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MEASURING EVERYDAY LIFE MOTOR ACTIVITIES
IN CHILDREN AND ADOLESCENTS WITH NEUROMOTOR IMPAIRMENTS

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Abstract

In pediatric neurorehabilitation, children and adolescents with congenital and acquired illnesses and injuries of the developing brain are treated and cared for. These patients often present neuromotor impairments that result in difficulties in executing everyday life motor activities, such as walking or grasping an object. They undergo intensive therapy programs with an emphasis on reducing these limitations and fostering their functional independence in everyday life. To assess the patients' progress during rehabilitation, usually, motor **capacity** (i.e., *what a child **can** do in a **standardized** environment*) is measured at the clinic. However, after discharge, motor **performance** (i.e., *what a child **does** do in its **habitual** environment*) becomes more important and it remains unclear whether children and adolescents can translate their improvements during rehabilitation into everyday life at home or school.

Wearable inertial sensors provide a promising solution to overcome this limitation. Technological progress has made these sensors small-sized, lightweight, energy-efficient, and thus applicable for unobtrusive long-term measurements of motor activities in the patients' habitual environment. However, to derive meaningful outcome measures of everyday life motor activities, the unlabeled raw data generated by these sensors needs to be analyzed by appropriate data processing algorithms. Over the last decade, many algorithms have been developed that were predominantly designed for adult patient populations and rarely for pediatric populations. Hence, existing algorithms needed to be adapted to the needs of pediatric rehabilitation and validated in children and adolescents with neuromotor impairments.

Therefore, the primary aim of this thesis was to develop and validate a data processing algorithm that derives clinically meaningful motor performance measures about the daily motor activities of children and adolescents with neuromotor impairments based on data from a wearable inertial sensor system. The secondary aim was to apply this new technology to pediatric patients to measure their motor performance after rehabilitation and investigate if children and adolescents can translate their motor capacity achieved during rehabilitation into daily life.

The thesis began with a systematic review to get an overview of the technological possibilities of wearable inertial sensors to quantify everyday life motor activities in people with mobility impairments. This part was followed by summarizing the mobility and self-care goals of children and adolescents undergoing rehabilitation and conducting an international survey with pediatric health professionals to identify the needs of pediatric rehabilitation. The findings of these studies led to the development of an algorithm that determines functional hand use with wrist sensors; the duration of lying, sitting, and standing positions with a trunk and a thigh sensor; the distance and speed of self-propelled wheeling periods with a wrist and a wheel sensor; and the duration, distance, and speed of walking periods with an ankle sensor.

As a next step, the algorithm was validated in the target population by three studies. The first study analyzed the accuracy of posture and mobility-related measures. It showed that the algorithm's measurement error in estimating the duration of lying, sitting, standing, self-propelled wheeling, and walking was less than 10%. The second study investigated the validity of the functional hand use measures. The correlation coefficient between the sensor-based and video-based measures was 0.7. The third study determined the accuracy of sensor-based gait speed estimations. It revealed that the algorithm's measurement error is small enough to detect clinically important changes of 0.1 m/s. These validity studies showed that the newly developed algorithm derives valid estimates of the children's and adolescents' motor performance.

In the final study of this thesis, children and adolescents with neuromotor impairments wore the sensors in their habitual environment after rehabilitation. This study revealed that children and adolescents with neuromotor impairments are less active on weekends than on school days and that their daily performed motor activities varied substantially between days. Consequently, we recommend measuring everyday life motor activities on seven consecutive days in future applications of the sensor system. This measurement protocol covers school days and weekend days, and the number of measurement days is sufficient to obtain reliable estimates of the children's and adolescents' motor performance. The study also showed that children and adolescents were willing to wear the sensors for a week in daily life.

Additionally, the same study investigated if children and adolescents with neuromotor impairments can translate their motor capacity achieved during rehabilitation into daily life by comparing their motor performance in daily life with their motor capacity assessed at the clinic. The capacity of children and adolescents explained only 13% to 58% of their motor performance in daily life. These weak correlations showed that motor assessments conducted at the clinic only partially reflect the patient's performance at home and school. This confirms that capacity and performance are two different constructs and underpins the need to complement clinical assessments with performance measures conducted in the patients' habitual environment. Moreover, it confirms that wearable sensors and the algorithm developed in this thesis capture essential information about the patients' functioning in daily life, which adds value to clinical practice and rehabilitation research.

Zusammenfassung

In der pädiatrischen Neurorehabilitation werden Kinder und Jugendliche mit angeborenen und erworbenen Erkrankungen und Verletzungen des sich entwickelnden Gehirns behandelt und betreut. Diese Patienten weisen häufig neuromotorische Beeinträchtigungen auf, die zu Schwierigkeiten bei der Ausführung motorischer Alltagsaktivitäten führen, wie z. B. beim Gehen oder Greifen eines Gegenstandes. Sie durchlaufen intensive Therapieprogramme, die darauf abzielen, diese Einschränkungen zu verringern und ihre Selbständigkeit im Alltag zu fördern. Um die Fortschritte der Patienten während der Rehabilitation zu erfassen, wird in der Regel die motorische **Leistungsfähigkeit** (d. h. *was ein Kind in einer **standardisierten** Umgebung tun **kann***) in der Klinik gemessen. Nach dem Austritt gewinnt jedoch die motorische **Leistung** (d. h. *was ein Kind in seiner **gewohnten** Umgebung **tut***) an Bedeutung, und es bleibt unklar, ob Kinder und Jugendliche ihre Fortschritte während der Rehabilitation in den Alltag zu Hause oder in der Schule übertragen können.

Tragbare Inertialsensoren bieten eine vielversprechende Lösung zur Bewältigung dieser Problematik. Der technologische Fortschritt hat diese Sensoren klein, leicht und energieeffizient gemacht, so dass sie für unaufdringliche Langzeitmessungen von motorischen Aktivitäten in der gewohnten Umgebung der Patienten geeignet sind. Um relevante Messwerte der motorischen Alltagsaktivitäten zu generieren, müssen die Rohdaten von diesen Sensoren jedoch mit geeignete Algorithmen analysiert werden. Im letzten Jahrzehnt wurden viele Algorithmen entwickelt, die überwiegend für erwachsene Patienten und nur selten für Kinder konzipiert wurden. Daher mussten die bestehenden Algorithmen an die Bedürfnisse der pädiatrischen Rehabilitation angepasst und bei Kindern und Jugendlichen mit neuromotorischen Beeinträchtigungen validiert werden.

Das primäre Ziel dieser Doktorarbeit war es daher, einen Algorithmus zu entwickeln und zu validieren, der, basierend auf Daten von tragbaren Inertialsensoren, klinisch relevante Messwerte der motorischen Alltagsaktivitäten von Kindern und Jugendlichen mit neuromotorischen Beeinträchtigungen generiert. Das sekundäre Ziel war es, diese neue Technologie bei pädiatrischen Patienten anzuwenden, um deren motorische Leistung nach der Rehabilitation zu messen und zu untersuchen, ob Kinder und Jugendliche ihre während der Rehabilitation erreichte motorische Kapazität im Alltag umsetzen können.

Die Doktorarbeit begann mit einer systematischen Literaturrecherche, um einen Überblick

über die technologischen Möglichkeiten von tragbaren Inertialsensoren zur Quantifizierung motorischer Alltagsaktivitäten von Personen mit eingeschränkter Mobilität zu erhalten. Anschließend wurden die Mobilitäts- und Selbstversorgungsziele von Kindern und Jugendlichen, die eine Rehabilitation durchliefen, zusammengefasst und eine internationale Umfrage unter Gesundheitsfachpersonen durchgeführt, um die Bedürfnisse der pädiatrischen Rehabilitation zu ermitteln. Die Ergebnisse dieser Studien führten zur Entwicklung eines neuen Algorithmus. Dieser berechnet den funktionellen Handeinsatz mit Handgelenksensoren; die Dauer in liegender, sitzender und stehender Position mit einem Oberkörper- und einem Oberschenkelsensor; die Distanz und Geschwindigkeit während dem aktiven Rollstuhlfahren mit einem Handgelenk- und einem Rollstuhlsensor sowie die Dauer, Distanz und Geschwindigkeit von Gangaktivitäten mit einem Knöchelsensor.

In einem nächsten Schritt wurde der Algorithmus in der Zielgruppe durch drei Studien validiert. Die erste Studie analysierte die Genauigkeit von haltungs- und mobilitätsbezogenen Messwerten. Es zeigte sich, dass der Messfehler des Algorithmus bei der Bestimmung der Dauer des Liegens, Sitzens, Stehens, aktiven Rollstuhlfahrens und Gehens weniger als 10% betrug. Die zweite Studie untersuchte die Validität der Messung des funktionellen Handgebrauchs. Der Korrelationskoeffizient zwischen den sensor- und videobasierten Messwerten betrug 0.7. Die dritte Studie ermittelte die Genauigkeit der sensorbasierten Bestimmung der Gehgeschwindigkeit. Es stellte sich heraus, dass der Messfehler des Algorithmus klein genug ist, um klinisch relevante Veränderungen von 0.1 m/s zu detektieren. Diese Validitätsstudien zeigten, dass der neu entwickelte Algorithmus valide Messwerte der motorischen Leistung von Kindern und Jugendlichen liefert.

In der letzten Studie dieser Doktorarbeit haben Kinder und Jugendliche mit neuromotorischen Beeinträchtigungen die Sensoren nach der Rehabilitation in ihrer gewohnten Umgebung getragen. Diese Studie ergab, dass Kinder und Jugendliche mit neuromotorischen Beeinträchtigungen an Wochenenden weniger aktiv sind als an Schultagen und dass ihre täglich ausgeführten motorischen Aktivitäten stark von Tag zu Tag variieren. Daher empfehlen wir, bei künftigen Anwendungen des Sensorsystems die motorischen Alltagsaktivitäten an sieben aufeinanderfolgenden Tagen zu messen. Dieses Messprotokoll beinhaltet Schultage und Wochenendtage, und die Anzahl der Messtage ist ausreichend, um reliable Messwerte über die motorische Leistung von Kindern und Jugendlichen zu erhalten. Die Studie zeigte auch, dass die Kinder und Jugendlichen bereit waren, die Sensoren eine Woche lang im Alltag zu tragen.

Die gleiche Studie untersuchte zudem, ob Kinder und Jugendliche mit neuromotorischen Beeinträchtigungen ihre während der Rehabilitation erreichte motorische Kapazität in den Alltag übertragen können, indem ihre motorische Leistung im Alltag mit ihrer in der Klinik erfassten motorischen Leistungsfähigkeiten verglichen wurde. Die motorische Leistungsfähigkeit von Kindern und Jugendlichen erklärte nur 13% bis 58% ihrer motorischen Leistung im Alltag. Diese geringen Zusammenhänge zeigen, dass die in der Klinik durchgeführten motorischen Tests die motorische Leistungen der Patienten zu Hause und in der Schule nur teilweise widerspiegeln. Dies bestätigt, dass Leistungsfähigkeit und Leistung zwei unterschiedliche Konstrukte sind, und unterstreicht die Notwendigkeit, klinische Tests mit Messungen in der gewohnten Umgebung der Patienten zu ergänzen. Darüber hinaus bestätigt es, dass tragbare Sensoren und der in dieser Doktorarbeit entwickelte Algorithmus wesentliche Informationen über die Funktionsfähigkeit der Patienten im Alltag erfassen, was einen Mehrwert für den klinischen Alltag und die Rehabilitationsforschung bringt.

1 General introduction

1.1 Pediatric neurorehabilitation

Approximately 7% of all children have some form of moderate disability, and 0.7% have a severe disability, with neurological disorders being the major cause of disability in childhood (deSousa and Rattue, 2004; Kurtz and Stanley, 1995). These children often present neurological impairments that result in difficulties in executing everyday life motor activities, such as walking or grasping an object. They undergo intensive therapy programs as in- or out-patients with the emphasis on reducing these limitations and fostering their functional independence in everyday life.

1.1.1 Children and adolescents with neuromotor impairments

The two most common health conditions leading to rehabilitation admission in children are cerebral palsy and acquired brain injury, which are briefly described in the following sections.

Cerebral palsy is defined as *"a group of permanent disorders in the development of movement and posture, causing activity limitations that are attributed to non-progressive disturbances that occurred in the developing fetal or infant brain. The motor disorders of cerebral palsy are often accompanied by disturbances of sensation, perception, cognition, communication, and behavior, by epilepsy, and by secondary musculoskeletal problems"* (Rosenbaum et al., 2007). It is the most common motor disability in childhood (Graham et al., 2016), with a prevalence of roughly 2 cases per 1'000 live births (Surveillance of Cerebral Palsy in Europe (SCPE), 2002). Among children with cerebral palsy, 28% cannot walk and 16% walk with assistance (Novak et al., 2012), 41% have apparent difficulties in stair climbing (Wichers et al., 2009), and 60% have more than minor problems with hand function (Arner et al., 2008). Besides these activity limitations, children with cerebral palsy often experience pain, fatigue, and social exclusion, which all affect their well-being and quality of life (Lindsay, 2016).

Acquired brain injury is defined as *"an overarching term applied to describe insults to the brain that are not congenital or perinatal in nature"* (Campbell, 2004). The mechanism of injury can be traumatic (e.g., falls or motor vehicle accidents) or non-traumatic (e.g., infections, strokes, or neoplasms). Acquired brain injuries are the leading cause of disability in children after infancy (Forsyth and Kirkham, 2012), with traumatic brain injuries being more common than non-traumatic brain injuries (Bedell, 2008; Moreau et al., 2013). The annual incidence of traumatic brain injuries requiring hospitalization is roughly 70 per 100'000 children, with a prevalence of long-term impairment and disability in 20% of the cases (Thurman, 2016). These children have difficulties in self-care, mobility, and social activities, even after rehabilitation and their functional recovery depends on many factors such as the severity of the injury or the age at injury (Galvin et al., 2010). Moreover, there is increasing evidence that children with an acquired brain injury have participation restrictions at home, at school, and in the community van Tol et al. (2011), which is related to decreased quality of life (King et al., 2003).

Besides cerebral palsy and acquired brain injury, there are other congenital or acquired injuries or illnesses of the nervous system leading to rehabilitation admission. Typical examples are spina bifida, Duchenne muscular dystrophy, peripheral neuropathy, and traumatic spinal cord injury. In this thesis, we used the umbrella term *children and adolescents with neuromotor impairments* to summarize this heterogeneous pediatric population. In this term, *adolescents* represent young people between 13 and 18 years of age. However, to increase the readability of the thesis, we often just wrote *children* instead of *children and adolescents*. Therefore, we want to point out that the word *children* also includes adolescents unless it is specified differently.

1.1.2 The aim of pediatric rehabilitation

The overall goal of pediatric rehabilitation is to foster the children's and adolescents' functioning in everyday life and improve the quality of life for the whole family. The process to achieve this goal is best understood in the context of the International Classification of Functioning, Disability, and Health (ICF) (Noetzel and Dosenbach, 2017). The ICF provides a standard language and a framework to describe functioning and disability as the interaction between the children's impairments on the level of body functions and body structures (e.g., muscle paresis or spasticity), their ability to execute a task or an action on the activity level (e.g., walking or eating), and their involvement in a life situation on the participation level (e.g., attending school or playing cards with family and friends) (World Health Organization, 2001). Moreover, these levels are influenced by the child's personal and environmental factors (e.g., accessibility of school buildings or attitudes of family members). Disability can be influenced on any of these levels, and rehabilitation can be targeted to improve the children's abilities or make changes to their environment depending on individual needs (World Health Organization, 2011). An interdisciplinary team of physicians, nurses, therapists, psychologists, and teachers gathers these needs at the beginning of rehabilitation and establishes a tailored rehabilitation program. In pediatric rehabilitation, the inclusion of parents in this process is widely advocated nowadays (An and Palisano, 2014; King and Chiarello, 2014). Thereby, the focus shifts from reducing impairments on the level of body functions to the children's participation in everyday life activities (Brogren Carlberg and Löwing, 2013; Law and Darrah, 2014).

1.1.3 Motor assessments in pediatric rehabilitation

Motor assessments have become an integral part of pediatric neurorehabilitation. They quantify the patients' functional abilities, and the outcomes are essential for setting goals, monitoring the children's progress over time, and evaluating therapeutic interventions (Schädler et al., 2006). Examples of widely-used motor assessments are the 10-meter walk test and the Gross Motor Function Measure to assess lower limb activities (Ammann-Reiffer et al., 2014; Avery et al., 2003; Graham et al., 2008) and the Melbourne Assessment to assess upper limb activities (Gerber et al., 2016; Randall et al., 2014). During the 10-meter walk test, a therapist records the time patients need to cover the middle 10 m of a 14 m long walkway.

The estimated walking speed serves as a surrogate to assess the children's walking abilities. The Gross Motor Function Measure contains 88 standardized tasks related to lying, sitting, crawling, standing, and walking. Here, the therapist rates the children's ability to complete these tasks. Similarly, the Melbourne Assessment comprises 14 unimanual tasks involving reaching, grasping, releasing, and manipulating objects. In this assessment, the therapist rates the children's movement range, accuracy, dexterity, and fluency in executing these tasks.

In these examples, but also generally in inpatient rehabilitation, the assessments are predominantly conducted at the clinic in a standardized environment and under ideal conditions. During the 10-meter walk test for example, children walk on a flat surface, without distraction by other persons, and with ideal lighting conditions. Standardized settings have the advantage of increasing the comparability between patients and the reliability of repeated measures because the assessments are completed under the same conditions. Moreover, patients have the possibility to demonstrate what they can do without getting challenged or distracted by the environment. According to the ICF, these assessments measure the patients' highest probable level of functioning, which is referred to as their motor **capacity** (World Health Organization, 2002). In other words, capacity measures reflect what a child **can** do in a **standardized** environment (Holsbeeke et al., 2009).

However, in daily life, the children interact with their social and physical environment, and their capacity might not reflect how they perform in their habitual environment. Going back to the example of the 10-meter walk test, children might show significant improvements in this standardized test during the course of rehabilitation. However, in everyday life, the children might still have difficulties walking on uneven surfaces, passing curbs, getting around in a crowded area, or going home at dawn. Moreover, the children might rarely use their regained walking abilities because of social exclusion or parents driving them by car. This example demonstrates the relevance of considering contextual factors in assessing the patients' functional abilities. In practice, we can incorporate these contextual factors by assessing what a child **does** do in his or her **habitual** environment (Holsbeeke et al., 2009) which, according to the ICF, is referred to as motor **performance** (World Health Organization, 2002). Hence, without assessing performance, it remains unclear whether children can translate their improvements in capacity into everyday life at home or school. Therefore, assessing the children's motor capacity should be complemented by assessments of their motor performance to get a comprehensive view of their functional abilities.

In current clinical practice, motor performance is predominantly assessed with self- or proxy-report questionnaires such as the Functional Mobility Scale (Ammann-Reiffer et al., 2014; Graham et al., 2004) or the Pediatric Motor Activity Log (Gerber et al., 2016; Uswatte et al., 2012). In the Functional Mobility Scale, parents rate their child's usual walking ability at home, at school, and in the community. Likewise, in the Pediatric Motor Activity Log, the parents rate how well and how often their child uses the more affected hand in activities of daily living. These questionnaires rely on the subjective perception of families and are prone to recall or proxy bias (Clanchy et al., 2011a; Holsbeeke et al., 2009). Consequently, there is a need for objective alternatives to assess motor performance in pediatric rehabilitation.

1.2 Measuring performance with wearable sensors

1.2.1 Sensor technology

Technological progress in the field of microelectromechanical systems enabled the development of small-sized, lightweight, and energy-efficient sensor modules (Garofalo, 2012). As a result, the sensor modules have become wearable, and their extended battery life allows for long-term measurements over multiple days. Therefore, wearable sensors provide a promising solution to assess motor performance objectively by enabling long-term measurements of motor activities in the children's habitual environment (Lang et al., 2020; Leuenberger and Gassert, 2011).

Accelerometers and pedometers are the most commonly used wearable devices to measure everyday life motor activities in patients with neuromotor impairments (Ainsworth, 2009; Cervantes and Porretta, 2010). Conventional outcomes of accelerometers are activity counts as well as intensity levels and energy expenditure estimations based on cut-points of these counts (Hey et al., 2014). However, even though these measures provide valid estimates about whole-body physical activity, they do not contain any information about the type and quality of performed activities (Bonomi and Westerterp, 2012; Rachele et al., 2012). In contrast, pedometers would be specific to walking activities and count the number of daily steps. However, they reveal reduced accuracy in people with altered gait patterns and slow walking speeds (Ainsworth, 2009; Melanson et al., 2004).

In contrast, combining accelerometers with gyroscopes and magnetometers to an inertial sensor module and placing these modules on different body segments would allow for more accurate and comprehensive measurements of the children's movements (Garofalo, 2012). Moreover, processing these sensor data with activity recognition algorithms enables determining the type, quantity, and quality of motor activities (Dobkin, 2013). For example, walking periods have been discriminated from other motor activities with sensor modules placed on each ankle before determining the covered distance and the limb asymmetry during these walking periods (Dobkin et al., 2011). Besides, inertial sensors can be complemented with other sensor technology such as temperature or barometric pressure sensors to gain further details about the children's activities (Lowe and Ólaighin, 2014). Barometric pressure sensors, for example, can be used to measure altitude changes and discriminate between standing and using an elevator or between level walking and stair climbing (Massé et al., 2015). Hence, we concluded that these wearable sensor modules are ideal for measuring everyday life motor activities in children and adolescents with neuromotor impairments.

In this thesis, we used a sensor module called ZurichMOVE. It was developed in a joint project of the Rehabilitation Engineering Laboratory and the Institute for Biomechanics at ETH Zurich and the Spinal Cord Injury Center at the Balgrist University Hospital. The module has been continuously improved and currently consists of a 3-axis accelerometer, a 3-axis gyroscope, a 3-axis magnetometer, and an altimeter (Popp et al., 2019). The internal storage capacity and the battery life of the sensor modules allow for continuous recordings of roughly 72 h at a sampling frequency of 50 Hz. The sensor modules have the size of a watch, are waterproof, and are made of biocompatible materials. These characteristics make the sensor modules suitable to be worn by patients in their everyday life. We use hook-and-loop straps of various lengths to place the sensor modules on the patient's trunk or limbs and adapters to attach the sensor modules to assistive devices (see **Figure 1.1**).

Figure 1.1 – Exemplary illustration of a wrist-worn ZurichMOVE sensor module and a second sensor module attached to the spokes of the wheel (created by Rehabilitation Engineering Laboratory, ETH Zurich).

1.2.2 Data processing algorithms

The analysis of the tremendous amount of data generated by these sensor modules requires appropriate data processing algorithms to determine clinically meaningful and valid performance measures of the patients' daily motor activities (Dobkin, 2013). Examples of such performance measures are the number of daily climbed stairs (Leuenberger et al., 2014), the ratio between active and passive wheelchair propulsion (Popp et al., 2016), and an index of hand use laterality (Leuenberger et al., 2017). The algorithms that determine these performance measures were developed in former theses of our research group and have been validated in adult patient populations.

However, the application of these sensor modules in a pediatric population is new, and we expected that existing algorithms could not be directly used in children and adolescents with neuromotor impairments for three main reasons. First, essential performance measures for children might not be covered by algorithms designed for adults because children are also engaged in child-specific and age-dependent activities, such as playing or school activities. Second, the magnitude of the acceleration signal is lower in children with small body sizes and short levers than in adults. Therefore, algorithms trained with data from adults might not reveal accurate results when applied to children with smaller body sizes than the subjects of the training data. Third, children and adolescents with neuromotor impairments present complex and heterogeneous motor disorders that result in a variety of altered movement patterns (Armand et al., 2016). However, existing algorithms are usually designed for a specific adult patient population; thus, they might not be robust or adaptive enough to deal with the full spectrum of movement patterns presented in a pediatric population. Consequently, we expected that existing algorithms must be adapted to children and adolescents with neuromotor impairments to derive meaningful and valid performance measures for our target population.

1.2.3 Number and placement of sensor modules

The measurement of motor performance with wearable sensors depends not only on the availability of the sensor technology and the validity of the derived performance measures but also on the children's and adolescents' willingness to wear the sensors in daily life. Previous studies have shown that wearable sensors need to be comfortable, discreet, and unobtrusive to be accepted by the end-users (Bergmann and McGregor, 2011; Dan, 2020; Mackintosh et al., 2019). In our case, we expected that the small-sized and lightweight sensor modules fulfill these requirements and that the acceptance depends mainly on the number and placement of sensors. Consequently, there is a need to minimize the number of body-worn sensors.

In contrast, increasing the number of sensors would enable a more detailed analysis of everyday life motor activities and increase the accuracy of the performance measures (Dan, 2020; Ahmadi et al., 2018). For example, a single sensor is sufficient to count the number of steps during walking periods (Paraschiv-Ionescu et al., 2019), while determining stride time and stride length would require four sensors placed on the lower extremities (Carcreff et al., 2018). Likewise, a single wrist sensor is enough to measure daily hand use (Leuenberger et al., 2017), while explicitly counting the number of reaching activities would require a sensor on the trunk, the upper arm, and the forearm (van Meulen et al., 2016). Therefore, selecting the best sensor configuration is a trade-off between maximizing information gain and minimizing the number of sensors (Lang et al., 2020).

This introduction demonstrated the importance of assessing motor performance in pediatric neurorehabilitation, showed the lack of objective performance measures in current clinical practice, and provided a promising solution to overcome this limitation by measuring performance with wearable inertial sensors. Accordingly, this thesis aimed to apply this technology in children and adolescents with neuromotor impairments, adapt it to the needs of pediatric neurorehabilitation, and use it to investigate the role of personal and environmental factors in translating rehabilitation progress into daily life.

1.3 Objectives of this thesis

The first goal of this thesis was to develop a data processing algorithm that derives clinically meaningful and valid motor performance measures about the daily motor activities of children and adolescents with neuromotor impairments based on data from a wearable inertial sensor system.

We expected the development process to be a trade-of between maximizing the number and accuracy of performance measures and minimizing the number of required sensors and thus the burden on children's and families' everyday lives. Consequently, we aimed to get an overview of existing algorithms, the derived performance measures, and the underlying sensor placements to get a thorough understanding of what is technologically feasible. Then, we aimed to identify the needs of families and pediatric health professionals to estimate what is clinically desirable. Eventually, we intended to adapt existing algorithms to the needs of pediatric rehabilitation and optimize the number of required sensors. In this thesis, we focused on school-aged children and adolescents because we expected that younger children and infants would have different needs regarding the performance measures and the size, weight, and placement of the sensor modules. Moreover, they represent the largest age group at our rehabilitation center.

Next, we planned to validate the new algorithm in children and adolescents with neuromotor impairments. Since there are many applications of wearable sensor systems in adult patient populations (Dobkin and Martinez, 2018), we expected the new algorithm to be composed of sub-algorithms that have been validated in adults. Further, we expected that these sub-algorithms might not reveal valid estimates in a pediatric population because of the children's smaller body sizes and because they present a variety of altered movement patterns (Armand et al., 2016), which is a challenge for data processing algorithms (Albert et al., 2017b; Dobkin, 2017). Hence, we intended to use the results of this validation process to improve our algorithm's accuracy and, eventually, derive valid estimations of motor performance.

The second goal of this thesis was to apply the new technology in children and adolescents with neuromotor impairments to measure their motor performance after rehabilitation. We planned that children and adolescents wear our sensor system in their habitual environment for multiple days. With this, we aimed to estimate the day-to-day variability of the children's and adolescents' motor activities, which would allow for a recommendation on how many measurement days are needed to obtain reliable estimates of their motor performance. Moreover, this project should reveal if children and adolescents are willing to wear the sensor system in daily life. Finally, we intended to compare the children's and adolescents' motor performance to their level of motor capacity and to identify personal and environmental factors that explain the difference between capacity and performance. Identifying these factors would be an essential milestone in improving the translation of rehabilitation progress into daily life and the children's and adolescents' independence in executing everyday life motor activities.

1.4 Thesis outline

This thesis is mainly composed of research articles that have already been published or submitted for publication. These articles were structured into four parts.

Part I: Technological possibilities To determine what is technologically feasible, we conducted a systematic review on the application of wearable inertial sensors to quantify everyday life motor activities in people with mobility impairments. We extracted the investigated activities and the performance measures used to quantify these activities. Moreover, we provided an overview of the underlying data processing algorithms and the required sensor placements. We published the protocol of this systematic review before the narrative synthesis of the review's results. We chose this two-stage publishing process to improve the quality of the search strategy, the selection process, and the data extraction before conducting the final literature search. The protocol of this systematic review is thoroughly described in **Chapter 2**, while the review's results are presented in **Chapter 3**.

Part II: Clinical needs In this part, we identified the needs of families and pediatric health professionals with two complementary projects. First, we investigated the mobility and self-care goals of children undergoing rehabilitation and provided a detailed priority list of motor activities in **Chapter 4**. Second, we conducted an international survey with doctors, nurses, and therapists; presented them with the performance measures extracted from the systematic review; and asked them to rate the clinical relevance of these measures for pediatric rehabilitation (**Chapter 5**). Finally, in **Chapter 6**, we merged the results of both projects, identified the clinically most relevant activities and performance measures, and developed an algorithm that estimates these measures with data of wearable inertial sensors. The latter was a trade-off between maximizing information gain and minimizing the number of required sensors.

Part III: Algorithm validation As a next step, we investigated the accuracy of our algorithm and determined the validity of the performance measures in three studies. Two studies used the same data. In these studies, children and adolescents with neuromotor impairments completed an activity circuit at the clinic while wearing our sensor system, and we made video recordings as a reference. The first study analyzed the accuracy of posture and mobility-related measures (**Chapter 7**), and the second study investigated the validity of hand use measures (**Chapter 8**). The third study required additional data collection since we determined the accuracy of sensor-based gait speed estimations by comparing them to the gait speed estimations of a pressure-sensitive walkway (**Chapter 9**). Eventually, we summarized the algorithm's validity in **Chapter 10**.

Part IV: Clinical application The preceding validity studies were conducted in supervised experiments at the clinic to allow for the inclusion of criterion measures. However, we aimed to develop a tool that will be used in the children's and adolescents' habitual environment. In this real-world setting, other factors such as the acceptance to wear the sensors, the completeness of data, and the naturally occurring day-to-day variability of motor activities must be considered.

Therefore, we evaluated the factors mentioned above in **Chapter 11**. In this study, children and adolescents with neuromotor impairments wore our sensor system for seven consecutive days in their habitual environment after rehabilitation. This enabled the recommendation of how many measurement days are needed to obtain reliable estimates of the children's and adolescents' motor performance. Moreover, we determined if the children and adolescents were willing to wear the sensors throughout the recommended measurement period.

The same study investigated if children and adolescents with neuromotor impairments can translate their rehabilitation progress into daily life (**Chapter 12**). Besides motor performance, we also measured the participants' motor capacity with motor assessments at the clinic and the participant's personal, social, and environmental factors with a series of questionnaires. Eventually, we investigated which of these contextual factors played a crucial role in translating capacity into performance after rehabilitation.

Technological possibilities Part I

2 Protocol of a systematic review on the application of wearable inertial sensors to quantify everyday life motor activity in people with mobility impairments

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2.1 Abstract

Background People with mobility impairments may have difficulties in everyday life motor activities and assessing these difficulties is crucial to plan rehabilitation interventions and evaluate their effectiveness. Wearable inertial sensors enable long-term monitoring of motor activities in a patient's habitual environment and complement clinical assessments which are conducted in a standardised environment. The application of wearable sensors requires appropriate data processing algorithms to estimate clinically meaningful outcome measures, and this review will provide an overview of previously published measures, their underlying algorithms, sensor placement, and measurement properties such as validity, reproducibility, and feasibility.

Methods We will screen the literature for studies which applied inertial sensors to people with mobility impairments in free-living conditions, described the data processing algorithm reproducibly, and calculated everyday life motor activity related outcome measures. Three databases (MEDLINE, EMBASE, and SCOPUS) will be searched with terms out of four different categories: Study population, measurement tool, algorithm, and outcome measure. Abstracts and full texts will be screened independently by the two review authors and disagreement will be solved by discussion and consensus. Data will be extracted by one of the review authors and verified by the other. It includes the type of outcome measures, the underlying data processing algorithm, the required sensor technology, the corresponding sensor placement, the measurement properties, and the target population. We expect to find a high heterogeneity of outcome measures and will therefore provide a narrative synthesis of the extracted data.

Discussion This review will facilitate the selection of an appropriate sensor setup for future applications, contain recommendations about the design of data processing algorithms as well as their evaluation procedure, and present a gap for innovative, new algorithms and devices.

Systematic review registration International prospective register of systematic reviews (PROSPERO): CRD42017069865.

2.2 Background

People with mobility impairments may have difficulties in executing activities of daily living (Activity Limitations), or they may experience problems in involvement in life situations (Participation Restrictions) (World Health Organization, 2002). Rehabilitation services aim to improve these people's abilities or make changes to their environment (World Health Organization, 2011), to achieve a high level of independence and eventually increase the quality of life. Clinical assessments to estimate patients' abilities and their rehabilitation progress are generally conducted in a standardised environment at a single time. Thus, they do not incorporate environmental and cognitive challenges of a patient's habitual environment (Del Din et al., 2016c) and might be inaccurate when the symptoms of the patient fluctuate over time (Del Din et al., 2016b). Recent advances in wearable sensor technologies enable objective and long-term monitoring of motor activities in a patient's habitual environment. They provide an opportunity to overcome the aforementioned limitations of clinical assessments and complement their outcome measures.

Accelerometers and pedometers are the most commonly used wearable devices to quantify everyday life motor activity in clinical trials and clinical practice (Ainsworth, 2009; Cervantes and Porretta, 2010). Conventional outcome measures of accelerometers are activity counts as well as intensity levels and energy expenditure estimations based on cut points of these counts (Hey et al., 2014). These measures provide relevant information about whole body physical activity, but they are non-specific and cannot determine movement patterns and types of activities performed (Bonomi and Westerterp, 2012). Pedometers recognize walking activities and count the number of steps during a day. However, they reveal reduced accuracy in people with altered gait patterns and slow walking speeds (Ainsworth, 2009; Melanson et al., 2004).

In contrast, using a combination of several inertial sensors, such as accelerometers and gyroscopes, together with sophisticated data processing algorithms allows estimating the quantity and quality of everyday life motor activities (Garofalo, 2012). Additional sensor technology such as magnetometers, barometers, wearable cameras, and heart rate monitors measure environmental factors or physiological responses to motor activities and can be combined with inertial sensors to gain further details about patients' activities (Dobkin, 2013; Lowe and Ólaighin, 2014). Technological progress in the field of microelectromechanical systems has made these devices small-sized, cost-effective, energy-efficient, and thus applicable for continuous long-term monitoring in unsupervised, free-living conditions (Garofalo, 2012). However, the analysis of this tremendous amount of unlabelled raw data requires appropriate data processing algorithms to determine clinically meaningful outcome measures of everyday life motor activity. Examples of such measures are a hand use laterality index (Brogioli et al., 2016), a ratio between active and passive wheelchair propulsion (Popp et al., 2016), and a number of daily climbed stairs (Leuenberger et al., 2014).

The relevance of these outcome measures depends on end users' perspectives and may be different for people with mobility impairments compared to non-disabled individuals.

For example, the amount of limping, use of assistive devices, and daily activity of affected limbs are more relevant to the first population. Altered movement patterns can also be a challenge for data processing algorithms (Albert et al., 2017b; Dobkin, 2017) and thus the transferability of algorithms which were evaluated in non-disabled individuals to people with mobility impairments could be limited. Therefore, this review will focus on the application of inertial sensor technologies to quantify everyday life motor activity in people with mobility impairments. It will provide an overview of existing outcome measures and their underlying data processing algorithms. Specifically, the following research questions will be addressed:

1. Which outcome measures have been used to quantify everyday life motor activity of people with mobility impairments under free-living conditions and what are their corresponding data processing algorithms?

2. Which inertial sensor technology (accelerometer or gyroscope), possibly in combination with additional wearable sensor technology, is required to assess these measures?

3. Where need inertial sensors be placed to assess these measures and minimally restrict activities of daily living?

4. In which patient populations were these measures applied and were they evaluated in terms of validity, reproducibility, or feasibility?

2.3 Methods/Design

This protocol was registered with the International prospective register of systematic reviews (PROSPERO) in June 2017 (registration number: CRD42017069865). The development and reporting of this protocol are in accordance with the checklist of the Preferred Reporting Items for Systematic Review and Meta-Analysis Protocols (PRISMA-P) (Shamseer et al., 2015).

2.3.1 Eligibility criteria

We will include full text articles written in English or German if they meet all of the following eligibility criteria. There will be no restrictions on year of publication:

Measurement tool The described system incorporates an accelerometer, a gyroscope, or both, and can optionally include additional sensors such as a magnetometer, a barometer, a wearable camera, a heart rate monitor, etc. All required devices must be body worn or attached to assistive devices (e.g. wheelchair). If the system relies on data from external (e.g. a smart home environment) or implanted devices (e.g. instrumented prosthesis), the article will be excluded.

Algorithm The algorithm describes the data processing of recorded raw data up to the resulting outcome measure. The algorithm must be described reproducibly in the article or references providing this information must be cited and publicly available. In addition, the algorithm must be applicable to unlabelled data of unrestricted, unsupervised long-term measurements. If an algorithm only works with predetermined movement recordings and thus with labelled data, such as in clinical gait analysis, the corresponding article will not be included in this review.

Outcome measure The output of the data processing algorithm must be a measure that quantifies an aspect of everyday life motor activity (e.g. number of reaching activities, gait symmetry, or use of assistive devices). Whole body activity counts and step counts, as well as physical activity levels and energy expenditure based on thresholds of these counts, will not be considered for this review, as they have already been well investigated (Jeran et al., 2016; Van Remoortel et al., 2012) and provide no innovation compared to the current clinical state of the art. Metrics that quantify an emergency situation (e.g. epileptic seizure or fall detection), a non-mobility related activity (e.g. sleep or food intake), or a disease-specific motor behaviour (e.g. freezing of gait in Parkinson's disease) will be excluded as well.

Study population We will include all articles that analysed data from children, adolescents, or adults with a diagnosed orthopaedic or neurological mobility impairment (e.g. cerebral palsy, stroke, osteoarthritis, etc.) or from those who need assistive devices in their daily life activities (e.g. crutches, wheelchairs, etc.). Study populations with mental or visual impairments as well as patients suffering from cardio-respiratory conditions will not be considered, as we assume that these populations do not present an altered movement pattern in everyday life motor activities compared to healthy controls. Infants will be excluded since they pose different requirements to a monitoring device for motor activities. Exceptions are possible if an article introduces a novel algorithm with highly relevant outcome measures for people with mobility impairments, but only preliminary data with healthy subjects are available.

2.3.2 Search strategy

We will conduct a systematic search of the literature in three databases: MEDLINE via the Ovid search engine including in-process and other non-indexed citations as well as EMBASE and SCOPUS via Elsevier's search engine. A preliminary search was conducted in July 2017 and will be repeated before completion of the review article.

The selected search terms can be grouped into five categories: (1) study population, (2) measurement tool, (3) data processing algorithm, (4) free-living condition, and (5) terms which incorporate categories three and four. The first category limits the search results to articles with a clinical application. It comprises both general terms (e.g. "patient", "disease", "rehabilitation", etc.) as well as specific health conditions ("spinal cord injury", "stroke", etc.). The second category includes the most frequently used synonyms of inertial sensors ("accelerometer", "gyroscope", "inertial measurement unit", etc.). The third category restricts the search results to articles containing a description of the data processing algorithms with terms such as "algorithm", "signal processing", "pattern recognition", etc. The search terms of the fourth category were selected to find algorithms that are applicable in free-living conditions (e.g. "everyday life", "daily living", etc.). The last category comprises two terms "activity classification" and "activity recognition". An OR operator will be used to link search terms within categories, while an AND operator will be used between categories. The final search strategy combines the categories as follows: [(1) AND (2) AND (3) AND (4)] OR [(1) AND (2) AND (5)]. Search fields will be used to restrict the search to title, abstract, and keywords. If applicable, medical subject headings (MeSH) and terms of the Emtree thesaurus will be used in the corresponding search engines. The complete list of search terms and the syntax of the search strategy are provided in Appendix A.

2.3.3 Selection process

Titles and abstracts of all articles retrieved using the search strategy described above will be screened by the two review authors independently to identify articles that potentially meet the eligibility criteria. The full text of these potentially eligible studies will be retrieved and independently assessed for eligibility by the same review authors. Disagreements will be resolved by discussion and consensus. For the data management of the selection process we will use Covidence, a Cochrane technology platform (http://www.covidence.org).

2.3.4 Data extraction

Data extraction from all included articles will be conducted by one of the review authors and checked by the other. Extracted information will include: outcome measures and method of the underlying data processing algorithm, type and placement of required sensor technology, study design and evaluation of the outcome measures, as well as study population. Discrepancies will be identified and resolved through discussion and consensus. Missing data will be requested from the authors of the respective article.

2.3.5 Data synthesis

The purpose of this review is to provide an overview of all published outcome measures that quantify everyday life motor activity. Most likely, they will be grouped in activity-independent (e.g., hand use laterality) and activity-dependent measures, which could be further subdivided into quantity (e.g., duration of sitting activities, number of climbed stairs) and quality measures (e.g., symmetry index of walking activities). We will conduct a narrative synthesis of the methods that were used to assess these outcomes. This will include the type and placement of required sensor technologies and a brief description of the underlying data processing algorithms. Further, we will provide an overview of how these measures were evaluated. This will cover the study population, the study design, and the type of analysis (e.g., validity, reproducibility, or feasibility). Our systematic review will provide readers with extensive information about measurement of everyday life motor activities in patient populations with wearable sensors and the presentation of the information will be divided into several categories, like outcome measures, sensor setup and technology, diagnosis, and study type.

2.4 Discussion

We expect to find a high heterogeneity of outcome measures to quantify everyday life motor activity and different study designs to evaluate them. Our preliminary search revealed that there would be mainly four different types of studies in our review: (1) Case-control studies that assessed the discriminant validity of its outcome measures, (2) clinical validity studies that correlated their outcome measures with a standardized clinical assessment in a specific patient population, (3) studies that evaluated the activity classification accuracy of their algorithm, and (4) concurrent validity studies that investigated the error of their outcome measures by comparing the outcomes of the wearable sensor technology with a reference method. These study types reveal different test statistics and cannot be compared with each other. The comparison between studies will be further complicated since they include different study populations. All this impedes a quantitative synthesis of the study results. Therefore, the primary purpose of this systematic review will be to provide a comprehensive overview of the methods of previous studies instead of synthesizing their results. Accordingly, it will grant researchers quick access to all studies that evaluated a specific outcome measure in a particular patient population.

Advances in wearable sensor technology enable long-term monitoring of everyday life motor activities in people with mobility impairments. This monitoring potentially provides important information to the rehabilitation process, as it describes the patient's motor abilities in his/her habitual environment. Many different devices and corresponding data processing algorithms have been developed over the last decade, and this review will provide an overview of these methods with a focus on outcome measures and clinical applications. It will facilitate the selection of an appropriate sensor setup for future applications and present a gap for innovative, new algorithms and devices.

3 Systematic review on the application of wearable inertial sensors to quantify everyday life motor activity in people with mobility impairments

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Authors' contributions: FR and RL developed the search strategy for this review and screened the search hits for eligibility. FR extracted and synthesized the relevant data and wrote the first draft of this review. Both authors contributed to the manuscript revision and read and approved the final manuscript.

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3.1 Abstract

Background Recent advances in wearable sensor technologies enable objective and long-term monitoring of motor activities in a patient's habitual environment. People with mobility impairments require appropriate data processing algorithms that deal with their altered movement patterns and determine clinically meaningful outcome measures. Over the years, a large variety of algorithms have been published and this review provides an overview of their outcome measures, the concepts of the algorithms, the type and placement of required sensors as well as the investigated patient populations and measurement properties.

Methods A systematic search was conducted in MEDLINE, EMBASE, and SCOPUS in October 2019. The search strategy was designed to identify studies that (1) involved people with mobility impairments, (2) used wearable inertial sensors, (3) provided a description of the underlying algorithm, and (4) quantified an aspect of everyday life motor activity. The two review authors independently screened the search hits for eligibility and conducted the data extraction for the narrative review.

Results Ninety-five studies were included in this review. They covered a large variety of outcome measures and algorithms which can be grouped into four categories: (1) maintaining and changing a body position, (2) walking and moving, (3) moving around using a wheelchair, and (4) activities that involve the upper extremity. The validity or reproducibility of these outcomes measures was investigated in fourteen different patient populations. Most of the studies evaluated the algorithm's accuracy to detect certain activities in unlabeled raw data. The type and placement of required sensor technologies depends on the activity and outcome measure and are thoroughly described in this review. The usability of the applied sensor setups was rarely reported.

Conclusion This systematic review provides a comprehensive overview of applications of wearable inertial sensors to quantify everyday life motor activity in people with mobility impairments. It summarizes the state-of-the-art, it provides quick access to the relevant literature, and it enables the identification of gaps for the evaluation of existing and the development of new algorithms.

3.2 Background

The protocol of this systematic review was published in advance (Rast and Labruyère, 2018), and the following introduction is an adapted and extended version of the introduction of that protocol.

People with mobility impairments may have difficulties in executing activities of daily living (activity limitations), or they may experience problems in involvement in life situations (participation restrictions) (World Health Organization, 2002). Rehabilitation services aim to improve these people's abilities or make changes to their environment (World Health Organization, 2011), to achieve a high level of independence and eventually increase the quality of life. Clinical assessments to estimate patients' abilities and their rehabilitation progress are generally conducted in a standardized environment at a single time. Thus, they do not incorporate environmental and cognitive challenges of a patient's habitual environment (Del Din et al., 2016c) and might be inaccurate when the symptoms of the patient fluctuate over time (Del Din et al., 2016b).

Recent advances in wearable sensor technologies enable objective and long-term monitoring of motor activities in a patient's habitual environment. They provide an opportunity to overcome the aforementioned limitations of clinical assessments and complement their outcome measures. Accelerometers are the most commonly used wearable devices to quantify everyday life motor activity in clinical trials and clinical practice (Ainsworth, 2009; Cervantes and Porretta, 2010). Conventional outcome measures of accelerometers are activity counts as well as intensity levels and energy expenditure estimations based on cut-points of these counts (Hey et al., 2014). These measures provide relevant information about whole-body physical activity, but they are non-specific and cannot determine movement patterns and types of activities performed (Bonomi and Westerterp, 2012). In contrast, using a combination of several inertial sensors, such as accelerometers and gyroscopes, together with sophisticated data processing algorithms, allows estimating the quantity and other characteristics of everyday life motor activities (Garofalo, 2012). Additional sensor technology such as magnetometers, barometers, wearable cameras, and heart rate monitors measure environmental factors or physiological responses to motor activities and can be combined with inertial sensors to gain further details about patients' activities (Dobkin, 2013; Lowe and Ólaighin, 2014). Technological progress in the field of micro-electromechanical systems has made these devices small-sized, cost-effective, energy-efficient, and thus applicable for continuous long-term monitoring in unsupervised conditions (Garofalo, 2012). However, continuous long-term monitoring generates a tremendous amount of unlabeled data that requires appropriate data processing algorithms to determine clinically meaningful outcome measures of everyday life motor activity. Typically, these algorithms detect a certain activity in unlabeled data as a first step (e.g., walking bouts or grasping an object) and then determine a measure to quantify the previously detected activity as a second step (e.g., walking speed or number of grasping activities).

The relevance of these outcome measures depends on end-users' perspectives and may be different for people with mobility impairments compared to non-disabled individuals. For example, the amount of limping, use of assistive devices, and daily activity of affected limbs are more relevant to the former population. Altered movement patterns can also be a challenge for data processing algorithms (Albert et al., 2017b; Dobkin, 2017) and thus the transferability of algorithms which were evaluated in non-disabled individuals to people with mobility impairments could be limited. Therefore, this review focused on the application of inertial sensor technologies to quantify everyday life motor activity in people with mobility impairments and provides an overview of existing outcome measures as well as their underlying data processing algorithms. Specifically, the following research questions were addressed: (1) Which outcome measures have been used to quantify everyday life motor activity of people with mobility impairments under free-living conditions, and what are their corresponding data processing algorithms? (2) Which inertial sensor technology (accelerometer or gyroscope), possibly in combination with additional wearable sensor technology, is required to assess these measures? (3) Where need inertial sensors be placed to assess these measures and minimally restrict activities of daily living? (4) In which patient populations were these measures applied, and were they and the required sensor system evaluated in terms of validity, reproducibility, or usability?

3.3 Methods

The detailed protocol of this review was published in advance (Rast and Labruyère, 2018) and its method section is roughly summarized in the following paragraphs.

The systematic search was conducted in three databases: MEDLINE, EMBASE, and SCOPUS. The selected search terms can be grouped into five categories: (1) study population (e.g., "patient", "stroke", etc.), (2) measurement tool (e.g., "accelerometer", "gyroscope", etc.), (3) data processing algorithm (e.g., "algorithm", "signal processing", etc.), (4) free-living condition (e.g., "everyday life", "daily living", etc.), and (5) two terms which incorporate categories three and four ("activity classification" and "activity recognition"). A first search was conducted in July 2017 and repeated in October 2019.

Title and abstracts (first step), as well as full-text articles (second step) were screened by the two review authors independently to identify articles that met the following eligibility criteria: (1) The study population involved children, adolescents, or adults with a diagnosed orthopedic or neurological mobility impairment or people who need assistive devices in their daily life activities, (2) the article used a measurement tool that incorporates a wearable accelerometer, gyroscope, or both, i.e., inertial measurement unit (IMU), and optionally includes additional sensors, (3) the article described the underlying data processing algorithm reproducibly or cited a publicly available reference, and (4) the output of the algorithm is a measure that quantifies an aspect of everyday life motor activity. Whole-body activity counts, as well as physical activity levels and energy expenditure based on thresholds of these counts, were not considered for this review, as they have already been well investigated (Jeran et al., 2016; Van Remoortel et al., 2012).

The used outcome measures and the method of the underlying data processing algorithm, the type and placement of required sensor technology, the study population as well as the study design were extracted from all included articles. Some studies investigated more than one sensor setup and data processing algorithm. In that case, only the method with the best performance or the recommended method was included in this review. If the outcome measures were not explicitly mentioned or described in the article, which was often the case in activity classification studies, it was assumed that activity detection enables to determine the duration of the activity or count the number of repetitions. The measures were then retrospectively grouped into four categories: (1) Maintaining and changing a body position, (2) walking and moving, (3) moving around using a wheelchair, and (4) activities that involve the upper extremity. The sensor placements were simplified by assigning the exact positions to one of the following body segments: head, trunk, upper arm, forearm, hand, pelvis, thigh, shank, foot, and assistive devices. Thus, sensors that were placed above the lateral malleoli and on the fifth lumbar vertebra were assigned to the shank and pelvis segment, respectively. To address the second part of the fourth research question, the study designs were allocated to one or several of seven different categories: Classification accuracy studies investigated the performance of the algorithm to recognize activities, while technical validity studies determined the accuracy of activity-related measures, both with regard to a reference method. Clinical validity studies correlated the outcome of the sensor system with the outcome of a clinical assessment. Between-day reliability studies investigated the consistency of the outcome when measuring it on two different days. Case/control studies compared the outcome between the target population and a control group. Interventional studies used the outcome to evaluate the effectiveness of an intervention, and observational studies incorporated different designs such as analyzing the changes of the outcome over time or comparing several outcomes within the same subject. Besides, it was determined if the studies assessed the usability of the sensor systems.

3.4 Results

3.4.1 Overview

The systematic search revealed 2272 hits, of which 31 were added retrospectively through reference screening of the included articles. After title and abstract screening, 473 articles remained for full-text screening, and, eventually, 95 articles fulfilled the predetermined eligibility criteria. The complete flow diagram of the screening procedure is shown in **Figure 3.1**. The main reason for exclusion was the study population, with 46% of all excluded articles. Many research projects developed a new algorithm to monitor motor activities in daily life and conducted a preliminary study with healthy subjects. These studies were not considered in this review, except for one study that recruited able-bodied individuals which performed an activity circuit in a wheelchair (Leving et al., 2018). The second most frequent exclusion criterion was the algorithm with 26%. It was either not described reproducibly (e.g., in cases of proprietary algorithms of commercial parties) or not applicable to unlabeled data.

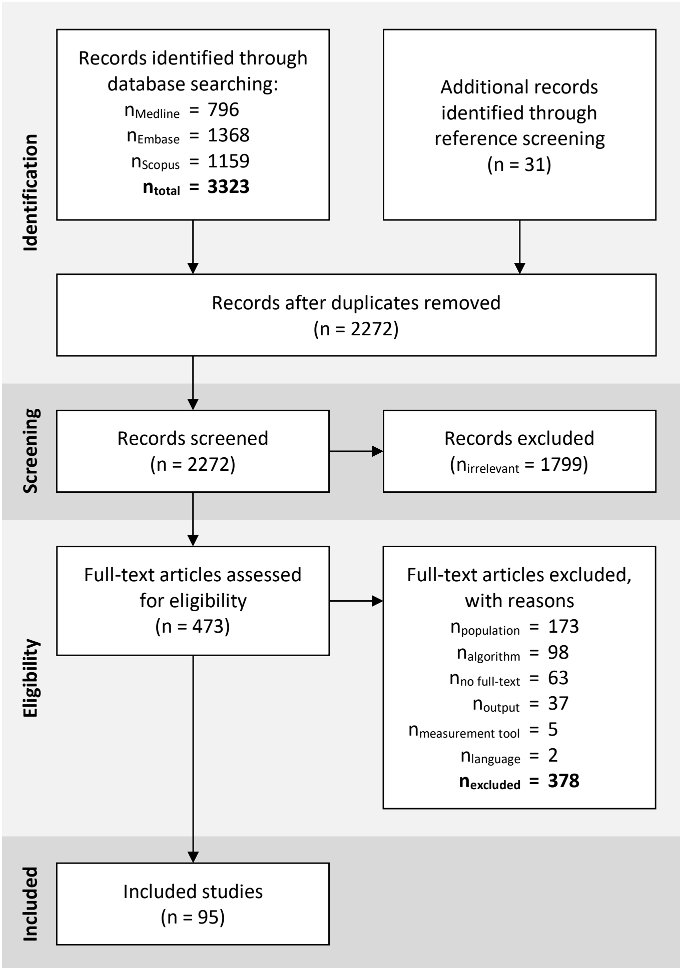

Figure 3.1 – Flow diagram according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) (Moher et al., 2009).

An overview of the used sensor technologies, the body segments on which sensors were placed, the study population in which the sensors were applied, and the used study designs for evaluating the outcome measures is provided in **Figure 3.2**. Note that most of the studies were allocated to several of the chosen categories.

