 ± 1.86	Y	0.469
PPV IMU - C7 (%)	43.5 ± 17.7	Y	63.7 ± 17.4	Y	0.017*
Dominant frequency 3D - Wrist (Hz)	0.89 ± 0.51	N	0.71 ± 0.19	Y	0.699
PPV 3D - Wrist (%)	47.6 ± 31.0	Y	54.6 ± 21.0	Y	0.548
Dominant frequency IMU - Wrist (Hz)	2.05 ± 1.37	N	3.05 ± 2.73	N	0.805
PPV IMU - Wrist (%)	54.9 ± 15.7	Y	45.3 ± 13.5	N	0.149

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Parameter	G1 - Children ($n = 11$)		G2 - Adults ($n = 10$)		p -value
	Mean $\pm$ SD	Norm.	Mean $\pm$ SD	Norm.	
Signal Complexity (Data-Driven)					
ApEn 3D - Pelvis	0.28 $\pm$ 0.08	N	0.31 $\pm$ 0.07	Y	0.275
ApEn IMU - Pelvis	0.49 $\pm$ 0.07	N	0.47 $\pm$ 0.10	Y	0.275
ApEn 3D - C7	0.27 $\pm$ 0.09	Y	0.34 $\pm$ 0.05	Y	0.033*
ApEn IMU - C7	0.51 $\pm$ 0.05	Y	0.49 $\pm$ 0.11	Y	0.623
ApEn 3D - Wrist	0.27 $\pm$ 0.05	Y	0.24 $\pm$ 0.06	Y	0.320
ApEn IMU - Wrist	0.40 $\pm$ 0.04	Y	0.37 $\pm$ 0.05	Y	0.185
Inter-segmental Coordination					
r (Wrist-C7) 3D	0.36 $\pm$ 0.20	Y	0.40 $\pm$ 0.20	Y	0.640
r (Wrist-C7) gyroscope	0.31 $\pm$ 0.13	Y	0.39 $\pm$ 0.14	Y	0.197
r (Wrist-C7) accelerometer	0.06 $\pm$ 0.16	N	0.16 $\pm$ 0.13	Y	0.113
r (Wrist-Pelvis) 3D	0.38 $\pm$ 0.13	Y	0.37 $\pm$ 0.10	Y	0.815
r (Wrist-Pelvis) gyroscope	0.22 $\pm$ 0.08	Y	0.12 $\pm$ 0.18	Y	0.125
r (Wrist-Pelvis) accelerometer	0.07 $\pm$ 0.14	Y	0.13 $\pm$ 0.12	Y	0.261
r (C7-Pelvis) 3D	0.56 $\pm$ 0.15	Y	0.28 $\pm$ 0.19	Y	0.001**
r (C7-Pelvis) gyroscope	0.35 $\pm$ 0.19	Y	0.16 $\pm$ 0.14	Y	0.019*
r (C7-Pelvis) accelerometer	0.40 $\pm$ 0.21	Y	0.34 $\pm$ 0.26	Y	0.568

Table A.8: Comparison between G1 (children, $n = 10$) and G2 (adults, $n = 10$) for all parameters computed in affordance task. Values are mean $\pm$ SD. *Norm.*: normality assessment per group via Shapiro-Wilk ($\alpha = 0.05$): Y = normal, N = non-normal. Statistical test: Welch's t -test (both normal) or Mann-Whitney U (at least one non-normal). * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$. Rows highlighted in green indicate a significant difference ($p < 0.05$); N/A indicates the test could not be computed (constant/zero values in both groups).

Parameter	G1 - Children (<i>n</i> = 10)		G2 - Adults (<i>n</i> = 10)		<i>p</i> -value
	Mean ± SD	Norm.	Mean ± SD	Norm.	
Speed and Acceleration					
Velocity Q3 - Pelvis (mm/s)	5.9 ± 4.5	Y	2.1 ± 0.9	N	0.007**
Max velocity - Pelvis (mm/s)	61.9 ± 67.4	N	30.4 ± 65.7	N	0.038*
Median velocity - Pelvis (mm/s)	3.2 ± 2.4	N	1.4 ± 0.4	Y	0.007**
Mean velocity - Pelvis (mm/s)	5.6 ± 4.9	N	2.1 ± 1.9	N	0.017*
Acceleration Q3 - Pelvis (m/s ²)	9.78 ± 0.20	Y	10.00 ± 0.07	Y	0.005**
Acceleration median - Pelvis (m/s ²)	9.75 ± 0.20	Y	9.99 ± 0.07	Y	0.005**
Velocity Q3 - C7 (mm/s)	15.9 ± 8.8	Y	9.7 ± 8.5	N	0.121
Max velocity - C7 (mm/s)	116.0 ± 85.9	N	76.4 ± 83.0	N	0.089
Median velocity - C7 (mm/s)	8.9 ± 5.0	Y	5.1 ± 3.7	N	0.064
Mean velocity - C7 (mm/s)	14.0 ± 8.1	Y	8.1 ± 7.0	N	0.104
Acceleration Q3 - C7 (m/s ²)	9.71 ± 0.09	Y	9.57 ± 0.12	N	0.014*
Acceleration median - C7 (m/s ²)	9.68 ± 0.09	Y	9.55 ± 0.12	N	0.017*
Velocity Q3 - Wrist (mm/s)	98.7 ± 45.4	Y	54.9 ± 29.2	Y	0.021*
Max velocity - Wrist (mm/s)	645.0 ± 214.0	Y	567.0 ± 376.0	N	0.241
Median velocity - Wrist (mm/s)	55.0 ± 30.2	Y	29.1 ± 16.7	Y	0.033*
Mean velocity - Wrist (mm/s)	80.2 ± 33.0	Y	47.8 ± 25.6	Y	0.025*
Acceleration Q3 - Wrist (m/s ²)	9.99 ± 0.26	Y	9.85 ± 0.26	Y	0.257
Acceleration median - Wrist (m/s ²)	9.61 ± 0.10	Y	9.54 ± 0.10	Y	0.179
Movement Smoothness					