Sensor technologies

All studies used an accelerometer, a gyroscope, or both (inclusion criteria) with a clear preference for accelerometers. These sensor technologies were combined with a barometric pressure sensor to detect changes in altitude, a magnetometer to measure the orientation relative to

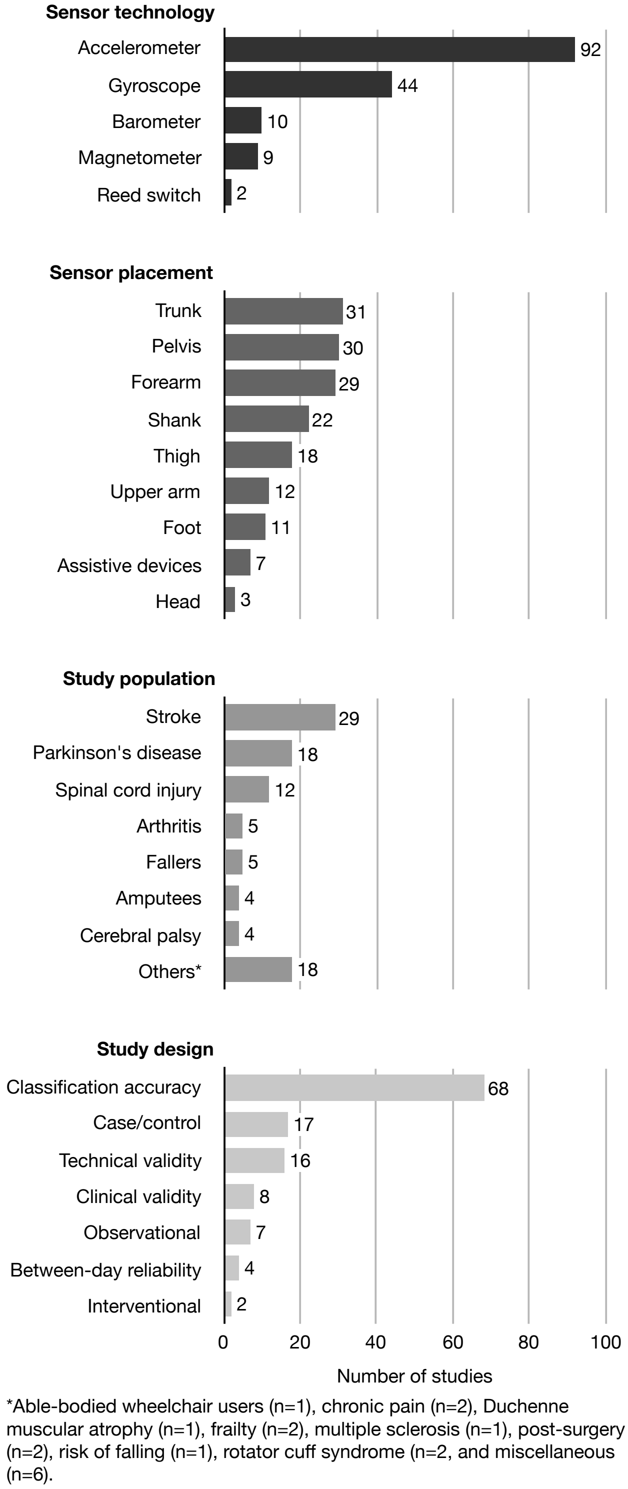

Figure 3.2 – Frequency distribution of the used sensor technologies, of the body segments on which sensors were placed, of the study population in which the sensors were applied, and of the used study designs to evaluate the outcome measures.

the earth's magnetic field, and a reed switch on the spokes of the wheelchair to determine revolutions of the wheel. Six studies used an instrumented insole with force-sensitive sensors (Fulk et al., 2012; Fulk and Sazonov, 2011; Hegde et al., 2017; Pappas et al., 2001; Sazonov et al., 2009; Zhang et al., 2013), and two studies used a first-person camera (Zhan et al., 2015; Zhang et al., 2019), all in combination with inertial sensors. These eight studies were not further considered in this review since they did not use inertial sensors as their primary measurement tool.

Sensor placement

The sensors were most frequently placed on the trunk, the pelvis, and the forearm but also on other body segments and on assistive devices. The frequency of chosen sensor positions depended mainly on the outcome measures. Studies that used outcomes related to body positions preferred a sensor on the trunk or a combination of trunk and thigh sensors. In contrast, studies that used outcomes related to activities of the upper extremities (incl. wheeling) placed the sensors on the arms with a clear preference of wrist sensors. There was no clear preference for sensor placement in studies with gait-related outcomes. Sensors were placed on the trunk, the pelvis, the shanks, and the feet. The sensor placement, in general, is strongly related to the underlying algorithm and, therefore, more thoroughly described in the subsequent chapters.

Study populations

Wearable inertial sensors were most frequently applied in stroke survivors, in patients with Parkinson's disease, and in patients with spinal cord injury. Fourteen different study populations were identified, which highlights the wide range of applications of wearable inertial sensors to quantify everyday life motor activity in people with mobility impairments.

Study designs

In terms of validity, the majority of the included studies evaluated the algorithm's activity classification accuracy. The methods of these studies differed considerably. Measurements were conducted under laboratory or free-living conditions. The number of sensors ranged from 1 to 17 and the number of classes/activities from 1 to 11. Moreover, the methods to split the data into training and testing samples varied, and the studies used inconsistent metrics to report their results. Technical and clinical validity studies were conducted less frequently. Technical validity studies determined predominantly the accuracy of gait parameters. Sensor-based outcome measures were compared to those of pressure-sensitive walkways, video recordings, stopwatches, or other validated sensor systems. In contrast, the clinical validity studies compared their sensor-based outcome measures to those of clinical assessments. These comparisons were unique for each clinical validity study of this review. Clinical studies were less frequent than validity studies. Here, sensor-based outcome measures were often applied in case/control studies, followed by observational and interventional studies. In terms of reproducibility, four studies determined the between-day reliability of their outcome measure. All of them evaluated gait-related outcomes, but they differed considerably in the chosen setting. Two studies assessed the usability of a sensor system by reporting inconvenience (Jeannet et al., 2011) and adverse events (Moore et al., 2017), respectively, while eight studies reported the wearing time of the sensors in daily life (Brodie et al., 2015; Brogioli et al., 2016; Coley et al., 2008b; Gerber et al., 2019a; Held et al., 2018; Popp et al., 2016; Razjouyan et al., 2018; Verlaan et al., 2015).

Outcome measures and underlying algorithms

All outcomes, as well as the underlying type and placement of sensors, are thoroughly described in the subsequent chapters. Each chapter is complemented with a table that provides a list of all outcome measures and how they were investigated in terms of study populations and study designs (**Table 3.1**, **Table 3.2**, **Table 3.3**, **Table 3.4**). The underlying data processing algorithms to detect activities in unlabeled data of this review followed either a biomechanical or a statistical machine learning approach. The former approach uses explicit, and a priori defined features that are specific to certain activities (e.g., the orientation of thigh during sitting). The concepts of this approach are described in the following chapters. The latter approach uses many unspecific features in combination with standard machine learning algorithms. A description of these algorithms is provided elsewhere (Preece et al., 2009), and the detected activity classes, as well as the used sensor type and placement, are listed in **Table 3.5**.

3.4.2 Maintaining and changing a body position

3.4.2.1 Activities and outcome measures

The studies of this review often detected lying (Andreu-Perez et al., 2017; Albert et al., 2017a; Capela et al., 2015, 2016; Cheng et al., 2018; Feldhege et al., 2015; Jalloul et al., 2016; Jeannet et al., 2011; Kiani et al., 1997, 1998; Massé et al., 2015; O'Brien et al., 2017; Razjouyan et al., 2018; Salarian et al., 2007; Sok et al., 2018; Zwartjes et al., 2010), sitting (Andreu-Perez et al., 2017; Albert et al., 2017a, 2012; Capela et al., 2015, 2016; Cheng et al., 2018; Coley et al., 2008a,b; Feldhege et al., 2015; Jalloul et al., 2016; Jeannet et al., 2011; Kiani et al., 1997, 1998; Massé et al., 2015; Lonini et al., 2016; O'Brien et al., 2017; Razjouyan et al., 2018; Recher et al., 2018; Rodríguez-Martín et al., 2013a; Roy et al., 2009; Salarian et al., 2007; Sok et al., 2018; Teknomo and Estuar, 2015; van Meulen et al., 2016; Verlaan et al., 2015; Wade et al., 2015; Zwartjes et al., 2010), and standing positions (Ahmadi et al., 2018; Andreu-Perez et al., 2017; Albert et al., 2017a, 2012; Capela et al., 2015, 2016; Cheng et al., 2018; Coley et al., 2008a,b; Feldhege et al., 2015; Gerber et al., 2019a; Jalloul et al., 2016; Jeannet et al., 2011; Kiani et al., 1997, 1998; Lipperts et al., 2017; Massé et al., 2015; Lonini et al., 2016; O'Brien et al., 2017; Razjouyan et al., 2018; Recher et al., 2018; Rodríguez-Martín et al., 2013a; Salarian et al., 2007; Sok et al., 2018;

van Meulen et al., 2016; Verlaan et al., 2015; Wade et al., 2015; Zwartjes et al., 2010) and, thus, estimated how long patients with mobility impairments maintain these positions in daily life. Some studies combined lying and sitting positions as sedentary behavior (Ahmadi et al., 2018; García-Massó et al., 2015; Gerber et al., 2019a; Lipperts et al., 2017). One study included a measure to assess the knee angle during these positions (Feldhege et al., 2015). Instead of quantifying the duration of body positions, it is also common to count the transitions between these positions. The transition between sitting and standing was frequently investigated (Andreu-Perez et al., 2017; Ejupi et al., 2017; Ganea et al., 2012; Hemmati and Wade, 2016; Massé et al., 2014; Najafi et al., 2013; Nguyen et al., 2017, 2018; Paraschiv-Ionescu et al., 2004; Pham et al., 2018; Recher et al., 2018; Rodríguez-Martín et al., 2013a,b, 2015; Roy et al., 2009; Salarian et al., 2007; Zwartjes et al., 2010), while only three studies detected the transition between lying and sitting (Andreu-Perez et al., 2017; Paraschiv-Ionescu et al., 2004; Roy et al., 2009). Three of these studies further discriminated between transitions and bending forward (Rodríguez-Martín et al., 2013a,b, 2015), and two additional studies specifically detected sit-to-walk transitions since they aimed to compare the timed up and go test with transitions in daily life (Bernad-Elazari et al., 2016; Iluz et al., 2016). Standing up was further analyzed in terms of speed (Bernad-Elazari et al., 2016; Ejupi et al., 2017; Ganea et al., 2012; Iluz et al., 2016; Najafi et al., 2013; Nguyen et al., 2017; Pham et al., 2018; Zwartjes et al., 2010), range of motion (Bernad-Elazari et al., 2016; Ejupi et al., 2017; Ganea et al., 2012; Iluz et al., 2016; Zwartjes et al., 2010), and smoothness (Bernad-Elazari et al., 2016; Iluz et al., 2016). Only one study detected transfers (i.e., moving from one surface to another without changing body position) (García-Massó et al., 2015).

3.4.2.2 Description of algorithms and sensor placement

Activity classification algorithms in the literature detected either body positions directly or the transitions between them. Both approaches are widely used and, eventually, enable to determine how long a specific position was maintained and to count the number of transitions.

Detection of body positions based on sensor orientation

The orientation of different body parts are distinct characteristics of different body positions (e.g., the orientation of the thigh is vertical during standing, while it is horizontal during lying and sitting). Estimating the orientation of body-worn sensors and applying predefined thresholds is a common approach to discriminate between body positions in daily life. The sensors were placed on the thigh to distinguish between sitting and standing positions (Feldhege et al., 2015; Lipperts et al., 2017; van Meulen et al., 2016; Verlaan et al., 2015; Zwartjes et al., 2010) as well as on the trunk (Zwartjes et al., 2010) or shank (Feldhege et al., 2015; van Meulen et al., 2016) to separate lying from the remaining positions. One study used the orientation of the pelvis to classify all three positions with a single sensor (Capela et al., 2016). Algorithms to estimate the sensor's orientation have already been summarized (Picerno, 2017) and are, therefore, not part of this review.

Detection of transitions based on trunk inclination

Standing up or sitting down is usually performed by leaning forward to maintain the center of mass over the feet. This characteristic and the trunk inclination angle can be used to detect transitions between sitting and standing in daily life. The challenge is to discriminate between sit-to-stand and stand-to-sit transitions. This distinction was accomplished by pattern recognition (Ganea et al., 2012; Jeannet et al., 2011; Rodríguez-Martín et al., 2013a,b, 2015; Salarian et al., 2007), by the orientation of the pelvis after the transition (Bernad-Elazari et al., 2016; Iluz et al., 2016), by the orientation change of the thigh during the transition (Hemmati and Wade, 2016; Nguyen et al., 2017, 2018; Paraschiv-Ionescu et al., 2004), and by estimating the difference in elevation with double integration of the acceleration signal in vertical direction (Coley et al., 2008b,a; Najafi et al., 2013; Paraschiv-Ionescu et al., 2004; Pham et al., 2018; Razjouyan et al., 2018) or with a barometric pressure sensor (Ejupi et al., 2017; Massé et al., 2014, 2015). Lying was often detected via the orientation of the trunk, as described above. Detecting lying and the transitions between sitting and standing requires only a single sensor on the trunk such as on the sternum (Coley et al., 2008a,b; Ejupi et al., 2017; Ganea et al., 2012; Jeannet et al., 2011; Massé et al., 2014, 2015; Najafi et al., 2013; Paraschiv-Ionescu et al., 2004; Razjouyan et al., 2018; Salarian et al., 2007), the waist (Rodríguez-Martín et al., 2013a,b, 2015), or the fifth lumbar vertebra (Bernad-Elazari et al., 2016; Iluz et al., 2016; Pham et al., 2018). Other studies used a trunk and a thigh sensor (Gerber et al., 2019a; Nguyen et al., 2017, 2018; Paraschiv-Ionescu et al., 2004) or just a thigh sensor (Hemmati and Wade, 2016), while the latter cannot discriminate between lying and sitting positions.

Measures to quantify body positions and transitions

The knee angle during lying, sitting, and standing was estimated with the differential signal of two sensors that were placed on the thigh and the ipsilateral shank (Feldhege et al., 2015). No other measures were used in the literature to assess specific characteristics of different postures in daily life. Standing up, however, was more thoroughly analyzed. The start and end point of this transition were defined as the minima before and after peak trunk inclination. These points reveal the duration and with it a measure to quantify how fast patients are standing up. Five studies used a sensor on the sternum (Ejupi et al., 2017; Ganea et al., 2012; Najafi et al., 2013; Nguyen et al., 2017; Zwartjes et al., 2010) and three a sensor on the fifth lumbar vertebra (Bernad-Elazari et al., 2016; Iluz et al., 2016; Pham et al., 2018) to measure trunk inclination. Moreover, peak trunk inclination (Ejupi et al., 2017; Ganea et al., 2012), peak trunk acceleration (Zwartjes et al., 2010), the range of acceleration (Bernad-Elazari et al., 2016; Ganea et al., 2012; Iluz et al., 2016; Zwartjes et al., 2010), and gyroscope signals (Bernad-Elazari et al., 2016; Iluz et al., 2016), as well as measures for smoothness (Bernad-Elazari et al., 2016; Iluz et al., 2016) were used to quantify standing up in daily life.

Table 3.1 – Overview of activities and measures regarding maintaining and changing a body position as well as the corresponding study populations and study designs.

Activity	Measure	Diagnosis / Impairment group	Study design
Maintaining a body position			
Lying	Duration	Amputees (Kiani et al., 1997, 1998), arthritis (Andreu-Perez et al., 2017; Lipperts et al., 2017), cerebral palsy (Ahmadi et al., 2018; Gerber et al., 2019a), Duchenne muscular atrophy (Jeannet et al., 2011), frail people (Razjouyan et al., 2018), multiple sclerosis (Feldhege et al., 2015), Parkinson's disease (Cheng et al., 2018; Jalloul et al., 2016; Salarian et al., 2007; Zwartjes et al., 2010), spinal cord injury (Albert et al., 2017a; García-Massó et al., 2015; Sok et al., 2018), stroke (Capela et al., 2015, 2016; O'Brien et al., 2017; Massé et al., 2015)	Between-day reliability (Gerber et al., 2019a), case/control (Cheng et al., 2018; Razjouyan et al., 2018), classification accuracy (Ahmadi et al., 2018; Albert et al., 2017a; Andreu-Perez et al., 2017; Capela et al., 2015, 2016; Feldhege et al., 2015; García-Massó et al., 2015; Jeannet et al., 2011; Kiani et al., 1997, 1998; Lipperts et al., 2017; Massé et al., 2015; O'Brien et al., 2017; Salarian et al., 2007; Sok et al., 2018; Zwartjes et al., 2010), interventional (Jeannet et al., 2011)
	Knee angle	Multiple sclerosis (Feldhege et al., 2015)	Technical validity (Feldhege et al., 2015)
Sitting	Duration	Amputees (Kiani et al., 1997, 1998; Teknomo and Estuar, 2015), arthritis (Andreu-Perez et al., 2017; Lipperts et al., 2017; Verlaan et al., 2015), cerebral palsy (Ahmadi et al., 2018; Gerber et al., 2019a), Duchenne muscular atrophy (Jeannet et al., 2011), frail people (Razjouyan et al., 2018), multiple sclerosis (Feldhege et al., 2015), Parkinson's disease (Albert et al., 2012; Cheng et al., 2018; Jalloul et al., 2016; Rodríguez-Martín et al., 2013a; Salarian et al., 2007; Zwartjes et al., 2010), post-surgery (Wade et al., 2015), rotator cuff syndrome (Coley et al., 2008a,b), spinal cord injury (Albert et al., 2017a; García-Massó et al., 2015; Sok et al., 2018), stroke (Capela et al., 2015, 2016; O'Brien et al., 2017; Massé et al., 2015; Recher et al., 2018; Roy et al., 2009; van Meulen et al., 2016), miscellaneous (Lonini et al., 2016)	Between-day reliability (Gerber et al., 2019a), case/control (Cheng et al., 2018; Coley et al., 2008a,b; Razjouyan et al., 2018; Verlaan et al., 2015), classification accuracy (Ahmadi et al., 2018; Albert et al., 2012, 2017a; Andreu-Perez et al., 2017; Capela et al., 2015, 2016; Feldhege et al., 2015; García-Massó et al., 2015; Jalloul et al., 2016; Jeannet et al., 2011; Kiani et al., 1997, 1998; Lipperts et al., 2017; Lonini et al., 2016; Massé et al., 2015; O'Brien et al., 2017; Recher et al., 2018; Rodríguez-Martín et al., 2013a; Roy et al., 2009; Salarian et al., 2007; Sok et al., 2018; Teknomo and Estuar, 2015; van Meulen et al., 2016; Wade et al., 2015; Zwartjes et al., 2010), interventional (Jeannet et al., 2011), observational (van Meulen et al., 2016)
	Knee angle	Multiple sclerosis (Feldhege et al., 2015)	Technical validity (Feldhege et al., 2015)

Standing	Duration	Amputees (Kiani et al., 1997, 1998), arthritis (Andreu-Perez et al., 2017; Lipperts et al., 2017; Verlaan et al., 2015), cerebral palsy (Ahmadi et al., 2018; Gerber et al., 2019a), Duchenne muscular atrophy (Jeannet et al., 2011), frail people (Razjouyan et al., 2018), multiple sclerosis (Feldhege et al., 2015), Parkinson's disease (Albert et al., 2012; Cheng et al., 2018; Jalloul et al., 2016; Rodríguez-Martín et al., 2013a; Salarian et al., 2007; Zwartjes et al., 2010), post-surgery (Wade et al., 2015), rotator cuff syndrome (Coley et al., 2008a,b), spinal cord injury (Albert et al., 2017a; Sok et al., 2018), stroke (Capela et al., 2015, 2016; O'Brien et al., 2017; Massé et al., 2015; Recher et al., 2018; van Meulen et al., 2016), miscellaneous (Lonini et al., 2016)	Between-day reliability (Gerber et al., 2019a), case/control (Cheng et al., 2018; Coley et al., 2008a,b; Razjouyan et al., 2018; Verlaan et al., 2015), classification accuracy (Ahmadi et al., 2018; Albert et al., 2012, 2017a; Andreu-Perez et al., 2017; Capela et al., 2015, 2016; Feldhege et al., 2015; Jalloul et al., 2016; Jeannet et al., 2011; Kiani et al., 1997, 1998; Lipperts et al., 2017; Lonini et al., 2016; Massé et al., 2015; O'Brien et al., 2017; Recher et al., 2018; Rodríguez-Martín et al., 2013a; Salarian et al., 2007; Sok et al., 2018; van Meulen et al., 2016; Wade et al., 2015; Zwartjes et al., 2010), interventional (Jeannet et al., 2011), observational (van Meulen et al., 2016)
	Knee angle	Multiple sclerosis (Feldhege et al., 2015)	Technical validity (Feldhege et al., 2015)
Changing a body position			
Lying ↔ sitting	# of transitions	Arthritis (Andreu-Perez et al., 2017), chronic pain (Paraschiv-Ionescu et al., 2004), stroke (Roy et al., 2009)	Classification accuracy (Andreu-Perez et al., 2017; Paraschiv-Ionescu et al., 2004; Roy et al., 2009)
Lying ↔ standing	# of transitions	Arthritis (Andreu-Perez et al., 2017)	Classification accuracy (Andreu-Perez et al., 2017)
Sitting ↔ standing/walking	# of transitions	Arthritis (Andreu-Perez et al., 2017), chronic pain (Paraschiv-Ionescu et al., 2004), fallers (Ejupi et al., 2017), frail people (Ganea et al., 2012), Parkinson's disease (Nguyen et al., 2017, 2018; Pham et al., 2018; Rodríguez-Martín et al., 2013a,b, 2015; Salarian et al., 2007; Zwartjes et al., 2010), post-surgery (Hemmati and Wade, 2016), risk of falling (Najafi et al., 2013), stroke (Massé et al., 2014; Recher et al., 2018; Roy et al., 2009)	Case/control (Ejupi et al., 2017; Ganea et al., 2012; Pham et al., 2018), classification accuracy (Andreu-Perez et al., 2017; Hemmati and Wade, 2016; Massé et al., 2014; Nguyen et al., 2017, 2018; Paraschiv-Ionescu et al., 2004; Pham et al., 2018; Recher et al., 2018; Rodríguez-Martín et al., 2013a,b, 2015; Roy et al., 2009; Salarian et al., 2007; Zwartjes et al., 2010), clinical validity (Najafi et al., 2013; Zwartjes et al., 2010)
	Duration	Fallers (Ejupi et al., 2017; Iluz et al., 2016), frail people (Ganea et al., 2012), Parkinson's disease (Bernad-Elazari et al., 2016; Nguyen et al., 2017; Pham et al., 2018; Zwartjes et al., 2010), risk of falling (Najafi et al., 2013)	Case/control (Bernad-Elazari et al., 2016; Ejupi et al., 2017; Ganea et al., 2012; Iluz et al., 2016; Pham et al., 2018), clinical validity (Bernad-Elazari et al., 2016; Najafi et al., 2013; Zwartjes et al., 2010), technical validity (Najafi et al., 2013; Nguyen et al., 2017)
	Trunk tilt angle	Fallers (Ejupi et al., 2017), frail people (Ganea et al., 2012)	Case/control (Ejupi et al., 2017; Ganea et al., 2012)
	Smoothness	Fallers (Iluz et al., 2016), Parkinson's disease (Bernad-Elazari et al., 2016)	Case/control (Bernad-Elazari et al., 2016; Iluz et al., 2016), clinical validity (Bernad-Elazari et al., 2016)
	Others[1]	Fallers (Iluz et al., 2016), frail people (Ganea et al., 2012), Parkinson's disease (Bernad-Elazari et al., 2016; Zwartjes et al., 2010)	Case/control (Bernad-Elazari et al., 2016; Ganea et al., 2012; Iluz et al., 2016), clinical validity (Bernad-Elazari et al., 2016; Zwartjes et al., 2010)
Transferring oneself			
Transferring oneself while sitting	Duration	Spinal cord injury (García-Massó et al., 2015)	Classification accuracy (García-Massó et al., 2015)

[1] range and maxima of acceleration and gyroscope signals of the trunk and the pelvis.

3.4.3 Walking and moving

3.4.3.1 Activities and outcome measures

The studies included in this review most frequently covered detecting walking bouts in everyday life of people with mobility impairments (Ahmadi et al., 2018; Albert et al., 2012, 2017a; Andreu-Perez et al., 2017; Barth et al., 2015; Brodie et al., 2015, 2016; Capela et al., 2015, 2016; Coley et al., 2008a,b; Cheng et al., 2018; Del Din et al., 2016a; El-Gohary et al., 2013; Feldhege et al., 2015; Gerber et al., 2019a; Godfrey et al., 2016; Hester et al., 2006a,b; Ihlen et al., 2016a,b; Jalloul et al., 2016; Jeannet et al., 2011; Kiani et al., 1997, 1998; Laudanski et al., 2015; Leuenberger et al., 2014, 2017; Lipperts et al., 2017; Lonini et al., 2016; Mancini et al., 2018; Massé et al., 2015; Moore et al., 2017; Najafi et al., 2013; Nguyen et al., 2017, 2018; O'Brien et al., 2017; Paraschiv-Ionescu et al., 2004, 2019; Popp et al., 2019; Razjouyan et al., 2018; Rodríguez-Martín et al., 2013a; Roy et al., 2009; Salarian et al., 2007; Sok et al., 2018; Teknomo and Estuar, 2015; Terrier et al., 2017; van Meulen et al., 2016; Verlaan et al., 2015; Wade et al., 2015; Wu et al., 2016; Xu et al., 2011; Zwartjes et al., 2010), followed by more specifically detecting turning periods while walking (Cheng et al., 2018; El-Gohary et al., 2013; Hester et al., 2006a,b; Mancini et al., 2018; Nguyen et al., 2017, 2018; Pham et al., 2017) and stair climbing (Albert et al., 2017a; Capela et al., 2015, 2016; Coley et al., 2005; Hester et al., 2006a,b; Laudanski et al., 2015; Leuenberger et al., 2014; Lipperts et al., 2017; Lonini et al., 2016; Massé et al., 2015; O'Brien et al., 2017; Recher et al., 2018; Sok et al., 2018; Teknomo and Estuar, 2015; Wade et al., 2015). Other, less frequently detected activities were walking sideways (Recher et al., 2018), walking while carrying an object (Hester et al., 2006a,b), walking on sloping surfaces (Capela et al., 2015; Hester et al., 2006a,b), and running (Cheng et al., 2018; Teknomo and Estuar, 2015). Several studies detected and counted steps during walking and stair climbing periods (Barth et al., 2015; Brodie et al., 2015; Del Din et al., 2016a; El-Gohary et al., 2013; Feldhege et al., 2015; Gerber et al., 2019a; Godfrey et al., 2016; Jeannet et al., 2011; Lipperts et al., 2017; Moore et al., 2017; Najafi et al., 2013; Paraschiv-Ionescu et al., 2019; Razjouyan et al., 2018; Terrier et al., 2017; Verlaan et al., 2015). This in turn enables the estimation of step frequency and cadence. Walking bouts were further analyzed in terms of temporo-spatial gait parameters (Ahmadi et al., 2018; Brodie et al., 2015; Del Din et al., 2016a; Gerber et al., 2019a; Ihlen et al., 2016a,b; Moore et al., 2017; Paraschiv-Ionescu et al., 2004; Terrier et al., 2017; van Meulen et al., 2016; Xu et al., 2011; Zwartjes et al., 2010), and joint kinematics (i.e. knee angle) (Feldhege et al., 2015; Gerber et al., 2019a). Turning periods were further analyzed in terms of duration (El-Gohary et al., 2013; Hester et al., 2006a,b; Mancini et al., 2018; Nguyen et al., 2017, 2018; Pham et al., 2017), turning angle (El-Gohary et al., 2013; Mancini et al., 2018; Pham et al., 2017), turning speed (El-Gohary et al., 2013; Mancini et al., 2018), smoothness (Mancini et al., 2018), mediolateral range of trunk acceleration (Mancini et al., 2018), and number of steps to complete a turn (El-Gohary et al., 2013). Stair climbing was often subclassified in ascending and descending (Albert et al., 2017a; Coley et al., 2005; Hester et al., 2006a,b; Laudanski et al., 2015; Leuenberger et al., 2014; Lipperts et al., 2017; Lonini et al., 2016; Massé et al., 2015; O'Brien et al., 2017), and one study developed an algorithm that recognized if stairs were climbed with a step-by-step or a step-over-step pattern (Laudanski et al., 2015).

3.4.3.2 Description of algorithms and sensor placement

The following chapters describe the concepts of the underlying algorithm and the used sensor placement to detect and quantify walking, turning, and stair climbing activities. Details about the detection of walking sideways, walking while carrying an object, walking on sloping surfaces, and running as well as stair climbing with a step-by-step or step-over-step can be found in **Table 3.5**.

Walking bouts and gait parameters

Detection of walking bouts Two approaches have been used in the studies included in this review to detect walking bouts of people with mobility impairments in unsupervised datasets. The first approach uses the signal magnitude or variance to discriminate walking from static activities such as sitting and standing. The data is labeled as walking if the signal exceeds a predefined threshold for a certain duration. For this purpose, studies used the acceleration signal of the pelvis (Del Din et al., 2016a; Ihlen et al., 2016a,b; Moore et al., 2017), thigh (Godfrey et al., 2016), shank (Nguyen et al., 2017, 2018), thigh and shank (Feldhege et al., 2015), or the angular rate of the pelvis (El-Gohary et al., 2013; Mancini et al., 2018). Some studies introduced additional criteria to avoid confusion with other activities. During valid walking bouts, the orientation of the pelvis (Del Din et al., 2016a; Moore et al., 2017) or thigh sensor (Godfrey et al., 2016) needs to be vertical or the hip angle, derived from the differential signal between the pelvis and the thigh sensors, needs to be in an extended position (Nguyen et al., 2017, 2018). The second approach more specifically detects steps in the signal, and a number of consecutive steps are seen as a walking bout. The initial contact of each step leads to a peak in the signals and these peaks appear with a certain frequency that is specific to walking. Thus, peak detection and optionally verifying if they appear within a predefined frequency band is a common method to detect steps in unlabeled data. This method has been implemented with the acceleration signal of the trunk (Brodie et al., 2015, 2016; Coley et al., 2008a,b; Massé et al., 2015; Najafi et al., 2013; Paraschiv-Ionescu et al., 2004, 2019; Razjouyan et al., 2018), pelvis (Del Din et al., 2016a; Moore et al., 2017; Paraschiv-Ionescu et al., 2019), thigh (Godfrey et al., 2016; Lipperts et al., 2017; Verlaan et al., 2015), ankle (Xu et al., 2011) or foot sensor (Zwartjes et al., 2010), as well as the gyroscope signal of the shank (Gerber et al., 2019a; Jeannet et al., 2011; Paraschiv-Ionescu et al., 2004; Salarian et al., 2007) or foot sensor (El-Gohary et al., 2013). Again, to reduce false-positive rates, peak detection has been combined with the vertical orientation of the trunk and thigh sensors while walking (Zwartjes et al., 2010). Another method to detect steps is to assess the similarity of the signal to pre-established templates. The similarity was assessed with dynamic time warping of the feet's gyroscope signal (Barth et al., 2015) and with cross-correlation of the shank's acceleration signal (Feldhege et al., 2015). A third method used the fact that the left and right foot are alternatively active and stationary during walking. Active and stationary phases were detected with a zero-velocity algorithm and by fusing the accelerometer and gyroscope signal of the feet sensors (van Meulen et al., 2016). Some studies used the first approach to detect walking bouts and the second to detect steps within these walking bouts, while two studies combined both approaches to detect walking bouts more specifically (Rodríguez-Martín et al., 2013a; Terrier et al., 2017). The detection of walking bouts enables to measure the number and duration of walking activities in everyday life, while the detection of steps, further, enables to count daily steps as well as to determine the cadence (Brodie et al., 2015, 2016; Jeannet et al., 2011; Paraschiv-Ionescu et al., 2019; Verlaan et al., 2015), stride time (Xu et al., 2011), and stride time variability (Brodie et al., 2015, 2016) of individual walking bouts. Besides, the cadence was also determined by frequency analysis of the acceleration signal without detecting each step individually (Paraschiv-Ionescu et al., 2019; Terrier et al., 2017).

Determination of gait parameters Deriving temporal gait parameters from previously detected walking bouts, such as the duration of stance, swing, and double support phase requires a segmentation of the gait cycle by identifying the initial and final contact of the feet with the ground. Three different approaches were used in the literature to identify these gait events in people with mobility impairments. The first approach assumes that the lower leg rotates forwards during the stance phase and backwards during the swing phase. Zero-crossings of the feet's gyroscope signal around the mediolateral axis before and after maximal backward angular rate (i.e., swing phase) were, therefore, detected to estimate the timing of the final and initial contacts, respectively (El-Gohary et al., 2013). As an alternative to zero-crossings, the maxima of forward angular rate were detected to estimate the timing of the gait events. This algorithm was applied to the gyroscope signal of the feet (Zwartjes et al., 2010) or the ankle sensors (Gerber et al., 2019a; Paraschiv-Ionescu et al., 2004). The second approach used distinct features of the pelvis' acceleration signal in a vertical direction. It was assumed that the initial contact corresponds to peak deceleration, while the final contact does to peak acceleration gain (Del Din et al., 2016a; Moore et al., 2017). The third approach determines the start and end points of the stationary phase (i.e., stance phase) of the feet sensors (van Meulen et al., 2016). Again, the stationary phase was detected with a zero-velocity algorithm.

Walking speed was derived directly by estimating the stride length and divide it by the stride time or indirectly by identifying a surrogate that correlates with walking speed. The stride length was determined with biomechanical models and kinematic chains to estimate the distance between the two feet, or with the inverted pendulum model in which the stride length can be derived from the height change of the center of mass, or with double integration of the feet's horizontal acceleration (Zwartjes et al., 2010). The biomechanical models required IMUs on both thighs and shanks (Gerber et al., 2019a; Paraschiv-Ionescu et al., 2004) as well as additionally on the pelvis and the feet (van Meulen et al., 2016), while the inverted pendulum model only needs the vertical acceleration signal of the pelvis (Del Din et al., 2016a; Moore et al., 2017). Several surrogates that are supposed to correlate with walking speed were described in the studies of this review. Namely, the root mean square of the acceleration signal at the pelvis (Terrier et al., 2017), or of the vertical velocity of the trunk (Brodie et al., 2015, 2016) as well as the stride time (Xu et al., 2011). Moreover, one study recognized comfortable and brisk walking as two distinct classes, which enables a dichotomous analysis of slow and fast walking speed (Ahmadi et al., 2018). Walking bouts were further analyzed regarding stability, foot clearance, and joint kinematics. Gait stability as a measure for risk of falling was determined with local dynamic stability (Ihlen et al., 2016a; Terrier et al., 2017) and entropy measures (Ihlen et al., 2016b) of the pelvis' acceleration signal. The knee angle was measured with the differential signal between the thigh and ankle sensors (Gerber et al., 2019a; Feldhege et al., 2015). And one study estimated the foot clearance with the position of the foot sensor (van Meulen et al., 2016).

Turning

Turns during walking bouts were detected whenever the turning angle or angular velocity around the vertical axis exceeded a predetermined threshold. The turning angle was derived from the trunk (Nguyen et al., 2017, 2018) or the pelvis sensor (Cheng et al., 2018; El-Gohary et al., 2013; Mancini et al., 2018; Pham et al., 2017). The detection of turns enables to count the number of turns in daily life. However, to derive other measures, the start and end point of these turns need to be detected, too. These time points were defined when the angular velocity of the pelvis sank below a predetermined threshold (El-Gohary et al., 2013; Mancini et al., 2018), or at the minima before and after peak turning angular velocity of the trunk (Nguyen et al., 2017, 2018), or at the minimum and maximum of the pelvis' turning angle (Pham et al., 2017). Knowing the start and end point of turning periods enables to determine its duration (El-Gohary et al., 2013; Mancini et al., 2018; Nguyen et al., 2017, 2018; Pham et al., 2017), turning angle (El-Gohary et al., 2013; Mancini et al., 2018; Pham et al., 2017), and turning speed (El-Gohary et al., 2013; Mancini et al., 2018) as well as the smoothness (Mancini et al., 2018), mediolateral range of trunk acceleration (Mancini et al., 2018), and the number of steps to complete a turn (El-Gohary et al., 2013).

Stair climbing

The range of motion at the hip joint is higher during stair climbing compared to level walking. This characteristic was used in two studies to recognize stair climbing activities in daily life. One study used the orientation of the thigh sensor to discriminate between stair climbing and level walking (Lipperts et al., 2017), while another one used the variance of the acceleration signal at the hip (Capela et al., 2015). A further distinct characteristic of stair climbing is the change in altitude. Several studies used a barometric pressure sensor to measure the altitude change during locomotion and discriminated between going up and down stairs as well as level walking (Leuenberger et al., 2014; Massé et al., 2015; O'Brien et al., 2017). Usually, the shank is rotating forward during the stance phase of walking trials. However, while ascending a flight of stairs, there is a period during the stance phase, in which the shank is rotating backward. One study used this fact to specifically recognize stair ascending periods with the gyroscope signal of the shank sensor (Coley et al., 2005). And lastly, one article used the timing of peak occurrence in the acceleration signal of the thigh sensor to discriminate between ascending and descending stairs (Lipperts et al., 2017).

Table 3.2 – Overview of activities and measures regarding walking and moving as well as the corresponding study populations and study designs.

Activity	Measure	Diagnosis / Impairment group	Study design
Walking			
Walking	Duration	Amputees (Kiani et al., 1997, 1998; Teknomo and Estuar, 2015), arthritis (Andreu-Perez et al., 2017; Hester et al., 2006b; Lipperts et al., 2017; Verlaan et al., 2015), cerebral palsy (Ahmadi et al., 2018; Gerber et al., 2019a; Paraschiv-Ionescu et al., 2019), chronic pain (Paraschiv-Ionescu et al., 2004), Duchenne muscular atrophy (Jeannet et al., 2011), fallers (Brodie et al., 2015), frail people (Razjouyan et al., 2018), multiple sclerosis (Feldhege et al., 2015), Parkinson's disease (Albert et al., 2012; Cheng et al., 2018; El-Gohary et al., 2013; Jalloul et al., 2016; Nguyen et al., 2017, 2018; Rodríguez-Martín et al., 2013a; Salarian et al., 2007; Zwartjes et al., 2010), post-surgery (Wade et al., 2015), risk of falling (Najafi et al., 2013), spinal cord injury (Albert et al., 2017a; Popp et al., 2019; Sok et al., 2018), stroke (Capela et al., 2015, 2016; Hester et al., 2006a; Laudanski et al., 2015; Leuenberger et al., 2014; Moore et al., 2017; Massé et al., 2015; O'Brien et al., 2017; Roy et al., 2009; van Meulen et al., 2016; Wu et al., 2016; Xu et al., 2011), miscellaneous (Brodie et al., 2016; Lonini et al., 2016)	Between-day reliability (Brodie et al., 2015; Gerber et al., 2019a; Moore et al., 2017), case/control (Brodie et al., 2015; Cheng et al., 2018; Razjouyan et al., 2018; Verlaan et al., 2015), classification accuracy (Ahmadi et al., 2018; Albert et al., 2012, 2017a; Andreu-Perez et al., 2017; Brodie et al., 2016; Capela et al., 2015, 2016; El-Gohary et al., 2013; Feldhege et al., 2015; Hester et al., 2006a,b; Jalloul et al., 2016; Jeannet et al., 2011; Kiani et al., 1997, 1998; Laudanski et al., 2015; Leuenberger et al., 2014; Lipperts et al., 2017; Lonini et al., 2016; Massé et al., 2015; Nguyen et al., 2017, 2018; O'Brien et al., 2017; Paraschiv-Ionescu et al., 2004, 2019; Popp et al., 2019; Rodríguez-Martín et al., 2013a; Roy et al., 2009; Salarian et al., 2007; Sok et al., 2018; Teknomo and Estuar, 2015; van Meulen et al., 2016; Wade et al., 2015; Wu et al., 2016; Xu et al., 2011; Zwartjes et al., 2010), interventional (Jeannet et al., 2011), observational (Godfrey et al., 2016; van Meulen et al., 2016), technical validity (Najafi et al., 2013; Nguyen et al., 2017)
	# of steps / cadence	Arthritis (Lipperts et al., 2017; Verlaan et al., 2015), cerebral palsy (Gerber et al., 2019a; Paraschiv-Ionescu et al., 2019), chronic pain (Terrier et al., 2017), Duchenne muscular atrophy (Jeannet et al., 2011), fallers (Brodie et al., 2015), frail people (Razjouyan et al., 2018), multiple sclerosis (Feldhege et al., 2015), Parkinson's disease (Barth et al., 2015; Del Din et al., 2016a; Godfrey et al., 2016), risk of falling (Najafi et al., 2013), stroke (Moore et al., 2017)	Between-day reliability (Brodie et al., 2015; Gerber et al., 2019a; Moore et al., 2017; Terrier et al., 2017), case/control (Brodie et al., 2015; Del Din et al., 2016a; Razjouyan et al., 2018; Terrier et al., 2017; Verlaan et al., 2015), clinical validity (Terrier et al., 2017), interventional (Jeannet et al., 2011), observational (Godfrey et al., 2016), technical validity (Barth et al., 2015; Feldhege et al., 2015; Jeannet et al., 2011; Lipperts et al., 2017; Moore et al., 2017; Najafi et al., 2013; Paraschiv-Ionescu et al., 2019)
	Temporal gait parameters	Cerebral palsy (Gerber et al., 2019a), Parkinson's disease (Del Din et al., 2016a), stroke (Moore et al., 2017)	Between-day reliability (Gerber et al., 2019a; Moore et al., 2017), case/control (Del Din et al., 2016a), technical validity (Moore et al., 2017)
	Walking speed / stride length	Fallers (Brodie et al., 2015), cerebral palsy (Ahmadi et al., 2018; Gerber et al., 2019a), chronic pain (Paraschiv-Ionescu et al., 2004; Terrier et al., 2017), Parkinson's disease (Del Din et al., 2016a; Zwartjes et al., 2010), stroke (Moore et al., 2017; van Meulen et al., 2016; Xu et al., 2011)	Between-day reliability (Brodie et al., 2015; Gerber et al., 2019a; Moore et al., 2017; Terrier et al., 2017), case/control (Brodie et al., 2015; Del Din et al., 2016a; Terrier et al., 2017), classification accuracy (Ahmadi et al., 2018), clinical validity (Terrier et al., 2017; Zwartjes et al., 2010), observational (van Meulen et al., 2016), technical validity (Moore et al., 2017; Paraschiv-Ionescu et al., 2004; Xu et al., 2011)

	Walking stability	Chronic pain (Terrier et al., 2017), fallers (Ihlen et al., 2016a,b)	Between-day reliability (Terrier et al., 2017), case/control (Ihlen et al., 2016a,b; Terrier et al., 2017), clinical validity (Terrier et al., 2017)
	Foot clearance	Stroke (van Meulen et al., 2016)	Observational (van Meulen et al., 2016)
	Knee angle	Cerebral palsy (Gerber et al., 2019a), multiple sclerosis (Feldhege et al., 2015)	Between-day reliability (Gerber et al., 2019a), technical validity (Feldhege et al., 2015)
Walking sideways	Duration	Stroke (Recher et al., 2018)	Classification accuracy (Recher et al., 2018)
Walking while carrying an object	Duration	Arthritis (Hester et al., 2006b), stroke (Hester et al., 2006a)	Classification accuracy (Hester et al., 2006a,b)
Turning	# of turns	Parkinson's disease (Cheng et al., 2018; El-Gohary et al., 2013; Mancini et al., 2018; Nguyen et al., 2017, 2018; Pham et al., 2017)	Case/control (Cheng et al., 2018; El-Gohary et al., 2013; Mancini et al., 2018), classification accuracy (Nguyen et al., 2017, 2018; Pham et al., 2017), clinical validity (Mancini et al., 2018)
	Duration	Arthritis (Hester et al., 2006b), Parkinson's disease (El-Gohary et al., 2013; Mancini et al., 2018; Nguyen et al., 2017, 2018; Pham et al., 2017), stroke (Hester et al., 2006a)	Case/control (El-Gohary et al., 2013; Mancini et al., 2018), classification accuracy (El-Gohary et al., 2013; Hester et al., 2006a,b), clinical validity (Mancini et al., 2018), technical validity (Nguyen et al., 2017, 2018; Pham et al., 2017)
	Turning angle	Parkinson's disease (El-Gohary et al., 2013; Mancini et al., 2018; Pham et al., 2017)	Case/control (El-Gohary et al., 2013; Mancini et al., 2018), clinical validity (Mancini et al., 2018), technical validity (Pham et al., 2017)
	Turning speed	Parkinson's disease (El-Gohary et al., 2013; Mancini et al., 2018)	Case/control (El-Gohary et al., 2013; Mancini et al., 2018), clinical validity (Mancini et al., 2018)
	Others[1]	Parkinson's disease (El-Gohary et al., 2013; Mancini et al., 2018)	Case/control (El-Gohary et al., 2013; Mancini et al., 2018), clinical validity (Mancini et al., 2018)
Walking on sloping surfaces	Duration	Arthritis (Hester et al., 2006b), stroke (Capela et al., 2015; Hester et al., 2006a)	Classification accuracy (Capela et al., 2015; Hester et al., 2006a,b)
Stair climbing			
Stair climbing	Duration	Amputees (Teknomo and Estuar, 2015), arthritis (Hester et al., 2006b; Lipperts et al., 2017), post-surgery (Wade et al., 2015), spinal cord injury (Albert et al., 2017a; Sok et al., 2018), stroke (Capela et al., 2015, 2016; Hester et al., 2006a; Laudanski et al., 2015; Leuenberger et al., 2014; Massé et al., 2015; O'Brien et al., 2017; Recher et al., 2018), miscellaneous (Coley et al., 2005; Lonini et al., 2016)	Classification accuracy (Albert et al., 2017a; Capela et al., 2015, 2016; Coley et al., 2005; Hester et al., 2006a,b; Laudanski et al., 2015; Leuenberger et al., 2014; Lipperts et al., 2017; Lonini et al., 2016; Massé et al., 2015; O'Brien et al., 2017; Recher et al., 2018; Sok et al., 2018; Teknomo and Estuar, 2015; Wade et al., 2015)
	# of steps	Arthritis (Lipperts et al., 2017)	Technical validity (Lipperts et al., 2017)
	Step-by-step vs. step-over-step	Stroke (Laudanski et al., 2015)	Classification accuracy (Laudanski et al., 2015)
Running			
Running	Duration	Amputees (Teknomo and Estuar, 2015)	Classification accuracy (Teknomo and Estuar, 2015)

[1] smoothness, mediolateral range of trunk acceleration, and number of steps to complete a turn.

3.4.4 Moving around using a wheelchair

3.4.4.1 Activities and outcome measures

The included articles in this review either specifically detected active self-propulsion of wheeling activities (Kooijmans et al., 2014; Popp et al., 2018) or discriminated between active self-propulsion and being pushed passively (Brogioli et al., 2016; Ding et al., 2011; Fortune et al., 2019; García-Massó et al., 2015; Hiremath et al., 2015; Leving et al., 2018; Popp et al., 2016). Studies that did not distinguish between active and passive wheeling bouts were not included in this review since they did not specifically address a motor activity. Active wheeling was further analyzed in terms of covered distance (Brogioli et al., 2016; Popp et al., 2016), speed (Brogioli et al., 2016; Leving et al., 2018) as well as the number of strokes and stroke frequency (Ojeda and Ding, 2014). Moreover, three studies allocated wheeling bouts either to maneuvering or covering longer distances (Brogioli et al., 2016; Leving et al., 2018; Popp et al., 2016), five studies differentiated between hand use during self-propulsion and other activities of daily living (Brogioli et al., 2016; Ding et al., 2011; Fortune et al., 2019; García-Massó et al., 2015; Hiremath et al., 2015), and one study detected playing basketball (Hiremath et al., 2015).

3.4.4.2 Description of algorithms and sensor placement

Many studies used a statistical machine learning approach and are already depicted in **Table 3.5**. The remaining concepts of the underlying algorithms and used sensor placements are described in the following section.

Wheeling bouts were detected by measuring the rotation of the wheel and setting predefined thresholds. The rotation of the wheel was measured with a gyroscope (Brogioli et al., 2016; Popp et al., 2016) or a reed switch (Ojeda and Ding, 2014) on the spokes of the wheelchair. The distinction between maneuvering and longer wheeling bouts was accomplished with two different approaches. The first approach simply defined wheeling bouts that are shorter than 5.12 s as maneuvering and the remaining bouts as longer wheeling bouts (Popp et al., 2016). The second approach used the acceleration signal of the wheel sensor and predefined, incremental thresholds to distinguish between non-wheeling bouts, maneuvering, as well as normal speed and high-speed bouts (Leving et al., 2018). Two studies separated active from passive wheeling propulsion whenever the acceleration signal of the wrist sensor exceeded a predefined threshold (Kooijmans et al., 2014; Leving et al., 2018). Another study specifically counted the number of strokes within wheeling activities and, with it, estimated the stroke frequency by means of peak detection of the acceleration signal of the upper arm, wrist, or wheelchair sensor (Ojeda and Ding, 2014). Besides, the speed and distance of active wheeling bouts were estimated by measuring the angular velocity and the radius of the wheel (Brogioli et al., 2016; Popp et al., 2016).

Table 3.3 – Overview of activities and measures regarding wheeling as well as the corresponding study populations and study designs.

Activity	Measure	Diagnosis / Impairment group	Study design
Moving around using a wheelchair			
Self-propelled wheeling	Duration	Able-bodied wheelchair users (Leving et al., 2018), spinal cord injury (Ding et al., 2011; Fortune et al., 2019; García-Massó et al., 2015; Hiremath et al., 2015; Kooijmans et al., 2014; Popp et al., 2016, 2018)	Classification accuracy (Ding et al., 2011; Fortune et al., 2019; García-Massó et al., 2015; Hiremath et al., 2015; Kooijmans et al., 2014; Leving et al., 2018; Popp et al., 2016, 2018)
	Distance	Spinal cord injury (Brogioli et al., 2016; Popp et al., 2016)	Clinical validity (Brogioli et al., 2016), technical validity (Popp et al., 2016)
	Speed	Able-bodied wheelchair users (Leving et al., 2018), spinal cord injury (Brogioli et al., 2016)	Classification accuracy (Leving et al., 2018), clinical validity (Brogioli et al., 2016)
	# of strokes / stroke frequency	Spinal cord injury (Ojeda and Ding, 2014)	Interventional (Ojeda and Ding, 2014), technical validity (Ojeda and Ding, 2014)
Maneuvering	Duration	Able-bodied wheelchair users (Leving et al., 2018), spinal cord injury (Popp et al., 2016)	Classification accuracy (Leving et al., 2018; Popp et al., 2016)
Playing basketball	Duration	Spinal cord injury (Hiremath et al., 2015)	Classification accuracy (Hiremath et al., 2015)

3.4.5 Upper extremities

3.4.5.1 Activities and outcome measures

The measures to quantify hand and arm use in daily life that were used in the studies of this review were allocated to one of the following three categories: (1) Non-specific hand and arm use regardless of the underlying activity, (2) specific hand and arm movements such as reaching, and (3) specific hand and arm activities that require a combination of movements (e.g., eating activity involves reaching, cutting, and lifting movements). The first category includes measures to quantify the amount (Bochniewicz et al., 2017; Capela et al., 2015, 2016; Coley et al., 2008b; Leuenberger et al., 2017; Zambrana et al., 2019; Zwartjes et al., 2010) and diversity (Hurd et al., 2013) of hand and arm use as well as the range of motion of shoulder (Coley et al., 2008a; Derungs et al., 2018; Held et al., 2018; van Meulen et al., 2016), elbow (Held et al., 2018; van Meulen et al., 2016), and hand movements (Rowe et al., 2014). The second category contains reaching (Biswas et al., 2014, 2015a,b, 2017; Held et al., 2018; Nguyen et al., 2018; van Meulen et al., 2016), lifting (Biswas et al., 2014, 2015a,b, 2017; Roy et al., 2009), and pouring (i.e. pro- and supination) movements (Biswas et al., 2014, 2015a,b, 2017), while reaching was further analyzed in terms of reaching distance (Held et al., 2018; van Meulen et al., 2016) and reaching direction (Nguyen et al., 2018). And the activities of the last category were writing and reading (Jalloul et al., 2016), opening a door (Hester et al., 2006a,b), hair combing (Lemmens et al., 2015; Roy et al., 2009), eating (Jalloul et al., 2016; Lemmens et al., 2015; Seiter et al., 2015), and drinking (Lemmens et al., 2015) as well as tooth brushing, shirt buttoning, pant lifting, and food cutting (Roy et al., 2009).

3.4.5.2 Description of algorithms and sensor placement

Non-specific hand and arm use

Hand and arm use in daily life is often measured with activity counts that are derived from the accelerometer signal of the wrist sensors. Applying a sensor on either side enables to estimate the hand use laterality, which is particularly relevant for people with unilateral impairments. Studies that based their outcomes solely on activity counts were not included in this review since they do not provide innovation to the state-of-the-art and are already well investigated and reviewed in the literature (Lang et al., 2013; Braito et al., 2018). Instead of measuring the amount of hand and arm use, one study included in this review developed an algorithm do determine the diversity of hand and arm movements by calculating the sample entropy of the upper and lower arm acceleration signals (Hurd et al., 2013). Still, the signals of sensors worn at the upper extremities are biased by movements of the lower extremity (e.g., walking leads to large numbers of activity counts at the wrists even though the arms are not actively used) and three approaches are described in the literature to overcome this issue. The first approach stratifies hand and arm use according to the underlying activity of the lower extremities (e.g., hand and arm use during sitting, standing, and walking). This enables the exclusion of passive arm swing while walking (Capela et al., 2015, 2016; Coley et al., 2008b;

Zwartjes et al., 2010). The second approach directly discriminates between functional and non-functional hand and arm use. This distinction was implemented by training a classifier with machine learning techniques (see **Table 3.5** for details about sensor type and placement) (Bochniewicz et al., 2017; Zambrana et al., 2019) and by limiting the range of functional hand movement (Leuenberger et al., 2017). Here, functional hand movement was defined whenever the orientation of the hand was within ±30° from the horizontal, and the range of hand movement in this section exceeded 30° in a 2 *s* period. The orientation of the hand was determined with an IMU on the wrist. And lastly, the third approach estimated the movement of specific joints of the upper extremities. Shoulder movement was determined by calculating the angle between the trunk and the upper arm sensor (Held et al., 2018; van Meulen et al., 2016), by estimating the arm elevation with the orientation of the upper arm sensor (Coley et al., 2008a), and by assessing the spatial distribution of the elbow position with a kinematic model and the orientation of the upper arm sensor (Derungs et al., 2018). Likewise, the elbow movement was determined by calculating the angle between the upper and lower arm sensors (Held et al., 2018; van Meulen et al., 2016), while the wrist and finger movements were detected with an IMU (incl. magnetometer) on the wrist and magnet on the index finger (Rowe et al., 2014).

Specific hand and arm movements

A more sophisticated approach to discriminate between functional and non-functional hand and arm use is to detect particular movement primitives such as reaching an object. One research group developed an algorithm that distinguishes between reaching, lifting, and pouring movements while making a cup of tea by using a single wrist sensor (Biswas et al., 2014, 2015a,b, 2017). Another study specifically detected lifting food towards the mouth (Roy et al., 2009), and three studies detected reaching movements (Held et al., 2018; Nguyen et al., 2018; van Meulen et al., 2016). These studies used a whole-body IMU system with up to 17 sensors, which raises questions about its applicability for long-term measurements in daily life. Reaching movements were further analyzed by measuring its range and direction with the difference between the hand and trunk positions (Held et al., 2018; van Meulen et al., 2016) and by classifying the movement into upwards, mid, and downwards reaching directions (Nguyen et al., 2018).

Specific hand and arm activities

All but one study and most of the activities of this category were detected with a statistical machine learning approach. The details about sensor placement are presented in **Table 3.5**. One study used a pattern recognition approach with template matching to discriminate between hair combing, eating, and drinking (Lemmens et al., 2015). The templates were based on the signals of seven IMUs (incl. magnetometer), and they were placed on the trunk as well as on the upper arm, forearm, and hand of each side.

Table 3.4 – Overview of activities and measures regarding upper extremities as well as the corresponding study populations and study designs.

Activity	Measure	Diagnosis / Impairment group	Study design
Non-specific hand and arm use			
n/a	Duration / Laterality	Parkinson's disease (Zwartjes et al., 2010), Rotator cuff syndrome (Coley et al., 2008b), stroke (Bochniewicz et al., 2017; Capela et al., 2015, 2016; Leuenberger et al., 2017; van Meulen et al., 2016; Zambrana et al., 2019)	Case/control (Bochniewicz et al., 2017), classification accuracy (Bochniewicz et al., 2017; Capela et al., 2015, 2016; van Meulen et al., 2016; Zambrana et al., 2019; Zwartjes et al., 2010), clinical validity (Bochniewicz et al., 2017; Leuenberger et al., 2017; Zwartjes et al., 2010), observational (Coley et al., 2008b)
n/a	Entropy	Arthritis (Hurd et al., 2013)	Case/control (Hurd et al., 2013)
n/a	Range of motion:		
	Shoulder	Rotator cuff syndrome (Coley et al., 2008a), stroke (Held et al., 2018; Derungs et al., 2018)	Observational (Coley et al., 2008a; Held et al., 2018; Derungs et al., 2018)
	Elbow	Stroke (Held et al., 2018)	Observational (Held et al., 2018)
	Wrist & finger	Stroke (Rowe et al., 2014)	Observational (Rowe et al., 2014)
Specific hand and arm movements			
Reaching	# and duration of reaching activities	Parkinson's disease (Nguyen et al., 2018), stroke (Biswas et al., 2014, 2015a,b, 2017; Held et al., 2018)	Classification accuracy (Biswas et al., 2014, 2015a,b, 2017; Nguyen et al., 2018), observational (Held et al., 2018)
	Reaching distance	Stroke (van Meulen et al., 2016)	Observational (van Meulen et al., 2016)
	Reaching direction	Parkinson's disease (Nguyen et al., 2018), stroke (van Meulen et al., 2016)	Classification accuracy (Nguyen et al., 2018), observational (van Meulen et al., 2016)
Lifting sth. to the mouth	Duration	Stroke (Biswas et al., 2014, 2015a,b, 2017; Roy et al., 2009)	Classification accuracy (Biswas et al., 2014, 2015a,b, 2017; Roy et al., 2009)
Pouring sth. (pro-/supination)	Duration	Stroke (Biswas et al., 2014, 2015a,b, 2017)	Classification accuracy (Biswas et al., 2014, 2015a,b, 2017)
Specific hand and arm activities			
Writing & reading	Duration	Parkinson's disease (Jalloul et al., 2016)	Classification accuracy (Jalloul et al., 2016)
Opening a door	Duration	Arthritis (Hester et al., 2006b), stroke (Hester et al., 2006a)	Classification accuracy (Hester et al., 2006a,b)
Hair combing	Duration	Stroke (Lemmens et al., 2015; Roy et al., 2009)	Classification accuracy (Lemmens et al., 2015; Roy et al., 2009)
Eating	Duration	Parkinson's disease (Jalloul et al., 2016), stroke (Lemmens et al., 2015), miscellaneous (Seiter et al., 2015)	Classification accuracy (Jalloul et al., 2016; Lemmens et al., 2015; Seiter et al., 2015)

Drinking	Duration	Stroke (Lemmens et al., 2015)	Classification accuracy (Lemmens et al., 2015)
Tooth brushing, shirt buttoning, pant lifting, food cutting	Duration	Stroke (Roy et al., 2009)	Classification accuracy (Roy et al., 2009)

Table 3.5 – Activity classes and sensor placement of the statistical machine learning approaches.

First author	# of classes	Names of classes	# of sensors	Sensor positions	Type of sensors
(Ahmadi et al., 2018)	4	Sedentary (lying & sitting), standing, comfortable walking, and brisk walking	2	Pelvis and forearm (dominant side)	ACC
(Albert et al., 2012)	4	Lying, sitting, standing, and walking	1	Pelvis	ACC
(Albert et al., 2017a; Sok et al., 2018)	6	Lying, sitting, standing, walking, stair climbing, and wheeling	1	Pelvis	ACC
(Andreu-Perez et al., 2017)	10	Lying, sitting, standing, lying-to-sitting, sitting-to-lying, lying-standing, standing-to-lying, sitting-to-standing, standing-to-sitting, and walking	1	Pelvis	ACC
(Biswas et al., 2015b, 2017)	3	Reaching & retrieving, lifting cup to mouth, and pouring & (un)locking	1	Forearm (affected side)	ACC & GYRO
(Brogioli et al., 2016; Popp et al., 2016)	2	Passive and active wheeling	4	Trunk, forearm (bilateral), and wheelchair	ACC & GYRO
(Capela et al., 2016)	6	Lying, sitting, standing, walking, stair climbing, and activities of daily living	1	Pelvis	ACC
(Capela et al., 2015)	6	Lying, sitting, standing, walking, stair climbing, and activities of daily living	1	Pelvis	ACC & GYRO
(Cheng et al., 2018)	6	Lying, sitting, standing, walking, stair climbing, and running	1	Pelvis	ACC & GYRO
(Ding et al., 2011)	4	Static, non-wheeling activity, passive wheeling, and active wheeling	2	Forearm (dominant side) and wheelchair	ACC (forearm) & RS (wheelchair)
(Fortune et al., 2019)	3	Static, non-wheeling activity, and active wheeling	3	Trunk and upper arm (bilateral)	ACC & GYRO
(García-Massó et al., 2015)	5	Sedentary (lying, sitting, and passive wheeling), transferring while sitting, active wheeling, housework, and arm-ergometer	2	Forearm (bilateral)	ACC
(Hester et al., 2006b)	10	Walking, walking on uneven surfaces, walking up a ramp, walking down a ramp, stair climbing up, stair climbing down, walking over an object, turning, walking while carrying an object, and opening a door	5	Forearm (bilateral), shank (bilateral), and walking aid	ACC & GYRO
(Hester et al., 2006a)	10	Walking, walking on uneven surfaces, walking up a ramp, walking down a ramp, stair climbing up, stair climbing down, walking over an object, turning, walking while carrying an object, and opening a door	2	Shank (right) and walking aid	ACC
(Hiremath et al., 2015)	7	Static, passive wheeling, active wheeling, housework, activities of daily living, arm-ergometer, and playing basketball	3	Upper arm (dominant side), forearm (dominant side), and wheelchair	ACC (upper arm & forearm) & GYRO (wheelchair)
(Jalloul et al., 2016)	7	Lying, sitting, standing, walking, eating, writing, and reading	6	Neck, upper arm (unilateral), forearm (unilateral), pelvis, thigh (unilateral), and shank (unilateral)	ACC & GYRO & MAG

(Kiani et al., 1997, 1998)	6	Lying, sitting, standing, transitions, walking, and unlabeled	3	Trunk, thigh (left & right)	ACC
(Laudanski et al., 2015)	5	Walking, stair climbing up (step over step), stair climbing up (step by step), stair climbing down (step over step), and stair climbing down (step by step)	2	Shank (bilateral)	ACC & GYRO
(Leuenberger et al., 2014)	3	Walking, stair climbing up, and stair climbing down	5	Trunk, forearm (bilateral), and shank (bilateral)	ACC & BARO
(Lonini et al., 2016)	5	Sitting, standing, walking, stair climbing up, and stair climbing down	1	Pelvis	ACC
(O'Brien et al., 2017)	6	Lying, sitting, standing, walking, stair climbing up, and stair climbing down	1	Pelvis	ACC & GYRO & BARO
(Popp et al., 2019)	4	Sedentary, low intensity, high intensity, and walking	3	Trunk, forearm (affected side), and shank (non-affected side)	GYRO & BARO
(Popp et al., 2018)	3	Low intensity, high intensity, and active wheeling	4	Trunk, forearm (bilateral), and wheelchair	ACC & GYRO
(Recher et al., 2018)	7	Sitting, standing, sitting-to-standing, standing-to-sitting, walking sideways, stair climbing, and moving objects	8	Trunk, pelvis, thigh (bilateral), shank (bilateral), and foot (bilateral)	ACC & GYRO & MAG
(Roy et al., 2009)	11	Supine-to-sitting, sitting, sitting-to-standing, walking, tooth brushing, hair combing, bowel movement, shirt buttoning, pant lifting, food cutting, and food lifting	8	Abdomen, lower back (bilateral), upper arm (bilateral), forearm (bilateral), thigh (affected side)	ACC
(Seiter et al., 2015)	6	Resting (lying & sitting), eating & leisure, cognitive training, medical fitness, kitchen work, and motor training	3	Forearm (bilateral) and thigh (non-affected side)	ACC
(Teknomo and Estuar, 2015)	4	Sitting, walking, stair climbing, and running	1	Shank (non-affected side)	ACC
(Wade et al., 2015)	4	Sitting, standing, walking, and stair climbing	5	Pelvis, thigh (bilateral), shank (bilateral)	ACC
(Wu et al., 2016; Xu et al., 2011)	1	Walking	2	Shank (bilateral)	ACC

number, ACC accelerometer, BARO barometric pressure sensor, GYRO gyroscope, MAG magnetometer, RS reed switch.

3.5 Discussion

This systematic review focused on the application of inertial sensor technologies to quantify everyday life motor activity in people with mobility impairments and provides an overview of existing outcome measures. It, further, describes the concepts of the underlying data processing algorithms as well as the types and placements of required sensors to derive these measures and, eventually, lists the designs and populations of all studies that evaluated the measures in terms of validity, reproducibility, and usability.

The included studies of this review covered a large variety of outcome measures and underlying data processing algorithms which can be grouped into four categories: (1) maintaining and changing a body position, (2) walking and moving, (3) moving around using a wheelchair, and (4) activities that involve the upper extremity. The validity or reproducibility of these outcomes measures was investigated in fourteen different patient populations, of which the majority comprised stroke survivors, patients with Parkinson's disease, and patients with spinal cord injury. Most of the studies evaluated the algorithm's accuracy to detect certain activities in unlabeled raw data, while others evaluated the outcome measures in terms of concurrent validity, discriminant validity, or reproducibility or applied them in an interventional or observational study. The type and placement of required sensor technologies depends on the activity and outcome measure and are thoroughly described in this review. The reproducibility of the outcome measures and the usability of the applied sensor setups were rarely reported.

This review is limited to applications of wearable inertial sensors that were optionally combined with other sensor technology. However, among the included articles, there were two measurement tools that have the potential to monitor everyday life motor activities without combining it with inertial sensors: insoles with force-sensitive sensors (Fulk and Sazonov, 2011; Fulk et al., 2012; Hegde et al., 2017; Pappas et al., 2001; Sazonov et al., 2009; Zhang et al., 2013) and first-person cameras (Zhan et al., 2015; Zhang et al., 2019). Even though instrumented insoles are reliable gait phase detectors (Pappas et al., 2001), their applicability for long-term measurements in daily life is limited since the user might change or take off the footwear during the measurement period, which in turn would lead to biased outcome measures. First-person cameras might be superior to inertial sensors from a technological perspective since they also provide information about the user's environment and social interactions (Tong et al., 2020). However, the application of wearable cameras in daily life also raises ethical questions, and it remains to be seen whether this technology will be accepted by the end-users and the community. Other technologies, such as external cameras, pressure-sensitive walkways, or instrumented furniture, could be used to quantify motor activities in daily life. Even though these technologies would allow for an in-depth analysis of motor activities, they are all limited to a specific area and, therefore, not feasible to monitor the patients' activities throughout the day. Consequently, we are still convinced that wearable inertial sensors are the preferred measurement tool to monitor everyday life motor activities in patients with mobility impairments. Amongst wearable sensors, accelerometers were the preferred technology in the articles of this review. Compared to gyroscopes, accelerometers do have a considerably lower power consumption (Leuenberger and Gassert, 2011) and are not susceptible to drift (Lowe and Ólaighin, 2014), which might explain their preference for unobtrusive long-term measurements in daily life.

The search strategy and eligibility criteria of this review were designed to get an overview of all reproducibly described algorithms that process unlabeled raw data of everyday life measurements into clinically meaningful outcome measures. Despite this systematic search, there are three reasons why the algorithms and outcome measures of this review are incomplete. First, proprietary algorithms of commercial devices and insufficiently described algorithms were not considered in this review, even though they might determine clinically meaningful outcome measures. Transparency of scientific methods (including the data processing algorithm) enables other researchers to interpret the results, to validate the method, and to replicate the study, which is essential to the development and evolution of science (National Academies of Sciences, Engineering, and Medicine, 2019). We, therefore, encourage the scientific community to use open-source algorithms or at least describe the used algorithm reproducibly. Second, only algorithms that are applicable to unlabeled raw data were included in this review, and, especially in the field of gait analysis, there are many algorithms available that determine a clinically meaningful outcome measure out of labeled walking trials (Vienne et al., 2017). These algorithms could be combined with an activity/walking detection algorithm and, thus, extend the variety of outcome measures to quantify everyday life motor activities. And third, algorithms that were evaluated in healthy subjects were not considered in this review, but might as well provide clinically meaningful outcome measures. However, whether these algorithms also work correctly in patients with mobility impairments, has to be shown in future research.

Neither a quality assessment of the included studies nor a meta-analysis regarding the accuracy or reproducibility of the described algorithms and outcome measures were conducted in this review. Although we acknowledge the benefit of these analyses, they are not feasible for the current review due to missing standards to assess the quality of activity classification studies and due to the large heterogeneity of the methods and data reporting of the studies. For example, we included two studies that evaluated an algorithm to detect walking and stair climbing in stroke survivors (Capela et al., 2016; Leuenberger et al., 2014). Even though these studies had a similar study population and study design, their algorithms' performance is still not comparable since their algorithms detected three and six activities, respectively, and the authors chose different metrics to report their results. One study reported sensitivity and specificity, while the other study reported F-scores. This example demonstrates the difficulty of determining which algorithms are superior, and the comparability between studies is even more complicated when the study population and study designs differ. We, therefore, encourage the scientific community to develop a standard to conduct such studies and to report the results consistently. We suggest that the study protocol either contains observations of the patients' daily motor activities in their habitual environment or an activity circuit that resembles everyday life and comprises activities not classified by the algorithm. We further recommend that the confusion matrix is reported, which allows determining a large variety of statistical measures to quantify the algorithm's performance. Moreover, we would like to point out the difference between measurement error and activity classification accuracy. Detecting sitting position with an accuracy of 90%, for example, does not necessarily mean that the error of estimating the sitting duration of a 24-hour measurement is 10%. In fact, a balanced occurrence of false positive and false negative detections would lead to a much smaller error. Although the measurement error is essential for future applications of the algorithm to daily life data, it is rarely reported in the literature. Therefore, we recommend future studies to determine the measurement error of their outcome measures instead of just reporting the activity classification accuracy.

The usability of wearable inertial sensors was hardly ever assessed or at least not reported in the studies of this review article. This finding is somewhat surprising since the end user's compliance and acceptance to wear the sensors throughout the measurement period is crucial to get comprehensive and unbiased data of the end user's motor activities in daily life. We believe that the usability of the sensor system depends predominantly on the number and size of sensors, on the location of sensor placement, and on how the sensors are attached to the body. Moreover, low usability of the sensor system might also interfere with the end-user's behavior in daily life. However, this has yet to be shown, and we, therefore, recommend that future studies consequently report the wearing time and the obtrusiveness of their sensor system.

3.6 Conclusions

This systematic review provides a comprehensive overview of applications of wearable inertial sensors to quantify everyday life motor activity in people with mobility impairments. It lists activities and outcome measures that have been covered in the literature and describes the concepts of the underlying data processing algorithms as well as the required sensor technologies. It, further, tabulates the study populations and the study designs of the included articles. This review, therefore, summarizes the state-of-the-art of existing sensor applications, it provides quick access to the relevant literature to the reader that is interested in quantifying certain activities in a specific patient population, and it enables the identification of gaps for the evaluation of existing and the development of new algorithms.

The studies of this review had a large methodological heterogeneity and reported their results inconsistently. This made it impossible to quantify and compare the validity, reproducibility, and usability of different sensor technologies, its underlying algorithms, and their outcome measures. Thus, this review neither provides recommendations about the favored type and placement of sensor technologies, nor a synthesis about the performance of different algorithms. Therefore, we recommend that future studies follow a standardized protocol and use consistent metrics to report their results.

In the literature, wearable inertial sensors are the preferred technology to monitor everyday life motor activities in patients with mobility impairments. We further expect the use of this technology to evolve substantially as more and more valid algorithms become available for patient populations that can capture different facets of everyday life, as can be seen in the healthy population.

Clinical needs Part II

4 Mobility and self-care goals of a heterogeneous pediatric population undergoing inpatient rehabilitation

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This is the peer reviewed version of the following article: Rast, F. M., & Labruyère, R. (2020). ICF mobility and self-care goals of children in inpatient rehabilitation. Developmental Medicine & Child Neurology, 62(4), 483–488, which has been published in final form at https://doi.org/10.1111/dmcn.14471. This article may be used for non-commercial purposes in accordance with Wiley Terms and Conditions for Use of Self-Archived Versions. This article may not be enhanced, enriched or otherwise transformed into a derivative work, without express permission from Wiley or by statutory rights under applicable legislation. Copyright notices must not be removed, obscured or modified. The article must be linked to Wiley's version of record on Wiley Online Library and any embedding, framing or otherwise making available the article or pages thereof by third parties from platforms, services and websites other than Wiley Online Library must be prohibited.

4.1 Abstract

Aim To devise a detailed priority list of family-centered rehabilitation goals on the activity level within the International Classification of Functioning, Disability and Health (ICF)-chapters "d4 Mobility" and "d5 Self-care" in a pediatric population with a broad range of health conditions.

Method Twenty-two months after implementing a systematic family-centered goal-setting process, rehabilitation goals of 212 inpatients were retrospectively allocated to the most detailed level of ICF categories by two independent researchers. The overall frequencies of these goals were calculated and stratified by health condition, functional independence, and age.

Results Ninety-three girls and 119 boys were included. Their mean age was 10 years and 9 months (SD: 4 years and 5 months). The five most frequent rehabilitation goals were "d4500 (ICF code) Walking short distances" (11%), "d4200 Transferring oneself while sitting" (9%), "d5400 Putting on clothes" (7%), "d451 Going up and down stairs" (6%), and "d4153 Maintaining a sitting position" (5%). These top goals varied in subgroups regarding the underlying health condition, functional independence, and age.

Interpretation The findings of this study are not generalizable due to the large heterogeneity in priorities. However, they can be used to incorporate families' needs into future research designs and the development of new technologies.

4.2 Introduction

The International Classification of Functioning, Disability, and Health (ICF) serves as a framework for describing functional health as the interaction between a person's physical or mental condition (level of body functions and body structures) and their ability to master everyday activities (activity level) as well as their involvement in life situations (participation level). Thus, disability and functioning are seen as an interactive and developing process that can be influenced on any of these levels (World Health Organization, 2001). In a rehabilitation context, the ICF framework can also be used for goal-setting, which is known to be effective for both understanding and changing human behavior (Eccles and Wigfield, 2002; Locke and Latham, 2002; Ostensjø et al., 2008). Furthermore, clear and functional goals enhance motivation and lead to improved outcomes (Eccles and Wigfield, 2002; Locke and Latham, 2002). In pediatric rehabilitation, collaborative goal-setting as part of a family-centered approach is widely advocated nowadays (An and Palisano, 2014; Nijhuis et al., 2008; King and Chiarello, 2014) and with it, the focus shifts from reducing impairments on the level of body functions to the children's participation in everyday activities (Brogren Carlberg and Löwing, 2013; Law and Darrah, 2014). This shift can also be seen in inpatient rehabilitation, where the emphasis now lies on reducing activity limitations with an effort to improve participation rather than on the body functions/structures level (Rosenbaum and Gorter, 2012). The main goal of inpatient rehabilitation is the increase of independence, a key to which are primarily those activities concerning mobility (ICF-chapter: d4) and self-care (ICF-chapter: d5) (Smits et al., 2019). Goals set within these ICF-chapters and their achievement might be an essential prerequisite for tackling goals at the participation level (Park and Kim, 2015), but can also positively affect the body functions/structures level ("backwards direction of connections") (Rosenbaum and Gorter, 2012). But what are relevant goals in this area in the heterogeneous, clinical pediatric population that we see in our rehabilitation centers? There are a number of publications describing the priorities and needs on the ICF-levels activity and participation among families of children with cerebral palsy (Chiarello et al., 2010; Law et al., 1998; Ostensjø et al., 2008) and of children with a broad range of health conditions (Verkerk et al., 2006). However, they mostly report their results on the superordinate ICF chapter-level (e.g., self-care, mobility, communication, etc.) or block-level (e.g., for the chapter "d4 Mobility": Changing and maintaining body position; Carrying, moving and handling objects; Walking and moving; Moving around using transportation). The primary aim of this study was to devise a detailed priority list of family-centered rehabilitation goals on the activity level within the ICF-chapters "d4 Mobility" and "d5 Self-care" in a pediatric population with a broad range of health conditions. The secondary aim was to investigate how this priority list depends on the children's health condition, level of functional independence, and age.

4.3 Method

In 2017, a systematic, family-centered goal-setting process was implemented at our rehabilitation center. Families visit our facilities before admission of the child/adolescent, and preliminary, attainable goals are discussed between families and a physician. At admission, families' needs and expectations are inquired during an interview with a standardized form. This form covers each domain of the ICF, and rehabilitation goals are formulated if appropriate. The results of this interview serve as a basis for establishing a tailored rehabilitation program. After approximately one week, an interdisciplinary team of physicians, nurses, therapists, psychologists, and teachers determines the final rehabilitation goals by incorporating families' needs and expectations, predetermined goals of the referring physician, medical history of the patient as well as observations and assessments during the first days of rehabilitation. Goal formulation follows specific, measurable, assignable, realistic, and time-related (SMART) criteria (Doran, 1981), uses positive language and considers resources and economic perspectives. For each patient, long-term goals are defined on the ICF participation level, which guide the subsequent goal-setting process. Middle-term and short-term goals are set on activity and body functions/structures levels, respectively. This study specifically addressed the middle-term goals on the activity level regarding mobility and self-care. Every other week, all rehabilitation goals are appraised by an interdisciplinary team and updated if necessary. Moreover, further interviews between families and health professionals can be demanded by both stakeholders to adapt rehabilitation goals accordingly. All personnel were trained in the implementation of the standardized goal-setting process.

4.3.1 Study population

Rehabilitation goals from all inpatients that stayed at the Rehabilitation Center for Children and Adolescents in Affoltern am Albis, Switzerland between January 2017 and October 2018 were retrospectively examined. Severe disability, surgery, or deteriorating functioning are exemplary reasons for inpatient rehabilitation at our center. Only infants and those without a signed consent were excluded from this study. Medical diagnoses were coded according to the WeeFIM II® impairment groups (e.g., stroke, brain dysfunction, neurological disorders, etc.) of the Uniform Data System for Medical Rehabilitation (UDSMR) (Uniform Data System for Medical Rehabilitation, 2016) by a trained research nurse. These impairment groups reflect the patients' primary health condition that led to rehabilitation admission. Brain dysfunction includes traumatic and non-traumatic acquired brain injuries and will be termed accordingly in this article. At admission, the functional independence of all participants was assessed with the Functional Independence Measure for Children (WeeFIM II®) by a trained nurse. The WeeFIM II® is an 18-item instrument to measure the daily life performance of children in three domains (self-care, mobility, and cognition). Each item is rated from 1 = total assistance to 7 = complete independence. The total score was normalized with the corresponding age-based normative score to obtain the Developmental Functional Quotient (WeeFIM_DFQ) (Tailor et al., 2013). Age-appropriate functioning is, therefore, reflected with a score of 100%.

4.3.2 Data processing

Two independent researchers coded all rehabilitation goals according to the ICF-blocks as well as the second and third levels of the ICF list of activities. The English version of the ICF 2018 was used as a reference with two additional sets of categories: (1) "d410 Changing a body position" was coded by determining both the starting and end position (e.g., "d4108 Sitting <=> standing"); (2) "d415 Maintaining a body position" was subclassified into "active" (e.g., sitting at the edge of the bed for 30 s) and "passive" (e.g., finding a comfortable sitting position in the wheelchair that can be maintained for four hours). Further, there is an overlap between the ICF categories "d4500 Walking short distances", "d4501 Walking long distances", and "d460 Moving around in different locations". Walking short and long distances are not only distinguished by the distance itself (the cut-off is at one kilometer) but also by the environment. Walking within a building belongs to walking short distances. Likewise, walking outdoors is part of walking long distances. Environmental aspects were, therefore, already covered by using these two categories and "d460 Moving around in different locations" was strictly ignored in this study. Disagreements between the two researchers were resolved through discussion and consensus. Finally, the frequencies of rehabilitation goals were counted for the overall study population as well as separately for children and adolescents with cerebral palsy and those with an acquired brain injury. Differences between these two subgroups regarding gender distribution, age at admission and duration of stay, as well as their WeeFIM_DFQ scores were statistically analyzed with the Fisher's exact test, the two-sample t-test, and the Wilcoxon rank-sum test. Besides, the whole study population was divided into subgroups regarding their level of functional independence (WeeFIM_DFQ ≤ 50%, WeeFIM_DFQ > 50%) and age (<6 years, 6-11 years, and >12 years). The WeeFIM_DFQ and a cutoff of 50% were chosen to make an age-independent distinction between high and low levels of functioning. The age groups were chosen to ensure comparability with previous research (Chiarello et al., 2010). The frequencies of rehabilitation goals were obtained for each subgroup. Descriptive statistics were used to explore the influence of the children's health condition, level of functional independence, and age on the priority of rehabilitation goals. This study was approved by the local ethics committee (BASEC Nr. 2018-01406).

4.4 Results

Two hundred eighty inpatients were screened for eligibility, and 196 fulfilled the inclusion criteria. Sixty-seven inpatients did not provide a signed consent, seven were younger than two years old, and ten did not stay long enough to complete the goal-setting process. Sixteen of the included inpatients completed two rehabilitation programs within the specified period, which resulted in a total of 212 cases. Their mean age was 10 years and 9 months (SD: 4 years and 5 months). The distribution of gender, age at admission, duration of stay, health condition, and WeeFIM_DFQ of the study population are illustrated in **Figure 4.1**.

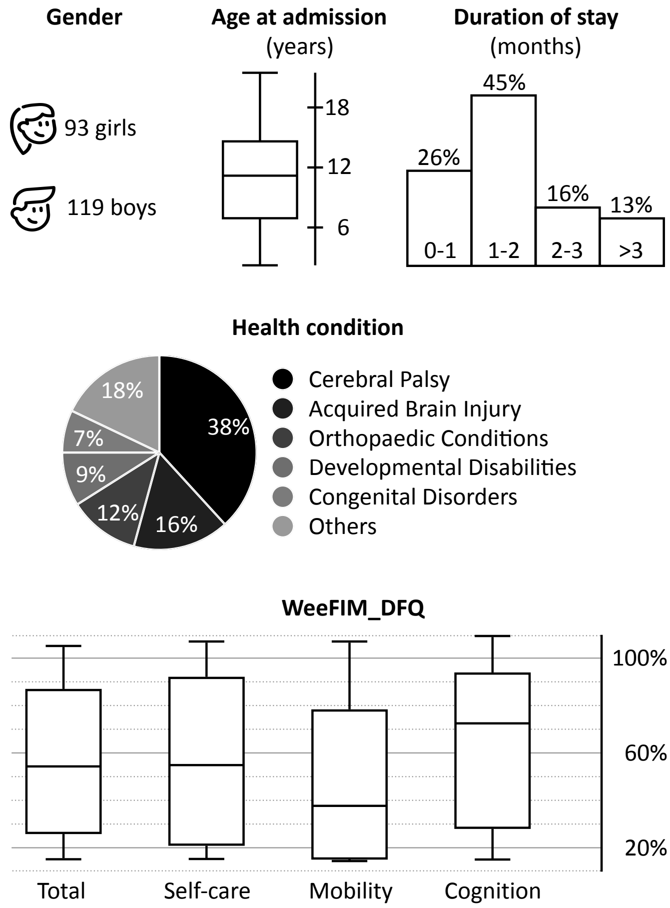
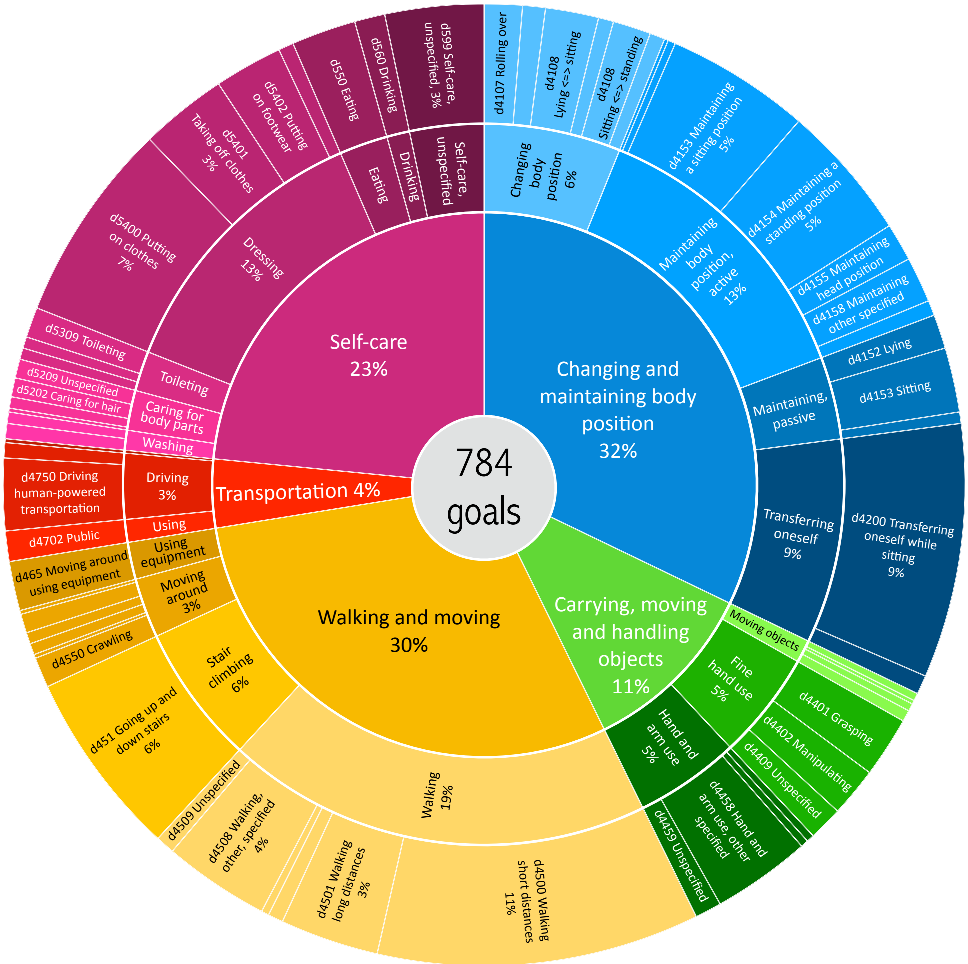


Figure 4.1 – The distribution of gender, age at admission, duration of stay, health condition, and WeeFIM_DFQ of the study population. WeeFIM_DFQ, age-normalized measure of functional independence for children (values >100% are possible and mean that children exceed the expected score for their age).

Overall, 784 rehabilitation goals were allocated to 63 different ICF categories and the five most frequent categories were "d4500 Walking short distances" (11%), "d4200 Transferring oneself while sitting" (9%), "d5400 Putting on clothes" (7%), "d451 Going up and down stairs" (6%), and "d4153 Maintaining a sitting position" (5%). The percentage reflects the number of goals in a specific category in relation to the total number of goals. It does not correspond to the percentage of children that had a goal in a specific category since children had three to four goals on average, and in some cases, more than one goal in the same category. The frequencies of all rehabilitation goals regarding mobility and self-care are visualized in **Figure 4.2**. The two largest subgroups regarding health condition were cerebral palsy and acquired brain injury comprising 38% and 16% of all children and adolescents, respectively. Their characteristics are shown in **Table 4.1**, while their top goals and those of the different subgroups regarding functional independence and age are depicted at the bottom of **Figure 4.2**. A complete list of all ICF categories and the corresponding number of rehabilitation goals is provided



Top 5 goals subdivided according to **impairment groups**

	All children (n=212)		Cerebral Palsy (n=81)		Acquired Brain Injury (n=34)	
1	Walking short distar	11%	Walking short distances	10%	Walking short distances	11%
2	Transfer while sitting	9%	Transfer while sitting	9%	Going up and down stairs	9%
3	Putting on clothes	7%	Putting on clothes	7%	Self-care, unspecified	6%
4	Going up and down	6%	Maintaining standing po	5%	Hand and arm use, other	6%
5	Maintaining sitting p	5%	Walking, other specified	5%	Walking long distances	5%

Top 3 goals subdivided according to **age** and **WeeFIM_DFQ** score

	< 6 years & WeeFIM_DFQ > 50% (n=11)		6-11 years & WeeFIM_DFQ > 50% (n=40)		> 12 years & WeeFIM _DFQ> 50% (n=66)	
1	Walking long distanc	10%	Walking short distances	14%	Walking short distances	15%
2	Putting on clothes	10%	Putting on clothes	11%	Transfer while sitting	8%
3	Six categories[1]	6%	Walking, other specified	7%	Going up and down stairs	8%

	< 6 years & WeeFIM_DFQ ≤ 50% (n=33)		6-11 years & WeeFIM _DFQ ≤ 50% (n=31)		> 12 years & WeeFIM_DFQ ≤ 50% (n=31)	
1	Maintaining sitting p	10%	Transfer while sitting	14%	Transfer while sitting	13%
2	Transfer while sitting	8%	Maintaining sitting posi	7%	Walking short distances	11%
3	Maintaining standin	7%	Two categories[2]	6%	Going up and down stairs	7%

[1]Maintaining a standing position, Maintaining a sitting position, Crawling, Hand and arm use, unspecified, Hand and arm use, other & Walking, other specified.
[2]Walking short distances & Going up and down stairs.
WeeFIM_DFQ = age-normalized measure of functional independence for children.

Figure 4.2 – The overall frequency distribution of all rehabilitation goals. The inner circle of the pie chart corresponds to the block categories of the International Classification of Functioning, Disability, and Health (ICF), while the mid and outer circle correspond to the second and third level of the ICF, respectively. The missing labels of the pie chart are listed in Appendix B. The table shows the top five goals of all children, children with cerebral palsy and those with an acquired brain injury as well as top three goals of three different age groups and two levels of functional independence.

in Appendix B. There are a few ICF categories of which the content is quite broad, but the allocated goals of the current study population were very specific. “d4450 Hand and arm use, other specified“ contains goals exclusively to improve the ability to use the more-affected hand in bimanual activities. This rehabilitation goal was the most frequent goal of the ICF-block “Carrying, moving and handling objects“. “d465 Moving around using equipment“ and “d4750 Driving human-powered transportation“ predominantly contain rehabilitation goals to improve wheelchair skills and riding a bicycle, respectively. And finally, goals of the category “d599 Self-care unspecified“ were formulated as improving independence in activities of daily living without specifying the activity itself.

Table 4.1 – Characteristics of the subgroups cerebral palsy and acquired brain injury as well as a between-group comparison.

	Cerebral palsy (n=81)	**Acquired brain injury (n=34)**	**p-value**
Girls / boys	42 / 39	8 / 26	0.01[a]
Age: mean ± SD	10 y and 9 mo ± 4 y and 2 mo	9 y and 9 mo ± 4 y and 7 mo	0.25[b]
Duration of stay: mean ± SD	42 ± 20 days	97 ± 99 days	<0.01[b]
WeeFIM_DFQ			
Total: median [iqr]	53% [61%]	74% [53%]	0.03[c]
Self-care: median [iqr]	44% [67%]	79% [67%]	0.03[c]
Mobility: median [iqr]	35% [55%]	73% [72%]	0.01[c]
Cognition: median [iqr]	72% [58%]	74% [53%]	0.30[c]

Between-group difference: [a]Fisher’s exact test, [b]Two-sample t-test, [c]Wilcoxon rank-sum test; SD, standard deviation; y, year; mo, month; WeeFIM_DFQ, age-normalized measure of functional independence for children (values >100% are possible and mean that children exceed the expected score for their age); iqr, interquartile range.

4.5 Discussion

This study provides a detailed priority list of family-centered rehabilitation goals on the activity level regarding mobility and self-care in a heterogeneous pediatric inpatient population. Walking was the most frequent goal with walking short distances having a higher priority than walking long distances. The second most frequent goal was actively maintaining a body position with standing and sitting having the highest priority within this category. Dressing was far more frequent than other self-care activities, and putting on clothes had the third-highest priority of all categories. Transfers and stair climbing were the fourth and fifth most frequent categories, respectively. Moving around using transportation as well as carrying, moving, and handling objects were the two ICF-blocks with the lowest priority in our study population. Rehabilitation goals were defined on 63 different activities, and the percentage of the most frequent goals was not greater than 11%. This demonstrates the large heterogeneity of rehabilitation goals and underlines that goals need to be assessed individually for each child.

4.5.1 Cerebral palsy and acquired brain injury

Children and adolescents with cerebral palsy had similar priorities compared to the overall pediatric population, which is most likely due to the large sample size of this subgroup. Still, other walking activities appeared in the top five goals of children with cerebral palsy, while stair climbing did not. Rehabilitation goals that were allocated to “d4508 Walking other, specified“ consisted of the improvement of the gait pattern (e.g., walking with an upright posture) as well as walking safely with and without assistive devices. Walking short distances had the highest priority in both children with cerebral palsy and those with an acquired brain injury. Apart from that, top goals differed remarkably between these two groups. Stair climbing was one of the top five goals in children with an acquired brain injury while it did not appear in the top goals of children with cerebral palsy. The opposite holds for the goals to improve in transferring and standing. However, these differences are rather explained by the level of functional independence than the underlying health condition, since the acquired brain injury group presented significantly higher levels of functional independence at admission compared to the cerebral palsy group. Further, there was a notable difference in self-care goals between these groups in our study population. Improving the ability to put on clothes was a top goal of children with cerebral palsy, while children with an acquired brain injury had the increase of independence in a broader range of self-care activities as one of their top goals. This might highlight the desire of families to regain the same level of independence in all self-care activities as before the brain injury. Dressing being the most frequent self-care goal in children with cerebral palsy was also observed in a previous study and might be explained by the time-consuming aspect of this activity in the daily routine of these families (Chiarello et al., 2010). Nonetheless, the differences found in this study, were not tested statistically and could also be explained by other factors that were not included in our analysis, and incorporating environmental factors (e.g., family support) or body functions (e.g., pain) might have led to different interpretations.

4.5.2 Functional independence and age

In our study population, we observed that the top three goals varied concerning the children’s level of functional independence and age. It appears that the abilities to maintain a sitting and standing position are more important in young patients with low levels of functional independence, while walking and stair climbing seems to be prioritized in older patients with higher levels of functional independence. The priority list could be influenced by the children’s ability to express their priorities. There is growing evidence that children above five years of developmental cognitive age have this ability (Costa et al., 2017), and this might partially explain the age group difference in this study. Another explanation of the age- and functioning-dependent priority differences could be the fact that the ability to sit and stand freely facilitates daily routines which are more often carried out by parents and caregivers in young and more severely affected patients. Dressing was a top goal of children with high levels of functional independence under 12 years of age, while it was not in the other groups.

Typically developing six-year-old children are often able to dress themselves independently (Summers et al., 2008), and the gained independence of typically developing peers might explain the increased priority of putting on clothes at that age. This age-dependency was also observed in a previous study that investigated family priorities of self-care activities in children with cerebral palsy (Chiarello et al., 2010). The frequency of goals to improve transfers, however, seems to be related to the level of functional independence rather than age. Still, transferring had the second-highest priority in older children with high levels of functional independence. We expect that the number of children that use a wheelchair to cover longer distances and are ambulatory at home increases with age and might explain this finding. The group consisting of young patients with high levels of functional independence had only a small sample size (n=11) and this, therefore, limits the external validity of their top goals. Again, the differences found in this study are observational, and future studies tackling this subject would profit from rigorous statistical testing.

4.5.3 Limitations and outlook

One limitation of the current study is the fact that the frequency of rehabilitation goals depends heavily on the specificity of the ICF categories. For example, dressing and eating are activities on the second ICF-level, and dressing contains five explicit sub-categories while eating is not further subclassified. Moreover, putting on clothes and taking them off was often part of the same goal expression and consequently allocated to both sub-categories. This, in turn, led to twice as many goals in the dressing category as there would have been without the existence of sub-categories. However, we chose to use the ICF as a framework for our study since it is a standardized and widely-used classification system. Still, we added two sets of categories that are described in the method section. These changes reduced the frequency of the sub-categories for the same reason as described above, but we are convinced that these changes improved the clinical meaningfulness of our results, since the categories are more precise. Furthermore, the linking of rehabilitation goals to the corresponding ICF category depends on the person that conducts the linking. We, therefore, recommend using published linking rules (Cieza et al., 2019) in future studies. Another issue in patients with longer durations of inpatient rehabilitation is that goals could have changed over time, and we decided to include these changes as separate goals in our study. Hence, a single patient could have had several goals in the same category, which in turn increased the frequency of that category. The impact of rehabilitation duration on the priority list requires statistical analysis and should be addressed in future research with larger sample sizes. And lastly, the current study only addressed ICF-chapters mobility and self-care. We, therefore, recommend that future research should investigate family priorities on the remaining chapters of the ICF activity level and incorporate potential confounders, such as pain, cognitive functions and a variety of environmental barriers and facilitators, to get a comprehensive understanding of families' expectations and goals of pediatric rehabilitation.

4.5.4 Conclusion

This study provides a detailed priority list of mobility and self-care goals in a pediatric population undergoing inpatient rehabilitation. The results demonstrate a large heterogeneity of rehabilitation goals, and underline that goals need to be assessed individually for each child, irrespective of the health condition or factors like age or functional independence. And still, the findings of our study can be used to incorporate families' need into the design of future research projects and the development of new technologies.

5 Clinical relevance of sensor-based outcomes to monitor everyday life motor activities of children and adolescents with neuromotor impairments: a survey with health professionals

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5.1 Abstract

In combination with appropriate data processing algorithms, wearable inertial sensors enable the measurement of motor activities in children's and adolescents' habitual environments after rehabilitation. However, existing algorithms were predominantly designed for adult patients, and their outcomes might not be relevant for a pediatric population. In this study, we identified the needs of pediatric rehabilitation to create the basis for developing new algorithms that derive clinically relevant outcomes for children and adolescents with neuromotor impairments. We conducted an international survey with health professionals of pediatric neurorehabilitation centers, provided them a list of 34 outcome measures currently used in the literature, and asked them to rate the clinical relevance of these measures for a pediatric population. The survey was completed by 62 therapists, 16 doctors, and 9 nurses of 16 different pediatric neurorehabilitation centers from Switzerland, Germany, and Austria. They had an average work experience of 13 ± 10 years. The most relevant outcome measures were the duration of lying, sitting, and standing positions; the amount of active self-propulsion during wheeling periods; the hand use laterality; and the duration, distance, and speed of walking periods. The health profession, work experience, and workplace had a minimal impact on the priorities of health professionals. Eventually, we complemented the survey findings with the family priorities of a previous study to provide developers with the clinically most relevant outcomes to monitor everyday life motor activities of children and adolescents with neuromotor impairments.

5.2 Introduction

In pediatric neurorehabilitation, children and adolescents with congenital and acquired illnesses and injuries of the developing brain are treated and cared for. These children and adolescents often present neurological impairments that result in difficulties in executing everyday life motor tasks, such as walking to school, grasping a glass of water, or transferring from a wheelchair to a car seat. They undergo intensive therapy programs as in- or out-patients with the emphasis on reducing these limitations and fostering their functional independence in everyday life. Here, motor assessments are essential for developing a patient-centered therapy plan, monitoring the children's progress over time, and providing families with objective information. These assessments are usually conducted at the clinic in a standardized environment. However, after discharge (in-patients) or between therapy sessions (out-patients), the children's social and environmental factors become more important. Hence, it remains unclear whether children can translate their improvements during rehabilitation into everyday life at home or school. Assessing the children's motor performance by measuring what children actually do in their habitual environment would overcome this limitation (Holsbeeke et al., 2009). Consequently, there is a need for scientifically sound tools to measure performance in children and adolescents with neuromotor impairments.

Today, motor performance is predominantly assessed with self- or proxy-report questionnaires, which are prone to recall or proxy bias (Clanchy et al., 2011a). Activity counts derived from body-worn accelerometers have been used as an objective and unbiased alternative to assess performance. While these counts provide valid estimates of total energy expenditure (Clanchy et al., 2011b) or non-specific hand use (Rast and Labruyère, 2022), they do not capture information about the type of performed activities (Rachele et al., 2012). In contrast, the use of multiple state-of-the-art motion sensor modules in combination with appropriate data processing algorithms would allow for the determination of activity-specific outcome measures (e.g., the time a child spent in a sitting position, the child's self-selected speed of walking periods, or how often a child was grasping an object in daily life, etc.). Over the years, a large variety of algorithms deriving different aspects of everyday life motor activities of people with mobility impairments have been developed (Rast and Labruyère, 2020c). However, the outcomes of these algorithms were predominantly designed for adult patient populations which triggers the question whether these outcomes are also relevant for children and adolescents with neurological impairments?

Even though it is technologically feasible to measure activity-specific outcomes with wearable sensor modules, it still requires the children's and adolescents' willingness to wear these devices in daily life. On the one hand, wearable sensors need to be comfortable, discreet, and unobtrusive to not affect daily behavior and to be accepted by the end-user (Bergmann and McGregor, 2011; Dan, 2020; Mackintosh et al., 2019). Consequently, there is a need to minimize the number of body-worn sensors. On the other hand, the amount of detail and accuracy of the sensor data correlates with the number of sensors that are worn in daily life (Dan, 2020; Ahmadi et al., 2018). Therefore, there is a trade-off between maximizing information and minimizing the number of sensors (Lang et al., 2020).

Developers of new algorithms that generate meaningful outcomes for children and adolescents with neurological impairments need to know the clinical needs of pediatric neurorehabilitation. With this information, developers can make decisions about the abovementioned trade-off. To determine the needs of children and families, we investigated their mobility and self-care rehabilitation goals on an activity level according to the International Classification of Functioning, Disability, and Health. The results of this study have been published elsewhere, and the five most frequent rehabilitation goals were walking short distances, transferring oneself while sitting, putting on clothes, going up and downstairs, and maintaining a sitting position (Rast and Labruyère, 2020a). In the current study, we aimed to complement the families' needs with the opinion of pediatric health professionals. We conducted a survey with doctors, nurses, and therapists of pediatric neurorehabilitation centers, provided them a list of outcome measures currently used in the literature (Rast and Labruyère, 2020c), and asked them to rate the clinical relevance of these measures for children and adolescents with neuromotor impairments. We aimed to provide a priority list of sensor-based outcomes for pediatric rehabilitation.

5.3 Materials and methods

5.3.1 Development and description of the survey

The survey comprised 34 items, each representing an outcome measuring the quantity or quality of a motor activity performed in daily life (**Table 5.1**). The items were derived from a systematic review providing an overview of all sensor-based outcome measures applied in people with mobility impairments (Rast and Labruyère, 2020c). Related items were grouped into categories, and each category contained a brief description of the outcomes and, if applicable, a graphical visualization of a fictitious measurement. An example of such a measurement is provided in **Figure 5.1**. At the end of each category, there was an open-ended question asking about possible other relevant outcomes not covered by the survey.

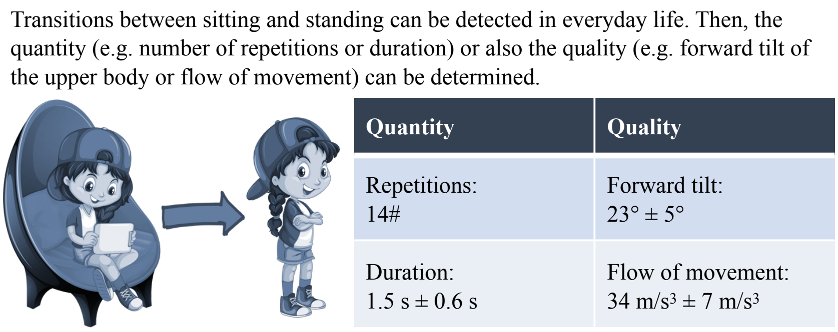

Figure 5.1 – An example of the presentation of two survey items: the quantity and quality of sit-to-stand transitions. The illustration was designed using resources from freepik.com.

Table 5.1 – Description and categorization of all 34 survey items.

ID	Item	Description
Arm and hand use		Upper limb movements can be measured separately for the left and right arm. This enables the quantification of the hand use laterality, the amount of unimanual and bimanual activities, and the diversity of upper limb movements.
1	Hand use (laterality)	
2	Hand use (uni-/bimanual)	
3	Hand use (diversity)	
Joint movement		Joint angles can also be measured. This can be used to quantify the number of repetitions and the range of motion of individual joints in everyday life.
4	Shoulder abd/add	
5	Elbow flex/ex	
6	Forearm pro/sup	
7	Wrist flex/ex	
8	Finger flex/ex	
9	Knee flex/ex	
Reaching & grasping		Reaching and grasping movements can be detected and evaluated in everyday life. This allows quantifying the number of repetitions as well as the range of reaching forward and sideward relative to the trunk.
10	Reaching (repetitions)	
11	Reaching (range)	
Maintaining a body position		Lying, sitting and standing can be recognized in everyday life and the duration a child spends in these body positions is measured. Lying can be subclassified as prone, supine, and side lying, and standing as upright, bending forward, or bending sideward.
12	Lying, sitting & standing	
13	Lying (prone/supine)	
14	Standing (upright/bent)	
Changing a body position		Transitions between sitting and standing can be detected in everyday life. Then, the quantity (e.g. number of repetitions or duration) or also the quality (e.g. forward tilt of the upper body or flow of movement) can be determined.
15	Standing up (quantity)	
16	Standing up (quality)	
Walking activity		Walking can be distinguished from other activities, and the daily walking activity can be divided into individual walking bouts. Then, the duration, distance and speed of these bouts can be determined.
17	Walking (duration)	
18	Walking (distance/speed)	
Gait parameters		Walking can be segmented into gait cycles which allows quantifying gait parameters such as step length, duration of the stance phase or step symmetry.
19	Walking (gait parameters)	
Risk of falling		From walking activities, different measures can be calculated that predict a child's risk of falling.
20	Risk of falling	
Walking (turning)		Obstacles or a side road can force a change of direction during walking activities. These turns can be analyzed regarding speed, angular change, number of steps, etc.
21	Walking (turning)	
Walking (slope)		The slope of covered walking routes can be measured which allows determining whether a child can walk in steep terrain. In addition, the gait pattern can be compared between level, uphill, and downhill walking.
22	Walking (slope)	
Stair climbing		Stair climbing periods and the covered number of steps can be recorded in everyday life (quantity). Furthermore, it can be distinguished between a step-by-step and a step-over-step pattern (quality).
23	Stair climbing (quantity)	
24	Stair climbing (quality)	
Use of walking aids		The use or non-use of assistive devices can be assessed for walking and other activities. Other measures, such as weight bearing or the orientation/position of the assistive device could be determined, too.
25	Use of walking aids	
Wheelchair		Wheeling activities can be detected and subclassified as passive wheeling (being pushed by a third person or a motor) or active self-propulsion. Furthermore, the covered distance and the speed can be determined.
26	Wheeling (active/passive)	
27	Wheeling (distance/speed)	
Activities of daily living		Various other activities of daily living can be detected, and the duration or the number of repetitions of these activities can be determined. Here, the activities were grouped because the possibilities are very diverse.
28	School activities	
29	Personal hygiene	
30	Dressing	
31	Eating & drinking	
32	Household activities	
33	Sports activities	
Energy expenditure		The intensity of physical activities can be measured and divided into three levels (low, medium and high intensity). This allows determining the daily energy expenditure.
34	Energy expenditure	

flex = flexion, ex = extension, pro = pronation, sup = supination, abd = abduction, add = adduction.

The participants were asked to rate the clinical relevance of each item/outcome measure on a four-point Likert scale, including the responses (1) very relevant, (2) relevant, (3) hardly relevant, and (4) not relevant for children with neuromotor impairments. Participants also had the possibility of not answering an item. At the beginning of the questionnaire, the participants were instructed to imagine that children or adolescents would wear a sensor system in their habitual environment, and the system would be able to derive the outcome measures described in the survey. Moreover, participants were asked to rate the clinical relevance from an interdisciplinary perspective.

We created the survey with the web application Findmind (https://findmind.ch). The content of the original survey is provided in Appendix C. The survey was pretested with a 28-year-old female physiotherapist, a 33-year-old male occupational therapist, and a 32-year-old female nurse to check and improve the clarity of the questions. Filling out the survey took roughly 15 min.

5.3.2 Distribution of the survey

The target populations were doctors, nurses, and therapists of pediatric neurorehabilitation centers in the German-speaking part of Europe. We sent the link of the online survey to the directors of 23 pediatric neurorehabilitation centers in Switzerland, Germany, and Austria. We asked them to forward this link to their medical, nursing, and therapy staff with the request to participate. We distributed the survey in April 2018, sent a reminder in May 2018, and closed the survey in August 2018.

The survey was password-protected to avoid unauthorized participation. The data collection was anonymous to protect the privacy of the participants, which in turn made it impossible to prevent multiple participation. The data was kept confidential and was encrypted with the Secure Socket Layer protocol.

5.3.3 Statistical analysis

For each item, the number of responses was counted for each response level. Then, missing values were imputed with the weighted mean of the k nearest-neighbors, with k being chosen as the number of participants. The estimates of the missing values were rounded to the nearest integer to reflect real responses.

The clinical relevance of the items was investigated with the median response and the mean rank. The mean rank was determined by ranking the responses of each participant and averaging the ranks of all participants for each item. The ranks were adjusted for ties by assigning the average of the ranks that would have been assigned without ties. Eventually, the items were sorted by their clinical relevance.

The random sample of this survey was not balanced across potential confounders such as the participants' health profession, their work experience in pediatric rehabilitation, and their workplace. Therefore, we investigated the influence of these confounders on the responses of the survey. The Kruskal-Wallis test was used to elaborate if the responses of each item differed between health professions. In case of significant differences, the Tukey's range test was applied for profession-wise comparisons. The relationship between work experience and the responses of each item was determined with the Spearman rank correlation coefficient. Since the majority of participants worked at the Swiss Children's Rehab, we decided to allocate the participants' workplace into two groups consisting of participants working at the Swiss Children's Rehab and those working at other rehabilitation centers. Then, the potential bias of responses from people working at the Swiss Children's Rehab was investigated with the Wilcoxon rank sum test. The alpha level of all statistical tests was set to 0.05, and the analysis was conducted with MATLAB R2018b (The MathWorks, Inc.; Natick; USA).

5.4 Results

The survey was filled out by 87 health professionals from 16 different pediatric neurorehabilitation centers. Hence, 70% of the centers that we contacted participated in this study. The participants' characteristics are illustrated in **Figure 5.2**. Forty-one participants worked at the Swiss Children's Rehab, while the remaining participants worked at different rehabilitation centers distributed across the German-speaking part of Europe.