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Parameter	G1 - Children (<i>n</i> = 10)		G2 - Adults (<i>n</i> = 10)		<i>p</i> -value
	Mean ± SD	Norm.	Mean ± SD	Norm.	
LDLJ-A IMU - Pelvis	-11.60 ± 1.11	Y	-10.70 ± 0.74	N	0.007**
Zero crossings ACC - Pelvis	1092 ± 353	Y	1513 ± 235	Y	0.006**
MAPR 3D - Pelvis	0.086 ± 0.122	N	0.043 ± 0.088	N	0.031*
MAPR IMU - Pelvis	0.000 ± 0.000	Y	0.000 ± 0.000	Y	N/A
SPARC 3D - Pelvis	-3.96 ± 1.56	Y	-2.92 ± 0.63	N	0.045*
SPARC Accelerometer - Pelvis	-0.05 ± 0.01	Y	-0.04 ± 0.01	N	0.026*
SPARC Gyroscope - Pelvis	-1.09 ± 0.68	Y	-0.25 ± 0.21	N	0.006**
Mean/max ratio 3D - Pelvis	0.14 ± 0.07	Y	0.17 ± 0.07	Y	0.261
Mean/max ratio IMU - Pelvis	0.95 ± 0.04	Y	0.96 ± 0.09	N	0.045*
Median/Q3 ratio 3D - Pelvis	0.57 ± 0.10	Y	0.68 ± 0.06	N	0.009**
Median/Q3 ratio IMU - Pelvis	0.55 ± 0.03	Y	0.56 ± 0.03	N	0.089
LDLJ-A IMU - C7	-12.00 ± 0.57	Y	-11.50 ± 0.84	N	0.045*
Zero crossings ACC - C7	973 ± 236	Y	1226 ± 217	Y	0.022*
MAPR 3D - C7	0.087 ± 0.083	N	0.077 ± 0.046	N	0.650
MAPR IMU - C7	0.000 ± 0.000	Y	0.000 ± 0.000	Y	N/A
SPARC 3D - C7	-3.48 ± 1.06	Y	-3.70 ± 0.54	Y	0.573
SPARC Accelerometer - C7	-0.05 ± 0.01	Y	-0.04 ± 0.02	N	0.121
SPARC Gyroscope - C7	-2.04 ± 1.47	Y	-1.20 ± 1.04	N	0.089
Mean/max ratio 3D - C7	0.13 ± 0.05	Y	0.13 ± 0.06	Y	0.840
Mean/max ratio IMU - C7	0.95 ± 0.02	Y	0.93 ± 0.13	N	0.212
Median/Q3 ratio 3D - C7	0.58 ± 0.10	Y	0.56 ± 0.06	Y	0.532
Median/Q3 ratio IMU - C7	0.55 ± 0.03	Y	0.55 ± 0.02	Y	0.811
LDLJ-A IMU - Wrist	-15.70 ± 0.62	Y	-15.20 ± 0.81	Y	0.155
Zero crossings ACC - Wrist	575 ± 70.6	Y	580 ± 105.0	Y	0.908
MAPR 3D - Wrist	0.138 ± 0.091	Y	0.169 ± 0.077	Y	0.415
MAPR IMU - Wrist	0.000 ± 0.000	Y	0.000 ± 0.000	Y	N/A
SPARC 3D - Wrist	-4.28 ± 0.88	Y	-4.81 ± 0.86	Y	0.189
SPARC Accelerometer - Wrist	-0.44 ± 0.18	Y	-0.35 ± 0.29	N	0.141
SPARC Gyroscope - Wrist	-5.04 ± 0.79	Y	-4.84 ± 0.62	Y	0.535
Mean/max ratio 3D - Wrist	0.13 ± 0.05	Y	0.10 ± 0.05	Y	0.113
Mean/max ratio IMU - Wrist	0.59 ± 0.15	Y	0.66 ± 0.18	Y	0.353
Median/Q3 ratio 3D - Wrist	0.53 ± 0.08	Y	0.52 ± 0.07	Y	0.660
Median/Q3 ratio IMU - Wrist	0.49 ± 0.03	N	0.53 ± 0.03	Y	0.026*
Efficiency					
Trajectory length - Pelvis (mm)	169 ± 147	N	63.9 ± 58.3	N	0.017*
Trajectory length - C7 (mm)	420 ± 244	Y	243 ± 210	N	0.104
Trajectory length - Wrist (mm)	2407 ± 991	Y	1434 ± 768	Y	0.025*
Control Strategy					
Dominant frequency 3D - Pelvis (Hz)	0.19 ± 0.14	N	0.24 ± 0.21	N	0.584
PPV 3D - Pelvis (%)	24.1 ± 26.7	N	24.7 ± 26.4	N	0.571
Dominant frequency IMU - Pelvis (Hz)	4.80 ± 2.79	Y	3.65 ± 2.36	Y	0.333
PPV IMU - Pelvis (%)	28.0 ± 33.6	N	32.0 ± 29.2	Y	0.427
Dominant frequency 3D - C7 (Hz)	0.26 ± 0.22	N	0.21 ± 0.17	N	0.539
PPV 3D - C7 (%)	25.6 ± 35.8	N	22.6 ± 30.2	N	0.571
Dominant frequency IMU - C7 (Hz)	3.04 ± 3.63	N	3.85 ± 2.94	Y	0.212
PPV IMU - C7 (%)	40.5 ± 33.0	Y	26.4 ± 23.5	Y	0.285
Dominant frequency 3D - Wrist (Hz)	0.42 ± 0.40	N	0.30 ± 0.30	N	0.401
PPV 3D - Wrist (%)	12.7 ± 28.0	N	23.5 ± 19.0	Y	0.021*
Dominant frequency IMU - Wrist (Hz)	3.87 ± 2.60	Y	4.13 ± 4.05	N	0.850
PPV IMU - Wrist (%)	35.3 ± 31.5	Y	41.5 ± 33.1	Y	0.671