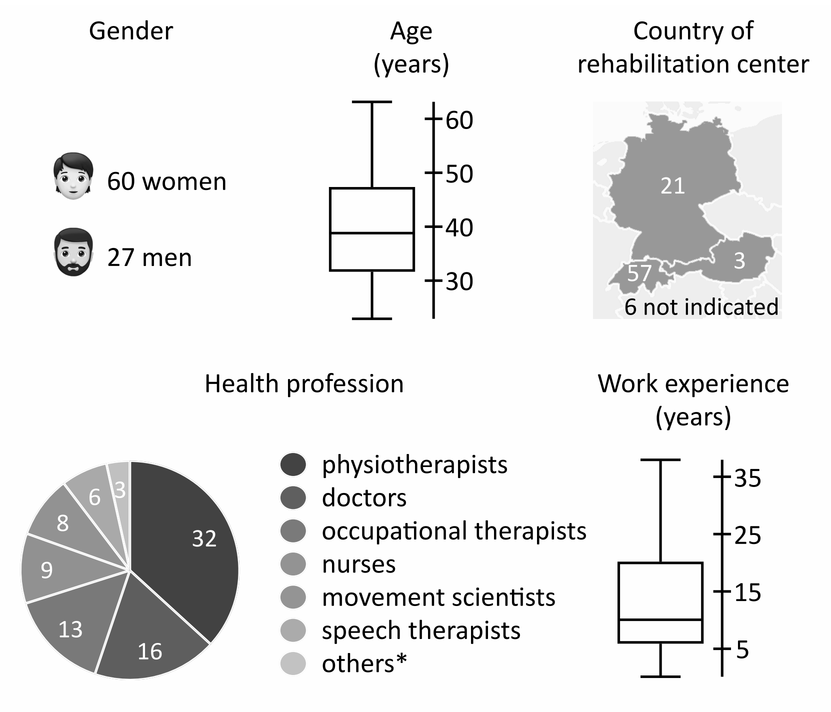

Figure 5.2 – Participants' characteristics. *1 sport therapist, 1 Special Education teacher, and 1 team of doctors and therapists.

Table 5.2 – Priority list of sensor-based outcome measures including the total counts of individual responses, the median response, and the mean rank of each outcome.

ID	Item	# very relevant	# relevant	# hardly relevant	# not relevant	# missing value	median	mean rank
12	Lying, sitting & standing	64	19	3	0	1	1	12.1
26	Wheeling (active/passive)	59	22	6	0	0	1	13.1
1	Hand use (laterality)	57	28	2	0	0	1	13.5
18	Walking (distance/speed)	54	30	3	0	0	1	13.9
17	Walking (duration)	51	31	4	1	0	1	14.6
20	Risk of falling	52	23	9	0	3	1	14.7
25	Use of walking aids	54	25	6	2	0	1	14.7
2	Hand use (uni-/bimanual)	49	33	5	0	0	1	14.9
31	Eating & drinking	48	31	6	1	1	1	15.5
23	Stair climbing (quantity)	42	42	3	0	0	2	15.7
15	Standing up (quantity)	42	35	8	0	2	2	16.2
30	Dressing	42	38	4	2	1	2	16.3
19	Walking (gait parameters)	42	34	8	0	3	1.5	16.3
11	Reaching (range)	44	31	11	0	1	1	16.4
9	Knee flex/ex	39	34	10	0	4	2	16.9
16	Standing up (quality)	41	34	11	1	0	2	17.0
5	Elbow flex/ex	40	32	11	0	4	2	17.3
29	Personal hygiene	38	38	7	2	2	2	17.4
8	Finger flex/ex	35	37	10	0	5	2	17.8
33	Sports activities	29	51	5	0	2	2	18.2
3	Hand use (diversity)	35	36	14	1	1	2	18.3
27	Wheeling (distance/speed)	33	43	10	1	0	2	18.5
7	Wrist flex/ex	30	44	9	0	4	2	18.7
6	Forearm pro/sup	32	38	11	1	5	2	18.7
34	Energy expenditure	35	34	15	2	1	2	18.7
24	Stair climbing (quality)	35	31	20	1	0	2	19.2
14	Standing (upright/bent)	28	42	14	0	3	2	19.5
13	Lying (prone/supine)	31	30	22	0	4	2	19.9
10	Reaching (repetitions)	26	40	16	1	4	2	20.3
4	Shoulder abd/add	23	45	16	0	3	2	20.8
28	School activities	26	38	18	4	1	2	21.2
21	Walking (turning)	18	44	18	2	5	2	21.9
22	Walking (slope)	15	51	20	0	1	2	22.2
32	Household activities	10	46	21	7	3	2	24.7

A median response of 1 = "very relevant" and 2 = "relevant"; flex = flexion, ex = extension, pro = pronation, sup = supination, abd = abduction, add = adduction.

The total counts of individual responses, the median response, and the mean rank of each item are listed in **Table 5.2**. The items are sorted in ascending order by their mean rank and thus start with the most relevant item for children and adolescents with neuromotor impairments. All items received a median rating of "very relevant" or "relevant". In total, 64 items were not answered, which leads to a rate of missing items of 2%.

The influences of the confounders on the relevance of the items are listed in **Table 5.3** (same order of items as in **Table 5.2**). The relevance of five items differed between health professionals, while the post-hoc, profession-wise comparison revealed only three significant differences.

Table 5.3 – Test statistics regarding the influence of confounders on rating the relevance of sensor-based outcome measures.

ID	Item	health profession		work experience		work place	
		χ^2	p-value	ρ	p-value	z-score	p-value
12	Lying, sitting & standing	4.5	0.48	0.00	0.99	-0.5	0.62
26	Wheeling (active/passive)	4.1	0.54	-0.04	0.73	-0.3	0.74
1	Hand use (laterality)	3.0	0.70	0.03	0.82	-1.5	0.13
18	Walking (distance/speed)	5.9	0.32	-0.02	0.84	**-2.8**	**0.00**
17	Walking (duration)	9.5	0.09	0.03	0.79	-0.5	0.62
20	Risk of falling	9.4	0.10	0.13	0.25	-1.7	0.09
25	Use of walking aids	**11.8**	**0.04**	-0.18	0.10	-0.7	0.50
2	Hand use (uni-/bimanual)	6.4	0.27	-0.17	0.11	-0.6	0.54
31	Eating & drinking	5.5	0.36	-0.08	0.44	0.7	0.51
23	Stair climbing (quantity)	9.3	0.10	-0.14	0.19	**-2.6**	**0.01**
15	Standing up (quantity)	5.5	0.36	**-0.23**	**0.03**	0.9	0.36
30	Dressing	6.4	0.27	-0.10	0.35	0.8	0.41
19	Walking (gait parameters)	2.2	0.82	-0.14	0.21	-1.1	0.28
11	Reaching (range)	8.2	0.15	0.00	0.98	-0.4	0.71
9	Knee flex/ex	2.2	0.82	-0.15	0.17	0.0	0.97
16	Standing up (quality)	7.1	0.22	-0.07	0.50	0.2	0.83
5	Elbow flex/ex	3.2	0.68	-0.21	0.05	0.4	0.70
29	Personal hygiene	2.3	0.81	-0.08	0.45	1.2	0.22
8	Finger flex/ex	1.8	0.88	-0.16	0.13	0.5	0.60
33	Sports activities	**13.3**	**0.02**	-0.15	0.16	-1.1	0.29
3	Hand use (diversity)	**12.6**	**0.03**	-0.16	0.15	1.3	0.21
27	Wheeling (distance/speed)	**13.6**	**0.02**	**-0.22**	**0.05**	0.1	0.90
7	Wrist flex/ex	8.5	0.13	-0.17	0.12	0.8	0.44
6	Forearm pro/sup	**11.4**	**0.04**	**-0.27**	**0.01**	**2.5**	**0.01**
34	Energy expenditure	8.0	0.16	0.01	0.93	-0.4	0.67
24	Stair climbing (quality)	3.2	0.67	**-0.27**	**0.01**	0.2	0.85
14	Standing (upright/bent)	6.9	0.23	**-0.26**	**0.02**	1.4	0.15
13	Lying (prone/supine)	6.2	0.29	**-0.24**	**0.03**	0.9	0.38
10	Reaching (repetitions)	9.4	0.09	**-0.24**	**0.02**	1.6	0.11
4	Shoulder abd/add	2.7	0.75	-0.14	0.19	1.0	0.32
28	School activities	8.8	0.12	**-0.28**	**0.01**	1.7	0.09
21	Walking (turning)	4.2	0.53	-0.20	0.06	0.7	0.51
22	Walking (slope)	8.2	0.15	-0.14	0.19	-0.8	0.42
32	Household activities	3.4	0.64	-0.21	0.05	**2.4**	**0.01**

bold numbers indicate a significant influence of the confounder on the rating of the item's relevance.

flex = flexion, ex = extension, pro = pronation, sup = supination, abd = abduction, add = adduction.

Nurses rated the relevance of measuring the use of assistive devices higher than movement scientists and the duration of sports activities higher than physiotherapists. Besides, occupational therapists rated the relevance of measuring pro- and supination of the forearm higher than nurses. The relevance of eight items significantly depended on the work experience of the participants. Negative correlation coefficients mean that the relevance of these items was rated higher with increasing work experience. Determining the distance and speed of walking activities and the number of climbed stairs received a higher rating from the staff working at the Swiss Children's Rehab while measuring pro- and supination of the forearm and the duration of household activities were rated as more relevant from the staff of other rehabilitation centers.

5.5 Discussion

In this survey, we investigated the clinical relevance of sensor-based outcomes to monitor everyday life motor activities of children and adolescents with neuromotor impairments.

On average, health professionals of pediatric neurorehabilitation centers rated all outcomes of the survey as being "relevant" or "very relevant" for children and adolescents with neuromotor impairments. None of the outcomes were classified as "hardly relevant" or "not relevant". Still, the relevance measured with the mean rank of all responses differed between outcomes resulting in the priority list shown in **Table 5.2**. In general, outcomes assessing the quantity of an activity were more relevant than those assessing the quality. For example, the number of climbed stairs was more relevant than the used stepping pattern, and the number of sit-to-stand transitions received a higher rating than how these transitions were executed. The same order was observed for upper limb measures and walking-related outcomes. We have two explanations for prioritizing quantity over quality. First, motor tests conducted at the clinic can capture the quality of an activity and might also reflect how children are doing this activity in daily life. However, how often children are doing this activity in daily life can only be captured with wearable sensors. Second, a top priority of pediatric rehabilitation is to gain independence in mobility and self-care activities (Chiarello et al., 2010). And to be independent, the capability to do an activity seems to be more important than how these activities are executed. Hence, assessing the quantity of activities is probably a better indicator of independence than assessing their quality.

In the following sections, we discuss the findings of this survey with regard to three main categories: maintaining and changing a body position, walking and moving, and upper limb activity.

5.5.1 Maintaining and changing a body position

The duration a child spends in a certain body position was the most relevant item and more important than changing between positions and assessing the quality of the posture. Nine health professionals wished to have two additional outcomes for wheelchair-bound children: the number of transfers and how often children get up from the floor in a sitting position on the wheelchair. The opinion of health professionals coincides with the families' needs as transferring oneself while sitting and maintaining a sitting and standing position were the most frequent rehabilitation goals in this category (Rast and Labruyère, 2020a). Five participants mentioned that kneeling and quadruped stance should be considered as well, especially for younger children.

5.5.2 Walking and moving

The distinction between active and passive wheeling periods was the most relevant item in this category. This is surprising since it is a rare rehabilitation goal of children and adolescents (Rast and Labruyère, 2020a) and shows the importance of complementing the families' needs with those of pediatric health professionals. Measuring the amount of active self-propulsion could be an indicator of independence or the level of physical activity in wheelchair-bound individuals (Popp et al., 2016), potentially explaining the clinical relevance of this item. Besides wheeling, the distance and speed of walking activities received the highest rating in this category. The ability to cover a certain distance on foot is also the most frequently set goal in pediatric rehabilitation (Rast and Labruyère, 2020a). It is important to reach destinations in daily life and could again be an indicator of independence. Moreover, walking speed is essential for children with neuromotor impairments to keep up with their peers (Buckon et al., 2007). All this could explain the high priority to measure distance and speed of daily walking activities with wearable sensors. Health professionals further rated the walking duration, the risk of falling, the use of walking aids, the number of climbed stairs, and the gait pattern as being more relevant than the distance and speed of wheeling periods, the stepping pattern of stair climbing periods, the turning behavior while walking, and the slope of covered walking routes. Regarding gait pattern, the majority of participants suggested segmenting the gait cycle into stance and swing phases and then determining the step length and the symmetry between the left and right sides.

5.5.3 Upper limb activity

The hand use laterality and the distinction between unimanual and bimanual activities were prioritized over detecting activities of daily living, measuring the range of motion, and assessing reaching activities. However, five participants mentioned the relevance of assessing shoulder flexion/extension. It was not part of the current survey, and it remains unclear if it would have received a higher rating than other joint movements. Still, the measurement of joints' range of motion seems to be more important on a functional level than in daily life. Regarding activities of daily living, health professionals favored the assessment of eating, drinking, and dressing compared to other activities. This is in line with family priorities (Chiarello et al., 2010; Rast and Labruyère, 2020a), with eating becoming more important for children with severe motor impairments (Chiarello et al., 2010).

5.5.4 Additional outcomes

The sensor-based outcomes of the current survey were derived from previous studies and did not cover the full spectrum of daily motor activities. Therefore, we added an open-ended question at the end of the survey and asked about other relevant outcomes. Mentioned activities were communicating, playing, crawling, jumping, and running. Moreover, other factors such as motivation, exhaustion, and the presence of a supervisor or assistant should be addressed, too. However, these factors and activities were mentioned by individual participants, and their priority with regard to the items of the survey remains unexplored.

5.5.5 Influence of health profession, work experience, and workplace

The opinion of nurses is not sufficiently reflected in the results of this study. Only nine nurses filled out the survey, even though they represent the largest subgroup of health professionals (Girardin et al., 2021). They would have given a higher relevance to the use of walking aids and sports activities compared to other health professions. However, more responses from nurses are needed to draw conclusions about their opinion, and collecting more data could alter the nurses' priorities set in this study. Measuring pronation and supination was more relevant for occupational therapists but did not become a top priority in this profession. The relevance of the remaining items did not differ between health professions showing a minimal influence of the participants' background on rating the relevance of sensor-based outcomes. An explanation could be that we encouraged the participants to rate the relevance from an interdisciplinary perspective.

In general, work experience was positively associated with the clinical relevance of sensor-based outcomes, and this correlation was statistically significant for eight survey items. However, the order of the priority list was hardly affected by work experience. For example, measuring the number of sit-to-stand transitions has rank 11 in the overall study population and rank 9 in participants with more than ten years of work experience. Moreover, seven of eight items influenced by work experience showed low priority for experienced and inexperienced health professionals. Hence, we conclude that work experience hardly influences the relevance of outcomes with high priority.

The rating of four items was significantly affected by the workplace. Two of them had low priority anyway, and we argue that the influence of the workplace is negligible for these items. But the distance and speed of walking activities and the number of climbed stairs were more relevant for the staff working at the Swiss Children's Rehab than for those working at other rehabilitation centers. This indicates a higher relevance of gait-related outcomes for our center and should be considered when interpreting and generalizing the results of the current survey.

5.5.6 Clinical needs of pediatric rehabilitation to monitor everyday life motor activities

The results of this survey only reflect the opinion of health professionals and should be complemented with family priorities to provide developers of new algorithms with a comprehensive view on the needs of pediatric rehabilitation. In **Figure 5.3**, we have linked the most relevant outcome measures of this survey with the family priorities of our preceding study (Rast and Labruyère, 2020a). The summary contains the top ten survey items and the top ten rehabilita-

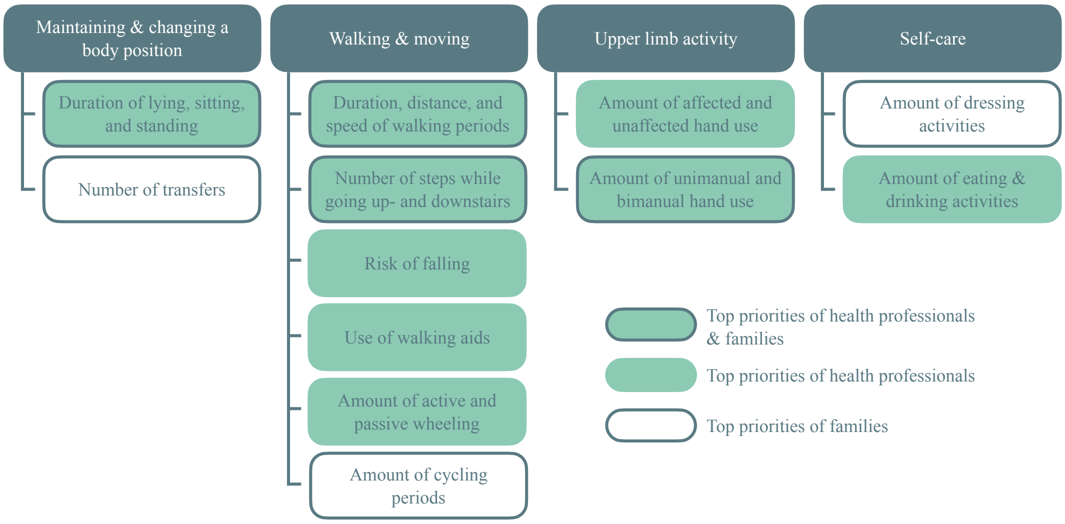

Figure 5.3 – Clinically most relevant outcomes to monitor everyday life motor activities with wearable sensors in children and adolescents with neuromotor impairments.

tion goals which were grouped into four categories: maintaining & changing a body position, walking & moving, upper limb activity, and self-care. We fused the duration, distance, and speed of walking periods to a single outcome measure. Moreover, the rehabilitation goals of walking short and long distances, maintaining a sitting and standing position, as well as putting on and taking of clothes were put together to be in line with the survey items. Eventually, the summary contains the twelve clinically most relevant outcomes to monitor everyday life motor activities.

So far, several sensor systems and algorithms have been developed for a pediatric population. These algorithms cover five of the twelve most relevant outcomes, namely the duration of body positions (Gerber et al., 2020; Lankhorst et al., 2019), the amount of active wheeling (Goodlich et al., 2020; Nooijen et al., 2015), the hand use laterality and the distinction between unimanual and bimanual activities (Braito et al., 2018), and the duration, distance, and speed of walking activities (Ahmadi et al., 2018; Carcreff et al., 2020b; Gerber et al., 2020; Goodlich et al., 2020; Lankhorst et al., 2019). However, none of these algorithms provide a comprehensive overview of these outcomes and based on the authors' knowledge, the remaining outcomes of the top twelve (i.e., the number of transfers, the risk of falling, the use of walking aids, the number of climbed stairs, and the amount of cycling, dressing, eating and drinking activities) have not been addressed, yet. Consequently, there is a clinical need for a new sensor system and algorithm that covers the most important outcomes for children and adolescents with neuromotor impairments.

5.5.7 Study limitations

This survey has four essential limitations. First, the presentation of the sensor-based outcomes might have had influenced their relevance rating. If applicable, the survey contained graphical visualizations of fictitious measurements (see **Figure 5.1**). This was required to ensure clarity about the meaning of the corresponding survey items. However, the availability and the quality of these visualizations could have resulted in higher priorities for outcome measures with meaningful charts and exemplary data. Second, we limited the survey distribution to the German-speaking part of Europe. We chose this approach to cover the opinion of our target population. However, it could affect the generalizability of the study results to other countries. Third, we expect that mainly technophiles participated in this survey which might be another source of bias. However, we believe this increased the relevance of all survey items similarly and only minimally affected their order in the priority list. Fourth, the response rate of health professionals was not determinable since the number of people who received the link to the online survey is unknown. This could have affected the representativeness of our survey, and based on these four limitations, the relevance of sensor-based outcome measures should be interpreted cautiously. Instead of considering their exact rank in the priority list, their trend of having higher or lower priority for children and adolescents with neuromotor impairments should be acknowledged.

5.5.8 Conclusion

This survey provides a priority list of sensor-based outcomes to monitor everyday life motor activities of children and adolescents with neuromotor impairments. It reflects the opinion of health professionals and was complemented with the opinion of families of a preceding study to identify the clinical needs of pediatric rehabilitation comprehensively. Knowing these needs will eventually help developers of new algorithms to make the trade-off between deriving clinically meaningful information and minimizing the burden for children and adolescents to wear the sensors in daily life.

6 Selection of performance measures and algorithm development

This chapter summarizes the results of **Chapter 3**, **Chapter 4**, and **Chapter 5**. It further describes the process of the algorithm development. Its content has not been published or submitted for publication.

6.1 Selection process

The process of selecting performance measures was a trade-off between maximizing information gain and minimizing the number of required sensors to ensure the children's and adolescents' compliance to wear the sensors in daily life. Besides, we considered the availability of data processing algorithms and the feasibility of determining the performance measures with wearable inertial sensors. Hence, we aimed to implement the performance measures depicted in **Figure 5.3** without jeopardizing feasibility.

6.2 Existing algorithms

Before this thesis, our research group developed several algorithms and validated them in adult patient populations. One algorithm determines the amount of affected and unaffected hand use with wrist sensors (Leuenberger et al., 2017). A second algorithm detects walking and stair climbing periods (Leuenberger et al., 2014) and estimates the walking speed with an ankle sensor (Werner et al., 2021). A third algorithm discriminates between active and passive wheeling and determines the distance and speed of active wheeling periods (Popp et al., 2016). It requires wrist sensors and an additional sensor on the spokes of the wheelchair. These algorithms were also used in this thesis because they covered four of the 12 performance measures of **Figure 5.3**, namely the duration, distance, and speed of walking periods, the number of steps while going up- and downstairs, the amount of active and passive wheeling, and the amount of affected and unaffected hand use.

Besides, the duration of lying, sitting, and standing positions and the number of sit-to-stand transitions were commonly determined with a trunk and a thigh sensor in previous studies (see section 3.4.2.2). Moreover, the use of walking aids and distinguishing between free and assisted walking has been accomplished with a sensor placed on walking aids (Hester et al., 2006a). The algorithms to detect body positions and the use of walking aids can easily be replicated from the literature and cover two more performance measures of **Figure 5.3**. Hence, they were also included in this thesis.

6.3 Explanation for excluding performance measures

In the following paragraphs, we explain why we could not include the remaining performance measures of **Figure 5.3**.

Number of transfers Improving the ability to transfer between the wheelchair and another seat was the second most frequent rehabilitation goal. Patients generally do these transfers in two ways. Either they shift sideways without standing up, or they stand up, pivot, and sit down again. The second way to transfer is covered in our algorithm by detecting sit-to-stand transitions. However, the first way is challenging to detect with wearable inertial sensors because the accuracy of measuring translational motions is diminished in long-term measurements (Kok et al., 2017). Therefore, we suggest using instrumented seats to detect these transfers in daily life (Ahad et al., 2021). However, developing and validating such a technology was beyond the scope of this thesis.

Risk of falling Measuring the risk of falling was amongst the top ten performance measures of pediatric health professionals. Even though there are a variety of solutions to measure fall risk with wearable inertial sensors (Ferreira et al., 2022), we still did not cover this outcome for two main reasons. First, the fall risk assessment can be completed in a standardized setting (Najafi et al., 2013), which was not the aim of this thesis. Second, fall risk measures need to be validated in long-term studies observing the number of falls in the target population (Ferreira et al., 2022). Such a long-lasting validity study was also beyond the scope of this thesis.

Amount of cycling periods Determining the amount of cycling activities was not implemented in this thesis. It had only ranked 10th on the priority list of families (which is why we included it in **Figure 5.3**) and was not a top priority of health professionals. Moreover, we had no algorithm available to detect cycling periods in daily life. Still, we included cycling activities in our validity study to challenge our walking detection algorithm (it needed the ability to discriminate between walking and cycling to achieve high classification accuracy). Moreover, we are in the process of publishing this dataset to allow for the validation of future algorithms detecting cycling.

Amount of unimanual and bimanual hand use Initially, we thought that previous studies discriminated between unimanual and bimanual activities (Braito et al., 2018). Later, when we tried to replicate their algorithms, we realized that they do not differentiate between bimanual activities (e.g., opening a bottle) and simultaneous activities of both hands (e.g., typing on a keyboard) (Bailey et al., 2014). This distinction, however, is essential for the therapists of our rehabilitation center and can hardly be achieved by wearable inertial sensors. Hence, we recommend using egocentric video recordings of the hands in future studies. Video recordings can capture the context of hand activities (Likitlersuang et al., 2019) and thus enable distinguishing between bimanual activities and simultaneous activities of both hands.

Amount of self-care activities Dressing was a top priority for families, and eating was a top priority for health professionals. We included self-care activities in the preceding studies because they comprise of motor activities. However, detecting these activities in daily life is difficult since they do not have a repetitive pattern such as walking or wheeling and they can be performed in different ways. Moreover, we claim that the level of independence in these activities is more relevant than determining how often these activities are performed in daily life. The level of independence can be measured with clinical assessments such as the Functional Independence Measure for Children (Kim et al., 2022), and we conclude that wearable inertial sensors are not the best option to measure the performance of self-care activities. Hence, we did not cover dressing and eating activities in this thesis.

6.4 The final selection of performance measures

The final selection of motor activities covered in this thesis is illustrated in **Figure 6.1**. The final algorithm was designed to determine the following performance measures:

- the duration of lying, sitting, and standing positions and the number of sit-to-stand transitions with a trunk and a thigh sensor,
- the functional hand use with wrist sensors,
- the distance and speed of self-propelled wheeling periods with a wrist and a wheel sensor,
- the duration, distance, and speed of walking periods, and the altitude change during stair climbing periods with an ankle sensor,
- and the discrimination between free and assisted walking with a sensor placed on walking aids.

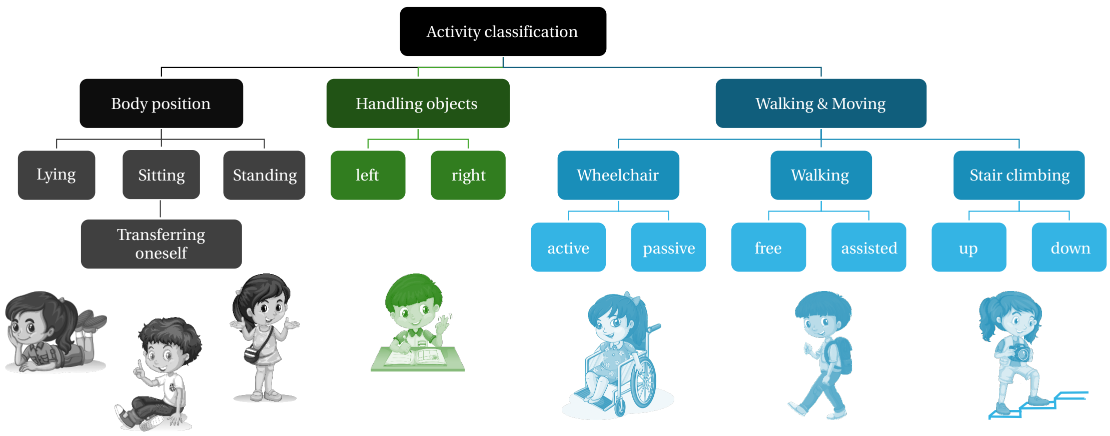

Figure 6.1 – Illustration of the final selection of motor activities covered in this thesis. This illustration was designed using resources from https://www.freepik.com.

6.5 Algorithm development

First, we fused existing algorithms of our research group and complemented them with algorithms replicated from the literature to get a single algorithm estimating the performance measures described above. Most algorithms needed modifications to comply with the data structure of the newest version of our sensor system and a rigorous bug fixing to run robustly with newly collected data. Then, we tested the performance of this algorithm in children and adolescents with neuromotor impairments. This step is thoroughly described in the following part of the thesis.

As expected, the first version of our algorithm did not reveal sufficient accuracy and required significant improvements to be applicable in children and adolescents with neuromotor impairments. These improvements were accomplished by adjusting the parameters of the signal processing, retraining the machine learning algorithms, and adding biomechanical constraints. However, in the case of walking detection these improvements were not sufficient, and we developed a new walking detection algorithm in this thesis. Eventually, the development of the algorithm was an iterative process of improving and reevaluating the algorithm's performance leading to the final version of the algorithm.

The following chapters of the thesis contain a detailed description of the final algorithm and the results of the three validity studies. The first study analyzed the accuracy of posture and mobility-related measures (**Chapter 7**), the second study investigated the validity of hand use measures (**Chapter 8**), and the third study determined the accuracy of sensor-based gait speed estimations (**Chapter 9**). Eventually, we summarized the algorithm's validity in **Chapter 10**.

Algorithm validation Part III

7 Accuracy of sensor-based classification of clinically relevant motor activities in daily life of children with mobility impairments

Fabian M. Rast, Florence Jucker and Rob Labruyère

Submitted to *Gait & Posture*.

Authors' contributions: FR, FJ, and RL contributed to the conception and design of the study. FR developed and optimized the data processing algorithms. FR and FJ recruited participants, collected the data, and performed the statistical analysis. All authors were involved in the data interpretation. FR wrote the first draft of the manuscript, while all authors contributed to manuscript revision and approved the final manuscript. FJ did her master thesis under the supervision of FR.

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This manuscript is under review at *Gait & Posture*, and the authors can share the submitted version anywhere at any time.
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7.1 Abstract

Background Wearable inertial sensors enable objective, long-term monitoring of motor activities in the children's habitual environment after rehabilitation. However, sophisticated algorithms are needed to derive clinically relevant outcome measures. Therefore, we developed three independent algorithms based on the needs of pediatric rehabilitation. The first algorithm estimates the duration of lying, sitting, and standing positions and the number of sit-to-stand transitions with data of a trunk and a thigh sensor. The second algorithm detects active wheeling periods and distinguishes it from passive wheeling with data of a wrist and a wheelchair sensor. The third algorithm detects walking periods, discriminates between free and assisted walking, and estimates the covered altitude change during stair climbing with data of a single ankle sensor and a sensor placed on walking aids.

Research question This study aimed to determine the accuracy of each algorithm in children undergoing rehabilitation.

Methods Thirty-one children and adolescents with various medical diagnoses and levels of mobility impairments performed a semi-structured activity circuit. They wore inertial sensors on both wrists, the sternum, and the thigh and shank of the less-affected side. Video recordings, which were labeled by two independent researchers, served as reference criteria to determine the algorithms' performance.

Results The activity classification accuracy was 97% for the posture detection algorithm, 96% for the wheeling detection algorithm, and 93% for the walking detection algorithm.

Significance This study presents three novel algorithms that provide a comprehensive and clinically relevant view of the children's motor activities. These algorithms are described reproducibly and can be applied to other inertial sensor technologies. Moreover, they were validated in children with mobility impairments and can be used in clinical practice and clinical trials to determine the children's motor performance in their habitual environment. To enable the evaluation of future algorithms, we published the labeled dataset.

7.2 Background

Pediatric rehabilitation aims to foster functional independence in everyday life activities of children with congenital and acquired illnesses and injuries. For most families with children undergoing rehabilitation, improvements in self-care and mobility activities are prioritized (Chiarello et al., 2010). Thereby, most rehabilitation goals are set about changing and maintaining body positions or walking and moving (Rast and Labruyère, 2020a). Hence, assessments covering these domains are essential to tailor therapy to the families' needs and monitor the children's progress over time.

In clinical practice, assessments are usually conducted in a standardized environment. Therefore, their outcomes reflect the children's highest probable level of functioning within this setting (i.e., motor capacity) (World Health Organization, 2002). However, it has been shown that capacity only partially explains how the children perform in their habitual environment after rehabilitation (i.e., motor performance) (Holsbeeke et al., 2009; Wittry et al., 2018). Consequently, there is a need to measure performance directly by bringing assessments into daily life.

Recent advances in wearable sensor technologies overcome the limitation mentioned above by enabling objective and long-term monitoring of motor activities in a patient's habitual environment (Leuenberger and Gassert, 2011). Recent studies validated such sensor technologies and their underlying data processing algorithms in children with mobility impairments (Ahmadi et al., 2018; Goodlich et al., 2020; Lankhorst et al., 2019; Nooijen et al., 2015). However, these algorithms do not provide a comprehensive view of the patients' activities, and they lack an estimation of clinically relevant outcome measures. Moreover, they were only validated in children with cerebral palsy and spina bifida, representing approximately one third of all children undergoing rehabilitation (Rast and Labruyère, 2020a). Hence, the validity in children with other mobility impairments is still unknown.

Here, we present a novel algorithm that was developed based on the findings of two preceding studies assessing the clinical needs of pediatric rehabilitation. The first study was an international survey with pediatric healthcare professionals, and the second study investigated the frequency of rehabilitation goals at our center (Rast and Labruyère, 2020a). The results revealed the demand to have three sub-algorithms that require different sensor-setups and can be used independently: The first sub-algorithm estimates the duration of lying, sitting, and standing positions and the number of sit-to-stand transitions with data of a trunk and a thigh sensor. The second sub-algorithm detects active wheeling periods and distinguishes them from passive wheeling with data of a wrist and a wheelchair sensor. The third sub-algorithm detects walking periods, discriminates between free and assisted walking, and estimates the covered altitude change during stair climbing with data of a single ankle sensor and a sensor placed on walking aids. The aim of this study was to validate the three sub-algorithms in children undergoing rehabilitation. Specifically, we investigated the algorithm's activity classification accuracy and determined the measurement error of the outcome measures.

7.3 Method

7.3.1 Participants & recruitment

A convenience sample of 31 children and adolescents was recruited at the Swiss Children's Rehab of the University Children's Hospital Zurich, Switzerland. These children were able to walk or use a manual wheelchair for household distances. Furthermore, they were between 4 and 20 years old, had cognitive abilities to follow instructions, had no wounds or other medical conditions that prevented sensor placement, and provided informed consent to participate in the study. The local ethics committee approved this study (BASEC Nr.: 2019-00487).

7.3.2 Procedure & equipment

Participants were equipped with five ZurichMOVE sensor modules, containing a 3-axis accelerometer, a 3-axis gyroscope, and an altimeter (Popp et al., 2019). The sensors were placed on both wrists, the sternum, and the thigh and ankle of the less-affected side with corresponding hook-and-loop straps (**Figure 7.1**). Additional sensors were placed on walking aids and the spokes of the wheelchair if applicable. Time synchronization between the sensors was achieved by a master-slave configuration using Bluetooth Low Energy.

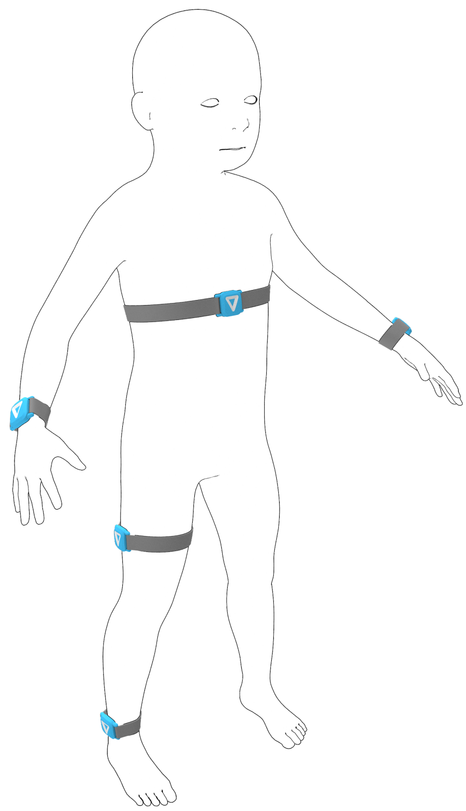

Figure 7.1 – Placement of the five body-worn sensors at both wrists, the sternum, and the thigh and ankle of the less-affected side.

All participants performed a semi-structured activity circuit at the rehabilitation center. They watched a movie on a tablet in their bedroom, played a self-selected game (e.g., card games, puzzles, etc.) in the living room, drank a glass of water in the restaurant, cycled in the gym hall, and played what they wanted to on the outdoor playground (e.g., catching and throwing balls, swinging, etc.). Participants were encouraged to walk, wheel, climb stairs, and take the elevator between these facilities, depending on their functional abilities. No instructions were given on how to do these activities so that the children moved as they would in real life. To increase comparability with everyday life, the circuit covered activities of the target population that could be recognized by the algorithm and such that could not, to challenge its performance. Video recordings from an external perspective served as reference criteria to determine the algorithm's performance. The sampling rates of all devices were set to 50 Hz, and timestamps were synchronized with the children clapping their hands in front of the camera.

7.3.3 Data processing

The three sub-algorithms are comprehensively described in appendix D and briefly summarized here:

1. The **posture detection algorithm** identifies lying, sitting, and standing positions with the orientation of the trunk and thigh sensors. It is assumed that both sensors are in a vertical orientation during standing and in a horizontal orientation during lying. In a sitting position, the thigh is usually oriented horizontally while the trunk remains vertical. The cut-point between the sensor's horizontal and vertical orientation were trained with the current dataset and a leave-one-subject-out approach. This approach reflects the algorithm's performance when applying it to a new subject without having training data of that subject as it would be the case in upcoming studies.
   Outcome measures: the algorithm derives the time spent in each position and the number of sit-to-stand transitions.

2. The **wheeling detection algorithm** discriminates between wheeling and non-wheeling periods with data of the wheelchair sensor and distinguishes between active and passive wheeling with the wrist sensor of the less-affected hand. The algorithm applies several thresholds to the angular rate of the wheel to detect wheeling periods (Popp et al., 2016). Then, the wheeling periods are segmented into 5.12 s windows and an overlap of 75%. And finally, the orientation of the less-affected hand is used to classify active and passive wheeling. The cut-point was again trained with the current dataset and a leave-one-subject-out approach.
   Outcome measures: the algorithm derives the total duration of active and passive wheeling separately.

3. The **walking detection algorithm** uses walking-specific characteristics of the ankle's gyroscope signal to discriminate between walking and non-walking periods. The accel-

eration signal of the sensor on the walking aid is used to distinguish between free and assisted walking. Moreover, the algorithm detects stair climbing periods with the altimeter of the ankle sensor. Whenever a child walks four consecutive steps and covers an altitude change between 7 and 49 cm per step, this period is considered stair climbing. Positive altitude changes are classified as ascending and negative ones as descending. **Outcome measures**: the algorithm derives the free and assisted walking duration and estimates the covered altitude change during stair climbing periods.

The sub-algorithms 1 & 3 were applied to data from all participants, while the wheeling detection algorithm was only applied to data from participants using a wheelchair.

Two researchers labeled the video recordings independently as lying, sitting, standing, and unknown (not visible). Sitting was sub-labeled as sitting, kneeling, being carried, active wheeling, passive wheeling, cycling, swinging, and sliding. Standing was sub-labeled as standing, free walking, assisted walking, going upstairs, going downstairs, and jumping. Disagreements lasting more than one second were discussed retrospectively. In the case of consensus, the labels were corrected. Otherwise, the labels were retained. We published the labeled dataset and added a detailed definition of the individual activities (Rast, 2021).

7.3.4 Statistical analysis

The algorithm's activity detection accuracy was calculated by the proportion of correctly predicted data samples over all predictions. We further calculated the sensitivity and precision for each activity separately:

$$sensitivity = \frac{TP}{TP+FN} \quad , \qquad precision = \frac{TP}{TP+FP} \quad , \tag{7.1}$$

with TP = true positive predictions, FN = false negative predictions, and FP = false positive predictions. Unknown periods (0.4%), as well as periods with disagreement in the video labels (4.2%) and periods in which the sensors were not placed correctly (1.9%), were ignored in this analysis. An accuracy, sensitivity, and precision of >90% was considered excellent, 80% to 90% good, 70% to 80% moderate, and less than 70% weak (Nooijen et al., 2015).

Moreover, the agreement of the algorithm's outcome measures with those of the reference system was determined with three different metrics. First, the measurement error was estimated as the difference between the algorithm's measures and those derived from the video labels (reference values). The smaller difference to one of the two reference values was used. The measurement error was determined for each participant separately. The measurement error represents agreement within the activity circuit. Second, the relative measurement error was determined by dividing the measurement error by the mean of the reference values. Relative measurement error reflects the agreement of long-term measurements. Third, the Spearman's rank correlation coefficient was calculated. These coefficients demonstrate the algorithm's ability to discriminate between participants despite measurement error.

7.4 Results

Twelve girls and 19 boys (11.8 ± 3.2 years) with various medical diagnoses and mobility impairments completed the study protocol. Their level of gross motor function, diagnosis, and use of mobility aids is shown in **Figure 7.2**. The activity circuit lasted 46 min on average,

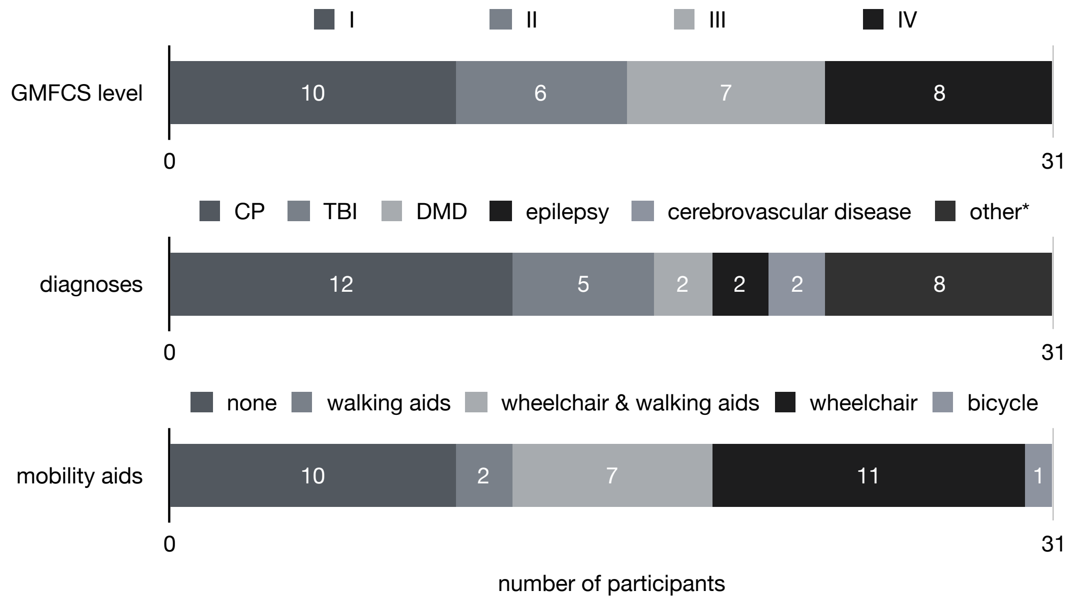

Figure 7.2 – Illustration of the participants' characteristics. GMFCS = gross motor function classification system; CP = cerebral palsy; TBI = traumatic brain injury; DMD = dissociative movement disorder. *chromosomal abnormality, congenital malformation syndrome, demyelinating disease, hereditary ataxia, multiple sclerosis, neoplasm, osteomyelitis & spina bifida.

and the performed activities depended on the participants' capabilities. An overview of the dataset is illustrated in **Figure 7.3**, and the resulting sample sizes of each activity are in line with previous studies (Ahmadi et al., 2018; Goodlich et al., 2020; Lankhorst et al., 2019; Nooijen et al., 2015). Nineteen participants were able to walk with or without walking aids, eleven were wheelchair-dependent, and one participant moved around on a bicycle. Seven of those who were able to walk also used a wheelchair for longer distances.

The between-researcher agreement of the video labels was 96%. The majority of disagreement occurred due to uncertainty about discriminating lying and sitting when participants were seated in the bed with a backward-tilted backrest and discriminating standing and walking in participants making small and discontinuous steps.

The accuracy, sensitivity, and precision of the three sub-algorithms are presented in three corresponding confusion matrices in **Figure 7.4**. The posture detection algorithm revealed excellent performance. Sensitivities and precisions to detect lying, sitting, and standing were greater than 93%. In case of misclassification, the three postures were confused with each

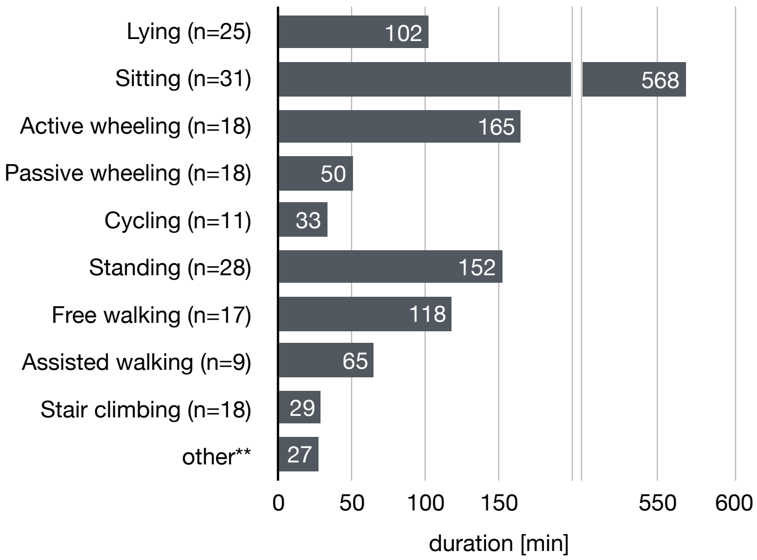

Figure 7.3 – Illustration of the collected dataset. n = number of participants performing that activity. **kneeling (n=5, 13 min), being carried (n=1, <1 min), sliding (n=1, <1 min), swinging (n=4, 13 min) & jumping (n=2, 1 min).

other but not with other activities, except for cycling. Roughly one-third of the cycling time was misclassified as standing. The wheeling detection algorithm revealed good to excellent performance, while the classification of active wheeling was more sensitive and precise than the classification of passive wheeling. Wheeling was confused with sitting and assisted walking but not with other activities. The walking detection per se revealed a sensitivity and precision of almost 90%, and the remaining 10% were mainly confused with standing. However, the discrimination between level walking and stair climbing was erroneous, resulting in a weak performance to detect stair climbing and decreased sensitivity and precision to detect level walking periods. Still, the distinction between free and assisted walking as well as between going up- and downstairs was almost perfect.

The measurement errors of the outcome measures are depicted in **Table 7.1**. The algorithm estimated the duration of lying, sitting, standing, active wheeling, and walking with an error of less than 10% (interquartile range of relative difference between the algorithm's measures and the reference values). The remaining performance measures revealed larger measurement errors. Systematic differences (median relative difference between the algorithm's measures and the reference values) were smaller than 10%, except for standing up and stair climbing measures, which were systematically underestimated by the algorithm. The correlation coefficients ranged between .77 for the number of sit-to-stand transitions and .99 for the duration of sitting and standing periods.

Predicted activities of…		Actual activities (based on video observations): Lying	Activities in sitting position								Activities in standing position						Precision	
		Lying	Sitting	Kneeling	Being carried	Active wheeling	Passive wheeling	Cycling	Sliding	Swinging	Jumping	Standing	Free walking	Assisted walking	Going upstairs	Going downstairs		
…posture detection	Lying	97 min	6 min	0 min	0 min	2 min	0 min	0 min	0 min	0 min	0 min	0 min	0 min	0 min	0 min	0 min	92%	
	Sitting	5 min	517 min	11 min	0 min	160 min	49 min	23 min	0 min	13 min	0 min	3 min	0 min	0 min	0 min	0 min	99%	
	Standing	0 min	7 min	1 min	0 min	0 min	0 min	9 min	0 min	0 min	1 min	145 min	114 min	65 min	13 min	16 min	95%	
	Sensitivity	95%	97%								99%						**97%**	
…wheeling detection	Non-wheeling	55 min	364 min	0 min		5 min	0 min	5 min		11 min		25 min	11 min	27 min	5 min	7 min	99%	
	Active wheeling	0 min	6 min	0 min		154 min	4 min	0 min		0 min		1 min	0 min	6 min	0 min	0 min	89%	90%
	Passive wheeling	0 min	3 min	0 min		5 min	45 min	0 min		0 min		0 min	0 min	0 min	0 min	0 min		84%
	Sensitivity	97%				93%		97%									**96%**	
						94%	90%											
…walking detection	Non-walking	101 min	563 min	13 min	0 min	164 min	49 min	31 min	0 min	12 min	1 min	130 min	10 min	6 min	3 min	2 min	98%	
	Free walking	0 min	4 min	0 min	0 min	1 min	0 min	1 min	0 min	1 min	0 min	16 min	84 min	0 min	1 min	2 min	86%	75%
	Assisted walking	0 min	1 min	0 min	0 min	0 min	0 min	0 min	0 min	0 min	0 min	4 min	0 min	51 min	1 min	1 min		87%
	Going upstairs	0 min	0 min	0 min	0 min	0 min	0 min	0 min	0 min	0 min	0 min	1 min	13 min	5 min	9 min	0 min		30%
	Going downstairs	0 min	0 min	0 min	0 min	0 min	0 min	0 min	0 min	0 min	0 min	0 min	11 min	2 min	0 min	12 min		46%
	Sensitivity	97%											90%				**93%**	
													71%	79%	65%	73%		

Figure 7.4 – Confusion matrices of the three sub-algorithms.

Table 7.1 – Measurement errors of the outcome measures.

outcome measures	**reference values**		**measurement error**		**relative measurement error**		**Spearman correlation**
	median	IQR	median	IQR	median	IQR	ρ
duration of lying periods	4.4 min	1.7 min	0.0 min	0.1 min	0%	3%	0.93
duration of sitting periods	27.8 min	25.2 min	-0.1 min	0.8 min	0%	5%	0.98
duration of standing periods	14.0 min	20.1 min	0.0 min	0.8 min	0%	6%	0.99
number of sit-to-stand transitions	5	3	-1	2	-20%	32%	0.77
duration of active wheeling	9.9 min	4.8 min	0.0 min	0.5 min	0%	5%	0.91
duration of passive wheeling	2.1 min	3.0 min	0.0 min	0.3 min	2%	19%	0.84
duration of all walking periods	10.7 min	5.2 min	0.1 min	0.9 min	0%	8%	0.94
duration of free walking periods	8.7 min	9.8 min	0.0 min	1.5 min	-3%	41%	0.91
duration of assisted walking periods	7.0 min	9.0 min	0.2 min	2.2 min	4%	26%	0.93
altitude change during going upstairs*	6.6 m	8.2 m	-0.7 m	2.4 m	-23%	52%	0.89
altitude change during going downstairs*	6.6 m	8.2 m	-1.0 m	0.8 m	-27%	32%	0.97

*this analysis was limited to indoor activities since it was impossible to determine the altitude change during slope walking periods occurring only outdoors. Indoors, the heights of each flight of stairs were known and the covered flights of stairs were counted in the video recordings.

7.5 Discussion

This study introduces and validates a novel algorithm to derive clinically relevant performance measures based on wearable inertial sensor data of children with mobility impairments. The algorithm performed excellent in detecting lying, sitting, and standing; good to excellent in detecting general walking periods as well as active and passive wheeling periods; and weak in discriminating between level walking and stair climbing.

The algorithm confused lying with sitting mainly when the children were lying while resting on their elbows and thus, having a relatively upright trunk orientation. Conversely, false positive lying detections occurred predominantly when the children were sitting and leaning forward (e.g., to pick up an object from the floor or lock the wheels of the wheelchair). These confusions can easily be explained since the algorithm relies on the orientation of the trunk to classify lying and sitting positions. Furthermore, we expect that these confusions hardly affect the overall lying and sitting duration of long-term measurements.

Cycling was often classified as standing rather than sitting, which can also be explained by the algorithm using the orientation of the thigh to discriminate between sitting and standing positions. In children with a lot of daily cycling activities, this would lead to overestimating weight-bearing activities, especially in wheelchair-dependent children. We suggest developing an algorithm that detects cycling periods specifically or using a protocol reporting daily cycling activities to overcome this limitation.

During the circuit, it happened that the trunk and thigh sensors slipped downward, and we replaced the sensors as soon as we realized it. These periods were detected in the video recordings and ignored in the data analysis since we intended to validate the algorithm and not the slip resistance of the straps. However, this can also happen in daily life and would lead to erroneous data. Therefore, sensors should be placed solidly on the children, and the families should be instructed to verify the sensor positions regularly.

If at all, sitting and assisted walking were misclassified as wheeling and decreased the precision of the wheeling detection algorithm. Wheeling periods in the video recordings were identified independent of the covered distance and underlying velocity, since this cannot be observed accurately. In contrast, the algorithm only detected wheeling periods in which the wheel exceeded an angular rate of 10°/s and a turn of 80° (Popp et al., 2016). This discrepancy could explain the confusion between sitting and wheeling. The confusion between assisted walking and wheeling occurred in a single participant. He was walking while we pushed his wheelchair alongside. This can happen in daily life as well, especially during transitions between wheeling and walking periods. However, we believe that these periods can be neglected compared to the duration of wheeling and walking in long-term measurements.

Periods of going up- and downstairs were detected with a weak precision of 30% and 46%. Free walking was often confused with stair climbing. In the reference system, we did not discriminate between level and slope walking, even though some children walked outdoors on slopes corresponding to three flights of stairs. Reducing the analysis to indoor periods revealed a higher precision of 44% and 60%. Still, stair climbing was often confused with walking and standing. More severely impaired children took adjusting steps when ascending and descending stairs and did small breaks on each step. The algorithm failed to detect these stair climbing patterns, and four consecutive steps are required to detect stair climbing with the current algorithm. Despite classification inaccuracy, the algorithm can still discriminate between participants with low and high stair climbing activity, indicated by correlation coefficients of 0.89 and 0.97.

A comparison of the results with previous literature is difficult due to the heterogeneity in study designs. There are dissimilarities in the study population, the measurement devices, the performed activity protocols, and the number and type of detected activities by the algorithms. Still, our novel algorithm outperforms previous algorithms validated in children with mobility impairments (Ahmadi et al., 2018; Goodlich et al., 2020; Lankhorst et al., 2019; Nooijen et al., 2015). This is remarkable for three main reasons. First, our study population has a larger variety in medical diagnoses and levels of impairments, which challenges the algorithm to find a solution that fits all. It has been shown that subgroup-specific algorithms or fully-personalized approaches reveal higher accuracies than those covering the whole population (Ahmadi et al., 2020). Second, none of the studies mentioned above included stair climbing as an activity of interest, and excluding stair climbing from our analysis would further increase the accuracy of our algorithm since stair climbing detection revealed the least accurate results in our study. And third, we determined the algorithm's performance with the whole dataset, while the other studies excluded or ignored transitions between activities (Ahmadi et al., 2018; Goodlich et al., 2020; Lankhorst et al., 2019) or disregarded activities lasting less than five seconds (Nooijen et al., 2015). We argue that transitions and short-lasting activities are challenging to detect, and they should be included in the analysis to reflect real-life data to increase the external validity of the study results.

Moreover, our study protocol included activities not classified by the algorithm to challenge activity detection and reflect everyday life activities, which is another strength of our study protocol. However, it has to be shown whether the amount of performed activities in our dataset reflects daily activities of children with mobility impairments, and it remains questionable if the results of this study can be transferred to long-term measurements in daily life. Hence, we encourage the research community to develop methodologies to validate wearable sensor technology and their underlying algorithms in the children's real world and not just during semi-structured activity circuits, even though the latter is recommended as a standard for such validity studies (Lindemann et al., 2014).

7.6 Conclusion

This study introduces three sub-algorithms that determine clinically meaningful outcome measures based on wearable inertial sensor data in the daily life of children with mobility impairments. The first algorithm determines the duration of lying, sitting, and standing as well as the number of sit-to-stand transitions with two sensors placed on the trunk and the thigh. The second algorithm measures the duration of active and passive wheeling periods with a wrist sensor and a sensor placed on the spokes of the wheelchair. And the third algorithm determines the duration of free and assisted walking as well as the altitude change covered during stair climbing periods with an ankle sensor and a sensor placed on walking aids. The sub-algorithms are well described, can be reproduced, and applied to other inertial sensor technologies. Moreover, they were validated in children with mobility impairments and can be used in clinical practice and clinical trials to determine the children's motor performance in their habitual environment. Besides, we published the labeled dataset enabling the evaluation of future algorithms.

8 Concurrent validity of different sensor-based measures: Activity counts do not reflect functional hand use in children and adolescents with upper limb impairments

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8.1 Abstract

Objective To investigate the concurrent validity of four different outcome measures to determine daily functional hand use with wrist-worn inertial sensors in children with upper limb impairments. We hypothesized that the commonly used activity counts are biased by walking and wheeling activities, while measures that exclude arm movements during these periods with activity detection algorithms or by limiting the analysis to a range of functional forearm elevation would lead to more valid estimates of daily hand use.

Design Concurrent validity study with video-based observations of functional hand use serving as the criterion measure.

Setting The participants were videotaped while performing an activity circuit at the rehabilitation center and wearing inertial sensors.

Participants A convenience sample of 30 school-aged children and adolescents with upper limb impairments.

Interventions Not applicable.

Main Outcome Measures Spearman rank correlation coefficients ρ between the criterion measure and four sensor-based measures: activity counts, combining activity counts with activity detection algorithms (arm activity counts), limiting activity counts to a functional range of forearm elevation (functional activity counts), and a threshold-based approach limited to the same range of forearm elevation (gross arm movements).

Results Activity counts ($\rho = 0.43$) and gross arm movements ($\rho = 0.57$) did not reveal valid estimates of daily hand use. In contrast, arm and functional activity counts correlated significantly stronger with the criterion measure and revealed valid correlation coefficients of 0.78 and 0.71, respectively.

Conclusions Activity counts should not be used to measure daily hand use since they are biased by walking and wheeling activities. Arm and functional activity counts provide better and valid alternatives. The selection of these two approaches depends on the availability and accuracy of activity detection algorithms and on the users' willingness to wear additional sensors in daily life.

8.2 Introduction

Children with acquired or congenital brain injuries often present upper limb impairments (Gazzellini et al., 2012) and report difficulties with daily manual activities (Arner et al., 2008). These children undergo intensive rehabilitation programs to improve their ability to handle objects and gain independence in age-related self-care activities (Rast and Labruyère, 2020a). Here, motor assessments are essential for developing a patient-centered therapy plan, monitoring the children's progress over time, and providing families with objective information. These assessments are usually conducted in a standardized setting at the clinic. Therefore, they reflect motor capacity (i.e., what children can do in a standardized environment) (Holsbeeke et al., 2009), and it remains unclear whether children can translate capacity into performance (what children actually do in their habitual environment) (Holsbeeke et al., 2009) after rehabilitation. Hence, valid measures of the children's hand use in daily life are needed to complement the children's assessment.

Wrist-worn inertial sensors allow for unobtrusive long-term measurements of hand movements in everyday life (Leuenberger and Gassert, 2011). However, these sensors record not only functional hand use (e.g., handling an object) but also non-functional hand use (e.g., dyskinesia) and whole-body movements (e.g., walking). Therefore, algorithms are required to process the collected raw data and derive clinically meaningful and valid outcome measures. Filtering the acceleration data and summing up the filtered data points for each second to derive activity counts (Tryon and Williams, 1996) is a widely used outcome to measure daily hand use in children (Braito et al., 2018; Goodwin et al., 2020). However, its validity has not been investigated thoroughly (Lang et al., 2020), and previous studies have shown that activity counts are biased by walking activities (Regterschot et al., 2021; Subash et al., 2022). Moreover, activity counts might also be biased by self-propulsion in wheelchair-dependent children. Although wheeling could be considered as functional hand use, it makes sense to exclude it from hand use measures since it is mobility-related and could be detected separately with a sensor on the spokes of the wheelchair (Popp et al., 2016). Walking and wheeling activities can be excluded with activity recognition algorithms to limit activity counts to non-mobility periods only (Regterschot et al., 2021) (subsequently called arm activity counts). However, this approach requires additional sensors and data processing algorithms, potentially decreasing the children's compliance to wear the sensors and the comparability between methods. A simple alternative requiring just the wrist sensors would be detecting and counting gross arm movements (Leuenberger et al., 2017). Here, arm movements are only included when the forearm elevation lies between ±30° around the horizontal plane (**Figure 8.1**) and the angular change within this range exceeds the threshold of 30° in a two-second-window. With this, functional hand use should be detected since it occurs predominantly in the horizontal plane (e.g., grasping an object on the table). At the same time, walking and wheeling are likely excluded since the forearm points downwards during these activities, and the forearm elevation lies outside the pre-defined range. A recent validity study has shown that gross arm movements were more specific than activity counts in detecting functional hand use but less sensitive (Subash et al., 2022), which might be because the threshold-based approach excludes functional hand movements having a smaller angular change than 30°.

The present study introduces a new approach to measure functional hand use (functional activity counts) by combining the advantages of activity counts and gross arm movements. In brief, we calculate activity counts to avoid excluding small hand movements but limit the analysis to periods with functional forearm elevations to exclude hand movements during walking and wheeling activities. It is a simple solution requiring just wrist-worn inertial sensors and is independent of complex activity recognition algorithms. We aimed to validate this new approach in children undergoing rehabilitation and compare the validity between activity counts, arm activity counts, functional activity counts, and gross arm movements to make recommendations for future studies on daily hand use of children. We hypothesized that activity counts are biased by walking and wheeling activities, while arm activity counts and functional activity counts would lead to more valid estimates of daily hand use.

8.3 Methods

We designed this study to investigate the concurrent validity (Salkind, 2010) of sensor-based hand use measures with video-based observations of functional hand use serving as the criterion measure. The participants were videotaped while performing activities of daily living and wearing inertial sensors to derive the sensor-based measures. The local ethics committee approved this study (BASEC Nr.: 2019-00487).

8.3.1 Participants

We used an existing dataset of 31 school-aged children and adolescents undergoing rehabilitation, which was established to validate sensor-based outcomes of upper and lower extremities (see **Chapter 7**). The children's abilities to handle objects were determined with the Manual Ability Classification System (MACS) (Eliasson et al., 2007). They were able to walk or use a manual wheelchair for household distances, had cognitive abilities to follow instructions, had no medical conditions that prevented sensor placement, and provided informed consent to participate in the study. A sample size of ≥30 is considered adequate for concurrent validity studies (Mokkink et al., 2019).

8.3.2 Equipment and procedure

Participants were equipped with five ZurichMOVE sensor modules containing a 3-axis accelerometer and gyroscope (Popp et al., 2019). The sensors were placed on both wrists, the sternum, and the thigh and ankle of the less-affected side with hook-and-loop straps (see **Chapter 7**). Data of the wrist sensors were used to derive the hand use measures. In addition, the ankle sensor and an additional sensor on the spokes of the wheelchair were used to detect walking and active wheeling periods, respectively. Data of the sternum and thigh sensors were not used in this study.

The participants were videotaped while performing a semi-structured activity circuit at the rehabilitation center (see **Chapter 7**). They watched a movie on a tablet in their bedroom, played a self-selected game (e.g., card games, puzzles, etc.) in the living room, drank a glass of water in the restaurant, cycled in the gym hall, and played a self-selected outdoor game on the playground (e.g., catching and throwing balls, swinging, etc.). Participants were encouraged to walk, wheel, climb stairs, and take the elevator between these facilities. No instructions were given on how to do these activities so that the children moved as they would in real life. The sampling rates of the camera and sensors were set to 50 Hz, and timestamps were synchronized with the children clapping their hands in front of the camera.

8.3.3 Criterion measure

Video recordings from an external perspective were used to derive video counts of each hand separately. Each instance of functional hand use was labeled as a single video count. These counts were summed for each minute and served as the criterion measure. We defined functional hand use as in a published coding scheme (Uswatte and Hobbs Qadri, 2009) but counted hand use differently. Task-related and non-task-related functional hand use were both considered as a video count. Non-functional hand movements and inactivity were not counted. Since we aimed to measure hand performance and not walking or wheeling performance, the use of walking aids and self-propulsion in the wheelchair were not counted, even though these hand activities have a functional purpose. Specific criteria are listed in **Table 8.1**. The goal of the video annotation was to determine the hand use frequency (number of repetitions) and not the duration of hand use. This is a major difference to the above-mentioned coding scheme. We argue that doing a hand activity twice within the same period compared to doing it once should result in higher performance measures.

Two raters labeled one-third of the data with a high interrater correlation of $\rho = 0.99$. We decided to label the remaining data with a single rater based on this result. This procedure shortened the time-consuming labeling process without decreasing data quality.

Table 8.1 – Specific criteria to label functional hand use in the video recordings (criterion measure).

Functional hand use = 1 video count	Non-functional hand use = 0 video counts
Interaction of the hand with an object (e.g., drinking a glass of water, pushing a button or scratching)	Touching an object without a functional purpose (e.g., resting the hand on the table)
Gestures (e.g., clapping or waving) Moving the arm or hand actively or passively without a functional purpose (e.g., dyskinesia)	
Clear initiation of an interaction without touching an object (e.g., start drawing a card and then realizing it is not your turn)	
Supporting oneself with the hand on the table or bed	
Functional hand use while walking or wheeling or being pushed in the wheelchair (e.g., opening a door or pushing the button of the elevator)	Arm swing while walking and self-propulsion in the wheelchair
Grasping a walking aid	Walking with a walking aid
Grasping the rail while stair climbing	
Catching and throwing was labeled separately, even if the ball was not released in between	
Playing a ball/shuttle with a racket was labeled each time, even if the racket was not released in between	
Shuffling cards and operating the touch screen was summarized to a single count, since individual interactions could not be separated.	

8.3.4 Sensor-based measures

The sensor-based hand use measures were calculated with four different approaches and for each hand separately:

1. Activity counts: The three-dimensional acceleration signals of the wrist sensors were band-pass filtered, resampled, and summed for each axis and second of data with an open-source MATLAB code (Brønd et al., 2017). Then, the vector magnitude of the three axes was determined, and 60 consecutive values were added to derive activity counts per minute. This approach was chosen to reflect the intensity of hand use (Bailey et al., 2014) rather than applying a threshold-based filter to determine the duration of hand use (Uswatte et al., 2000).

2. Arm activity counts: Walking and wheeling periods were detected and then ignored before estimating activity counts. They were detected with an activity recognition algorithm having an accuracy of >93% (see **Chapter 7**). Then, the acceleration signal of these periods was set to zero before applying approach 1 to the adjusted signal.

3. Functional activity counts: The estimation of activity counts was limited to periods with functional forearm elevations (**Figure 8.1**). First, the acceleration and gyroscope signal of the wrist sensors were fused to determine the pitch angle (the angle between the forearm axis and a horizontal plane), and functional forearm elevation was defined as the range of pitch angles between -30° and +30° (Leuenberger et al., 2017). Then, the acceleration signal was set to zero whenever the pitch angle was outside this range. Finally, approach 1 was applied to the adjusted acceleration signal.

4. Gross arm movements: A comprehensive description of this approach has been published earlier (Leuenberger et al., 2017) and is briefly summarized here. The data were segmented into windows of 2 *s* with 75% overlap, resulting in 120 windows per minute. For each window, arm movement was counted as a gross movement if the sum of a change of forearm orientation in yaw (the angle between the forearm axis and the sagittal plane) and elevation is more than 30°, but only if the movement occurred within a range of forearm elevation between -30° and +30° (**Figure 8.1**). Hence, the peak value of this approach is 120 gross arm movements per minute.

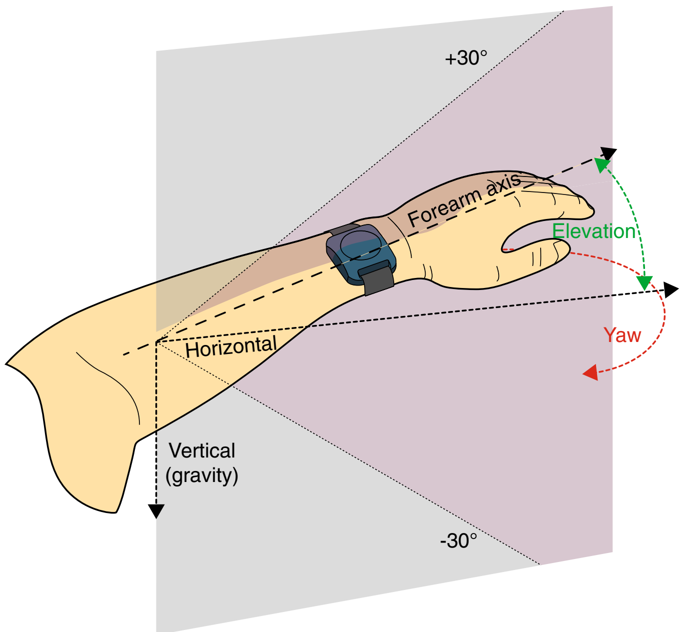

Figure 8.1 – Illustration of the forearm angles extracted from the sensor data. Elevation is the angle between the horizontal and the forearm axis and yaw is the angle covered in lateral movements. The red area in the vertical plane illustrates the region where gross arm movements are identified and movements outside of this area are not captured by the algorithm. Note that shoulder abduction, flexion and rotation as well as elbow flexion can influence elevation and yaw. Note: From Leuenberger K, Gonzenbach R, Wachter S, Luft A, Gassert R. A method to qualitatively assess arm use in stroke survivors in the home environment. Med Biol Eng Comput. 2017;55(1):141-150, p. 144. Copyright © 2016, International Federation for Medical and Biological Engineering. CC BY.

8.3.5 Statistical analysis

We determined the concurrent validity with the Spearman rank correlation between the sensor-based hand use measures and the video counts for each participant separately. The median and interquartile range of these correlation coefficients was calculated for each approach, and medians of >0.70 were considered valid (Terwee et al., 2007). Non-parametric testing was applied since the outcomes were not normally distributed. The comparison of the validity between approaches was completed with the Wilcoxon test. Again, non-parametric testing was used since the correlation coefficients were not normally distributed. The alpha level was set to 0.05/6 = 0.008 to correct for multiple comparisons. We conducted the data processing and statistical analysis in MATLAB R2018b (The MathWorks, Inc.).

8.4 Results

One participant had to be excluded from the dataset because his hands were often not visible in the video recordings. The resulting dataset contained 30 participants and 23.1 hours of daily activities (the circuit lasted 46 min on average), of which 3.5 hours were walking and 2.5 hours were active wheeling. It comprised data of 12 girls and 18 boys (11.8 ± 3.3 years; range: 6.1-18.1 years) with various medical diagnoses and different levels of upper limb impairment. The participants' characteristics are shown in **Figure 8.2**.

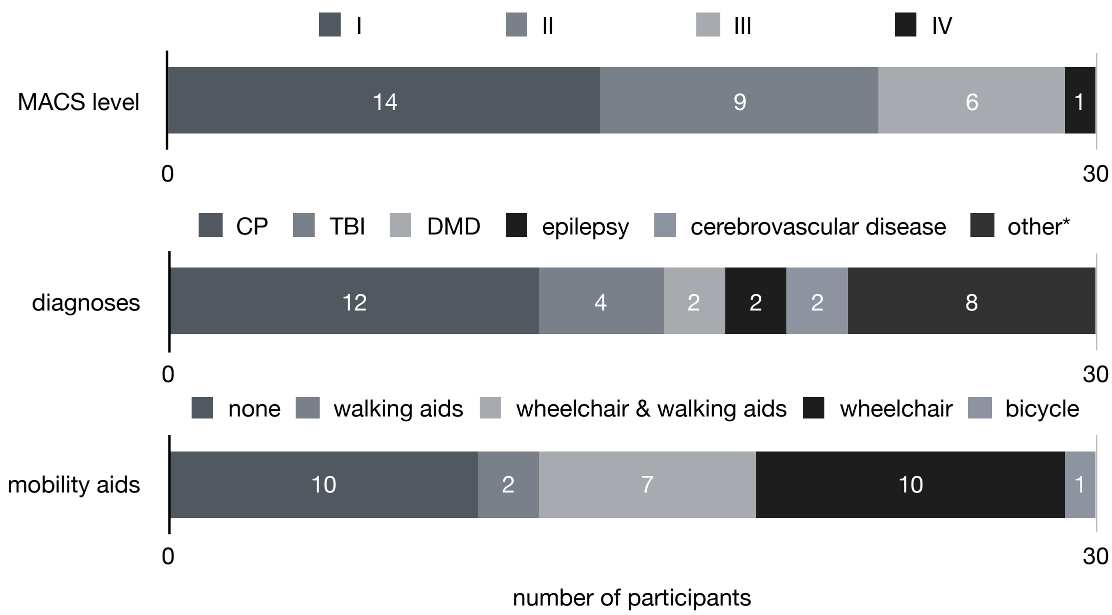

Figure 8.2 – Participant's characteristics. MACS = manual ability classification system; CP = cerebral palsy; TBI = traumatic brain injury; DMD = dissociative movement disorder;
* = chromosomal abnormality, congenital malformation syndrome, demyelinating disease, hereditary ataxia, multiple sclerosis, neoplasm, osteomyelitis & spina bifida.

Their abilities to handle objects ranged from MACS I (i.e., handles objects easily and successfully) to MACS IV (i.e., handles a limited selection of easily managed objects in adapted situations). Nineteen participants were able to walk for household distances, ten were wheelchair-dependent, and one participant moved around on a bicycle. Seven of those who were able to walk also used a wheelchair for longer distances.

8.4.1 Concurrent validity of hand use measures

The sensor-based hand use measures in relation to the criterion measure are illustrated in **Figure 8.3**. Green and blue data points indicate one minute containing only walking or wheeling activities, respectively, while the remaining minutes are shown in gray. The latter can include other activities than walking and wheeling or a mix between walking, wheeling, and other activities.

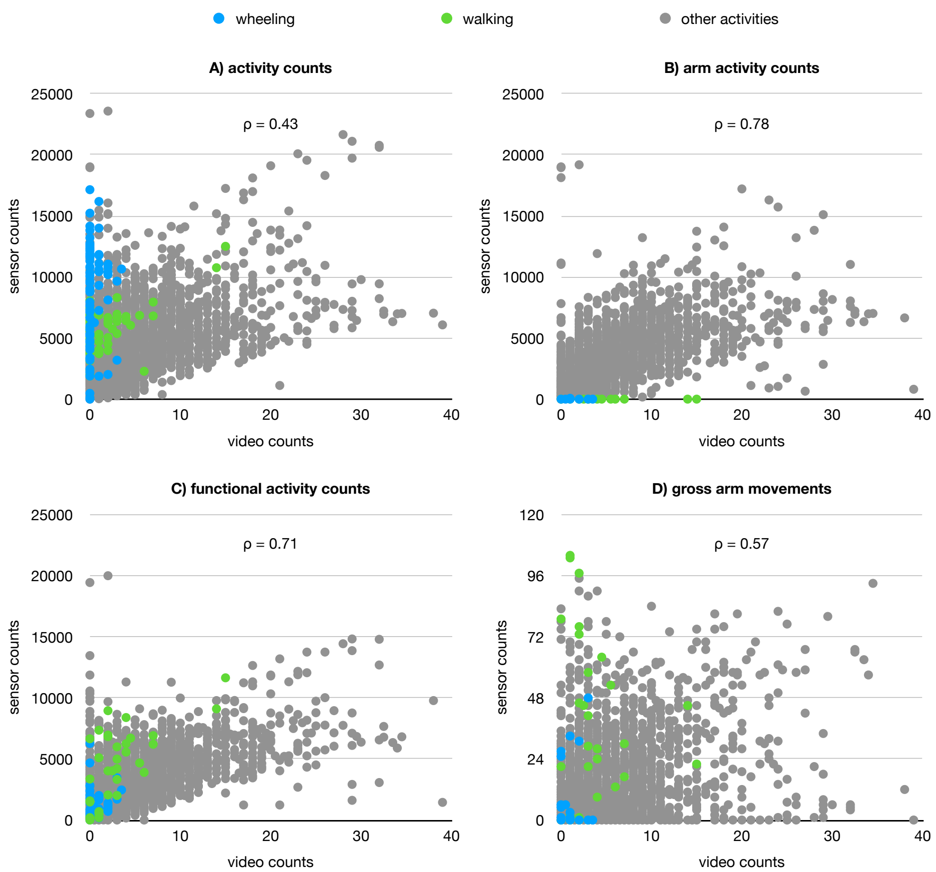

Figure 8.3 – Scatter plot of the sensor-based hand use measures in relation to the criterion measure. Green and blue data points indicate a one minute period containing just walking and wheeling activities, respectively, while the remaining periods are shown in gray. These data points can comprise other activities than walking and wheeling or a mix between walking, wheeling, and other activities. ρ = median Spearman rank correlation coefficient of all participants.

The correlation coefficients of activity counts and gross arm movements were 0.43 and 0.57, respectively. They were smaller than the desired value of 0.70 and did not provide valid estimates of daily hand use. In contrast, arm activity counts and functional activity counts revealed correlation coefficients of 0.78 and 0.71, respectively, and provided valid estimates of daily hand use. Moreover, these two measures correlated significantly stronger with the criterion measure than activity counts and gross arm movements. Arm activity counts showed the strongest relationship with video counts, while the difference to functional activity counts was not statistically significant. The median and interquartile range of the correlation coefficients and the results of the approach-wise comparison are visualized in **Figure 8.4**.

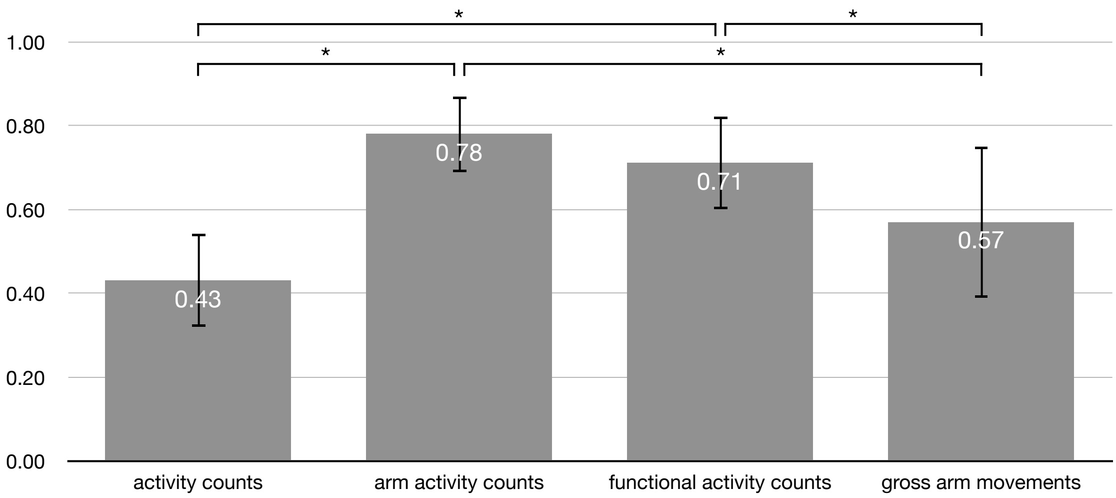

Figure 8.4 – Comparisons between sensor-based hand use measures. The bars show the median, while the error bars represent the interquartile range of the correlation coefficients. *p-value < 0.008.

8.5 Discussion

This study introduced a new approach measuring daily hand use with wrist-worn inertial sensors. The approach ignores undesirable hand movements during walking and wheeling activities by limiting the analysis to a functional range of forearm elevation without requiring additional sensors. Moreover, we validated this new hand use measure in children undergoing rehabilitation and compared its validity with other hand use measures described in the literature.

We showed that the well-established activity counts did not reveal valid estimates of functional hand use. This contradicts another validity study conducted in children with hemiplegic cerebral palsy (Dawe et al., 2019). However, their study protocol was completed in a seated position. In our study, walking and wheeling periods resulted in high activity counts, even though the hand was not (i.e., arm swing) or rarely used (e.g., opening a door while walking). This finding is illustrated by the blue and green data points being close to the vertical axis of **Figure 8.3.A**. Similarly, gross arm movements also did not reveal valid estimates of hand use. Here, the actual hand use during walking and wheeling was represented more accurately. However, many hand activities were not detected as gross arm movements. This is illustrated by the gray data points being close to the horizontal axis of **Figure 8.3.D** being a unique characteristic of gross arm movements, presumably caused by the threshold-based approach. These findings confirm the results of previous studies conducted in healthy adults and in stroke survivors showing that activity counts lack specificity and gross arm movements lack sensitivity in detecting functional hand use (David et al., 2021; Subash et al., 2022). In contrast, using an activity recognition algorithm and setting the activity counts to zero during walking and wheeling periods improved the validity significantly and resulted in valid estimates of daily hand use. Similar results have recently been shown in adult stroke survivors (Regterschot et al., 2021) and we argue that this finding can be generalized to any target population which walks or wheels in everyday life. However, it has to be noted that the arm activity counts algorithm can only be generalized to other target populations if the activity recognition algorithm is also validated for the same population. Moreover, functional hand use during the excluded activities and whole-body movements not detected by the algorithm will still bias the hand use measure. For example, grasping the rail while stair climbing resulted in the green data points on the horizontal axis of **Figure 8.3.B** with high video counts, and jumping on a trampoline resulted in the gray data points in the top left corner of **Figure 8.3.B**. Therefore, advanced and accurate activity recognition algorithms are needed to improve the validity of sensor-based hand use measures. A viable alternative to using activity recognition is provided by the newly presented functional activity counts that also revealed valid estimates of daily hand use. This is encouraging since the validity of our new measure is non-inferior to combining activity counts with an activity recognition algorithm. At the same time, it does not require additional sensors and might increase the patients' compliance to wear the sensors in everyday life situations. Nevertheless, functional hand use with a forearm elevation being outside the functional range and non-functional hand movements with a forearm elevation within the functional range will still bias the hand use measure. For example, excessive wheeling might explain the blue data points in **Figure 8.3.C** having higher sensor counts than video counts. Machine learning algorithms which discriminate between functional and non-functional hand use might overcome this limitation (Lum et al., 2020), but their applicability and validity in children with upper limb impairments has to be investigated first.

Based on our findings, we encourage the research community to stop using activity counts of wrist-worn sensors to measure daily hand use in clinical trials. This outcome might as well reflect changes in the walking or wheeling behavior of the study participants rather than reflecting changes in actual hand use. Instead, we suggest combining activity counts with activity recognition algorithms or limiting the analysis to a functional range of forearm elevation as more valid alternatives to activity counts. The former approach seems to be superior. Still, its validity depends on the availability and accuracy of activity detection algorithms and on the users' willingness to wear additional sensors in daily life. Moreover, the comparability between studies will decrease if different algorithms are used.

8.5.1 Study limitations

The criterion measure used in this study counts each instance of functional hand use. These instances were not subdivided in terms of duration or complexity of hand use, which might explain the scatter in the data. For example, scratching oneself and drinking a glass of water were labeled as a single video count, while they differ in duration and complexity. We chose this approach since we wanted more repetitions of hand activities to result in higher performance measures even if they were completed in a short period. Moreover, it was more reliable to count hand activities than determining their exact start- and endpoint. Consequently, it remains unclear whether sensor-based hand use measures also reflect the duration or complexity of hand use in daily life, and innovative criterion measures are needed for such validity studies.

Our new approach revealed valid estimates of hand use on average, but not for each participant separately. This is shown by the interquartile range of correlation coefficients in **Figure 8.4**. The correlation coefficients of individual participants are listed in **Table 8.2** and subdivided according to the participants' MACS-level. The validity of hand use measures was comparable between subgroups with different MACS-levels. However, these findings should be interpreted with caution due to small subgroups and because the MACS has only been validated for children with cerebral palsy. Besides, there are low correlation coefficients of individual participants which could be caused by certain activities (e.g., puzzling only required small hand movements but resulted in many video counts) or the type of movement disorders (e.g., elbow flexion contractures would keep the forearm within the functional range during whole-body movements and dyskinesia would lead to bursts in the acceleration signal). However, the impact of movement disorders on the validity of hand use measures has to be shown in larger studies with balanced subgroups, including typically developing children.

Wrist-worn accelerometers capture hand use indirectly by measuring the movement of the forearm. This can be justified since arm movement is typically required to position the hand for daily manual activities, and our study results show that this indirect measurement provides valid estimates of hand use. However, wrist-worn accelerometry will not capture fine hand use such as typing on a keyboard. Additional sensors on the fingers (Rowe et al., 2014), measuring the activity of hand muscles (Sadarangani et al., 2017), or egocentric video recordings of the hand (Likitlersuang et al., 2019) would overcome this limitation. Still, their usability and validity in children with upper limb impairments have to be investigated first.

Table 8.2 – Correlation coefficients between video-based and sensor-based hand use measures of all participants and sensor-based approaches stratified by the participants' ability to handle objects.

Subject	MACS level	activity counts	arm activity counts	functional activity counts	gross arm movements
ID03	1	0.03	0.82	0.85	0.70
ID08	1	0.51	0.81	0.66	0.47
ID09	1	0.62	0.66	0.68	0.21
ID10	1	0.51	0.78	0.85	0.63
ID11	1	0.38	0.87	0.80	0.37
ID13	1	0.65	0.77	0.85	0.42
ID16	1	0.17	0.88	0.91	0.54
ID18	1	0.66	0.80	0.68	0.34
ID22	1	0.53	0.85	0.85	0.73
ID26	1	0.37	0.84	0.71	0.47
ID27	1	-0.21	0.37	0.36	0.80
ID28	1	0.14	0.78	0.72	0.61
ID29	1	0.48	0.81	0.71	0.68
ID31	1	-0.08	0.64	0.52	0.71
Median (MACS = 1)		**0.43**	**0.80**	**0.72**	**0.57**
ID01	2	0.18	0.67	0.53	0.12
ID05	2	0.23	0.64	0.72	0.62
ID06	2	0.67	0.56	0.72	0.20
ID12	2	0.53	0.78	0.75	0.74
ID14	2	0.73	0.61	0.67	0.38
ID19	2	0.43	0.54	0.43	0.35
ID20	2	0.70	0.87	0.86	0.68
ID23	2	0.35	0.86	0.78	0.83
ID24	2	0.30	0.86	0.88	0.84
Median (MACS = 2)		**0.43**	**0.67**	**0.72**	**0.62**
ID02	3	0.44	0.66	0.42	0.02
ID04	3	0.31	0.71	0.33	0.05
ID15	3	0.40	0.78	0.68	0.76
ID17	3	0.45	0.46	0.24	-0.03
ID25	3	0.42	0.71	0.78	0.63
ID30	3	0.78	0.89	0.89	0.81
Median (MACS = 3)		**0.43**	**0.71**	**0.55**	**0.34**
ID07	4	0.43	0.83	0.64	0.54
Median (MACS = 4)		**0.43**	**0.83**	**0.64**	**0.54**
Median (all MACS levels)		**0.43**	**0.78**	**0.71**	**0.57**

The children's abilities to handle objects were determined with the Manual Ability Classification System (MACS) .

8.6 Conclusion

Activity counts derived from wrist-worn accelerometers are not a valid measure of daily hand use in children with upper limb impairments, and we encourage the research community to stop using activity counts as an outcome measure. Combining activity counts with activity detection algorithms or limiting them to a functional forearm elevation provide more valid alternatives to measure hand use in daily life. The selection of these two approaches depends on the availability and accuracy of activity detection algorithms and on the users' willingness to wear additional sensors in daily life. We recommend limiting the analysis to a functional forearm elevation since it is easy to implement and helps providing comparable results between studies.

9 Accuracy and comparison of sensor-based gait speed estimations under standardized and daily life conditions in children undergoing rehabilitation

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Authors' contributions: FR, SA, and RL contributed to the conception and design of the study. CW developed and optimized the data processing algorithm. FR and SA recruited participants, collected the data, and performed the statistical analysis. All authors were involved in the data interpretation. FR wrote the first draft of the manuscript, while all authors contributed to manuscript revision and approved the final manuscript. SA did her master thesis under the supervision of FR.

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9.1 Abstract

Background Gait speed is a widely used outcome measure to assess the walking abilities of children undergoing rehabilitation. It is routinely determined during a walking test under standardized conditions, but it remains unclear whether these outcomes reflect the children's performance in daily life. An ankle-worn inertial sensor provides a usable opportunity to measure gait speed in the children's habitual environment. However, sensor-based gait speed estimations need to be accurate to allow for comparison of the children's gait speed between a test situation and daily life. Hence, the first aim of this study was to determine the measurement error of a novel algorithm that estimates gait speed based on data of a single ankle-worn inertial sensor in children undergoing rehabilitation. The second aim of this study was to compare the children's gait speed between standardized and daily life conditions.

Methods Twenty-four children with walking impairments completed four walking tests at different speeds (standardized condition) and were monitored for one hour during leisure or school time (daily life condition). We determined accuracy by comparing sensor-based gait speed estimations with a reference method in both conditions. Eventually, we compared individual gait speeds between the two conditions.

Results The measurement error was 0.01 ± 0.07 m/s under the standardized and 0.04 ± 0.06 m/s under the daily life condition. Besides, the majority of children did not use the same speed during the test situation as in daily life.

Conclusion This study demonstrates an accurate method to measure the children's gait speed during standardized walking tests and in the children's habitual environment after rehabilitation. It only requires a single ankle sensor which hopefully increases wearing time and data quality of measurements in daily life. Moreover, this study showed that most children did not use the same speed in the two conditions, which encourages the use of wearable inertial sensors to assess the children's walking performance in their habitual environment following rehabilitation.

9.2 Background

Pediatric rehabilitation aims to foster functional independence in everyday life activities of children with congenital and acquired illnesses and injuries. For most families with children undergoing rehabilitation, improvements in self-care and mobility activities are prioritized (Chiarello et al., 2010), and thereby, most rehabilitation goals are chosen in the domain of walking (Rast and Labruyère, 2020a). Therefore, assessing gait-related outcomes is essential to tailor therapy to the families' needs and monitor the children's progress over time.

The 10-meter walk test is the most widely used clinical assessment to determine gait speed in patients with neurological conditions (Graham et al., 2008). This outcome often serves as a surrogate to assess the children's overall walking abilities. Besides, increasing gait speed is essential since many children want to keep up with their peers (Buckon et al., 2007). The 10-meter walk test is conducted under standardized conditions, and it is currently unclear whether children can translate their improvements into daily life after rehabilitation. To close this knowledge gap, appropriate measurement tools to assess the children's gait speed in their habitual environment are needed.

Technological progress has made wearable inertial sensors small-sized, cost-effective, energy-efficient, and thus ideal for conducting long-term measurements in daily life (Garofalo, 2012). Hence, many algorithms with different approaches were developed to estimate gait speed based on sensor data (Yang and Li, 2012). To be sensitive, these algorithms must provide accurate gait speed estimations with a measurement error smaller than the minimally important change (MIC) for children undergoing rehabilitation. The MIC has been well investigated in adults with various pathologies and lies between 0.10 m/s and 0.20 m/s (Bohannon and Glenney, 2014). There is some evidence that the MIC for children lies within a similar range (Moreau et al., 2016; Oeffinger et al., 2008), and we used a MIC of 0.10 m/s as a benchmark to evaluate the algorithm's measurement error in this study.

Based on the authors' knowledge, only two studies investigated the measurement error of sensor-based gait speed estimations in children with walking impairments (Brégou Bourgeois et al., 2014; Carcreff et al., 2018). These studies validated three different sensor configurations and their underlying algorithms. Two algorithms revealed measurement errors smaller than the MIC. However, the usability of the related sensor configurations for long-term measurements in daily life is questionable. The first algorithm uses data of a foot-worn sensor (Brégou Bourgeois et al., 2014; Carcreff et al., 2018), but children often change or take off their footwear during daily life. The second algorithm requires sensors placed on each thigh and shank (Carcreff et al., 2018), and the need to wear four sensors simultaneously might decrease children's compliance. The third algorithm uses a single ankle-worn sensor (Carcreff et al., 2018), but the algorithm resulted in a measurement error larger than the MIC. Since we believe that this sensor configuration is the preferred choice in terms of usability, an improved algorithm with accurate gait speed estimations based on a single ankle-worn sensor is needed.

Consequently, the first aim of this study was to determine the measurement error of an improved algorithm that estimates gait speed based on data of a single ankle-worn inertial sensor in children undergoing rehabilitation. We investigated on which ankle the sensor needs to be placed to optimize accuracy and whether the measurement error is smaller than the MIC. The second aim of this study was to compare children's gait speed between standardized and daily life-like conditions.

9.3 Methods

9.3.1 Participants & recruitment

A convenience sample of 24 children and adolescents was recruited at the Swiss Children's Rehab of the University Children's Hospital Zurich, Switzerland. These children were able to walk household distances and had the rehabilitation goal to improve their walking abilities. Further inclusion criteria were: age between 4 and 20 years, cognitive abilities to follow instructions, and informed consent to participate in the study. Exclusion criteria were exacerbating pain during walking and open skin lesions at the ankle. The local ethics committee has classified the study as not requiring approval (BASEC Nr.: Req-2017-00958).

9.3.2 Procedure & equipment

Participants were equipped with two wearable inertial sensors (Popp et al., 2019). The sensors were placed above the lateral malleoli with corresponding hook-and-loop straps (**Figure 9.1**). The 3-axis accelerometer and gyroscope signals were used for data processing. Besides, participants were equipped with a video camera (YI 4K Action Camera, YI Technology, Shanghai, China). The camera was fixed to the chest with a harness, facing downward to take video recordings of the feet. The sampling rate of both devices was set to 50 Hz, and timestamps were synchronized by quickly rotating one sensor in front of the camera.

To study the gait speed in a standardized condition, participants completed four 10-meter walk tests at different speeds. They were instructed to walk at their self-selected speed during the first two trials. Then, they were asked to walk at a slower speed, and for the last trial, they had to walk as fast as they safely could without running. This setting was chosen to reflect the variability of gait speeds in daily life and challenge the algorithm with slow and fast walking trials. The GAITRite (CIR Systems, Franklin, USA), an 8 m pressure-sensitive walkway, was used as a reference to determine the measurement error of the sensor-based gait speed estimation. The GAITRite proprietary software derived the average gait speed $v_{reference,\ standardized}$ for each participant and walking trial.

During the daily life condition, participants wore the sensor system for one hour while having leisure or school time at the clinic. As a reference, we placed marks on the floor of straight hallways (5-25 m apart) and determined the durations participants needed to cover those distances from the chest video recordings to calculate the actual gait speed $v_{reference,\ dailylife}$.

Uninterrupted walking trials between two marks were analyzed. This condition was chosen to challenge the algorithm with non-standardized walking trials and to determine the children's daily gait speed at the clinic.

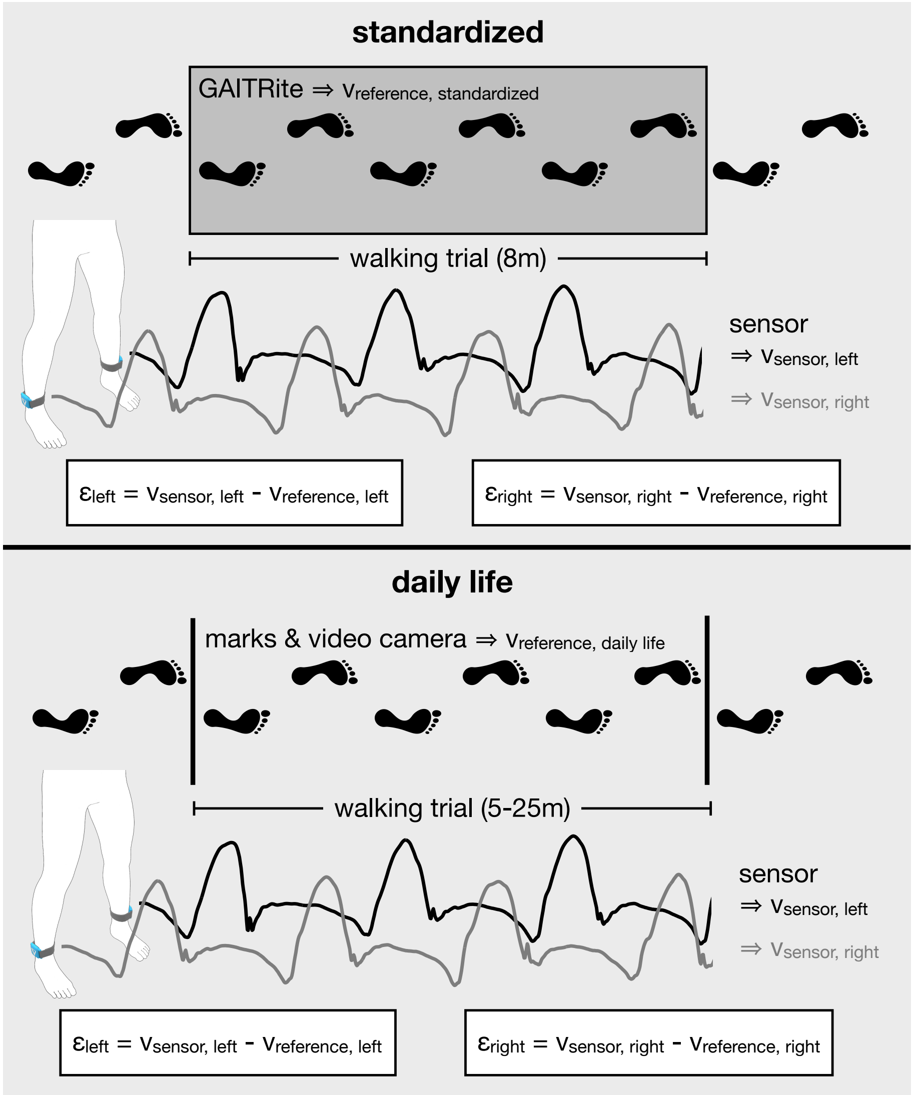


Figure 9.1 – Procedure to determine the measurement error ϵ of both sides and in both conditions.

9.3.3 Data processing

Walking trials were defined by stepping on and off the GAITRite under standardized conditions and stepping over a mark in daily life. These time points were determined from the video recordings. The sensor-based walking speed was estimated from the ankle-worn sensors, by extracting the stride duration and stride length calculated by an algorithm originally developed for the spinal cord injured population. The algorithm uses adaptive thresholds to detect steps, making it robust across various gait deficits (Werner et al., 2021). The algorithm was applied to the sensor data of all walking trials, for the left and right sides separately, to calculate the average gait speed $v_{sensor,\ standardized}$ and $v_{sensor,\ dailylife}$. The procedure to determine gait speeds and measurement error is illustrated in **Figure 9.1**.

9.3.4 Statistical analysis

The absolute error $\epsilon_{absolute} = |v_{sensor} - v_{reference}|$ was used to analyze which side reveals more accurate gait speed estimations. Participants were divided into two groups. Participants with similar impairments of their legs were allocated to the symmetrical group. In contrast, the asymmetrical group comprised participants with a unilateral impairment or with a more affected leg. For each walking trial, the difference of $\epsilon_{absolute}$ between the left and right sides for the symmetrical group and between the more and less affected sides for the asymmetrical group was calculated. These differences were non-normally distributed. Consequently, the median was calculated for each participant, including all walking trials of both conditions. The Wilcoxon signed-rank test was applied to determine whether the measurement error differed between the two sides.

Further analyses were conducted on single ankle sensors, taking only the side selected based on the absolute error differences introduced above. The selection process is depicted in **Figure 9.2** and justified in the discussion section. The 95% limits of agreement (LoA) between the sensor-based gait speed estimations and the reference values were calculated separately for both conditions (Bland and Altman, 1999). Then, the smallest detectable change (SDC) was estimated by multiplying the LoA with $\sqrt{2}$ (de Vet et al., 2006) and was then compared to the MIC (0.1 m/s). To calculate the measurement error of the average gait speed over several walking trials, the standard deviation of the measurement error was divided by the square root of the number of walking trials. This provides a method to determine how many walking trials are required to reach SDCs smaller than the MIC.

For each participant, the average gait speed of all walking trials during daily life was compared to the average gait speed of the two 10-meter walk tests with self-selected speed. The number of participants who walked faster, slower, and equally fast in daily life than the standardized condition was counted. Walking speeds were considered to be equal if their difference was less than the MIC.

9.4 Results

Seven girls and 17 boys (12.3 ± 3.3 years) with various medical diagnoses completed the study protocol. The participants' diagnoses, their individual walking abilities, measured with the walking scale of the Gillette Function Assessment Questionnaire (GFAQ) (Novacheck et al., 2000), and their use of walking aids and orthoses are listed in **Table 9.1**.

Table 9.1 – Patients' walking abilities and side comparison of the absolute measurement error.

Symmetrical impairment

ID	GFAQ	Diagnosis	Walking aids	Orthoses	Median difference[1] (m/s)	p-value
2	10	hereditary ataxia	none	none	-0.02	0.27
8	10	encephalopathy	none	none	0.00	0.54
9	7	neoplasms	assistance from another person	none	0.01	0.05
11	9	dissociative movement disorder	none	none	0.00	0.59
12	8	traumatic brain injury	none	none	-0.01	0.11
13	5	cardiogenic shock	none	foot lifter (both sides)	0.00	0.84
14	7	genetic disorder	posterior walker	ankle-foot (both sides)	0.02	0.13
20	8	dissociative movement disorder	crutches (both sides)	none	-0.01	0.57
22	6	traumatic brain injury	posterior walker	none	-0.03	**0.03**
24	5	cerebral palsy	posterior walker	ankle-foot (both sides)	0.00	0.64

Asymmetrical impairment

ID	GFAQ	Diagnosis	Walking aids	Orthoses	Median difference[1] (m/s)	p-value
1	8	traumatic brain injury	none	none	-0.03	**0.00**
3	8	traumatic spinal cord injury	none	none	-0.02	0.20
4	6	neoplasms	posterior walker	none	-0.01	0.43
5	10	traumatic brain injury	none	none	0.00	0.67
6	8	neoplasms	crutch (right side)	none	**0.21**	**0.01**
7	6	cerebral palsy	posterior walker	ankle-foot (both sides)	0.01	0.69
10	9	cerebrovascular disease	none	none	0.01	0.64
15	8	polytrauma	crutches (both sides)	ankle-foot (left side)	-0.05	**0.00**
16	8	cerebral palsy	crutches (both sides)	ankle-foot (left side)	-0.01	0.94
17	8	cerebral palsy	none	none	-0.01	0.30
18	7	polyneuropathy	none	foot lifter (left side)	**-0.09**	**0.01**
19	6	cerebral palsy	none	ankle-foot (both sides)	-0.02	0.25
21	8	traumatic brain injury	none	none	0.00	0.72
23	8	cerebral palsy	none	none	0.00	1.00

[1]The median difference of the absolute measurement error: left - right side in the symmetrical group and more affected - less affected side in the asymmetrical group. Large and statistically significant differences are indicated with bold numbers.
GFAQ = Walking scale of the Gillette Functional Assessment Questionnaire.

The median GFAQ was 8 with an interquartile range of 1.8. Thirteen participants required walking aids, orthoses, or assistance from another person, while the remaining 11 participants walked without assistance.

Missing values occurred at the fast walking trial of participant 17 and the first walking trial with the self-selected speed of participant 23 due to failure of the GAITRite. In daily life, the number of performed walking trials varied and ranged from 1 to 13. On average, walking trials contained 15 steps during the standardized condition and 22 steps in daily life. This resulted in an overall dataset of 230 walking trials and 4'360 steps.

For each participant, the difference of measurement errors between sides and the statistical test results are shown in **Table 9.1**. Children with symmetrical impairment revealed either small or non-significant differences between the measurement error of the left and right sides. This indicates that there is no clear favorable side in these patients, and we arbitrarily decided to continue the analysis with the data of the right side. However, two children with an asymmetrical impairment revealed large and significant differences between the measurement errors of the more and less affected sides. Thus, we decided to continue the analysis with the side revealing smaller measurement errors in this group. This was usually the less affected side unless children had worn only one orthosis. In this case, it was the side with the orthosis (**Figure 9.2**).

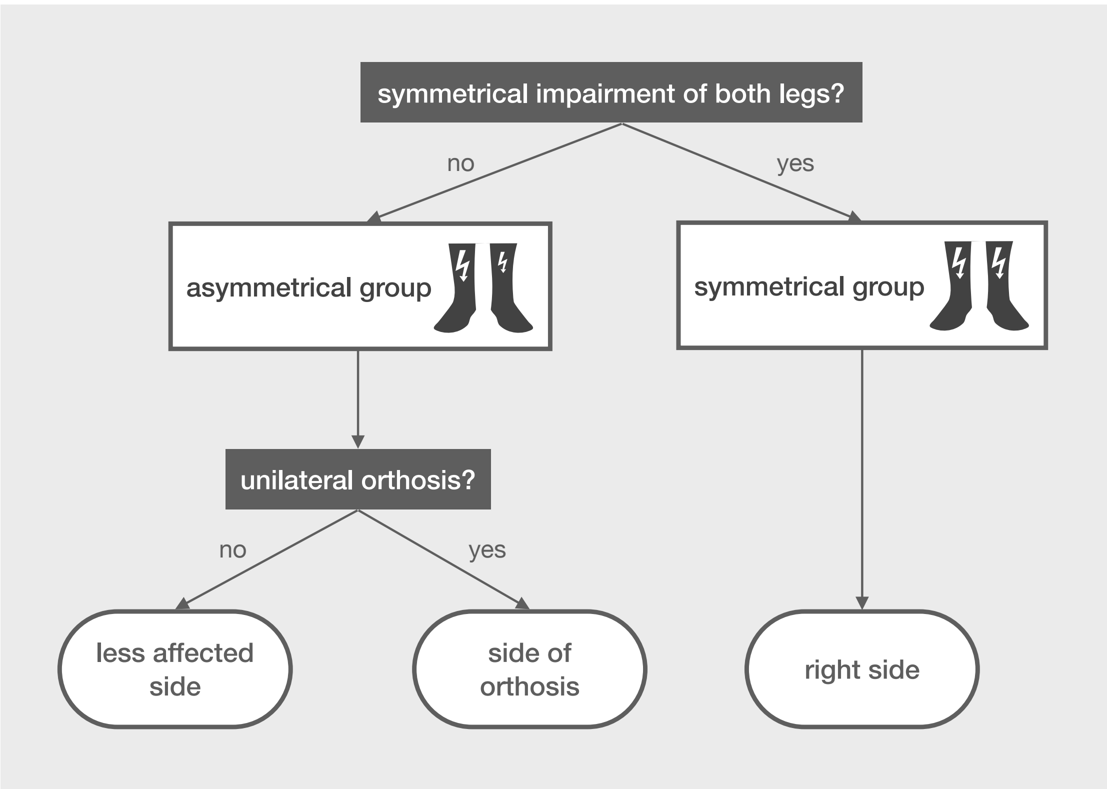


Figure 9.2 – Decision tree for the placement of a single ankle sensor.

The measurement errors of gait speed estimations based on a single ankle sensor were 0.01 ± 0.07 m/s (LoA: ±0.13 m/s) under the standardized, and 0.04 ± 0.06 m/s (LoA: ±0.12 m/s) under the daily life condition, respectively, and are visualized in **Figure 9.3**. The SDC was 0.19 m/s for the standardized and 0.18 m/s for the daily life condition. Therefore, the measurement error of single walking trials is too large to detect MIC. However, averaging the gait speed estimations of four walking trials would be accurate enough to detect MICs in both conditions.

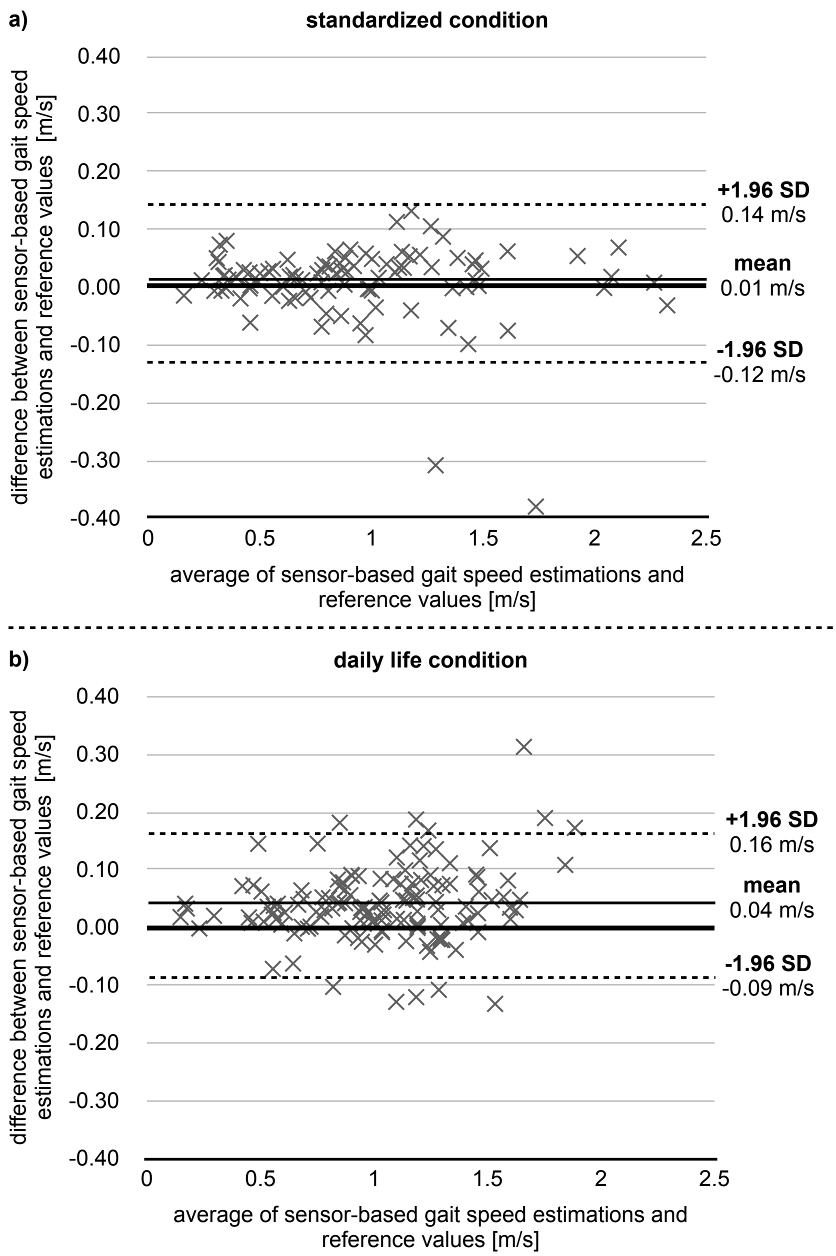


Figure 9.3 – Bland-Altman plots of the gait speed estimations in standardized (a) and daily life conditions (b).

Individual differences in gait speed between the two conditions are shown in **Figure 9.4**. Seven children walked faster during the 10-meter walk test (by at least the MIC), while also seven children walked faster in daily life. The remaining ten participants walked equally fast in both conditions.