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Parameter	G1 - Children (<i>n</i> = 10)		G2 - Adults (<i>n</i> = 10)		<i>p</i> -value
	Mean ± SD	Norm.	Mean ± SD	Norm.	
Signal Complexity (Data-Driven)					
ApEn 3D - Pelvis	0.40 ± 0.26	Y	0.60 ± 0.21	N	0.089
ApEn IMU - Pelvis	1.16 ± 0.41	Y	1.58 ± 0.52	N	0.038*
ApEn 3D - C7	0.20 ± 0.12	Y	0.20 ± 0.09	Y	0.932
ApEn IMU - C7	1.16 ± 0.26	Y	1.32 ± 0.38	N	0.162
ApEn 3D - Wrist	0.19 ± 0.08	Y	0.18 ± 0.09	Y	0.754
ApEn IMU - Wrist	0.67 ± 0.10	Y	0.67 ± 0.10	Y	0.976
Inter-segmental Coordination					
<i>r</i> (Wrist-C7) 3D	0.39 ± 0.22	Y	0.41 ± 0.15	Y	0.855
<i>r</i> (Wrist-C7) gyroscope	0.11 ± 0.11	N	0.14 ± 0.13	Y	0.473
<i>r</i> (Wrist-C7) accelerometer	0.03 ± 0.06	Y	0.07 ± 0.08	Y	0.207
<i>r</i> (Wrist-Pelvis) 3D	0.27 ± 0.19	Y	0.25 ± 0.11	Y	0.806
<i>r</i> (Wrist-Pelvis) gyroscope	0.06 ± 0.10	Y	0.05 ± 0.07	Y	0.746
<i>r</i> (Wrist-Pelvis) accelerometer	0.02 ± 0.06	Y	0.02 ± 0.05	Y	0.953
<i>r</i> (C7-Pelvis) 3D	0.51 ± 0.15	Y	0.38 ± 0.16	Y	0.062
<i>r</i> (C7-Pelvis) gyroscope	0.28 ± 0.23	Y	−0.02 ± 0.20	N	0.003**
<i>r</i> (C7-Pelvis) accelerometer	0.21 ± 0.14	Y	0.14 ± 0.18	N	0.141

Appendix B: Use of Artificial Intelligence

This study was prepared with the occasional assistance of artificial intelligence tools, including ChatGPT and Claude. Their use was strictly limited to language and technical support, such as improving the clarity and style of the text, refining scientific terminology, and assisting with programming. In particular, Claude was used as a support tool for code development, debugging, and implementing graphical outputs.

All AI-generated suggestions were critically reviewed and revised before being incorporated into the study. AI tools were not used to generate scientific content, conduct analyses, interpret results, or draw conclusions. All methodological decisions, data analyses, interpretations, and scientific conclusions presented in this study are entirely my own, based on the relevant scientific literature and developed under the guidance of my supervisors.

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