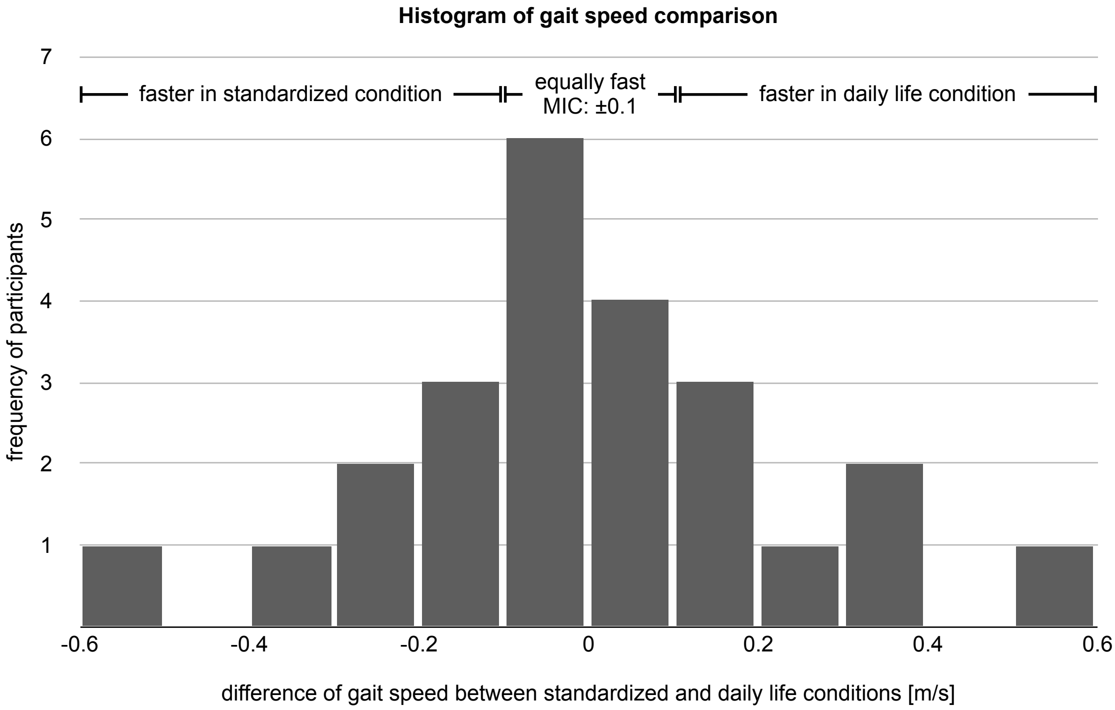


Figure 9.4 – Histogram of the individual gait speed differences between the standardized and the daily life condition. MIC = minimal important change.

9.5 Discussion

In this study, we determined the accuracy of a novel algorithm that estimates gait speed based on data of a single ankle-worn inertial sensor in a heterogeneous sample of children and adolescents undergoing rehabilitation. We investigated on which ankle the sensor should be placed to optimize accuracy and how many walking trials need to be recorded to get accurate gait speed estimations. Furthermore, we explored whether children use different self-selected gait speeds in standardized and daily life-like conditions.

In most participants, we observed no difference in measurement errors of gait speed estimations based on data of the left and right ankles or the less and more affected sides. However, two participants had large and significant differences between the measurement errors of the more and less affected sides. Participant 6 has a hemiparesis and revealed smaller measurement errors on the less affected side. The detection of mid-stance failed due to excessive toe walking on the more affected side. This resulted in wrong boundary conditions for the double integration of the acceleration signal and an overestimation of the stride length. In contrast, participant 18 showed smaller measurement errors on the more affected side. This participant has a bilateral peroneal nerve paralysis that is more severe on the left side. Wearing a foot lifter orthosis on this side resulted in a heel strike gait pattern on the more affected side, which has been observed in previous studies and with other orthoses, too (Ricardo et al., 2021). This gait pattern improved the detection of gait events and most likely explains the smaller measurement errors. Similar results were observed in participants 15 and 16 who wore the orthosis on just one side. Consequently, we recommend placing the sensor as shown in the decision tree in **Figure 9.2**. Still, this recommendation is mainly based on the results of two participants and has to be confirmed with the results of future studies.

As seen in **Figure 9.3**, the algorithm overestimated gait speed slightly, and this overestimation was larger in daily life than in the standardized condition. This difference can be explained by the chosen reference method of the daily life condition. We assumed that children walked straight between two consecutive marks on the floor. However, as confirmed by the video recordings, this was not always the case and led to underestimated gait speeds in the reference values. Hence, we expect that the true systematic error in daily life is smaller than reported in this study and comparable to that of the standardized condition. This justifies why we did not correct for systematic errors when comparing the gait speed between standardized and daily life conditions.

Except for two outliers in the standardized condition, the random error was larger in daily life compared to the standardized condition. We believe that the larger variance of walking trials in daily life can explain the larger error observed in **Figure 9.3.b**. This higher variance could be due to changes in the walking direction (e.g., due to obstacles), interactions with others, etc. Both outliers occurred during the fast walking trial of two participants and could be explained by data loss due to short stride durations and the too low sampling rate of 50 Hz to capture the actual movement.

We did not investigate the relationship between gait speed and measurement error since gait speed varied between participants. A dependency between speed and error would bias our calculation of how many walking trials are required to reach accurate gait speed estimations, but based on the dataset of this study, recording four walking trials is adequate to determine the average gait speed.

The LoA in this study (0.13 m/s) are narrower than that of a similar study (0.21-0.26 m/s) investigating the accuracy of ankle sensor-based gait speed estimations in children with cerebral palsy (Carcreff et al., 2018). Even though they reported more accurate results using the foot sensor data (0.12-0.24 m/s) compared to that of the ankle position, our method with a single ankle sensor provides a level of accuracy comparable to these higher accuracy values. However, the comparison is difficult since the previous study reported measurement errors of individual strides instead of walking trials of several steps, and averaging the gait speed over multiple strides might lead to more accurate results.

The majority of participants did not choose the same walking speed during the 10-meter walk test and in daily life at the clinic. Half of these participants walked faster, and the other half slower during the test. This is in line with previous research investigating the gait speed of children with cerebral palsy in both conditions, observing a highly heterogeneous behavior in terms of gait speed selection (Carcreff et al., 2020a). Children's behavior seems to be different from that of adults with neuromotor impairments (Shah et al., 2020) or healthy adults (Takayanagi et al., 2019), who mostly walk faster during the standardized tests. Nevertheless, all of these studies emphasize that gait speed in a test situation and that in daily life can be significantly different. This encourages the use of wearable inertial sensors to assess the children's walking performance after rehabilitation in their habitual environment at home and school. Furthermore, future research could also identify personal and environmental factors that explain why some children walk faster and some slower in the test than in daily life.

The validation protocol was a key component of our study. While previous studies determined the accuracy of the related algorithms by walking trials of standardized conditions and self-selected speed (Brégou Bourgeois et al., 2014; Carcreff et al., 2018), we also instructed our participants to additionally walk at a slower and faster pace, and further, implemented a method to estimate the walking speed of daily life by video analysis and used it as a reference. This protocol added variance to the collected data and reflected real-world data more comprehensively, challenging the algorithm, and leading to a more valid estimation of the measurement error. Still, the daily life condition in our study comprised only straight and flat hallways inside the clinic, while the children's habitual environment might also include curvy walking paths and uneven surfaces. This increase in variability might lead to larger measurement errors. Moreover, our algorithm needs to be combined with a walking detection algorithm to be applicable to unlabeled daily life data. This might further increase the measurement error of gait speed estimations since non-walking episodes falsely labeled as walking could lead to abnormal gait speed estimations. Besides, using gait speed as a surrogate to detect changes in the children's overall walking capacity due to an intervention depends not only on the measurement error but also on the children's behavior during the measurement. Therefore, future studies should address the test-retest reliability in the standardized condition and the between-day reliability in daily life to determine the SDC considering the measurement error and other sources of variance such as the child's motivation or daily activities.

9.6 Conclusions

We evaluated a novel algorithm that determines gait speed based on a single ankle-worn inertial sensor in children undergoing rehabilitation. The accuracy was comparable to previously reported algorithms and superior in terms of the number and position of required sensors. This is a clear advantage that hopefully increases the wearing time and thus data quality when monitoring children's gait over multiple days. The comparison of the children's self-selected gait speed between the standardized test and in daily life showed that the majority of children did not use the same speed in the two conditions, which encourages the use of wearable inertial sensors to assess the children's walking performance in their habitual environment following rehabilitation.

10 Summary and conclusion of the algorithm's validity to measure motor performance in children and adolescents with neuromotor impairments

This chapter summarizes the results of **Chapter 7**, **Chapter 8**, and **Chapter 9**. Its content has not been published or submitted for publication.

10.1 Validity of sensor-based performance measures

10.1.1 Posture and mobility detection

The algorithm estimated the duration of lying, sitting, standing, active wheeling, and walking with a measurement error of less than 10%. Further, the distinction between free and assisted walking was almost perfect. Since more than 90% accuracy is considered excellent (Nooijen et al., 2015), we concluded that the posture and mobility algorithm provides valid estimates of the performance measures mentioned above.

In contrast, the measurement error of counting sit-to-stand transitions and determining the altitude change during stair climbing periods was larger than 30%. Despite smoothing the orientation signal of the thigh sensor, the algorithm often misclassified cycling periods as sit-to-stand transitions. This explains the large measurement error, and we did not use the number of sit-to-stand transitions in the following studies of this thesis. Besides, the algorithm often failed to detect stair climbing in children taking adjusting steps and making small breaks on each step. This led to large measurement errors in these children. Still, despite measurement error, the algorithm was able to discriminate between participants with low stair climbing activity and those with high stair climbing activity. Therefore, we continued using this outcome in the subsequent studies.

10.1.2 Distance and speed of active wheeling periods

Our algorithm determines the daily covered distance while wheeling actively in two steps. First, active wheeling periods are detected and separated from passive wheeling and non-wheeling periods. Then, the algorithm estimates the distance and speed of these active wheeling periods. On the one hand, the accuracy of detecting active wheeling periods depends on the arm movements of the wheelchair user and the algorithm's ability to classify these periods. Therefore, we evaluated our algorithm's ability to detect active wheeling periods in children and adolescents with neuromotor impairments and found a sensitivity of 94% and a precision of 90%. On the other hand, the algorithm's accuracy of estimating the distance and speed depends just on the movement of the wheel and the sensor's accuracy in measuring this movement. Hence, we assumed that it is independent of the wheelchair user. The accuracy in estimating wheeling distance has been investigated in adults with a spinal cord injury before this thesis (Popp et al., 2016). The accuracy was larger than 98%. Consequently, we did not reevaluate the algorithm's accuracy in children and adolescents with neuromotor impairments. Further, we assumed that the measurement error has a similar magnitude for wheeling speed estimations because the estimation of speed is required to determine the distance. Eventually, we concluded that our algorithm provides valid estimations of the children's active wheeling distance and speed.

10.1.3 Distance and speed of walking periods

Like the wheeling sub-algorithm, the walking sub-algorithm detects walking periods as a first step and determines the distance and speed of these periods as a second step. However, in this case, we assumed that the accuracies of these two steps depend on the patient wearing the sensor. Hence, we evaluated our algorithm's performance in children and adolescents with neuromotor impairments with two subsequent validity studies. The first study investigated the algorithm's walking detection accuracy and revealed a sensitivity of 90% and a precision of 86%. Besides, the measurement error in determining the walking duration was 8%.

The second study investigated the smallest detectable change of our algorithm's gait speed estimations which was approximately 0.2 m/s and larger than the desired value of 0.1 m/s. This measurement error corresponds to the gait speed estimation of a single walking trial. However, in long-term measurements, we can reduce the amount of random error by averaging the gait speed of multiple walking trials. Our analysis revealed that averaging the gait speed estimations of four walking trials is enough to decrease the smallest detectable change to 0.1 m/s. Hence, we concluded that our algorithm provides valid estimations of the children's daily walking speed.

We did not directly determine the accuracy of measuring the covered walking distance in the preceding studies. However, the walking distance is calculated by multiplying the walking duration with the walking speed. Hence, we assumed that estimating the walking distance has a similar accuracy as estimating the walking duration and the walking speed.

10.1.4 Daily hand use

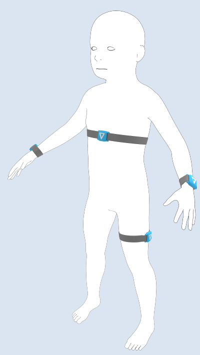
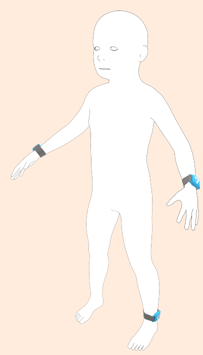
The widely-used hand use measure (i.e., activity counts) and the hand use measure of our research group (i.e., gross arm movements) did not reveal valid estimates of daily hand use in children and adolescents with neuromotor impairments. However, limiting activity counts to a functional forearm elevation (i.e., functional activity counts) or combining them with activity detection algorithms (i.e., arm activity counts) revealed sufficient validity to measure hand use in daily life. The former relies just on two wrist-worn sensors, while the latter requires additional sensors on the ankle and the spokes of the wheel to exclude walking and wheeling periods from the analysis. Hence, we decided to use functional activity counts in the following studies of this thesis to minimize the number of body-worn sensors (see section 10.2).

10.2 Willingness to wear the sensors

In **Chapter 7**, all children and adolescents wore five sensors for roughly one hour while completing an activity circuit. We placed the sensors on both wrists, the trunk, and the thigh and ankle of the less affected side. After the circuit, we asked the first 20 participants to wear the sensors for another 23 hours at the rehabilitation center. We aimed to get preliminary results on the children's and adolescents' willingness to wear the sensors in long-term measurements.

A questionnaire at the end of this measurement period revealed that the sensors were not or only a little obtrusive. However, four out of 20 participants were not willing to wear the sensors throughout the measurement period. Therefore, we decided to reduce the number of sensors for the subsequent studies of this thesis. We did this by dividing the children into subgroups. We distinguished between children with an upper limb impairment, children who are using a wheelchair, and ambulatory children. Children with an upper limb impairment were going to wear wrist sensors to measure their daily hand use. However, since most children at our rehabilitation center have at least a mild form of upper limb impairment, we decided to equip all children with the wrist sensors. Children who are using a wheelchair were going to wear a trunk and a thigh sensor in addition to the wrist sensors to measure the duration they spent in a lying, sitting, and standing position. Besides, we were going to place a sensor on their wheelchair to determine the wheeling activity. In contrast, ambulatory children were going to just wear an ankle sensor in addition to the wrist sensors to measure their walking activity. If applicable, we were going to place a sensor on their walking aids to distinguish between free and assisted walking. The final sensor configurations and the corresponding valid performance measures are depicted in **Table 10.1**.

Table 10.1 – The sensor configurations and corresponding performance measures of children who are using a wheelchair and ambulatory children.

Study group	Children who are using a wheelchair	Ambulatory children
Body-worn sensor configuration		
Additional sensors	Spokes of the wheelchair	Walking aids (if applicable)
Valid performance measures	**Hand use** • Hand use (more affected) • Hand use (less affected) • Use ratio **Body positions** • Duration in lying position • Duration in sitting position • Duration in standing position **Wheeling activity** • Active wheeling distance • Active wheeling speed • Active / total wheeling distance	**Hand use** • Hand use (more affected) • Hand use (less affected) • Use ratio **Walking and stair climbing** • Walking duration • Assisted / free walking duration • Walking distance • Average walking speed • Going upstairs • Going downstairs

Clinical application Part IV

11 Acceptability of wearable inertial sensors to monitor everyday life motor activities, completeness of data, and day-to-day variability of motor performance measures in children and adolescents with neuromotor impairments

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Authors' contributions: FR and RL contributed to the conception and design of the study. FR and SH recruited participants, collected the data, and performed the statistical analysis. All authors were involved in the data interpretation. FR wrote the first draft of the manuscript, while all authors contributed to manuscript revision and approved the final manuscript. SH did her master thesis under the supervision of FR.

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11.1 Abstract

Monitoring the patients' motor activities in a real-world setting would provide essential information on their functioning in daily life. In this study, we used wearable inertial sensors to monitor motor activities of children and adolescents with congenital and acquired brain injuries. We derived a set of clinically meaningful performance measures and addressed the following research questions: Is the target population willing to wear the sensors in their habitual environment? Which factors lead to missing data, and can we avoid them? How many measurement days are needed to obtain reliable estimates of the children's and adolescents' motor performance? The study participants wore our sensor system for seven consecutive days during waking hours. First, we derived the daily hand use of all participants, the duration of different body positions and the wheeling activity of individuals using a manual wheelchair, and walking-related measures in individuals being able to walk. Then, we analyzed the reasons for missing data and determined the reliability of the performance measures. The large majority (41 of 43 participants) was willing to wear the sensor system for a week. However, forgetting to reattach the sensors after charging them overnight and taking them off during bathing and swimming was the main contributor to missing data. Consequently, improved battery life and waterproofness of the sensor technology are essential requirements for measurements in daily life. Besides, five of eleven performance measures showed significant differences between weekdays and weekend days. The reliability, measured with the intraclass correlation coefficient, ranged between 0.82 and 0.98. Seven measurement days were enough to obtain reliable outcomes for all but two performance measures, in which the lower bound of the confidence interval was slightly below the desired level of 0.8. In children and adolescents with neuromotor impairments, we recommend monitoring everyday life motor activities on seven consecutive days. The target population accepted this measurement protocol, it covers school days and weekend days, and the number of measurement days is sufficient to obtain reliable estimates of motor performance.

11.2 Introduction

Children and adolescents with congenital or acquired brain injuries often have difficulties in executing everyday life motor activities, such as grasping a glass of water, transferring from a wheelchair to a car seat, or walking to school. They undertake intensive rehabilitation programs as in- or out-patients with an emphasis on fostering their functional independence in these activities. To monitor the children's progress over time and evaluate the effect of therapeutic interventions, usually, motor capacity ("what a child can do") is measured in a standardized environment at the clinic. In the habitual environment outside of the clinic, however, motor performance ("what a child does do") becomes much more important, and it remains unclear whether children can translate their improvements during rehabilitation into everyday life (Holsbeeke et al., 2009; Smits et al., 2014; World Health Organization, 2002). Consequently, there is a need to assess motor performance to quantify what children and adolescents do in their habitual environment.

Self-report or proxy-report measures can be used to assess motor performance. However, these tools rely on the subjective perception of these children and adolescents, or their parents, and are prone to recall and proxy bias (Clanchy et al., 2011a). Wearable inertial sensors overcome the limitation of subjectivity by enabling objective monitoring of motor activities in real-world settings (Lang et al., 2020). However, the most commonly used outcome measure to assess performance is activity counts, which quantifies the general level of physical activity rather than the type and quality of activities performed (Rachele et al., 2012). Therefore, sophisticated algorithms are needed to derive activity-specific and clinically meaningful performance measures from data of wearable sensors.

We developed such an algorithm based on the findings of two preceding studies investigating the needs of pediatric rehabilitation (Rast and Labruyère, 2020a, 2021). The current algorithm determines functional hand use with wrist sensors; the duration of lying, sitting, and standing positions with a trunk and a thigh sensor; the distance and speed of self-propelled wheeling periods with a wrist and a wheel sensor; the duration, distance, and speed of walking periods, and the altitude change during stair climbing periods with an ankle sensor; and discriminates between free and assisted walking with a sensor placed on walking aids. Then, we verified the validity of this algorithm in three prior studies. They showed sufficient criterion validity of the hand use measures (Rast and Labruyère, 2022), good to excellent activity classification accuracy except for stair climbing (Rast et al., 2021), and accurate gait speed estimations (**?**).

These validity studies were conducted in supervised experiments at the clinic to allow for the inclusion of criterion measures. However, in real-world settings, other factors such as the acceptance to wear the sensors, the completeness of data, and the naturally occurring day-to-day variability of motor activities must be considered. On the one hand, incomplete datasets could occur due to non-wearing time or technical issues of the sensor system leading to missing or biased estimates of the users' daily motor activities (Stephens et al., 2018). On the other hand, a sufficient number of repeated measurement days is needed to capture the day-to-day variability of motor activities and obtain reliable estimates of the patients' overall activity levels. The literature suggests measuring performance over a week to incorporate variability between weekdays and differences between weekdays and weekends (Sonenblum et al., 2012; Dollman et al., 2009; Clemes and Biddle, 2013). However, this has to be reevaluated in our newly developed performance measures. Moreover, the recommendation on how many measurement days are needed will depend not only on maximizing the reliability of the performance measures but also on the children's and adolescents' willingness to wear the sensors and minimizing the burden to their everyday lives.

Therefore, we aimed to determine our sensor system's acceptability, the completeness of data, and the performance measure's reliability in a real-word setting. Children and adolescents with neuromotor impairments wore our sensor system for seven consecutive days in their habitual environment, including school days and weekend days, and we addressed the following research questions: Are children and adolescents with neuromotor impairments willing to wear the sensors in daily life? Are there other issues leading to missing data or data with insufficient quality? How many measurement days are needed to derive reliable estimates of motor performance?

11.3 Materials and Methods

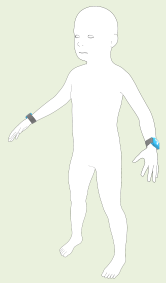
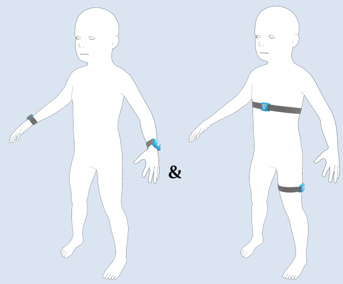
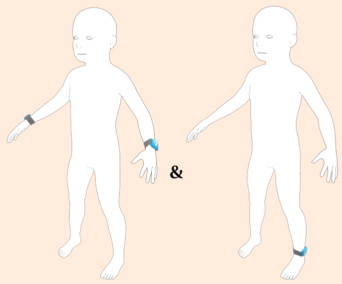
This study was part of a larger ongoing study investigating the influence of contextual factors on translating rehabilitation progress into daily life. The local ethics committee approved the study protocol (BASEC-No.: 2020-00724).

11.3.1 Participants

We recruited school-aged children and adolescents with congenital or acquired injuries or illnesses of the central or peripheral nervous system. They fulfilled the following inclusion criteria: Ability to wheel or walk for household distances, ability to transfer between a wheelchair and a chair over a standing position in individuals who used a wheelchair, living with the mother, father, or psychological parent during the whole measurement period, no wounds or other medical conditions that prevented sensor placement, cognitive abilities to understand and follow basic verbal instructions, and signed consent form.

The participants were allocated to two of three subgroups to minimize the number of body-worn sensors and derive clinically meaningful performance measures. All participants were part of the upper limb group in which we measured their daily hand use with wrist-worn sensors. Additionally, they were allocated either to the wheelchair group or the walking group based on their primary mobility at home. In the wheelchair group, we measured the duration they spent in different body positions and their wheeling activities with additional sensors on the trunk and the thigh, while walking-related performance measures were determined in the walking group with an additional sensor on the ankle. The three subgroups and the corresponding body-worn sensor configurations and performance measures are illustrated in **Table 11.1**.

Table 11.1 – Study groups, body-worn sensor configurations, and performance measures.

Groups	Upper limb group	Wheelchair group*	Walking group*
Body-worn sensor configurations			
Performance measures	**Hand use** • Hand use (more affected) • Hand use (less affected) • Use ratio	**Body positions** • Duration in lying position • Duration in sitting position • Duration in standing position **Wheeling activity** • Active wheeling distance • Active wheeling speed • Active / total wheeling distance	**Walking and stair climbing** • Walking duration • Assisted / free walking duration • Walking distance • Average walking speed • Going upstairs • Going downstairs

*Besides body-worn sensors, we fixated additional sensors on the spokes of the wheelchair in the wheelchair group, and on walking aids in the walking group.

11.3.2 Equipment and procedure

The study procedure comprised three parts. First, we determined the participants' motor abilities with motor assessments at the clinic to describe the study population's levels of motor impairment. Second, we monitored their motor performance with wearable inertial sensors for seven days. Afterwards, we asked the participants to rate the obtrusiveness of the sensor system. In in-patients, we conducted the motor assessments during the last week of their stay at the clinic and measured their motor performance two to four weeks after rehabilitation. We chose this time interval to allow for a habituation phase at home after the in-patient rehabilitation. In out-patients, the measurement of motor performance started directly after the motor assessments. The motor assessments included the Melbourne Assessment 2 (MA2) to measure the quality of upper limb movements (Randall et al., 2014), and the Gross Motor Function Measure (GMFM) to determine the capacity of gross motor activities (Avery et al., 2003). Here, we performed dimensions B (sitting) and D (standing) in the wheelchair group and dimensions D and E (walking, running, and jumping) in the walking group.

To measure performance, participants were equipped with multiple ZurichMOVE sensor modules containing an accelerometer, a gyroscope, and an altimeter (Popp et al., 2019). One of the authors demonstrated the placement of the sensors with corresponding hook-and-loop straps on the first day and provided accompanying instructions on usage and charging of the devices. All participants wore a sensor on each wrist. Those of the wheelchair group wore additional sensors on the trunk and the thigh, and we fixated a sensor on the spokes of their wheelchair. The straps of the trunk and the thigh had a silicone strip on the inside to prevent them from slipping down. Participants of the walking group wore a sensor on the ankle of their less-affected leg, and, if applicable, we fixated sensors on their walking aids. We instructed the participants to wear the sensors during the day and charge them overnight. Besides, they needed to take off the sensors during bathing and swimming activities. They received a leaflet and instruction videos to ensure the proper replacement of the sensors (Rast, 2020a,b). Moreover, they were encouraged to journalize each non-wearing period. After seven days, the participant rated the obtrusiveness of the sensor system as not obtrusive, little obtrusive, or very obtrusive.

11.3.3 Data analysis

We removed non-wearing periods based on the participants' journals and visual inspections of the sensor data. Measurement days with non-wearing periods resulting in less than ten hours of data were considered invalid and were not analyzed (Rich et al., 2013). Saturdays and Sundays without non-wearing periods resulting in less than ten hours of data were kept since we assumed the participants were sleeping in. We summarized the numbers and reasons for missing or invalid measurement days. These reasons were divided into a) concerning all sensors at once or b) concerning a single sensor only. Eventually, we determined the performance measures for each valid measurement day as follows:

Upper limb group The functional hand uses of the more and less affected sides were estimated with functional activity counts. Conventional activity counts were determined (Brønd et al., 2017) but limited to periods with functional forearm elevations to minimize bias from walking and wheeling activities (Rast and Labruyère, 2022). These counts were summed to derive the daily hand use, and the use ratio was calculated by dividing the counts of the more affected hand by the counts of the less affected hand.

Wheelchair group First, lying, sitting, and standing positions were classified with the orientation of the thigh and trunk sensors (Rast et al., 2021). Then, we derived the time spent in each position per day based on these classifications. Wheeling periods were detected with the sensor on the wheel and by applying predefined rules to the gyroscope data (Popp et al., 2016). Subsequently, these wheeling periods were classified as active or passive wheeling with the orientation of the wrist sensor of the dominant hand (Rast et al., 2021). First, the wheeling speed was determined by multiplying the angular rate with the radius of the wheel. Then, active wheeling speed and distance were calculated by averaging and integrating the wheeling speed during all active wheeling periods, respectively. Moreover, the ratio between active wheeling and total wheeling distance was determined.

Walking group Specific characteristics of the ankle's gyroscope signal were used to identify walking periods (Rast et al., 2021). These periods were further classified as level walking or stair climbing based on the altimeter of the ankle sensor (Rast et al., 2021). In level walking periods, the walking speed and distance were determined by segmenting the data into individual gait cycles and deriving each stride length and stride time (?Werner et al., 2021). Besides, level walking periods were separated into free and assisted walking based on the walking aid's acceleration signal (Rast et al., 2021). Eventually, we determined the duration, distance, and mean speed of all level walking periods, the ratio between assisted and total walking duration, and the altitude change while going up- and downstairs.

11.3.4 Statistical analysis of the day-to-day variability

We fitted a linear mixed-effects model to each performance measure Y:

$$Y_{ij} = \mu + \alpha_i + \beta_j + \epsilon_{ij} \quad , \tag{11.1}$$

where α_i is the fixed effect of weekday i and β_j is the random effect of participant j. We assumed that the random effects and the residuals are normally distributed as

$$\beta_j \overset{iid}{\sim} \mathcal{N}\left(0, \sigma^2_{participants}\right), \qquad \epsilon_{ij} \overset{iid}{\sim} \mathcal{N}\left(0, \sigma^2_{residuals}\right) \tag{11.2}$$

Mixed models were chosen, since they allow for the inclusion of incomplete datasets. Participants without any valid measurement day were excluded from this analysis. Then, we conducted an F-test with the fixed effects to determine whether the performance measures differed significantly between weekdays. Post-hoc analyses were done by pairwise comparisons between the estimated marginal means of each weekday, and p-values were adjusted for multiple comparisons with Tukey's method. Afterward, we calculated relative reliability with the intra-class correlation coefficient (ICC) as follows (Shrout and Fleiss, 1979):

$$ICC(3,k) = \frac{\sigma^2_{participants}}{\sigma^2_{participants} + \frac{\sigma^2_{residuals}}{k}} \tag{11.3}$$

where k is the number of measurement days. Initially, we set $k = 7$ to reflect an ICC of the average performance measure of seven measurement days. Confidence intervals of the ICC scores were estimated with bootstrapping. Then, we determined the minimum number of required measurement days $k_{ICC>0.8}$ to obtain an ICC score of which the confidence interval is above 0.8. This value reflects acceptable reliability (Trost et al., 2005). Finally, we determined absolute reliability with the smallest detectable change (SDC) (de Vet et al., 2006):

$$SDC = 1.96 * \sqrt{2} * \frac{\sigma_{residuals}}{\sqrt{7}} \tag{11.4}$$

For interpretability, SDC can be expressed as a percentage value, the SDC%, which was defined as follows (Flansbjer et al., 2005):

$$SDC\% = \frac{SDC}{grandmean} * 100. \tag{11.5}$$

To estimate the sample size, we used the method from Walter et al. (Walter et al., 1998) With an expected ICC score of 0.9, we would need 24 participants in each subgroup to reject the null hypothesis (ICC = 0.8) with a Type I error of 5%. We determined the performance measures in MATLAB R2018b (MathWorks, Natick, Massachusetts, USA) and conducted the statistical analysis in R 4.1.2. (R Core Team, Vienna, Austria).

11.4 Results

The upper limb group consisted of 43 participants. Eleven of those used a manual wheelchair (wheelchair group), and 31 walked for household distances (walking group). One participant was only recruited for the upper limb group. In the walking group, six participants used a walker, two used crutches, and two used both devices in daily life. The remaining 21 participants walked freely. The participants' demographics, motor abilities, and obtrusiveness ratings are listed in **Table 11.2**.

Table 11.2 – Participants' demographics, motor abilities and obtrusiveness rating.

	Upper limb group	Wheelchair group	Walking group
Demographics			
Sample size	43	11	31
Gender (female/male)	15/28	4/7	11/20
Age (years)	11.9 [8.8,13.7]	11.7 [9.2,13.0]	11.9 [8.7,14.0]
Diagnoses (cerebral palsy/acquired brain injury/spina bifida/other)	21/10/6/6*	9/2/0/0	11/8/6/6*
Motor assessments			
MA2 more affected side (%)	67.4 [50.6,92.1]	NA	NA
MA2 less affected side (%)	89.1 [76.6,93.5]	NA	NA
GMFM-B (%)	NA	58.3 [37.1,74.2]	NA
GMFM-D (%)	NA	7.7 [5.1,15.4]	82.1 [67.9,94.9]
GMFM-E (%)	NA	NA	75.0 [40.6,94.1]
Questionnaire			
Obtrusiveness (not/little/very/missing)	25/14/1/3	8/2/1/0	16/12/0/3

The numbers are counts or medians [25th, 75th percentile]. *Hereditary neuropathy (2), congenital malformation of the brain (2), brain atrophy (1), paralytic gait (1). MA2 = Melbourne Assessment 2; GMFM = Gross motor function measure, B = sitting, D = standing, E = walking, running & jumping.

Most participants rated wearing the sensors as not obtrusive and all but one as not or little obtrusive. Furthermore, 14% of the measurement days were missing or invalid because of reasons concerning all the sensors at once. Additionally, specific performance measures could not be determined because the data of single sensors were missing. The rate of missing measurement days ranged between 0% and 26% and depended on the sensor position. The number and reasons for missing values are shown in **Table 11.3**. Forgetting to put on the sensors in the morning, forgetting to reattach them after showering or bathing, and prolonged swimming activities were the main reasons for non-wearing periods, resulting in 20 invalid measurement days with less than ten hours of data. Two children refused to wear the sensors after one and two days, respectively, resulting in 11 missing measurement days. Families often forgot to charge the sensors on assistive devices or did not replace them in the morning, which resulted in 20 missing measurement days. The sensor on the thigh slipped down to the shank on nine measurement days, resulting in confusion between sitting and standing positions and thus in invalid datasets.

Table 11.3 – Numbers and reasons for missing measurement days divided into concerning all sensors at once or a single sensor only.

Reasons concerning all sensors		Reasons concerning single sensors	Sensor position					
			Wrist	Trunk	Thigh	Wheel	Ankle	Aid
Not willing to wear the sensors	11	Not worn/fixated	1			7	1	4
Invalid: wearing time < 10h	20	Forgot to charge				7		2
Sickness/injury/quarantine	8	Technical issue	5			6	9	
Holiday	3	Sensor slipped down			9			
Sum of missing measurement days	42	Sum of missing measurement days	6	0	9	20	10	6
Total number of measurement days	301	Total number of measurement days	301	77	77	77	217	70
Missing measurement days [%]	14%	Missing measurement days [%]	2%	0%	12%	26%	5%	9%

The results of the day-to-day variability, including the F-test, the ICC, and the SDC are shown in **Table 11.4**. Descriptive statistics of the wearing time, the performance measures, and the pairwise comparison between weekdays are illustrated in Appendix E. Participants without valid measurement days were excluded from this analysis explaining the altered number of participants and missing values in **Table 11.4** compared to **Table 11.2** and **Table 11.3**. Five performance measures showed significant differences between weekdays. Participants were less active on Saturday and Sunday than on school days. This trend was observed in all performance measures related to the duration or amount of a motor activity except for stair climbing. Measures about an activity's characteristic such as ratios or speed were similar across weekdays. The ICC(3,7) ranged between 0.82 and 0.98. Upper limb-, standing-, and walking-related performance measures revealed higher ICC scores and would require one to two measurement days to obtain reliable outcomes. The remaining performance measures would require 5 to 8 measurement days. The SDC% ranged between 16% and 98%, with lower values for upper limb and speed-related measures, and for the duration of sitting and walking activities.

Table 11.4 – Day-to-day variability of each performance measure.

	Descriptive statistics			Fixed effects		Random effects		Intra-class correlation (ICC)			Smallest detectable change (SDC)	
Performance measures	$n_{participants}$	missing	mean ± SD	F-statistic	p-value	$\sigma_{participants}$	$\sigma_{residuals}$	ICC(3,7)	95%-CI	$k_{ICC>0.8}$	SDC	SDC[%]
Hand use (more affected) [kilo counts]	42	14%	1673 ± 742	4.64	0.00	682	277	0.98	0.98 - 0.99	1	291 kilo counts	17%
Hand use (less affected) [kilo counts]	42	14%	2247 ± 885	7.26	0.00	825	334	0.98	0.97 - 0.99	1	349 kilo counts	16%
Use ratio [%]	42	14%	76 ± 20	0.51	0.80	56	8	0.98	0.98 - 0.99	1	8%	NA
Duration in lying position [min]	10	20%	115 ± 121	0.88	0.51	90	81	0.90	0.87 - 0.98	5	85 min	74%
Duration in sitting position [min]	10	20%	531 ± 147	1.96	0.09	108	98	0.89	0.85 - 0.98	5	103 min	19%
Duration in standing position [min]	10	20%	55 ± 66	3.14	0.01	54	31	0.95	0.94 - 0.99	2	33 min	60%
Active wheeling distance [m]	10	36%	830 ± 715	2.66	0.03	516	485	0.89	0.83 - 0.98	5	508 m	61%
Active wheeling speed [m/s]	10	36%	0.32 ± 0.11	0.30	0.93	0.08	0.09	0.85	0.83 - 0.98	7	0.09 m/s	28%
Active / total wheeling distance [%]	10	36%	50 ± 22	0.86	0.53	18	17	0.89	0.76 - 0.99	8	17%	NA
Walking duration [min]	29	11%	59 ± 39	4.27	0.00	35	19	0.96	0.95 - 0.98	2	20 min	34%
Assisted / total walking duration [%]	9	14%	42 ± 33	0.93	0.48	25	23	0.91	0.80 - 0.98	5	24%	NA
Walking distance [m]	29	11%	1328 ± 1245	2.00	0.07	1075	653	0.95	0.95 - 0.98	2	685 m	52%
Average walking speed [m/s]	29	13%	0.72 ± 0.22	1.29	0.27	0.20	0.09	0.97	0.97 - 0.98	2	0.10 m/s	14%
Going upstairs [m]	26	13%	21 ± 26	0.68	0.67	16	20	0.82	0.79 - 0.95	8	21 m	98%
Going downstairs [m]	26	13%	-19 ± 22	0.80	0.57	15	17	0.84	0.81 - 0.94	7	18 m	96%

$n_{participants}$ = number of participants; SD = standard deviation; CI = confidence interval; $k_{ICC>0.8}$ = number of required measurement days to obtain an ICC score of which the confidence interval is above 0.8.

11.5 Discussion

This study investigated the acceptability of wearable inertial sensors to monitor everyday life motor activities, the completeness of data, and the reliability of motor performance measures in children and adolescents with neuromotor impairments.

11.5.1 Acceptability and completeness of data

The large majority of children and adolescents was willing to wear the sensors for a week and perceived them as only minimally affecting their everyday life motor activities. This is in line with previous studies investigating the acceptability of wrist-worn sensors in typically developing children (Mackintosh et al., 2019), and a waist-worn sensor in children with cerebral palsy (Wiedmann et al., 2021). Refusing to wear the sensors resulted only in 4% of missing values in our study. However, there were other issues leading to missing or invalid measurement days. The rates of missing values depended on the sensor setup and ranged between 11% and 36%. Insufficient wearing time, loose thigh sensors, and issues related to charging and replacing the sensors were the main reasons for missing measurement days. Our sensors' waterproofness allowed for short showers but not for bathing and swimming activities. The latter resulted in prolonged non-wearing periods, especially because of forgetting to reattach the sensors afterwards. Hence, improving the sensors' waterproofness would decrease the rate of invalid measurement days. Still, non-wearing periods can probably not be prevented completely, and future studies should implement strategies to impute missing sensor data (Stephens et al., 2018). The thigh sensor could be firmly attached with adhesive tape, but studies using this approach had similar rates of missing values (Schneller et al., 2017; Duncan et al., 2018). The battery life of wearable sensors needs to be improved to avoid having to charge the sensors overnight and allow 24h-measurements over a week. Our algorithm relies on gyroscope data and Bluetooth communication between sensors to derive valid estimates of motor performance. However, these technologies have a high energy consumption and currently prevent longer measurements than two to three days.

11.5.2 Day-to-day variability of performance measures

Children and adolescents were less active on weekends compared to school days. This confirms the findings of comparable studies (Gerber et al., 2019a; Van Wely et al., 2012; Bloemen et al., 2019), and underpins the need to measure performance on weekend days and weekdays to capture the children's and adolescents' motor activities comprehensively (Mâsse et al., 2005).

The ICC and SDC values of our study correspond to average performance measures of seven repeated measurement days. All ICC scores exceeded the desired value of 0.8, indicating sufficient reliability to discriminate patients with different levels of motor performance. However, the SDC values seem to be rather large, implying a large between-day variability of motor performance. Consequently, we recommend measuring performance over a week, even though the ICC scores of some performance measures suggest that fewer measurement days would be sufficient. The heterogeneous study population with various diagnoses and different levels of motor impairment might have led to a large between-subject variability which explains the high ICC scores despite day-to-day variability of motor performance.

Hand use and walking-related measures revealed higher relative and absolute reliability than the wheelchair group and stair climbing measures. The SDC% of the different body positions' durations were comparable to previous findings in children with cerebral palsy (Gerber et al., 2019a). We suggest measuring body positions with a 24h protocol to improve reliability. Otherwise, the lying and sitting durations depend more on the waking and non-wearing time than on the patients' actual performance, which could explain the large day-to-day variability in these measures. The wheeling-related performance measures were less reliable than in adults, for whom only four measurement days are sufficient to obtain reliable outcomes (Schneider et al., 2018). An explanation could be the larger wheeling activity in adult patient populations and that underpins the need to measure performance over a week in children and adolescents with neuromotor impairments. In contrast, walking-related measures were more reliable than previous findings in children with cerebral palsy (Gerber et al., 2019a; Ishikawa et al., 2013). However, the comparability is limited due to differences in the study population and the number of measurement days. The altitude change during stair climbing periods revealed the lowest reliability coefficients in this study. An explanation could be the limited accuracy to detect stair climbing periods (Rast et al., 2021), which adds a source of error to the day-to-day variability.

11.5.3 Study limitations

This study has three main limitations. First, the sample sizes of the wheelchair group and ambulatory children using walking aids were smaller than the desired value of the sample size calculation. This explains the larger confidence intervals in these groups, and the estimated numbers of required measurement days to obtain reliable outcomes might be too high. Still, the null hypothesis was rejected in six of the seven corresponding performance measures, indicating sufficient power in these subgroups. Another limitation would be the heterogeneity of the study population. The findings of this study might depend on age or the underlying diagnoses. However, this has to be shown in larger studies with sufficient participants in each subgroup. Last, the variability between days is composed of actual differences in movement behavior and measurement error of the sensors and the algorithm. These sources of variability cannot be disentangled with the chosen study design. Therefore, improvements in sensor technology and the underlying algorithm might enhance the reliability of performance measures. However, this needs to be investigated in future studies.

11.6 Conclusion

In children and adolescents with neuromotor impairments, we recommend monitoring everyday life motor activities on seven consecutive days. The target population accepted this measurement protocol, it covers school days and weekend days, and the number of measurement days is sufficient to obtain reliable estimates of motor performance. However, the battery life of the chosen sensor technology should last for a week, too. This would decrease the non-wearing time during waking hours, in which the sensors ran out of battery or the users forgot to reattach the sensors after charging them. Moreover, it allows for 24h-measurements and a comprehensive view of the patients' daily activities.

12 The influence of personal and environmental factors on translating rehabilitation progress into daily life

Fabian M. Rast and Rob Labruyère

An intermediate analysis of an ongoing study.

Authors' contributions: FR and RL contributed to the conception and design of the study. FR recruited participants, collected the data, and performed the statistical analysis. Both authors were involved in the data interpretation. FR wrote the first draft of the manuscript, and both authors contributed to the manuscript revision. Both authors read and approved the final manuscript.

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This chapter has not been published or submitted for publication, yet. Still, we intend to submit the final results of this study in *Developmental Medicine & Child Neurology* after completing the data collection.

12.1 Abstract

Introduction During rehabilitation, motor assessments are used to evaluate the children's progress on a capacity level (i.e., *what a child* ***can*** *do in a* ***standardized*** *environment*). However, it remains unclear whether children can translate capacity into performance (i.e., *what a child* ***does*** *do in its* ***habitual*** *environment*) after rehabilitation. Therefore, we designed a cross-sectional study investigating the relationship between capacity and performance and how contextual factors affect this relationship. Here, we present an intermediate analysis of this study.

Patients and methods So far, we recruited 43 school-aged children and adolescents with neuromotor impairments and assessed their capacity with the Melbourne Assessment 2, the Gross Motor Function Measure, and the 10m walk test. Afterwards, participants wore inertial sensors for a week at home and at school to measure their performance. Finally, we conducted multiple regression analyses to explain the difference between capacity and performance with contextual factors, which were assessed with a questionnaire after the measurement week.

Results Capacity measures explained 13% to 58% of the children's and adolescents' performance, and contextual factors improved the prediction by 3% to 33%. Specifically, higher levels of well-being explained slower walking speeds in daily life compared to the test situation, and children and adolescents with fewer problems with their physical and social environment revealed longer walking distances with faster speeds as expected from the corresponding capacity measures.

Conclusion Our findings underpin the need to complement clinical assessments with performance measures conducted in the patients' habitual environment to get a comprehensive view on the patient's functioning. Moreover, we identified personal and environmental factors that partially explained the difference between capacity and performance, showing the importance of these factors in pediatric rehabilitation. However, the amount of unexplained variance suggests that the relationship between capacity, performance, and contextual factors cannot be generalized, and individualized approaches are needed to identify contextual factors that affect the translation of rehabilitation progress into daily life.

12.2 Introduction

In pediatric neurorehabilitation, children and adolescents with congenital and acquired illnesses and injuries of the developing brain are treated and cared for. These patients often present neuromotor impairments that result in difficulties in executing everyday life motor tasks, such as grasping a glass of water, transferring from a wheelchair to a car seat, or walking to school. Therefore, they undergo intensive therapy programs as in- or out-patients with an emphasis on reducing these limitations and fostering their functional independence in everyday life. To assess the children's progress during rehabilitation, motor capacity (i.e., *what a child* ***can*** *do in a* ***standardized*** *environment*) is usually measured at the clinic. However, after discharge (in-patients) or between therapy sessions (out-patients), motor performance (i.e., *what a child* ***does*** *do in its* ***habitual*** *environment*) becomes more important and it remains unclear whether children and adolescents can translate their improvements during rehabilitation into everyday life at home or school.

Previous research has shown a high correlation between capacity and performance in children and adolescents with neuromotor impairments (Holsbeeke et al., 2009; Smits et al., 2010; Burgess et al., 2021) and a moderate correlation between the changes within these constructs (Smits et al., 2014). In these studies, the authors used a proxy-report questionnaire to assess motor performance which might be prone to recall or proxy bias (Clanchy et al., 2011a; Holsbeeke et al., 2009). In two recent studies, accelerometers have been used as an objective alternative to measure performance with activity counts. They found a moderate correlation between motor capacity and activity counts (Suk et al., 2021) and no association between the change scores of these measures (Halma et al., 2020). Activity counts quantify the children's and adolescents' general level of physical activity. Hence, they do not provide any information about the type and quality of performed activities (Rachele et al., 2012). Therefore, the selected measures do not assess the same aspect of motor activities, which could explain the weaker associations found in these studies. However, studies have to compare like with like to allow for objective and clinically meaningful comparisons between capacity and performance (Rast and Labruyère, 2020b). Consequently, there is a need to measure performance for specific activities.

We developed a sophisticated algorithm deriving activity-specific and clinically meaningful performance measures from data of wearable inertial sensors. We designed this algorithm to fulfill the needs of pediatric rehabilitation as a first step (see **Chapter 4** (Rast and Labruyère, 2020a) and **Chapter 5**), and validated it in children and adolescents with neuromotor impairments as a second step (see **Chapter 7**, **Chapter 8** (Rast and Labruyère, 2022), and **Chapter 9**). Next, we aimed to use this tool to investigate the relationship between capacity and performance for specific aspects of motor activities.

Even though we compared like with like in this study, we still expected to find unexplained variance. Individuals with the same level of capacity might show different levels of performance. Qualitative research revealed personal, social, and environmental factors as well as daily activity opportunities as barriers and facilitators to perform activities in everyday life (Shields et al., 2012). Besides, overprotective parents have been identified as a barrier to be physically active (Earde et al., 2018), while autonomy supportive parents could favor the translation of capacity into performance (Newman, 2018). Hence, we screened the literature for questionnaires covering the aforementioned contextual factors. We found three questionnaires that were validated in our target population: The KIDSCREEN to assess the children's and adolescents' well-being, the Child and Adolescent Scale of Environment (CASE) to identify problems with the physical and social environment, and the Parenting Behaviours and Dimensions Questionnaire (PBDQ) to cover the parenting style. Therefore, we incorporated these contextual factors in this study and investigated their role in translating capacity into performance in children and adolescents with neuromotor impairments. Specifically, we addressed the following research questions:

1. Can we predict the children's and adolescents' motor performance after rehabilitation with their motor capacity assessed at the clinic?
2. Can contextual factors explain the difference between capacity and performance?

We hypothesized that higher levels of well-being, fewer problems in the physical and social environment, and an autonomy supportive parenting style improve the translation of capacity into performance after rehabilitation.

12.3 Method

This is an intermediate analysis of an ongoing, cross-sectional study comprising three successive parts. First, we conducted motor assessments at the clinic to quantify the participants' motor capacity. Second, the participants wore the sensor system in their habitual environment to estimate their motor performance. Third, the participants' parents filled out a series of questionnaires to assess the participants' contextual factors. The detailed study protocol is described in the following paragraphs and was approved by the local ethics committee (BASEC-No.: 2020-00724).

12.3.1 Study participants and group allocation

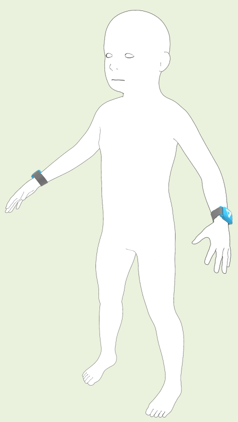
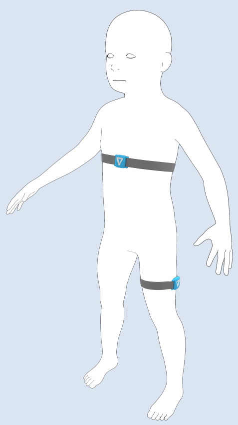
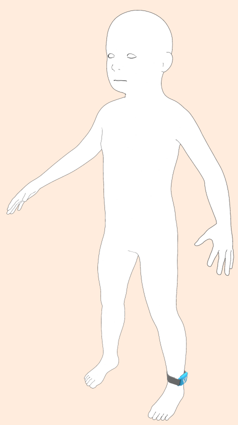
The study population of this study is the same as in **Chapter 11**. We recruited school-aged children and adolescents with congenital or acquired injuries or illnesses of the central or peripheral nervous system. They fulfilled the following inclusion criteria:

- ability to wheel or walk for household distances
- for individuals who are using a wheelchair: ability to transfer between a wheelchair and a chair over a standing position

- living with the mother, father, or psychological parent during the whole measurement period
- no wounds or other medical conditions that prevented sensor placement
- cognitive abilities to understand and follow basic verbal instructions
- participants understand German or English
- signed consent form of adolescents (≥ 14 years of age) and a legal guardian of all children

The participants were allocated to two of three subgroups to allow for meaningful comparisons between capacity and performance and minimize the number of body-worn sensors. All participants were part of the upper limb group in which we measured their daily hand use with wrist-worn sensors. Additionally, they were allocated either to the wheelchair group or the walking group based on their primary mobility at home. In the wheelchair group, we measured the duration they spent in a standing position with additional sensors on the trunk and the less affected thigh, while walking-related performance measures were determined in the walking group with an additional sensor on the less affected ankle. The three subgroups, the corresponding capacity and performance measures, and the body-worn sensor configurations are illustrated in **Table 12.1**.

Table 12.1 – Study groups, the corresponding capacity and performance measures, and the body-worn sensor configurations.

Study group	**Upper limb group**	**Wheelchair group**	**Walking group**
Primary mobility at home	Manual wheelchair or walking	Manual wheelchair	Walking
Motor assessments (capacity measures)	• MA2	• GMFM-D	• GMFM-E • 10m walk test
Measuring motor activities (performance measures)	• Hand use (more affected side) • Use ratio	• Duration in standing position	• Walking distance • Walking speed
Body-worn sensor configuration			

GMFM = Gross Motor Function Measure (D: standing, E: walking, running & jumping), MA2 = Melbourne Assessment 2.

12.3.2 Procedure

The general procedure is comprised of three parts. First, a trained examiner conducted motor assessments at the clinic to quantify the participants' motor capacity in a standardized setting (see section 12.3.3). Second, the participants wore the sensor system for five school days and two weekend days in their habitual environment. This duration is recommended to obtain reliable estimates of the participants' motor activities (see **Chapter 11**). Then, we applied the algorithm described in appendix D to derive the participants' motor performance (see section 12.3.4). And third, the participants' parents filled out a series of questionnaires to determine personal and environmental factors (see section 12.3.5). In in-patients, we conducted the motor assessments during the last week of their stay at the clinic and measured their motor performance two to four weeks after rehabilitation. We chose this time interval to allow for a habituation phase at home after the in-patient rehabilitation. In out-patients, the measurement of motor performance started directly after the motor assessments. The detailed study protocol differed between the three study groups and is described in the following sections.

12.3.3 Motor assessments (motor capacity)

We conducted the Melbourne Assessment 2 (MA2) with participants of the upper limb group, the Gross Motor Function Measure (GMFM) with participants of the wheelchair and the walking group, and the 10m walk test with participants of the walking group.

MA2 We conducted the MA2 with both upper limbs separately. It is a 14-item assessment tool to measure the quality of upper limb movements in four dimensions: movement range, accuracy, dexterity, and fluency (Gerber et al., 2019b; Randall et al., 2014). The items involve reaching, grasping, releasing, and manipulating objects and are scored by a trained examiner. We divided the achieved score by the maximum score for each dimension and averaged the results across the four dimensions. This resulted in a percentage value for the more affected side $MA2_{more\ affected}$ and the less affected side $MA2_{less\ affected}$. Besides, we calculated the ratio between the more and less affected sides as follows:

$$MA2_{ratio} = \frac{MA2_{more\ affected}}{MA2_{less\ affected}} * 100 \tag{12.1}$$

GMFM The GMFM is an 88-item assessment tool to measure the capacity of gross motor activities in five dimensions (A: Lying and Rolling, B: Sitting, C: Crawling and Kneeling, D: Standing, and E: Walking, Running and Jumping). A trained examiner rates each item according to the following scoring key. 0 = does not initiate, 1 = initiates, 2 = partially completes, and 3 = completes. We conducted dimensions B and D with participants of the wheelchair group and dimensions D and E with those of the walking group. However, for the analysis, we only considered dimension D in the wheelchair group to determine their standing capacity

$GMFM_{standing}$, and dimension E in the walking group to determine their walking capacity $GMFM_{walking}$. We estimated the final scores with the Gross Motor Ability Estimator Scoring Software to get interval-scaled measures and account for missing values (Avery et al., 2003).

10m walk test The participants walked four times on a 14 m long walkway while we recorded the time they needed to cover the middle 10 m. Hence, we excluded acceleration and deceleration phases (Sorsdahl et al., 2008). We instructed the participants to walk at their normal, comfortable speed during the first two repetitions. During the subsequent repetitions, we instructed them to walk as fast as they can but so that they were still feeling safe and without running (Graser et al., 2016). For the analysis, we only considered the walking speed of the fastest trial $v_{max,test}$ since we claim that fast walking speed is a more valid representation of capacity than self-selected speed. All participants walked with their regular shoes, orthoses, and walking aids because participants with a more severe walking impairment could not walk without assistance and to ensure equal conditions for all participants.

12.3.4 Measuring motor activities (motor performance)

This part of the study procedure has been described comprehensively in sections 11.3.2 to 11.3.4. We equipped the participants with multiple ZurichMOVE sensor modules (Popp et al., 2019). We attached the sensor modules on both wrists to measure daily hand use in the upper limb group, on the trunk and the less affected thigh to measure the standing activity in the wheelchair group, and on the less affected ankle to measure walking activity in the walking group. The body-worn sensor configurations are illustrated in **Table 12.1**. Additionally, we fixated a sensor module on the spokes of the wheelchair and on walking aids. However, we did not analyze the data of these sensor modules. We instructed the participants to wear the sensors during the day and charge them overnight. They needed to take off the sensors during bathing and swimming activities and were encouraged to journalize each non-wearing period.

We removed non-wearing periods based on the participants' journals and visual inspections of the sensor data. Measurement days without non-wearing periods and those lasting longer than ten hours were considered as valid (Rich et al., 2013). Then, we determined the following five performance measures for each valid measurement day of weekday i. These five performance measures are a selection of valid and reliable measures allowing for a meaningful comparison to a corresponding capacity measure. In the upper limb group, we estimated the functional hand uses of the more and less affected sides with functional activity counts. Conventional activity counts were determined (Brønd et al., 2017) but were limited to periods with functional forearm elevations to minimize bias from walking and wheeling activities (so called functional activity counts, see **Chapter 8**, Rast and Labruyère (2022)). Eventually, we summed these counts to estimate the functional activity counts of the more affected $fAC_{more\ affected,i}$ and less affected side $fAC_{less\ affected,i}$, and we calculated the ratio between the more and the less affected side $fAC_{ratio,i}$ as performance measures. In the wheelchair group, the algorithm detected lying, sitting, and standing positions with the orientation of the trunk and thigh sensors (see section D.3), and we derived the time participants were spending in a standing position $t_{standing,i}$. In the walking group, the algorithm detected walking periods and classified them as level walking or stair climbing based on data of the ankle sensor (see section D.5). Then, we derived the time participants were level walking $t_{walking,i}$, and estimated the covered distance of all walking periods containing seven or more strides $s_{walking,i}$ (Werner et al., 2021). Eventually, we determined the average walking speed of these walking periods $v_{mean,daily\ life,i}$.

Last, we estimated the participants' weekly motor performance by averaging the performance measures of all weekdays. Missing measurement days were imputed with linear mixed-effects models to account for systematic differences between weekdays (see **Chapter 11**). Here, a model was fitted for each performance measure with participants as random effects and weekdays as fixed effects. Missing values were only imputed if enough measurement days of individual participants were available to obtain reliable estimates of motor performance. Otherwise, the whole data of corresponding participants were omitted. One measurement day was sufficient for the hand use measures, while two days were needed for the measures of the wheelchair and the walking groups (see **Chapter 11**). The average performances of the five selected measures were calculated as follows:

$$fAC_{more\ affected} = \frac{1}{7}\sum_{i=1}^{7} fAC_{more\ affected,i} \tag{12.2}$$

$$fAC_{ratio} = \frac{\sum_{i=1}^{7} fAC_{more\ affected,i}}{\sum_{i=1}^{7} fAC_{less\ affected,i}} \tag{12.3}$$

$$t_{standing} = \frac{1}{7}\sum_{i=1}^{7} t_{standing,i} \tag{12.4}$$

$$s_{walking} = \frac{1}{7}\sum_{i=1}^{7} s_{walking,i} \tag{12.5}$$

$$v_{mean,daily\ life} = \frac{\sum_{i=1}^{7} s_{walking,i}}{\sum_{i=1}^{7} t_{walking,i}} \tag{12.6}$$

12.3.5 Questionnaires (personal and environmental factors)

KIDSCREEN This questionnaire assesses the subjective health-related quality of life and well-being of the child from his/her perspective (Ravens-Sieberer et al., 2005). We used the KIDSCREEN-27, which covers the dimensions of physical well-being, psychological well-being, autonomy & parent relation, peers & social support, and school environment (Ravens-Sieberer et al., 2007). We followed the manual to generate the overall $KIDSCREEN$ score (Ravens-Sieberer and the European KIDSCREEN Group, 2006). Missing values were imputed with the nearest-neighbor method. Higher scores indicate feeling happy in life and school, feeling physically fit, feeling accepted, and indicate a good relationship between parents and children.

CASE This scale measures the impact of problems experienced with physical, social, and attitudinal environment features of the child's home, school, and community. It further addresses problems related to the quality or availability of services or assistance that the child receives or might need (Bedell, 2004). The overall $CASE$ score was calculated by summing the item responses and dividing this number by the maximum possible score (Bedell, 2011). Missing values were substituted with the mean score. High scores indicate a greater extent of environmental problems.

PBDQ This is a comprehensive self-report parenting measure to identify the core dimensions of contemporary parenting behavior (Reid et al., 2015). Its dimensions are emotional warmth, punitive discipline, anxious intrusiveness, autonomy support, permissive discipline, and democratic discipline. Missing values were substituted with the mean of the corresponding subscale. We averaged the six subscales to get the overall $PBDQ$ score (Reid et al., 2015). Higher $PBDQ$ scores stand for an autonomy-supportive parenting behavior that is administered in a responsive and contingent manner.

The KIDSCREEN is available in German, while we had to translate the CASE and the PBDQ to German prior to this study. We used an independent forward-backward translation procedure, and the authors of the original questionnaires approved the back translation.

12.3.6 Statistical analysis

The statistical analysis contained two steps using two successive linear regression models to answer the research questions stated above.

Predicting performance with capacity The first set of regression models predicted the participants' motor performance with their motor capacity and had the following generic form:

$$Y_{performance} = \beta_0 + \beta_1 * X_{capacity} + \epsilon_1 \tag{12.7}$$

We repeated this regression analysis for each performance measure and used the following equations:

$$\begin{aligned}
\ln fAC_{more\ affected} &= \beta_0 + \beta_1 * MA2_{more\ affected} \\
&\quad + \beta_2 * MA2_{less\ affected} + \epsilon_1 && (12.8) \\
fAC_{ratio} &= \beta_0 + \beta_1 * MA2_{ratio} + \epsilon_1 && (12.9) \\
\ln t_{standing} &= \beta_0 + \beta_1 * GMFM_{standing} + \epsilon_1 && (12.10) \\
\ln s_{walking} &= \beta_0 + \beta_1 * GMFM_{walking} + \beta_2 * X_{orthosis} + \epsilon_1 && (12.11) \\
v_{mean,daily\ life} &= \beta_0 + \beta_1 * v_{max,test} + \epsilon_1 && (12.12)
\end{aligned}$$

Initially, we modeled the hand use of the more affected hand with the capacity measure of the same side only. However, we realized that the performance depends on the capacity of the contralateral side, too. Hence, we included the capacity measures of both sides in the final model. Besides, we added a logical vector $X_{orthosis}$ to predict the walking distance. In general, we conducted the GMFM without orthosis. In some participants of the walking group however, it was contra-indicated to take off the orthosis (e.g., due to a recent surgery). These participants did the GMFM with orthosis, and we corrected their capacity in the regression models. Moreover, we applied a log-transformation to the performance measures in case of heteroscedasticity or non-normality of the residuals. Eventually, we determined the F-statistic of each model to estimate if the capacity measures contributed significantly to the prediction of motor performance.

The role of contextual factors The second set of regression models predicted the difference between capacity and performance ϵ_1 with the outcomes of the questionnaires as follows:

$$\epsilon_1 = \beta_0 + \beta_1 * KIDSCREEN + \beta_2 * CASE + \beta_3 * PBDQ + \epsilon_2 \quad , \tag{12.13}$$

with ϵ_1 being the residuals of the first set of regression models. Positive values correspond to participants revealing larger performance measures as predicted by their capacity measures. In comparison, negative values correspond to participants revealing smaller performance measures as predicted by their capacity measures. We used the z-scores of the response variable and the predictors to increase the model's interpretability and comparability. Eventually, we conducted t-tests to identify contextual factors which significantly explained the difference between capacity and performance.

Since we included three predictors in our models, and it is recommended to use ten observations per predictor (Neter et al., 1990), the data of 30 participants is needed for each model. Therefore, we intended to recruit 30 participants in each subgroup.

12.4 Results

So far, we have recruited 43 children and adolescents with neuromotor impairments. All participants took part in the upper limb group. Eleven of those used a manual wheelchair and participated in the wheelchair group, while 31 walked for household distances and participated in the walking group. One participant was only recruited for the upper limb group. One child was not willing to wear the sensors in daily life, which led to a drop-out in the upper limb and the walking groups. In the wheelchair group, one participant did not provide valid data because the thigh sensor slipped down to the shank. There was a technical issue with the ankle sensor in the walking group, which led to a second drop-out in this group. Six participants used a walker, two used crutches, and two used both devices in daily life. The remaining 19 participants walked unassisted. The participants' characteristics are listed in **Table 12.2**.

Table 12.2 – Participants' characteristics.

Study group	Upper limb group	Wheelchair group	Walking group
Sample size (recruited)	43	11	31
Drop-outs	1 (compliance)	1 (sensor slip)	2 (1 compliance and 1 technical issue)
Sample size (analyzed)	42	10	29
Gender (female/male)	14/28	3/7	9/20
Age (years)	11.9 [8.8,13.8]	11.5 [8.8,12.4]	12.2 [8.9,14.1]
Diagnosis (cerebral palsy/ acquired brain injury/spina bifida/other)	21/9/6/6*	8/2/0/0	10/7/6/6*

The numbers are counts or medians [25th, 75th percentile]. *Hereditary neuropathy (2), congenital malformation of the brain (2), brain atrophy (1), paralytic gait (1).

The results of the first set of regression analyses are illustrated in **Figure 12.1**. Data points lying above the regression lines correspond to participants revealing larger performance measures as predicted by their capacity measures. In comparison, those lying below the regression lines correspond to participants revealing smaller performance measures as predicted by their capacity measures. The coefficients of determination R^2 are listed in **Table 12.3** and ranged between 0.13 and 0.58. The predictabilities of the hand use ratio, the walking distance, and the walking speed were larger than those of the more affected hand use and the standing duration. The capacity measures contributed significantly to the prediction of motor performance for all outcome measures except for standing duration.

Table 12.3 – R^2 and statistical tests of the regression analyses.

Performance measures	1. regression analysis			2. regression analysis						
	R^2	CAPACITY		R^2	KIDSCREEN		CASE		PBDQ	
		F-value	p-value		Est.	p-value	Est.	p-value	Est.	p-value
More affected hand use	0.15	3.56	**0.04***	0.08	0.34	0.08	0.11	0.52	-0.12	0.51
Hand use ratio	0.44	30.8	**<0.01***	0.03	0.00	0.99	0.16	0.36	-0.07	0.70
Standing duration	0.13	1.23	0.30	0.18	0.25	0.74	-0.26	0.71	0.56	0.34
Walking distance	0.58	18.2	**<0.01***	0.22	-0.39	0.07	-0.41	**0.03***	0.17	0.43
Walking speed	0.51	28.1	**<0.01***	0.33	-0.39	**0.04***	-0.52	**0.00***	0.21	0.26

*p-value < 0.05; CASE = Child and Adolescent Scale of Environment ; Est = Estimated coefficient; PBDQ = Parenting Behaviours and Dimensions Questionnaire; R^2 = coefficient of determination.

The results of the second set of regression analyses are listed in **Table 12.3**. The contextual factors explained the difference between motor performance and motor capacity by 3% to 33%. The predictabilities for measures of the wheelchair and the walking groups were larger than those of the upper limb group. The *KIDSCREEN* and the *CASE* were significantly associated with translating walking capacity into daily life. Specifically, higher levels of well-being explained slower walking speeds in daily life compared to the test situation. A similar but

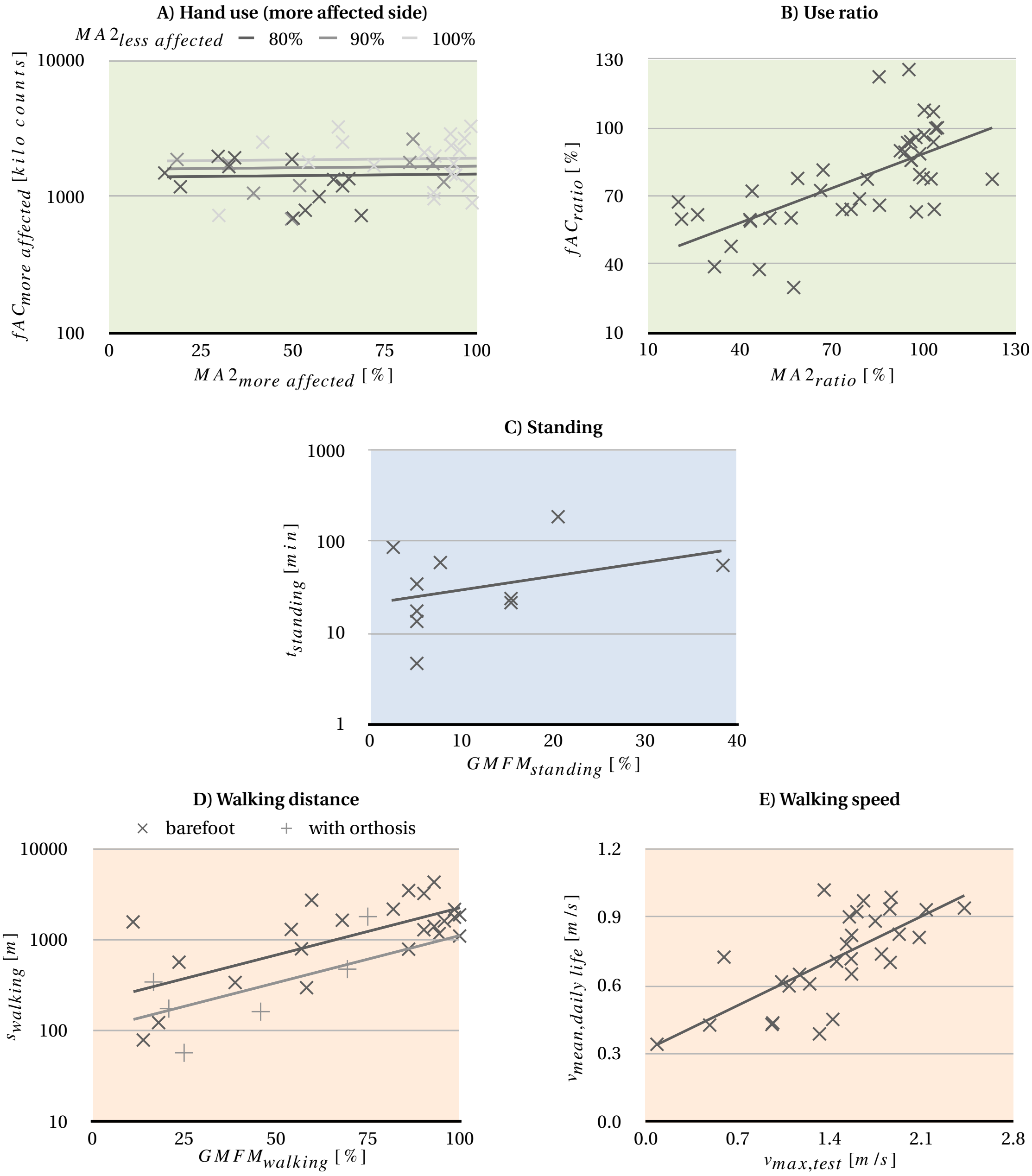


Figure 12.1 – Regression analyses. The Figures A-E show a scatter plot of the five capacity measures and the corresponding performance measures. The vertical axes of Figures B and E have a linear scale, while those of Figures A,C, and D have a logarithmic scale. Figures B, C, and E represent the relationship between capacity and performance with a simple linear regression line. Figure D contains two lines: one for the participants completing the Gross Motor Function Measure barefoot and one for those completing the test with orthosis. In Figure A, three regression lines are shown representing a selection of three different capacity levels of the less affected side.

non-significant relation was observed for higher levels of well-being and shorter walking distances in daily life and more frequent hand use of the more affected side. Besides, participants with fewer problems with their physical and social environment revealed longer walking distances with faster speeds as expected from the corresponding capacity measures. The $PBDQ$ was not associated with the difference between capacity and performance.

12.5 Discussion

This is an ongoing study addressing two research questions: First, can we predict the children's and adolescents' motor performance after rehabilitation with their motor capacity assessed at the clinic? Second, can contextual factors explain the difference between capacity and performance? The sample sizes of the upper limb group and the walking group are sufficiently large to draw conclusions, while the data collection of the wheelchair group is still ongoing. Hence, the final analysis of this group might reveal different results than the intermediate analysis shown here.

12.5.1 Predicting performance with capacity

We found a significant association between capacity and performance for four out of five comparisons made in this study. However, the unexplained variance of performance ranged between 42% and 87%. This means that two patients with the same capacity level can reveal substantial performance differences. In the wheelchair group, for example, four children had the same standing capacity of 5%, while their standing duration in daily life ranged from 5 to 35 minutes per day. This confirms the conclusion that capacity and performance are two different constructs (Holsbeeke et al., 2009), and underpins the need to complement clinical assessments with performance measures conducted in the patients' habitual environment.

The hand use of the more affected side in daily life was significantly related to the capacity of both hands. However, the predictability was only 15%. This finding is comparable to a previous study using the same capacity measures as in this study and performance measures derived from proxy-report questionnaires (Park et al., 2021). Still, we expected to find a stronger relationship between capacity and performance since we used an objective performance measure and ruled out a potential recall and proxy bias. We have two explanations for the low predictability of daily hand use. First, the motor assessment used in this study, the MA2, only contains unimanual activities. However, the capacity of the more affected hand during bimanual activities, the trunk control, and even the capacity of the lower limbs might also explain the hand use in daily life. Second, our performance measure, functional activity counts, does not capture hand use quality, limiting its ability to discriminate between patients with high and low-quality hand use in daily life. Supplementing wrist-worn sensors with sensors on the fingers (Rowe et al., 2014) or with egocentric video recordings (Likitlersuang et al., 2019) would allow for an in-depth analysis of the hand use in daily life and provide a promising solution to overcome the limitation mentioned above. However, their usability for long-term measurements has to be shown in future studies.

The predictability of the hand use ratio was 44% and considerably larger than that of the more affected hand use. Hence, the involvement of the more affected hand in upper limb activities is more related to upper limb impairment than the total amount of hand use. However, calculating the ratio between sides might also rule out potential bias affecting both hands equally, thus, reducing noise in the capacity and performance measures and explaining the higher association in this comparison.

The only performance measure of this study that was not significantly associated with the corresponding capacity measure was the standing duration in daily life, which we investigated in the wheelchair group. However, this group contains only ten complete datasets, which is insufficient to make the final conclusion of the statistical significance test. The smaller sample size of the wheelchair group compared to the walking group can be explained by the narrow inclusion and exclusion criteria. We only included children and adolescents who could transfer between a wheelchair and a chair over a standing position allowing for a meaningful comparison between their standing capacity and the standing duration in daily life. However, if they could walk for household distances, they were already allocated to the walking group. These narrow eligibility criteria are reflected in the results of the capacity measures. The $GMFM_{standing}$ ranged between 3% and 38% in the wheelchair group, while the $GMFM_{walking}$ ranged between 11% and 100% in the walking group. The limited variance in standing capacity might explain the low predictability of the standing duration in daily life. However, this finding has to be confirmed in the final analysis of this study.

The walking performance revealed stronger associations with their corresponding capacity measures than the other performance measures investigated in this study. The $GMFM_{walking}$ explained 58% of the covered walking distance in daily life, and the fast walking speed during the test situation explained 51% of the average walking speed in daily life. This finding is comparable to previous studies conducted on children with cerebral palsy. These studies explained 33% of the daily step count with an index of the participants' gait impairment (Wilson et al., 2015), 40% of the daily step count with the $GMFM_{walking}$ (Wittry et al., 2018), 30% of the time spent walking with the $GMFM_{walking}$ (Wittry et al., 2018), and 79% of the median walking speed in daily life with the median walking speed during a test situation (Carcreff et al., 2020a). The large variety of predictabilities found in these studies might be explained by the heterogeneity of the study population and the selection of outcome measures. Still, the unexplained variance in all these comparisons reinforces that clinically derived outcome measures should be complemented by performance measures collected in the children's and adolescents' habitual environments to provide a comprehensive view of the patients' functionality. The strength of our approach is that we also assessed personal and environmental factors and aimed to explain the remaining variance with these factors.

12.5.2 The role of contextual factors

Our study found that lower levels of well-being and fewer problems in the participants' physical and social environment were associated with higher levels of walking performance as predicted by the corresponding capacity measures. The latter confirms our hypothesis, and we suggest using the CASE or a similar questionnaire to identify problems in the physical or social environment of ambulatory children undergoing rehabilitation. However, the negative association between well-being and translating capacity into performance is contrary to our hypothesis. Previous studies showed a positive association between walking frequency and fatigue (Husain et al., 2022) and between fatigue and depressive symptoms (van Gorp et al., 2021), which could partially explain our finding. However, future studies have to confirm this argumentation.

The contextual factors used in this study could only explain 3% to 33% of the difference between capacity and performance. This raises the question if we were using the right questionnaires, and future studies should explore the role of other personal and environmental factors in translating capacity into performance. However, it could also mean that the relationship between capacity, performance, and contextual factors cannot be generalized. For each patient, a different set of contextual factors could be relevant to their current life situation. This, in turn, would weaken the relevance of specific contextual factors on a group level. Hence, we suggest investigating the role of contextual factors on an individual level.

12.5.3 Study limitations

This study has four main limitations. First, it is a cross-sectional study. Hence, longitudinal study designs are needed to show that fewer problems in the children's and adolescents' environment would lead to increased levels of motor performance. Second, we recruited participants with a variety of different neurological diagnoses. This has the advantage of reflecting the population we treat at our rehabilitation center. However, the relationship between capacity and performance could be different in each subgroup, and homogeneous study populations might reveal stronger relationships between capacity, performance, and contextual factors. Third, there is a lack of evidence about the validity and reliability of the chosen capacity measures, especially in conditions other than cerebral palsy (Ammann-Reiffer et al., 2014; Gerber et al., 2016). This might have introduced a source of bias in this study. Forth, we compared similar capacity and performance measures but not identical measures. The latter might have revealed stronger relationships between capacity, performance, and contextual factors. However, advances in capacity and the performance measures are needed to allow for such comparisons.

12.6 Conclusions

Our findings underpin the need to complement clinical assessments with performance measures conducted in the patients' habitual environment to get a comprehensive view on the patient's functioning. Moreover, we identified personal and environmental factors that partially explained the difference between capacity and performance, showing the importance of these factors in pediatric rehabilitation. However, the amount of unexplained variance suggests that the relationship between capacity, performance, and contextual factors cannot be generalized, and individualized approaches are needed to identify contextual factors that affect the translation of rehabilitation progress into daily life. Therefore, we recommend using the CASE or a similar questionnaire to identify problems in the physical or social environment of children and adolescents undergoing rehabilitation.

13 General discussion

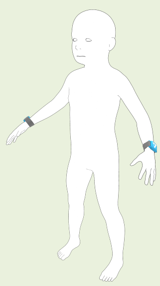
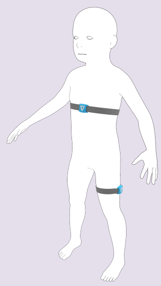
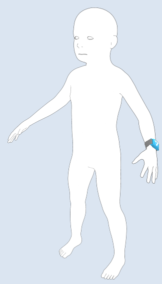
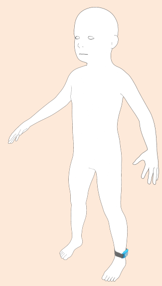
13.1 Summary of the thesis

13.1.1 Measuring motor activities with wearable inertial sensors in children and adolescents with neuromotor impairments

The primary aim of this thesis was to develop a data processing algorithm that derives clinically meaningful and valid motor performance measures about the daily motor activities of children and adolescents with neuromotor impairments based on data from a wearable inertial sensor system. The secondary aim was to apply the new technology in children and adolescents with neuromotor impairments to measure their motor performance after rehabilitation. We evaluated if a measurement period of one week is enough to capture the day-to-day variability of motor activities and obtain reliable estimates of motor performance and if children and adolescents are willing to wear the sensor system throughout this measurement period.

The final algorithm comprises four independent parts requiring different sensor placements and determining a different set of valid performance measures. Hence, in future measurements of motor activities, the number and placement of sensors will depend on the desired outcomes and can be adjusted to the patients' and therapists' needs in a modular way. The four different sensor configurations and the corresponding performance measures are illustrated in **Table 13.1**.

Table 13.1 – The four different sensor configurations and the corresponding performance measures.

	Hand use	Body positions	Wheeling activity	Walking activity
sensor placement			 & wheel (required)	 & walking aid (optional)
performance measure	• Hand use (more affected) • Hand use (less affected) • Use ratio	Duration spent in a… • …lying position • …sitting position • …standing position	• Active wheeling distance • Active wheeling speed • Active / total wheeling distance	• Walking duration • Walking distance • Average walking speed • Assisted / total walking duration*

*requires an additional sensor on the walking aid

13.1.1.1 Hand use

Our algorithm determines the daily functional hand use of the more and less affected side separately and calculates the use ratio between the more and less affected side based on data from wrist-worn sensors. It counts the number of hand movements throughout a day. These counts are limited to periods with a functional forearm elevation to exclude hand movements while walking and self-propelling a wheelchair. The correlation coefficient between these sensor-based counts and video-based counts of functional hand use was 0.71, confirming the concurrent validity of these counts. Considering day-to-day variability, a change in average daily hand use of more than 17% between two one-week measurement periods can be regarded as a real change in functional hand use. The wrist sensors were well accepted by children and adolescents with neuromotor impairments. However, in many cases, the sensors were worn the wrong way. Either they were inverted as if the clock face would be upside down, or they were placed on the wrong hand (e.g., the right wrist sensor on the left hand and vice versa), although the letters L and R were stitched on the corresponding straps. Usually, we were able to detect these misplacements because the forearm is more often in a supinated than in a pronated orientation which is reflected in the sensor data. Hence, we adjusted the sensor data accordingly. Still, we recommend improving the labeling of the left and right wrist sensors to ensure attaching them correctly in future measurements.

13.1.1.2 Body positions

We used the orientation of two sensors, placed on the trunk and the less affected thigh, to discriminate between lying, sitting, and standing with a sensitivity and precision of at least 93%. Eventually, the algorithm derived the patients' daily durations spent in these positions with a small measurement error of 3% to 6%. However, we determined this accuracy in a supervised setting. In a real-world setting, we observed that the thigh sensor slipped down to the shank in 12% of the measurement days, even though the straps had a silicone strip on the inside that should prevent the sensor from slipping down. This issue led to a misclassification between sitting and standing and increased the measurement error in real-world applications of the sensor system. Hence, we suggest improving the attachment of the thigh sensor before using the sensor system to measure the patients' lying, sitting, and standing performance in daily life.

In our measurement protocol, the participants wore the sensors during their waking time and charged them overnight. This was necessary because the sensors' battery life only lasted for two to three days and not for the desired period of one week. This is problematic since forgetting to put on the sensors in the morning was a major contributor to non-wearing time. Moreover, participants were sleeping in, especially on weekends. Both decreased the validity and reliability of the performance measures, and we expect that the daily lying and sitting durations depend more on the waking and non-wearing time than on the actual performance. However, we assume that the standing duration is less affected by these issues. This assumption is supported by the relatively small "smallest detectable change" of 33 min

for the standing duration compared to 85 min and 103 min for the lying and sitting durations. This is one explanation for limiting the analysis to standing duration in **Chapter 12**. Still, we recommend measuring body positions with a 24h protocol in future applications of the sensor system. However, this requires a battery life of one week, so the sensors no longer have to be taken off for recharging.

Besides measuring the duration of body positions, we also aimed to count the number of sit-to-stand transitions throughout a day. We intended to use this measure in children using a wheelchair and count the number of transfers they are doing over a standing position. However, our algorithm systematically underestimated the number of these transitions by 20% and revealed a random measurement error of 32%. Hence, our algorithm's accuracy needs to be improved before the sensor system can be used to measure the number of transfers in the daily life of children using a wheelchair.

13.1.1.3 Wheeling activity

This part of the algorithm detects wheeling periods with data from the wheelchair sensor and discriminates between active and passive wheeling with data from the wrist sensor of the dominant hand. Active wheeling periods can be detected with a sensitivity of 94% and a precision of 90%. Eventually, the algorithm determines the average speed during active wheeling periods, the daily distance covered with active wheeling, and the proportion of active wheeling distance to the total wheeling distance. Considering day-to-day variability, a change in these performance measures of 0.1 m/s, 508 m, and 17 percentage points between two one-week measurement periods can be regarded as a real change in the patient's daily wheeling performance.

The handling and acceptance of the wrist sensor have already been discussed in section 13.1.1.1. Regarding the sensor placed on the wheel, families often forgot to charge the sensor or did not reattach it in the morning. This led to a data loss in 14% of the measurement days. Consequently, the sensor's battery life should last for a week, or the families should be reminded to charge and reattach the sensor. This would increase the data quality of measuring wheeling activity in future applications of the sensor system. In our study, we called the families on the second measurement day to solve possible problems with charging and reattaching the sensors. However, in the early stages of that study, we did not explicitly mention the sensor on the wheelchair. Then, after realizing the problem of forgetting the sensor on the wheelchair, we specifically asked if they charged that sensor which substantially reduced the problem.

13.1.1.4 Walking activity

Our algorithm detects walking periods and estimates the duration, distance, and speed of these periods based on data from a single ankle sensor. We placed this sensor on the less affected side unless patients had worn only one orthosis. In this case, we placed the sensor on the side with the orthosis. The selected sides revealed smaller measurement errors regarding the gait speed estimation. Children and adolescents with neuromotor impairments were willing to wear this ankle sensor for a week, and they attached and charged the sensor without difficulties.

The daily walking duration can be determined with a measurement error of 8% and the average gait speed with an error of 0.1 m/s. For the latter, averaging the gait speed of at least four walking periods is required. The measurement error of estimating the daily walking distance was not determined in this thesis and assumed to have a similar magnitude as the measurement errors of the duration and speed estimations. We conclude that our algorithm provides valid estimates of the children's and adolescents' daily walking duration, distance, and speed. Considering day-to-day variability, a change in these performance measures of 20 min, 685 m, and 0.1 m/s between two one-week measurement periods can be regarded as a real change in the patient's daily walking performance.

As an add-on, we can also determine the proportion of the assisted walking duration to the total walking duration. The distinction between free and assisted walking was highly accurate. However, it requires an additional sensor on the patient's walking aid. Similar to the sensor on the wheelchair, families also forgot to charge or reattach the sensor on the walking aid. This led to the same problems with the same solutions as described in section 13.1.1.3. Besides, the use of walking aids differed considerably between days. Patients need to change the proportion of assisted to total walking duration by 24 percentage points between two one-week measurement periods to be considered a real change in the patient's daily use of the walking aid.

We also aimed to distinguish between level walking and stair climbing with the barometric pressure signal of the ankle sensor and determine the altitude change during stair climbing periods. However, our algorithm failed to detect stair climbing in more severely impaired children and adolescents making adjusting steps and small breaks after each step. This led to large measurement errors of 52% for ascending stairs and 32% for descending stairs. Besides, the day-to-day variability of the altitude change during stair climbing periods was larger than that of the other performance measures. This finding indicates that the measurement error also affects long-term measurements of the stair climbing activity since the between-day variability is composed of actual differences in movement behavior and the measurement error of the algorithm. Hence, the algorithm's ability to detect stair climbing needs to be improved before it can be used to measure the children's and adolescents' stair climbing activity in daily life.

13.1.1.5 Conclusions

The algorithm derives valid estimates of the functional hand use with wrist sensors, the duration spent in a lying, sitting, and standing position with a trunk and a thigh sensor, the distance and speed of active wheeling periods with a wrist and a wheel sensor, and the duration, distance, and speed of walking periods with an ankle sensor as well as the proportion of assisted to total walking duration with an additional sensor on the walking aid.

We recommend measuring daily motor activities over a week to cover systematic differences between school days and weekend days and obtain reliable estimates of the performance measures mentioned above. Moreover, children and adolescents with neuromotor impairments are willing to wear the sensors throughout this measurement period.

Ideally, the battery life of the sensors lasts for a week, too. This would decrease the non-wearing time during waking hours, in which the sensors run out of battery or the users forget to reattach the sensors after charging them. Further, it allows for 24h measurements and a comprehensive view of the patients' daily motor activities.

13.1.2 The role of contextual factors in translating rehabilitation progress into daily life

The final aim of this thesis was to investigate the interrelationship between motor capacity, motor performance, and contextual factors in children and adolescents with neuromotor impairments. First, we quantified the children's and adolescents' motor capacity with motor assessments at the clinic and measured their motor performance with our sensor system in their habitual environment. Then, we aimed to reflect how well children and adolescents can translate rehabilitation progress into daily life by determining the difference between motor capacity and motor performance with the first set of linear regression models. Finally, we conducted a second set of regression analyses to identify personal and environmental factors that explain the difference between capacity and performance, thus playing a crucial role in translating rehabilitation progress into daily life. We assessed these contextual factors with a questionnaire.

We limited this analysis to the following five performance measures: functional hand use of the more affected side, hand use ratio, standing duration, walking distance, and average walking speed. The remaining performance measures were not included in this study because of insufficient validity or a lack of corresponding capacity measures.

The selected capacity measures could only explain 13% to 58% of the children's and adolescents' performance. These low predictabilities show that motor assessments conducted at the clinic do not completely reflect the patient's performance at home and at school. This confirms the conclusion that capacity and performance are two different constructs and underpins the need to complement clinical assessments with performance measures conducted in the patients' habitual environment. Moreover, it confirms that wearable sensors and the algorithm developed in this thesis capture essential information about the patients' functioning in daily life, which could add value to clinical practice.

In the second analysis of this study, we found that fewer problems in the patients' physical and social environment were significantly associated with higher levels of walking performance as predicted by the corresponding capacity measures. These problems were assessed with the Child and Adolescent Scale of Environment (CASE). Therefore, we recommend using the CASE or a similar questionnaire to identify problems in the physical or social environment of children and adolescents undergoing rehabilitation.

Even though the CASE was significantly associated with the difference between capacity and performance, we could only explain 3% to 33% of this difference. This finding raises the question which other factors could explain the remaining variance of translating capacity into performance after rehabilitation. We believe that a different set of contextual factors could be relevant for each patient depending on her or his current life situation. However, with this assumption, it would be difficult to identify these factors on a group level. Hence, we suggest investigating the role of contextual factors on an individual level in future studies.

13.2 Thesis contributions

13.2.1 Literature review and state of the art of wearable sensors to measure everyday life motor activities

The data collected with wearable sensors needs to be processed by sophisticated algorithms to derive activity-specific and meaningful outcome measures for patients and health care providers. Over the last decade, a large variety of such algorithms have been developed by the research community and in former theses of our research group (Leuenberger et al., 2014, 2017; Popp et al., 2016). Consequently, we started this thesis with a large-scale systematic review to get an overview of these algorithms (**Chapter 2** & **Chapter 3**). This review lists activities and outcome measures that have been covered in the literature and describes the concepts of the underlying algorithms as well as the required sensor technologies and sensor placements. Further, it tabulates the study populations and the study designs of the included articles. This review, therefore, summarizes the state of the art of existing sensor applications, it provides quick access to the relevant literature to the reader that is interested in quantifying certain activities in a specific patient population, and it enables the identification of gaps for the evaluation of existing and the development of new algorithms.

The review included 95 articles, of which only five applied wearable sensors in a pediatric population. This finding confirmed our expectation that the application of wearable sensors in pediatric rehabilitation is relatively new and revealed the large research gap in our target population.

We published the protocol and the results of this systematic review in *Systematic Reviews* (Rast and Labruyère, 2018) and in the *Journal of Neuroengineering and Rehabilitation* (Rast and Labruyère, 2020c). The latter has made it into the Editor's picks 2020:
https://jneuroengrehab.biomedcentral.com/editors-picks

13.2.2 Clinical priorities of sensor-based outcomes

Up to here, this thesis determined the technological possibilities to measure everyday life motor activities. However, measuring all aspects of daily motor activities would require dozens of sensors which we assumed would be too obtrusive and would jeopardize the children's and adolescents' willingness to wear the sensor system in daily life. Hence, we aimed to identify the clinical priorities of sensor-based outcomes to develop an algorithm covering as many of the clinically relevant outcomes as possible with as few sensors as necessary. We achieved this goal with two complementary projects. First, we conducted an international survey with doctors, nurses, and therapists; presented them with the outcome measures extracted from the systematic review; and asked them to rate the clinical relevance of these measures for pediatric rehabilitation (**Chapter 5**). Second, the opinion of pediatric health professionals was complemented with the opinion of families by investigating the mobility and self-care goals of children undergoing rehabilitation (**Chapter 4**). These two projects resulted in a detailed priority list of health professionals and one of families. While the former is specific to the application of wearable sensors and was an important milestone in this thesis, the latter goes beyond this application. It is the first study showing the specific goals of children undergoing rehabilitation and their parents, and it could serve as a benchmark to incorporate families' needs into the design of future research projects and the development of new technologies. It was published in the renowned journal *Developmental Medicine & Child Neurology* (Rast and Labruyère, 2020a), and was honored with the Anna Müller Grocholski Award in 2019. Additionally, we presented the findings of both studies at the annual meeting of the European Academy of Childhood Disability (EACD) 2019.

13.2.3 Algorithm development, availability, and applicability

Next, we fused existing algorithms of our research group and complemented them with algorithms replicated from the literature to get a single algorithm estimating a selection of the most clinically relevant outcome measures (see **Chapter 6**):

- the functional hand use with wrist sensors,
- the duration spent in a lying, sitting, and standing position with a trunk and a thigh sensor,
- the distance and speed of active wheeling periods with a wrist and a wheel sensor,
- and the duration, distance, and speed of walking periods with an ankle sensor as well as the proportion of assisted to total walking duration with an additional sensor on the walking aid.

These performance measures were validated in three separate studies (**Chapter 7**, **Chapter 8**, and **Chapter 9**).

As expected, the first version of our algorithm did not reveal sufficient accuracy and required significant improvements to be applicable in children and adolescents with neuromotor impairments. These improvements were accomplished by adjusting the parameters of the signal processing, retraining the machine learning algorithms, and adding biomechanical constraints. However, in the case of walking detection these improvements were not sufficient, and we developed a new walking detection algorithm in this thesis. The final version of the algorithm reveals valid estimates of motor performance in children and adolescents with neuromotor impairments (**Chapter 10**). It is reproducibly described in Appendix D, and can easily be replicated by software engineers making it available for research and industry.

Two studies are under review at *Gait & Posture* and *Journal of NeuroEngineering and Rehabilitation*, while one study was successfully published in *Archives of Physical Medicine and Rehabilitation* (Rast and Labruyère, 2022). The findings of these validity studies were further presented at the annual meeting of the European Society for Movement Analysis in Adults and Children (ESMAC) 2020 (Rast et al., 2020a,b).

Even though our algorithm was optimized for children and adolescents with neuromotor impairments, we expect it will also reveal valid estimates of motor performance in adults and other patient populations. There are two reasons supporting our expectations. First, we aimed to apply our algorithm to children and adolescents with different body heights and thus used predominantly data being independent of the user's body height (e.g., we preferred using the angular velocity of the shank rather than the velocity of the ankle). This particularity made our algorithm applicable to small children and fully-grown adolescents, as we showed in this thesis, and thus, most certainly also to adults. Second, our algorithm relies on activity-specific instead of patient-specific features to discriminate between activities. Examples of activity-specific features are the trunk and thigh being vertical during standing, the hand facing downward during wheeling, and the shank alternately rotating forward and backward during walking. These features are hardly affected by the execution of a particular activity, which makes our algorithm robust against a variety of altered movement patterns and, thus, applicable to other patient populations. Still, our algorithm's threshold values to classify activities were trained with our target population, and optimal thresholds are most likely specific to patient populations or even individual patients (Ahmadi et al., 2020; Carcreff et al., 2019). Hence, we recommend retraining and reevaluating our algorithm in other patient populations before applying it in clinical studies.

In this thesis, we used a sensor module called ZurichMOVE, and our algorithm requires its 3-axis accelerometer and 3-axis gyroscope data. The sensor module was developed by our research group and is not easily accessible outside our university. Nevertheless, we assume that our algorithm can be applied to any sensor module containing an accelerometer and a gyroscope with similar specifications as the ZurichMOVE sensors and providing access to the raw data. The three axes of alternative sensor modules will probably not point in the same direction as those of the ZurichMOVE sensor module. In this case, the data must be transformed with a rotation matrix before applying our algorithm. Moreover, we suggest conducting a small validation study to confirm the applicability of our algorithm to other sensor technologies. For example, a participant could perform a series of motor activities while wearing both sensor modules concurrently, and our algorithm should reveal similar results when applied to the data of both sensor modules.

13.2.4 Measurement period and sensor reports

In **Chapter 11** of this thesis, we studied the day-to-day variability of motor activities in children and adolescents with neuromotor impairments and their acceptance to wear the sensors in daily life. Based on this study, we recommend measuring daily motor activities over a week to cover systematic differences between school days and weekend days and obtain reliable estimates of the performance measures derived with our algorithm. Moreover, we could show that children and adolescents with neuromotor impairments are willing to wear the sensors throughout this measurement period. This study is under review at *Frontiers in Rehabilitation Sciences* and we presented the results at the annual meeting of the EACD 2022. The same study lists the smallest detectable change for each performance measure. This information is essential for interpreting the results of two one-week measurements in future applications of the sensor system, and to determine real changes in the patients' motor performance in longitudinal data.

Example reports of such one-week measurements visualizing the outcomes of our algorithm are shown in **Figure 13.1** to **Figure 13.4** on the following pages. These sensor reports can be used in the future to measure the motor performance of children and adolescents with neuromotor impairments. We envision two main applications. First, the performance measures could serve as an outcome in clinical trials investigating the effect of an intervention on a performance level. Second, the sensor system could be applied in clinical practice to obtain the patients' motor performance before, during, and after rehabilitation. Here, we think the sensor reports are particularly useful for patients with a planned rehabilitation stay (e.g., for re-rehabilitation or after elective surgery). In these patients, their motor performance could be obtained before rehabilitation which would not be possible in patients requiring rehabilitation after an acute injury or illness. The pre-rehabilitation measurement has two main advantages. First, the sensor reports could reveal specific patterns of motor performance and allow for setting goals that are tailored to the patients' needs in everyday life. Second, the change in performance between the pre-rehabilitation and the post-rehabilitation measurements could be used to quantify the extent to which these goals were met and evaluate the effect of rehabilitation on the patients' everyday life. Nevertheless, we think a discussion of the sensor reports with the patients' families is inevitable, since the sensor data does not contain any information about environmental factors. During this discussion, specific patterns of motor performance could be linked to potential physical and social challenges in the patients' habitual environments. With this, the sensor reports presented in this thesis could support the rehabilitation process by providing objective and valid information about the patients' everyday life activities rather than relying just on clinical tests and assessments conducted in a standardized environment at the clinic.

Even though the content of these sensor reports would add value to clinical practice, it still requires a lot of time and resources to generate and use them. First, the measurement needs to be planned and organized in advance. Second, the sensor system needs to be delivered to the patient's home, and the sensor handling needs to be explained to the participating family. Third, the collected data needs to be processed and visualized by a person with programming skills. Last, the generated reports need to be discussed by health professionals and families. Hence, we think creating these resources and finding free time in the busy clinical routing are the main challenges for implementing the sensor reports in clinical practice.

13.2.5 Complementing clinical tests with wearable sensors and assessing contextual factors

Eventually, in the last study of this thesis (**Chapter 12**), we compared the clinical tests with the measurements in daily life in children and adolescents with neuromotor impairments. In this study, we could clearly show that the clinical tests do not sufficiently reflect how well the children and adolescents perform in their habitual environment after rehabilitation. This finding underpins the need to complement clinical tests with performance measures collected with wearable sensors in the patients' habitual environment to get a comprehensive view on the patient's functioning. Again, this shows the added value of the sensor reports developed in this thesis for clinical practice.

The same study identified contextual factors that partially explained the difference between clinical tests and performance in daily life, showing the importance of these factors in pediatric rehabilitation. Two of the questionnaires used in this study to assess contextual factors, namely the Child and Adolescent Scale of Environment (CASE) and the Parenting Behaviors and Dimensions Questionaire (PBDQ), were only available in English. We translated them to German using an independent forward-backward translation procedure, and the authors of the original questionnaires approved the back translations. Eventually, we published the German versions of these questionnaires on our institute's website (Labruyère and Rast, 2020a,b), making them available for German-speaking patients and scientists.

This study is still ongoing and has not been published or submitted for publication yet. Still, we intend to submit the final results of this study in *Developmental Medicine & Child Neurology*, and we presented preliminary results at the annual meeting of the EACD 2022.

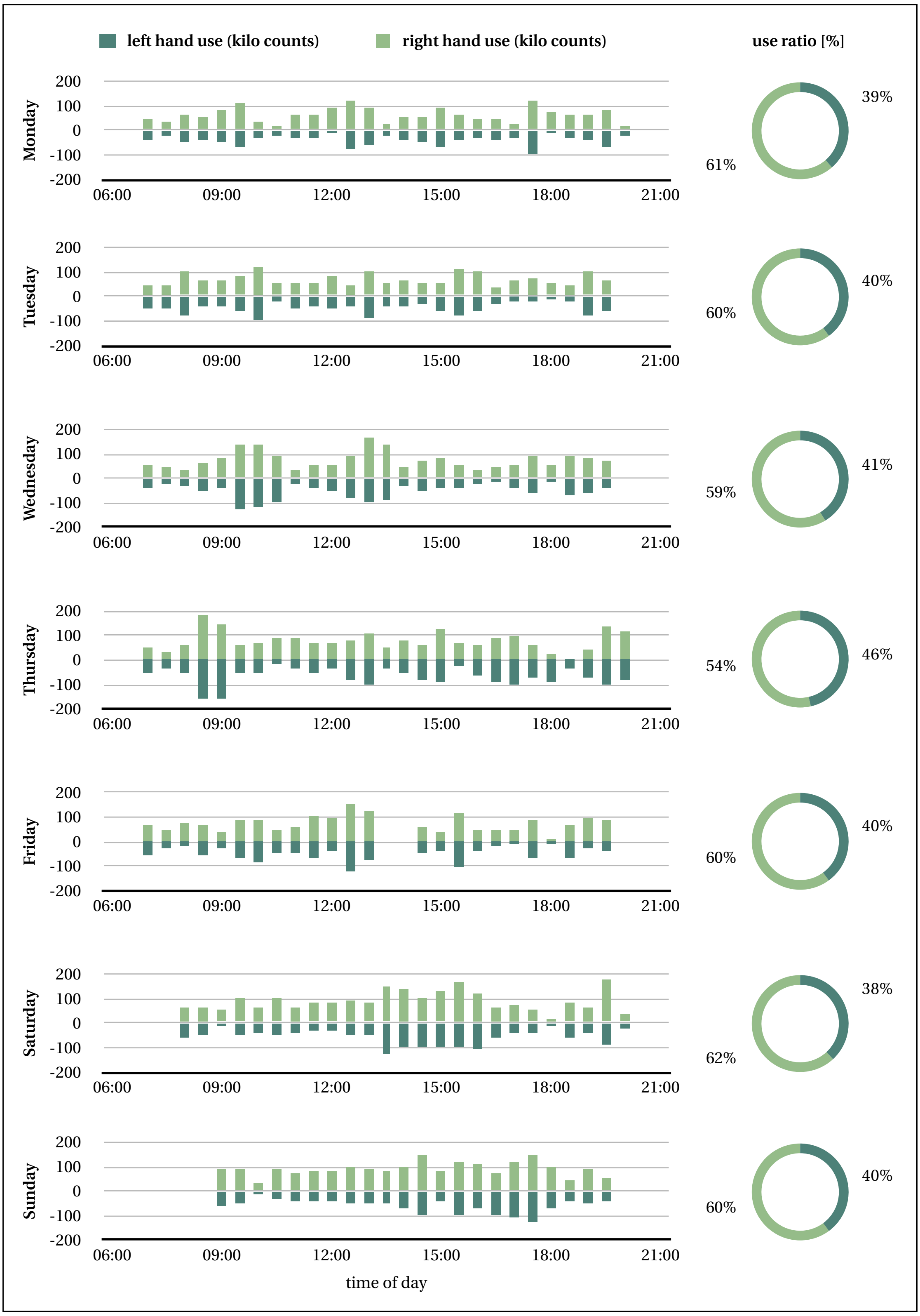


Figure 13.1 – Example report of the hand use measures.

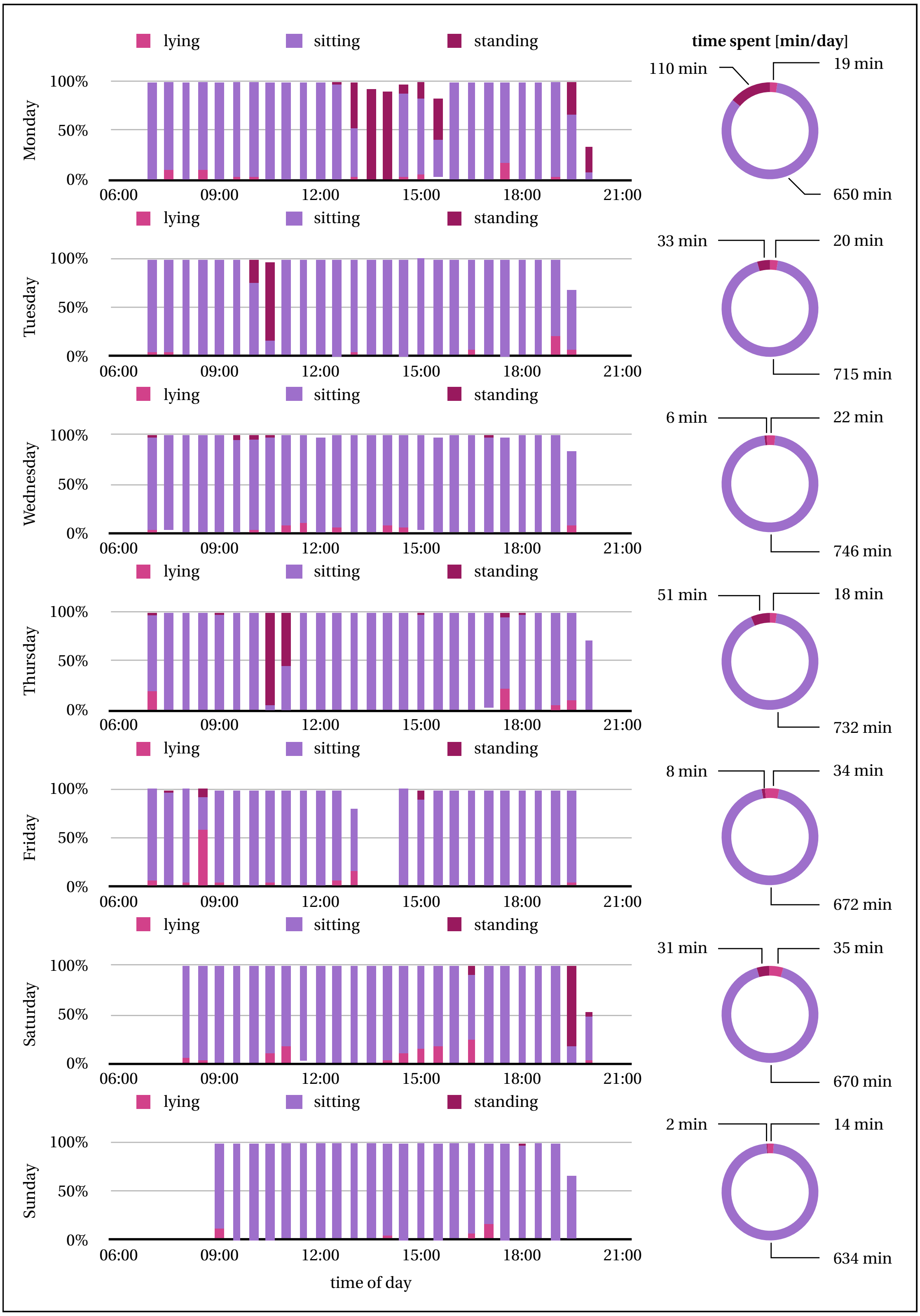


Figure 13.2 – Example report of the duration spent in lying, sitting, and standing positions.

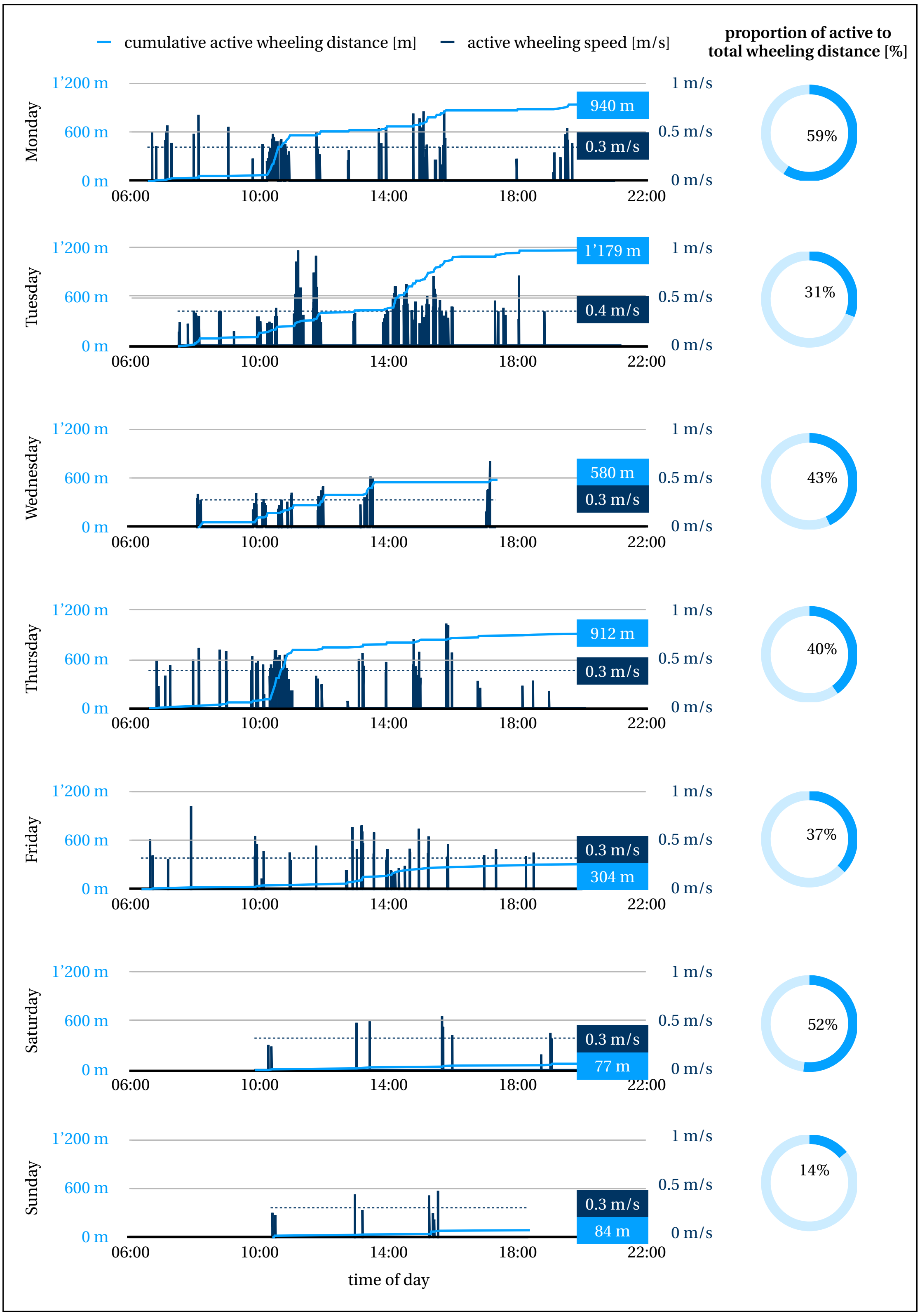


Figure 13.3 – Example report of the distance and speed of active wheeling periods, and the proportion of active to total wheeling distance. The total wheeling distance is derived of active and passive wheeling periods.

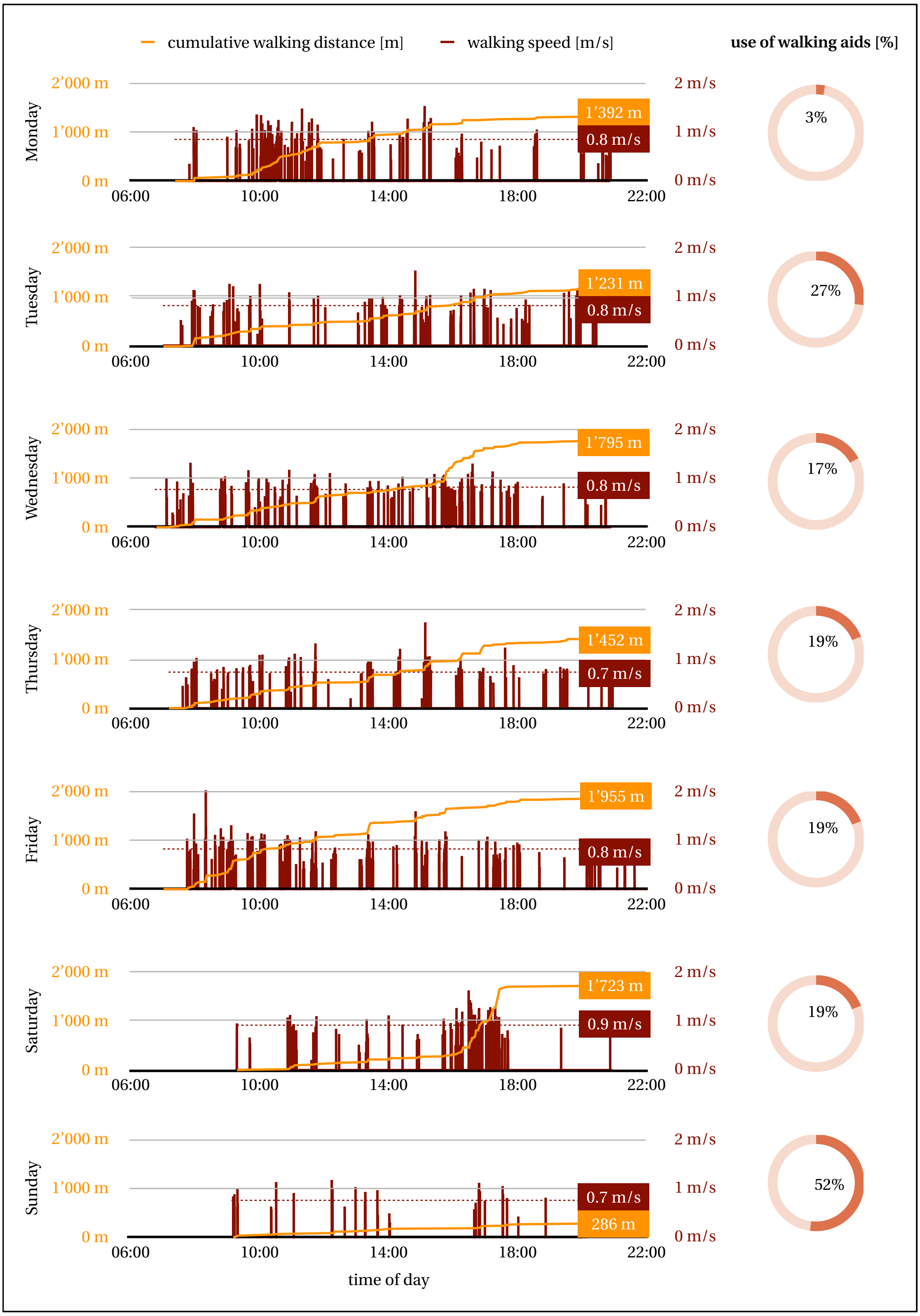


Figure 13.4 – Example report of the distance and speed of walking periods, and the use of walking aids indicated as the proportion of assisted to total walking duration.

13.3 Outlook

13.3.1 Improvements of the sensor technology

In **Chapter 11**, we also investigated how often and why children and adolescents were not wearing the sensors during the measurement period. The reason leading to most of the non-wearing periods was forgetting to reattach the sensors after taking them off, either to charge them overnight or to avoid damage during bathing and swimming activities. Taking off and charging the sensors was necessary because of our sensor technology's insufficient battery life and waterproofness. The resulting non-wearing periods caused a bias in the performance measures and decreased the data quality of the sensor reports. Thus, non-wearing periods should be prevented as much as possible. Hence, improving the sensor's battery life and waterproofness, allowing for continuous recordings for a whole week, and wearing them during bathing and swimming activities would be essential improvements to the sensor technology to increase the data quality of future measurements.

Besides non-wearing periods, we also found issues related to the correct placement of the sensors modules leading to data of insufficient quality. First and foremost, we frequently observed the trunk and thigh sensors slipping down to the belly and shank, respectively, even though the straps had a silicone strip on the inside that should prevent the sensors from slipping down. Therefore, we suggest wearing a tight vest with an inserted sensor module to keep the trunk sensor on the sternum and attaching the thigh sensor with adhesive tape to fixate it on the thigh. Besides this issue with the trunk and thigh sensors, we also noticed that some patients wore the wrist sensors incorrectly (see section 13.1.1.1). Hence, we suggest placing a sticker on top of the wrist sensors, indicating the correct orientation of the sensor (e.g., a drawn clock face or a smiley).

Moreover, the sensor technology used in this thesis stores the data on an internal drive. Thus, we only had access to the data retrospectively, which was adequate for answering this thesis's research questions. However, making the data visible to children and adolescents while they are wearing the sensors, for example, by streaming the data with Bluetooth Low Energy to a smartphone or computer, would enable giving feedback about their performance in daily life. This feedback could be used to motivate the children and adolescents to use their re-learnt motor skills during rehabilitation in everyday life. For example, they could more often decide to climb the stairs instead of taking the elevator because they can see and share their daily achievements on their smartphones. Another application could be to remind hemiplegic patients to use their affected hands in everyday life. Both applications have the potential to support neurorehabilitation by improving the patient's motor performance in daily life. However, the possible effect of this kind of feedback on children's and adolescents' behavior has to be shown in future studies (Lynch et al., 2018).

13.3.2 Improvements of the algorithm's outcomes

In this thesis, we identified the clinical needs for measuring everyday motor activities in **Chapter 4** and **Chapter 5**, and we developed an algorithm that determines as many of the clinically relevant outcomes as possible. Still, the final version of our algorithm does not cover all relevant outcomes, and the following paragraphs show possibilities of how the missing outcomes could be determined in the future.

Number of transfers Improving the ability to transfer between the wheelchair and another seat was the second most frequent rehabilitation goal of children and adolescents with neuromotor impairments. However, patients often do these transfers by shifting sideways without standing up, and this movement is a challenge to detect with wearable inertial sensors because the accuracy of measuring translational motions is diminished in long-term measurements (Kok et al., 2017). Therefore, we would prefer using instrumented seats to detect these transfers in daily life (Ahad et al., 2021) over using inertial sensors and trying to improve the underlying activity classification algorithm.

Number of steps while going up- and downstairs Stair climbing was among the top priorities of health professionals and families. However, our algorithm was not sensitive enough to detect stair climbing periods accurately. This low sensitivity was particularly evident in more severely impaired children taking adjusting steps when ascending and descending stairs and making small breaks on each step. This stair climbing pattern is difficult to detect with data from inertial sensors since it also contains standing periods explaining the confusion between stair climbing and standing. A promising solution to overcome this limitation would be complementing inertial sensors with depth cameras, providing information about the patients' environments. Future algorithms could use these data to detect pathways and stairs in the patients' surroundings and distinguish whether patients walked on flat surfaces or stairs (Zhang et al., 2019).

Specificity of hand use measures Our algorithm determines daily hand use with wrist-worn instead of hand-worn inertial sensors. This discrepancy can be justified since arm movement is typically required to position the hand for daily manual activities, and the results in **Chapter 8** show that this indirect measurement provides valid estimates of hand use. However, wrist-worn sensors do not capture fine hand use such as typing on a keyboard or specific movement primitives such as grasping. If this specificity of hand use detection is desired, we suggest upgrading the hardware with additional sensors on the fingers (Rowe et al., 2014), with electrodes measuring the muscle activity (Sadarangani et al., 2017), or with egocentric video recordings to capture the context of hand use (Likitlersuang et al., 2019). Still, the usability and validity of these technologies in children and adolescents with neuromotor impairments have to be investigated first.

Self-care activities Dressing was a top priority for families, and eating was a top priority for health professionals. However, detecting these activities in daily life is difficult since they do not have a repetitive pattern such as walking or wheeling and they can be performed in different ways. Moreover, we claim that the level of independence in these activities is more relevant than determining how often these activities are performed in daily life, and the level of independence can be measured with clinical assessments such as the Functional Independence Measure for Children (Kim et al., 2022). Therefore, we suggest using clinical assessment to quantify deficits and improvements in self-care activities rather than developing algorithms that detect these activities based on data from wearable sensors.

Quality of movement In the survey of **Chapter 5**, outcomes assessing the quantity of an activity were more relevant than those assessing the quality. For example, the number of climbed stairs was more relevant than the used stepping pattern, and the number of sit-to-stand transitions received a higher rating than how these transitions were executed. The same order was observed for upper limb measures and walking-related outcomes. We have two explanations for prioritizing quantity over quality. First, motor tests conducted at the clinic can capture the quality of an activity and might also reflect how children are doing this activity in daily life. However, how often children are doing this activity in daily life can only be captured with wearable sensors. Second, a top priority of pediatric rehabilitation is to gain independence in mobility and self-care activities (Chiarello et al., 2010). And to be independent, the capability to do an activity seems to be more important than how these activities are executed. Hence, assessing the quantity of activities is probably a better indicator of independence than assessing their quality.

However, besides measuring motor activities in the patients' habitual environment, wearable inertial sensors can also be used to complement the therapist's ratings during clinical assessments. Here, patients are wearing the sensors while performing a series of tests at the clinic, and the sensor data provides additional information about the patient's movement quality. Examples of such applications are estimating the quality of gait (Werner et al., 2021) or the quality of upper limb movements (Werner et al., 2022). Eventually, the algorithms developed in these studies could be combined with the algorithms developed in this thesis to bring clinical assessments into daily life and determine the quality of movement during everyday life motor activities.

13.3.3 Towards clinical implementation of the algorithm developed in this thesis

Even though we developed an algorithm that derives clinically meaningful and valid estimates about the children's and adolescents' motor performance in daily life, it is currently unclear whether therapists would also use this information in clinical practice and for what purpose. Hence, we have already started a qualitative study to explore these questions. We will measure the motor performance of several patients before rehabilitation and discuss the sensor data with three focus groups, including occupational, physical, and sports therapists, to verify if the clinical implementation of our new technology is desired and if further developments are needed.

If the clinical implementation is desired at our rehabilitation center, we will launch a follow-up project to improve the sensor system and the data processing algorithm according to the requirements of clinical practice. One of these requirements, which was not addressed in this thesis, is the speed of data generation. Therapists have already pointed out that the process from downloading the data to obtaining the results should require just a few clicks and take just a few minutes (Routhier et al., 2020). At the moment, we are far from fulfilling this requirement because the data needs to be processed in several time-consuming steps. First, non-wearing periods need to be removed based on the patients' journals and visual inspections of the sensor data resulting in a dataset for each wearing period. Then, the algorithm determines the performance measures for each dataset, fuses the measures of the same day, and plots the results. This step runs automatically. However, the results need a plausibility check to detect possible sensor misplacements and unrealistic spikes in the sensor data. In these cases, the sensor data needs to be adjusted manually and reprocessed by the algorithm. The whole procedure takes roughly an hour and requires programming skills. Hence, accelerating and automating this procedure would be essential in implementing the new technology in clinical practice.

Besides the speed of data generation, the time and resources required to plan and execute a measurement could also be a barrier to clinical implementation. In this thesis, a researcher was traveling to the patient's home to attach the sensors and instruct the families about the sensor handling. Furthermore, in some cases, it was necessary to restart the sensors due to technical issues. Currently, the time needed to start or even restart a measurement seems to be inappropriate for daily clinical practice and cannot be reimbursed by health insurance companies. Consequently, we recommend improving the reliability of the sensor technology to minimize the need to restart a measurement and decreasing the complexity of the sensor handling. The latter could be accomplished, for example, by increasing the sensor's battery life and waterproofness. This would eliminate the need to take off and charge the sensors, and thus also the need for a charging station.

Even though we foresee these barriers to clinical implementation, we regard wearable inertial sensors as a promising technology to measure motor performance in pediatric neurorehabilitation and, thus, assess the patients' functioning in everyday life; and the achievements of this thesis laid the foundation for implementing this technology into clinical practice and rehabilitation research.

Acknowledgments

This thesis is the result of more than five years of research conducted at the Swiss Children's Rehab of the University Children's Hospital Zurich and the Rehabilitation Engineering Laboratory (RELab) of ETH Zurich. I had the opportunity to work at both institutions, which allowed me to gain insights from both a clinical and a technological perspective and thus obtain a thorough understanding of the research topic. Hence, I would like to express my sincere gratitude to Rob Labruyère of the Swiss Children's Rehab and Roger Gassert of the RELab for initiating and promoting this productive research collaboration and for trusting in me to realize your ideas.

Rob, I am extremely grateful for your assistance and guidance throughout my studies. I would like to thank you for the many fruitful discussions we had at the office or while running through the woods around the rehabilitation center. I have always appreciated your constructive, encouraging, and motivating feedback. You contributed significantly to all my projects, you revised hundreds of paragraphs that I wrote, you challenged me in many ways, and you also cared about my personal life. Thank you for being such a knowledgeable mentor and an empathic friend during all these years.

Roger, I would like to extend my deepest gratitude for your support. You have always seen the bigger picture of my projects and asked the right questions. Your insightful feedback pushed me to sharpen my thinking and brought my work to a higher level. Sadly, your health condition prevented you from supervising me until the end of my thesis. I wish you all the energy and strength you need for your recovery.

In this sense, I would like to thank Bill Taylor, Professor at the Laboratory for Movement Biomechanics of ETH Zurich, who stepped in as the supervisor of my thesis and ensured that I could complete and defend my work. Moreover, I would like to express my gratitude to Olivier Lambercy for taking over the leadership of the RELab. Your incredible effort allowed us doctoral students to continue our work successfully, and I really appreciate and respect what you have been doing for us. I am also thankful for your valuable feedback during my progress reports and the assessment competence group meetings. Your critical view of clinical assessments and your ideas to improve the quality and significance of these assessments have been inspiring and helped me to advance my projects.

Furthermore, I would like to thank Christopher Newman of the Lausanne University Hospital (CHUV) for helping me design the clinical study and sharing your expertise in pedatric neurohabilitation and your experience in measuring motor activities with wearable sensors. You further agreed to complement my doctoral examination committee, consisting of Bill Taylor, Rob Labruyère, and Olivier Lambercy. I would like to thank you all for reading and evaluating my thesis.

Next, I would like to thank all former and current members of the Pediatric Rehabilitation Research Group for the many interesting discussions and for creating such an amazing environment to work in. Specifically, I would like to thank Huub van Hedel for leading this multidisciplinary and extraordinary team and for giving me the opportunity to be a part of it. A special thank goes to Seraina Aschwanden, Florence Jucker, Silvia Herren, and Nadja Delliehausen, who conducted their master thesis in my projects. They recruited dozens of participants, collected and processed terabytes of data, and reduced my workload substantially. I really appreciate your work.

I would also like to acknowledge my colleagues from the RELab. Specifically, I want to thank Kaspar Leuenberger for providing his codes regarding the preprocessing of sensor data, Werner Popp for providing his wheeling detection algorithm for adults with a spinal cord injury, and Charlotte Werner for providing her codes regarding gait detection. Besides, I would like to express my gratitude to all ZurichMOVE users for sharing your experiences in handling the sensor system and Stefan Schneller for providing photos and artworks of the sensor modules.

I am also very grateful to all the children and adolescents who participated in my studies and their willingness to wear the sensor system in daily life or during my experiments.

I am thankful for the financial support that I received for my projects from the Walter Muggli Fund of the ACCENTUS Foundation, the Children's Research Center of the University Children's Hospital of Zurich, the Clinical Research Priority Program for Neuro-Rehab of the University of Zurich, the Anna Mueller Grocholski Foundation, the Fondation Gaydoul, and the Vontobel Foundation.

Finally, I would like to thank my parents for teaching me positive thinking and stamina, my parents-in-law for being always there for me when I needed you, my daughter Luana for all the happy distractions to rest my mind outside of research, and my wife Aselia for your support during all these years, for always believing in me, and for your unconditional love.

Affoltern am Albis, May 2022 Fabian

A Search strategy

This appendix corresponds to the Additional file 1 of **Chapter 2**, Rast and Labruyère (2018) and contains a complete list of search terms and the syntax of the search strategy.

A.1 Search categories and Boolean operators

1. People with mobility impairments
2. Inertial sensor technology
3. Data processing algorithms
4. Free-living conditions
5. Activity recognition or classification
6. Animal studies

1 AND [(2 AND 3 AND 4) OR (2 AND 5)] NOT 6

A.2 Database-specific search terms

Medline (Ovid)

1. exp disabled persons/ or exp motor skills disorders/ or exp rehabilitation/ or exp patients/ or exp "diseases (non mesh)"/ or ("handicap*" or "disab*" or "disorder*" or "rehabilitation*" or "disease*" or "patients" or "motor impairment*" or "dysfunction*" or "syndrome*" or "brain injur*" or "spinal cord injur*" or "palsy" or "paralysis" or "*paresis" or "hypertonia" or "spasticity" or "meningitis" or "myopath*" or "neuropath*" or "stroke").ti,ab,kw.
2. "actigraph*".ti,ab,kw. or exp accelerometry/ or "actimetry".ti,ab,kw. or "acceleromet*".ti,ab,kw. or "gyroscope".ti,ab,kw. or "magnetomet*".ti,ab,kw. or exp magnetometry/ or "inertial sensor*".ti,ab,kw. or "inertial measurement unit*".ti,ab,kw. or "imu".ti,ab,kw. or "motion sensor*".ti,ab,kw. or "movement sensor*".ti,ab,kw.
3. ("algorithm*" or "signal process*" or "data process*" or "pattern recogni*").ti,ab,kw. or exp computing methodologies/ or exp Pattern Recognition, Automated/
4. "daily living*".ti,ab,kw. OR "daily life".ti,ab,kw. OR "adl".ti,ab,kw. OR "everyday life".ti,ab,kw. OR "free living".ti,ab,kw. OR "outdoor*".ti,ab,kw. OR "home".ti,ab,kw. OR "hand activit*".ti,ab,kw. OR "arm activit*".ti,ab,kw. OR "walking activit*".ti,ab,kw. OR (daily ADJ3 activit*).ti,ab,kw. OR exp "Activities of Daily Living"/
5. ((classif* adj3 activit*) or (recogni* adj3 activit*)).ti,ab,kw.
6. exp animal/ not exp human/

Embase

1. ’disabled person’/exp or ’disability’/exp or ’rehabilitation’/exp or ’patient’/exp or ’diseases’/exp or (’handicap*’ or ’disab*’ or ’disorder*’ or ’rehabilitation*’ or ’disease*’ or ’patients’ or ’motor impairment*’ or ’dysfunction*’ or ’syndrome*’ or ’brain injur*’ or ’spinal cord injur*’ or ’palsy’ or ’paralysis’ or ’paresis’ or ’hypertonia’ or ’spasticity’ or ’meningitis’ or ’myopath*’ or ’neuropath*’ or ’stroke’):ti,ab,de

2. ’actigraph*’:ti,ab,de OR ’actimetry’/exp OR ’actimetry’:ti,ab,de OR ’acceleromet*’:ti,ab,de OR ’accelerometry’/exp OR ’accelerometer’/exp OR ’gyroscope’:ti,ab,de OR ’magnetomet*’:ti,ab,de OR ’magnetometry’/exp OR ’inertial sensor*’:ti,ab,de OR ’inertial measurement unit*’:ti,ab,de OR ’imu’:ti,ab,de OR ’motion sensor*’:ti,ab,de OR ’movement sensor*’:ti,ab,de

3. ’algorithm*’:ti,ab,de OR ’signal process*’:ti,ab,de OR ’data process*’:ti,ab,de OR ’pattern recogni*’:ti,ab,de OR ’information processing’/exp OR ’signal processing’/exp

4. ’daily living*’:ti,ab,de OR ’daily life’:ti,ab,de OR ’adl’:ti,ab,de OR ’everyday life’:ti,ab,de OR ’free living’:ti,ab,de OR ’outdoor*’:ti,ab,de OR ’home’:ti,ab,de OR ’hand activit*’:ti,ab,de OR ’arm activit*’:ti,ab,de OR ’walking activit*’:ti,ab,de OR (daily NEAR/3 activit*):ti,ab,de OR ’daily life activity’/exp

5. (classif* NEAR/3 activit*):ti,ab,de OR (recogni* NEAR/3 activit*):ti,ab,de

6. ’animal’/exp NOT ’human’/exp

Scopus

1. TITLE-ABS-KEY ("handicap*" OR "disab*" OR "disorder*" OR "rehabilitation*" OR "disease*" OR "patients" OR "motor impairment*" OR "dysfunction*" OR "syndrome*" OR "brain injur*" OR "spinal cord injur*" OR "palsy" OR "paralysis" OR "*paresis" OR "hypertonia" OR "spasticity" OR "meningitis" OR "myopath*" OR "neuropath*" OR "stroke")
2. TITLE-ABS-KEY("actigraph*" OR "actimetry" OR "acceleromet*" OR "gyroscope" OR "magnetomet*" OR "inertial sensor*" OR "imu" OR "inertial measurement unit*" OR "motion sensor*" OR "movement sensor*")
3. TITLE-ABS-KEY("algorithm*" OR "signal process*" OR "data process*" OR "pattern recogni*")
4. TITLE-ABS-KEY ("daily living*" OR "daily life" OR "adl" OR "everyday life" OR "free living" OR "outdoor*" OR "home" OR "hand activit*" OR "arm activit*" OR "walking activit*" OR (daily W/2 activit*))
5. TITLE-ABS-KEY ((classif* W/2 activit*) OR (recogni* W/2 activit*))
6. INDEXTERMS (animal AND NOT human)

B List of all rehabilitation goals

This appendix corresponds to the Figure S1 of **Chapter 4**, Rast and Labruyère (2020a) and it provides a list of all ICF categories and the corresponding number of rehabilitation goals.

ICF block	Color code	2nd ICF level	3rd ICF level	Count	%
Changing and maintaining body position (d410-d429)		d410 Changing basic body position	d4107 Rolling over	10	1.3%
			d4108 Changing basic body position, other specified (kneeling <=> standing)	6	0.8%
			d4108 Changing basic body position, other specified (lying <=> sitting)	14	1.8%
			d4108 Changing basic body position, other specified (lying <=> standing)	4	0.5%
			d4108 Changing basic body position, other specified (sitting <=> standing)	10	1.3%
			d4109 Changing basic body position, unspecified	4	0.5%
		d415 Maintaining a body position	d4150 Maintaining a lying position	1	0.1%
			d4152 Maintaining a kneeling position	2	0.3%
			d4153 Maintaining a sitting position	38	4.8%
			d4154 Maintaining a standing position	36	4.6%
			d4155 Maintaining head position	10	1.3%
			d4158 Maintaining a body position, other specified	12	1.5%
			d4159 Maintaining a body position, unspecified	4	0.5%
		d415 Maintaining a body position, passive	d4150 Maintaining a lying position, passive	9	1.1%
			d4153 Maintaining a sitting position, passive	17	2.2%
			d4159 Maintaining an unspecified body position, passive	3	0.4%
		d420 Transferring oneself	d4200 Transferring oneself while sitting	67	8.5%
			d4209 Transferring oneself, unspecified	5	0.6%
Carrying, moving and handling objects (d430-d449)		d430 Lifting and carrying objects	d4301 Carrying in the hands	2	0.3%
			d4305 Putting down objects	1	0.1%
			d4308 Lifting and carrying, other specified	2	0.3%
		d435 Moving objects with lower extremities	d4351 Kicking	3	0.4%
		d440 Fine hand use	d4401 Grasping	16	2.0%
			d4402 Manipulating	13	1.7%
			d4409 Fine hand use, unspecified	9	1.1%
		d445 Hand and arm use	d4452 Reaching	2	0.3%
			d4454 Throwing	2	0.3%
			d4458 Hand and arm use, other specified	26	3.3%
			d4459 Hand and arm use, unspecified	7	0.9%
Walking and moving (d450-d469)		d450 Walking	d4500 Walking short distances	85	10.8%
			d4501 Walking long distances	26	3.3%
			d4502 Walking on different surfaces	4	0.5%
			d4503 Walking around obstacles	2	0.3%
			d4508 Walking, other specified	28	3.6%
			d4509 Walking, unspecified	5	0.6%
		d451 Going up and down stairs	d451 Going up and down stairs	49	6.3%
		d455 Moving around	d4550 Crawling	8	1.0%
			d4551 Climbing	1	0.1%
			d4553 Jumping	3	0.4%
			d4554 Swimming	3	0.4%
			d4558 Moving around, other specified	5	0.6%
			d4559 Moving around, unspecified	1	0.1%
		d465 Moving around using equipment	d465 Moving around using equipment	13	1.7%
Moving around using transportation (d470-d489)		d470 Using transportation	d4702 Using public motorized transportation	8	1.0%
		d475 Driving	d4750 Driving human-powered transportation	19	2.4%
			d4751 Driving motorized vehicles	4	0.5%
		d480 Riding animals for transportation	d480 Riding animals for transportation	1	0.1%
		d510 Washing oneself	d5100 Washing body parts	4	0.5%
			d5101 Washing whole body	3	0.4%
			d5200 Caring for skin	1	0.1%

1

ICF block	Color code	2nd ICF level	3rd ICF level	Count	%
Self-care (d510-d599)		d520 Caring for body parts	d5201 Caring for teeth	3	0.4%
			d5202 Caring for hair	5	0.6%
			d5209 Caring for body parts, unspecified	5	0.6%
		d530 Toileting	d5300 Regulating urination	3	0.4%
			d5301 Regulating defecation	3	0.4%
			d5309 Toileting, unspecified	8	1.0%
		d540 Dressing	d5400 Putting on clothes	53	6.8%
			d5401 Taking off clothes	23	2.9%
			d5402 Putting on footwear	18	2.3%
			d5403 Taking off footwear	4	0.5%
		d550 Eating	d550 Eating	17	2.2%
		d560 Drinking	d560 Drinking	8	1.0%
		d599 Self-care, unspecified	d599 Self-care, unspecified	26	3.3%
			Total	784	100%

C Survey with health professionals

This appendix corresponds to the Supplementary file 1 of **Chapter 5**, and shows the content of the original survey.

Everyday life motor activities of children and adolescents

This is an English translation of the survey, which was originally written in German.

Wearable inertial sensors are ideal for monitoring everyday life motor activity. During my doctoral thesis I would like to adapt an existing sensor system to the needs of pediatric rehabilitation. In doing so, I depend on your experience. This survey will give you the opportunity to optimize the sensor system according to your needs and to gain meaningful insight into everyday life motor activities of your patients. For more information about the sensor system, please visit the following website: http://zurichmove.com/

Completing the survey takes about 15 minutes. It can be interrupted at any time and continued later.

Thank you very much for participating in my survey!

Response options

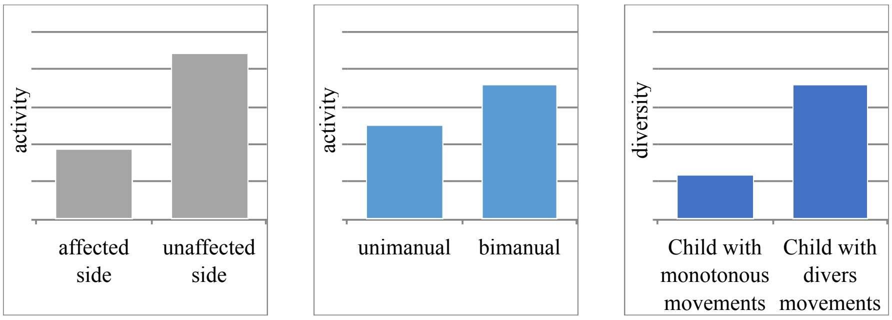
For answering the questions, please imagine that the children and adolescents wear the sensors at home/in their habitual environment which allows for the quantification of their everyday life motor activities (ICF[1] qualifier performance).

On the following pages, possible outcome measures are explained and their results are presented on the basis of a fictitious measurement. Please rate the relevance of these outcome measures for the rehabilitation of children and adolescents. Please answer the questions from an interdisciplinary perspective.

[1] International Classification of Functioning, Disability, and Health

Upper limb activity

Upper limb activities can be measured separately for the left and right arm. This enables the quantification of the hand use laterality, the amount of unimanual and bimanual activities, and the diversity of upper limb activities.



	very relevant	relevant	hardly relevant	not relevant	no answer
1. affected vs. unaffected	◯	◯	◯	◯	◯
2. unimanual vs. bimanual	◯	◯	◯	◯	◯
3. diversity	◯	◯	◯	◯	◯

If you think other outcome measures would be more relevant in this category, please describe them in the comments box below:

Joint movement in daily life

Joint angles can also be measured. This can be used to quantify the number of repetitions and the range of motion of individual joints in everyday life. Examples from the literature are listed below. The same measurement could be applied to other joints or linked to specific activities (please specify the joints and activities in the comment field if needed).

Fictitious measurement	Supination
# repetitions	335
range of motion	15° ± 3°

	very relevant	relevant	hardly relevant	not relevant	no answer
4. shoulder ab-/adduction	○	○	○	○	○
5. elbow flexion/extension	○	○	○	○	○
6. pro-/supination	○	○	○	○	○
7. wrist flexion/extension	○	○	○	○	○
8. finger flexion/extension	○	○	○	○	○
9. knee flexion/extension	○	○	○	○	○

If you think other outcome measures would be more relevant in this category, please describe them in the comments box below:

Reaching & grasping

Reaching and grasping movements can be detected and evaluated in everyday life. This allows quantifying the number of repetitions as well as the range of reaching forward and sideward relative to the trunk.

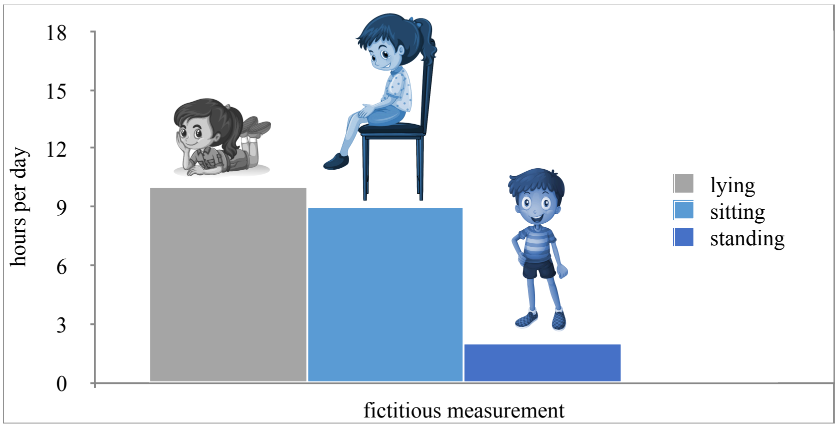
Fictitious measurement	Reaching
# repetitions	75
range (forward)	23 cm ± 11 cm
range (sideward)	14 cm ± 4 cm

	very relevant	relevant	hardly relevant	not relevant	no answer
10. number of repetitions	◯	◯	◯	◯	◯
11. range	◯	◯	◯	◯	◯

If you think other outcome measures would be more relevant in this category, please describe them in the comments box below:

Body positions

Lying, sitting and standing can be recognized in everyday life and the duration a child spends in these body positions is measured. Lying can be subclassified as prone, supine, and side lying, and standing as upright, bending forward, or bending sideward. Other subclassifications or body positions could also be assessed (please specify in the comments field if needed).

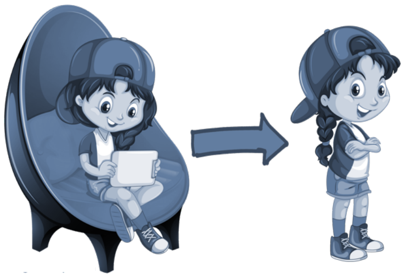


	very relevant	relevant	hardly relevant	not relevant	no answer
12. lying, sitting, and standing	○	○	○	○	○
13. lying: prone, supine, etc.	○	○	○	○	○
14. standing: upright, bent forward, etc.	○	○	○	○	○

If you think other outcome measures would be more relevant in this category, please describe them in the comments box below:

Changing a body position

Transitions between sitting and standing can be detected in everyday life. Then, the quantity (e.g. number of repetitions or duration) or also the quality (e.g. forward tilt of the upper body or flow of movement) can be determined. Transitions between other body positions could also be assessed (please specify in the comments field if needed).



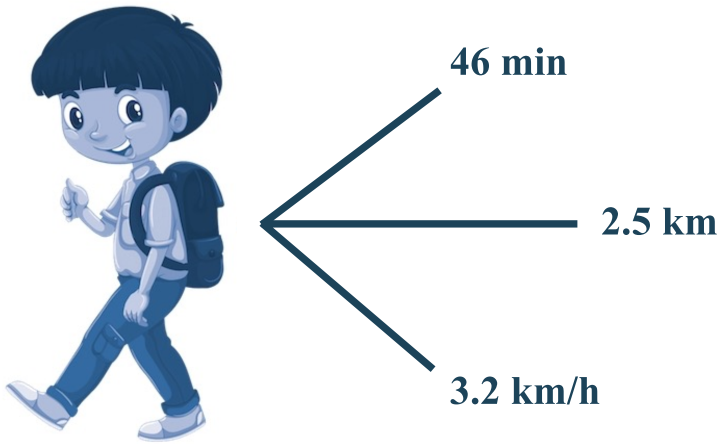
Quantity	Quality
Repetitions: 14#	Forward tilt: 23° ± 5°
Duration: 1.5 s ± 0.6 s	Flow of movement: 34 m/s³ ± 7 m/s³

	very relevant	relevant	hardly relevant	not relevant	no answer
15. quantity: sitting <-> standing	○	○	○	○	○
16. quality: sitting <-> standing	○	○	○	○	○

If you think other outcome measures would be more relevant in this category, please describe them in the comments box below:

Walking activity

Walking can be distinguished from other activities, and the daily walking activity can be divided into individual walking bouts. Then, the duration, distance and speed of these bouts can be determined.

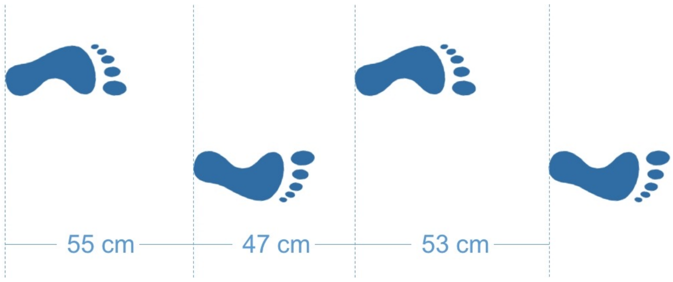


	very relevant	relevant	hardly relevant	not relevant	no answer
17. duration	◯	◯	◯	◯	◯
18. distance, speed	◯	◯	◯	◯	◯

If you think other outcome measures would be more relevant in this category, please describe them in the comments box below:

Gait parameters

Walking can be segmented into gait cycles which allows quantifying gait parameters such as step length, duration of the stance phase or step symmetry. Please describe the gait parameters in the comment field which are particularly relevant for the rehabilitation of children and adolescents.



	very relevant	relevant	hardly relevant	not relevant	no answer
19. gait parameters	◯	◯	◯	◯	◯

If you think other outcome measures would be more relevant in this category, please describe them in the comments box below:

Walking (risk of falling)

From walking activities, different measures can be calculated that predict a child's risk of falling.

	very relevant	relevant	hardly relevant	not relevant	no answer
20. risk of falling	◯	◯	◯	◯	◯

If you think other outcome measures would be more relevant in this category, please describe them in the comments box below:

Walking (turning)

Obstacles or a side road can force a change of direction during walking activities. These turns can be analyzed regarding speed, angular change, number of steps, etc. Please describe the outcome measures in the comment field which are particularly relevant for the rehabilitation of children and adolescents.

	very relevant	relevant	hardly relevant	not relevant	no answer
21. walking (turning)	○	○	○	○	○

If you think other outcome measures would be more relevant in this category, please describe them in the comments box below:

Walking (slope)

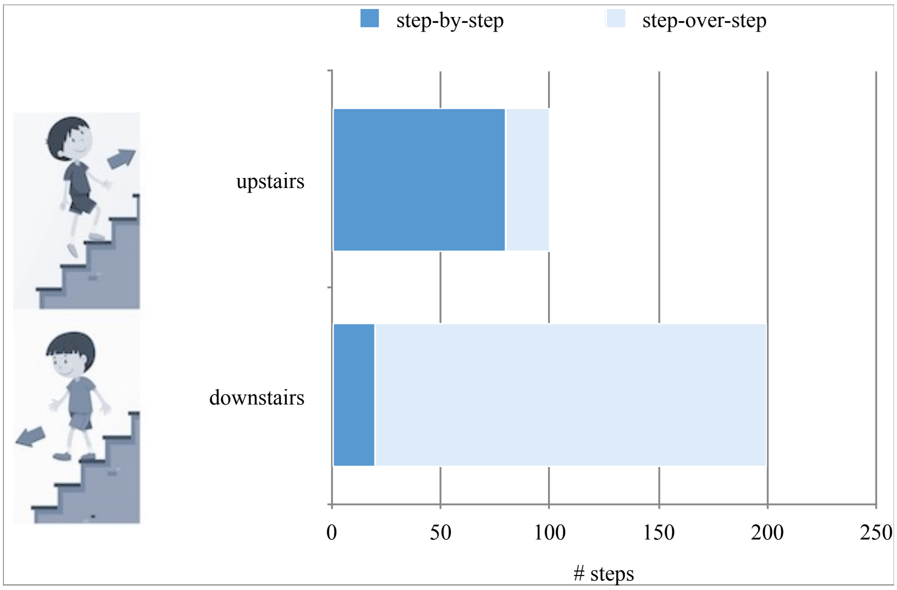
The slope of covered walking routes can be measured which allows determining whether a child can walk in steep terrain. In addition, the gait pattern can be compared between level, uphill, and downhill walking.

	very relevant	relevant	hardly relevant	not relevant	no answer
22. walking (slope)	○	○	○	○	○

If you think other outcome measures would be more relevant in this category, please describe them in the comments box below:

Stair climbing

Stair climbing periods and the covered number of steps can be recorded in everyday life (quantity). Furthermore, it can be distinguished between a step-by-step and a step-over-step pattern (quality).

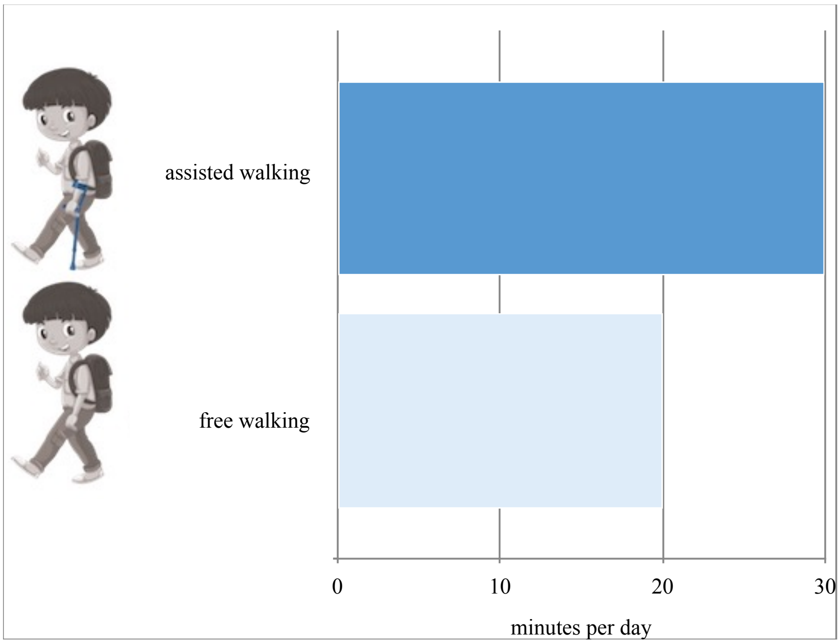


	very relevant	relevant	hardly relevant	not relevant	no answer
23. number of steps	○	○	○	○	○
24. step-by-step vs. step-over-step pattern	○	○	○	○	○

If you think other outcome measures would be more relevant in this category, please describe them in the comments box below:

Use of walking aids

The use or non-use of assistive devices can be assessed for walking and other activities. Other measures, such as weight bearing or the orientation/position of the assistive device could be determined, too. (please describe them in the comment field if needed).

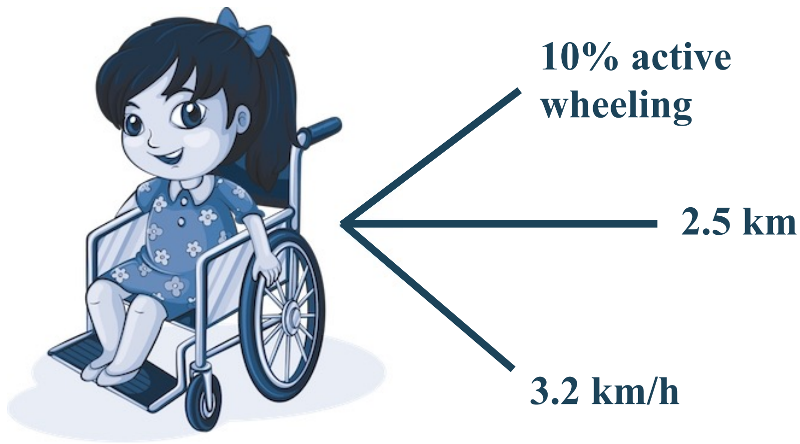


	very relevant	relevant	hardly relevant	not relevant	no answer
25. Use of aids during walking activities	◯	◯	◯	◯	◯

If you think other outcome measures would be more relevant in this category, please describe them in the comments box below:

Wheelchair

Wheeling activities can be detected and subclassified as passive wheeling (being pushed by a third person or a motor) or active self-propulsion. Furthermore, the covered distance and the speed can be determined. Other outcome measures such as the frequency of active strokes or the maneuvering of the wheelchair would also be determined (please describe them in the comment field if needed).

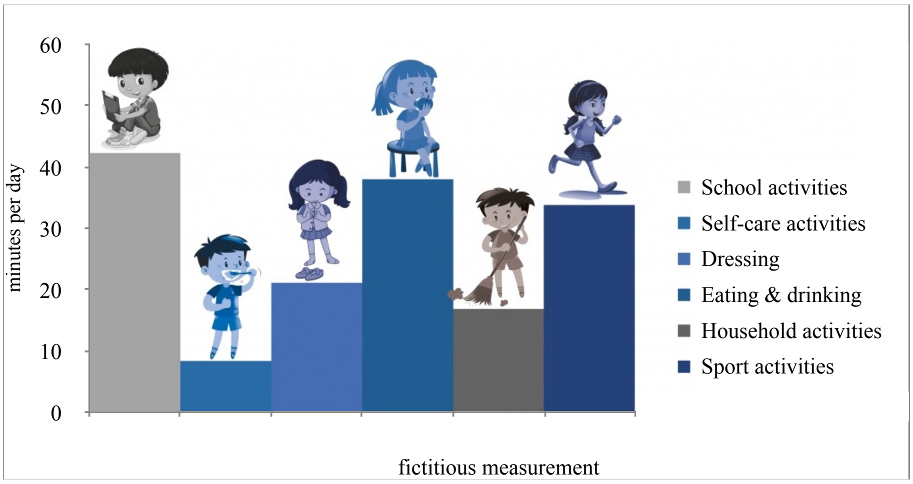


	very relevant	relevant	hardly relevant	not relevant	no answer
26. active vs. passive	◯	◯	◯	◯	◯
27. distance, speed	◯	◯	◯	◯	◯

If you think other outcome measures would be more relevant in this category, please describe them in the comments box below:

Activities of daily living

Various other activities of daily living can be detected, and the duration or the number of repetitions of these activities can be determined. Here, the activities were grouped because the possibilities are very diverse. If certain activities seem particularly relevant to you, please list them in the comment field.

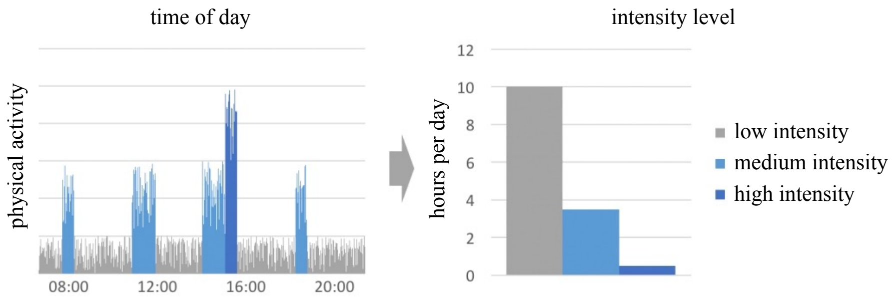


	very relevant	relevant	hardly relevant	not relevant	no answer
28. school activities (reading, writing)	◯	◯	◯	◯	◯
29. personal hygiene	◯	◯	◯	◯	◯
30. dressing	◯	◯	◯	◯	◯
31. eating & drinking	◯	◯	◯	◯	◯
32. household activities	◯	◯	◯	◯	◯
33. sports activities	◯	◯	◯	◯	◯

If you think other outcome measures would be more relevant in this category, please describe them in the comments box below:

Energy expenditure

The intensity of physical activities can be measured and divided into three levels (low, medium and high intensity). This allows determining the daily energy expenditure.



	very relevant	relevant	hardly relevant	not relevant	no answer
34. energy expenditure	◯	◯	◯	◯	◯

If you think other outcome measures would be more relevant in this category, please describe them in the comments box below:

What's missing?

The outcome measures in this survey were derived from previous research projects and do not cover all possibilities. If you missed a relevant outcome for the assessment of everyday life motor activities in children and adolescents when filling out this survey, please describe it in the comment field below:

Imagine there would be a sensor system available in the future that derives the outcome measures of this survey. Would you use it to monitor everyday life motor activities?

- ◯ Yes
- ◯ No

Demographic data

Your age (years): ____

Your gender :

- ◯ female
- ◯ male

Profession:

- ◯ doctor
- ◯ movement scientist
- ◯ occupational therapist
- ◯ physiotherapist
- ◯ nurse
- ◯ sport therapist
- ◯ other: _________

Work experience in pediatrics (years): ____

Workplace: _____________________

Credits

The illustrations of this survey were designed using resources from freepik.com

D Posture and mobility detection algorithm

This appendix corresponds to the Supplementary file 1 of **Chapter 7** and contains a comprehensive description of the three sub-algorithms.

D.1 Abstract

The algorithm can be divided into three independent parts using different sensor setups:

1. The posture detection algorithm detects lying, sitting, and standing positions based on data of the trunk and thigh sensors.

2. The wheeling detection algorithm detects wheeling periods with data of the wheelchair sensor and discriminates between active and passive wheeling with data of the wrist sensor of the dominant hand.

3. The walking detection algorithm detects walking periods and differentiates between level walking and stair climbing with data of a single ankle sensor. Further, the algorithm discriminates between free and assisted walking with data of the sensor attached to a walking aid.

D.2 Raw data

We used the data of inertial measurement units containing a 3-axis accelerometer, a 3-axis gyroscope, and a barometric pressure sensor, as well as Bluetooth Low Energy for time synchronization (see **Figure D.1**) (Popp et al., 2019). However, the algorithm can be applied to

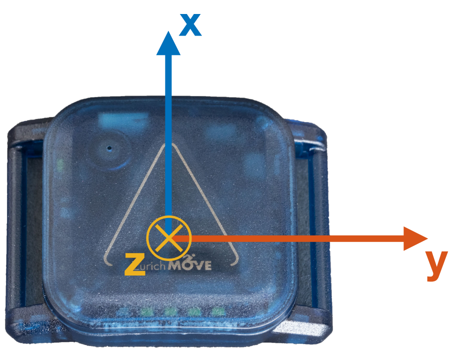


Figure D.1 – The ZurichMOVE sensor and its coordinate system (created by Rehabilitation Engineering Laboratory, ETH Zurich).

any measurement unit containing the required sensor modalities. The raw data needs to be resampled to 50 Hz, and the signals must be measured in or converted to the following units:

- acceleration $a \Rightarrow m/s^2$
- angular rate $\omega \Rightarrow \ ^\circ/s$
- barometric pressure $p \Rightarrow Pa$

D.3 Posture detection algorithm

This part of the algorithm detects lying, sitting, and standing positions based on data of the trunk and thigh sensors.

D.3.1 Sensor placement

The trunk sensor needs to be placed on the sternum with the x-axis facing toward the belly button. The thigh sensor needs to be placed mid-thigh on the lateral side of the less-affected leg. Here, the x-axis faces toward the knee (see **Figure D.2**).

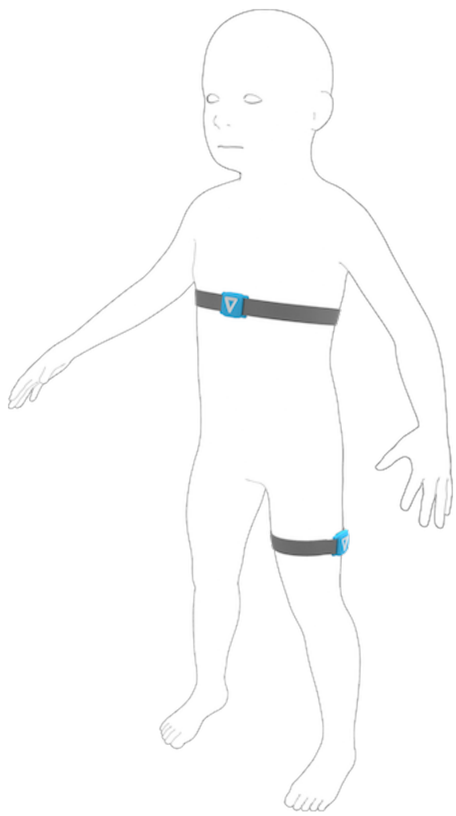


Figure D.2 – Sensor placement of the posture detection algorithm (created by Rehabilitation Engineering Laboratory, ETH Zurich).

D.3.2 Orientation estimation

Before estimating the orientation of the sensor, the algorithm corrects the offset and drift of the gyroscope signal (Leuenberger et al., 2015). First, still phases are detected by applying a 2nd order high-pass filter (cut-off frequency = 0.5 Hz), a low-pass filter (cut-off frequency = 2 Hz), and a threshold of 1 $°\backslash s$ (Lötters et al., 1998). Then, the drift of the gyroscope signal is estimated by piecewise low-pass filtering of each axis, linearly interpolating between the still phases, and limiting the slew rate of the signal to 500 $\mu°\backslash s\backslash s$. And finally, this drift is subtracted from the raw gyroscope measurements.

To estimate the orientation of the sensor, the acceleration and the corrected gyroscope signals are fused with the open-source algorithm of S. Madgwick (Madgwick et al., 2011). The filter gain β was set to 0.03 which provided optimal performance in previous experiments (Madgwick et al., 2011). The output is a vector containing the quaternions of each sample $\vec{q} = [q_0\ q_1\ q_2\ q_3]^T$. In the neutral position ($\vec{q} = [1\ 0\ 0\ 0]^T$), the z-axis points towards the floor.

As the last step, the pitch angle of the sensor's orientation is derived from the quaternions. The pitch angle is defined as the deviation of the sensor's orientation from its neutral position around a new y-axis after rotating the sensor around its z-axis. It is calculated with the following equation:

$$\varphi = \arcsin\Big(2(q_0 q_2 - q_3 q_1)\Big) * \frac{180}{\pi}$$

This angle is filtered using a 5th order low-pass filter (cut-off frequency = 0.1 Hz). An angle of 0° represents a horizontal orientation, while an angle of ±90° represents a vertical orientation. Negative values result when the x-axis of the sensor points downward, and positive values result when the x-axis points upward. The former corresponds to a standing position, while the latter would correspond to a handstand position. Signals of which the mean of the whole measurement period exceeds 0° are multiplied by -1 since we assume that the sensor was placed upside down rather than the participant being in this position for a prolonged time.

D.3.3 Classification of lying, sitting, and standing

In lying, both sensors are horizontal while they are vertical during standing. In sitting, however, the thigh sensor is horizontal and the trunk sensor is vertical. A vertical thigh sensor and a horizontal trunk sensor is uncommon and probably reflects a standing position with bending forward. Hence, the algorithm classifies this scenario as standing. The thresholds to distinguish between a horizontal and vertical orientation were trained with labeled data of children with mobility impairments and a decision tree by minimizing the Gini's Diversity Index. The resulting thresholds are $T_{trunk} = -35.9°$ and $T_{thigh} = -48.4°$.

D.3.4 Outcome measures

After detecting lying, sitting, and standing positions, the algorithm determines the duration the participant spent in each position throughout the measurement period. Moreover, the number of transitions between a sitting and a standing position are counted. The minimal duration between two consecutive sit-to-stand transitions was set to 2 min to avoid an overestimation in noisy data or during cycling periods.

D.4 Wheeling detection algorithm

This part of the algorithm detects wheeling periods with data of the wheelchair sensor and discriminates between active and passive wheeling with data of the wrist sensor of the dominant hand.

D.4.1 Sensor placement

The wheelchair sensor needs to be placed on the spokes of the wheelchair, with the z-axis being parallel to the axis of the wheel. The direction of the z-axis does not matter since the algorithm assumes that the participant more frequently wheels forward than backward. The wrist sensor is worn on the dominant hand as a watch. The x-axis faces toward the fingers (see **Figure D.3**). The user selects the dominant hand by placing a single sensor on the corresponding wrist. If data of both wrist sensors are available, the algorithm uses the side which reveals a higher acceleration magnitude during wheeling periods.

Figure D.3 – Sensor placement of the wheeling detection algorithm (created by Rehabilitation Engineering Laboratory, ETH Zurich).

D.4.2 Classification of non-wheeling activities, active wheeling and passive wheeling

This part of the algorithm is an adapted version of a previously published algorithm that was developed for patients with a spinal cord injury (Popp et al., 2016). The feature selection process was repeated with data of children with mobility impairments and the resulting algorithm is described in the following sections.

D.4.2.1 Detection of wheeling periods

This part depends solely on the z-axis of the wheelchair sensor $a_{wheel,z}$ and $\omega_{wheel,z}$. As a first step, it is verified if the z-axis of the sensor is in a horizontal orientation which is the case if the sensor is fixed to the spokes of the wheel. In this case, the acceleration signal due to gravity is close to zero. In contrast, the signal is close to 9.81 m/s^2 if the sensor is lying around in neutral position. Therefore, periods in which $a_{wheel,z}$ is $> 0.5 * 9.81$ m/s^2 for longer than 1 min are classified as non-wheeling activities and ignored during the following steps. Before applying this cut-off, the signal is processed with a low-pass filter (cut-off frequency = 0.05 Hz).

Then, plateaus in the gyroscope signal of five samples in a row or longer are set to zero to remove gyroscope data with low quality. The resulting signal is used to detect wheeling periods in three steps: identifying preliminary wheeling periods, classifying them as valid and invalid wheeling periods, and fusing valid wheeling periods by analyzing the rest phases between two consecutive wheeling periods. First, a threshold ($|\omega_{wheel,z}| > 0.4°/s$) is applied to identify preliminary wheeling periods. Second, for each period, the following heuristic rules are used to detect valid wheeling periods:

- $\max|\omega_{wheel,z}| > 10°/s$
- $Var(\omega_{wheel,z}) > 1°/s$
- $\int |\omega_{wheel,z}| dt > 80°$

Third, valid wheeling periods that are less than 2 s apart are fused. In addition, rest phases between two valid wheeling periods that contain more than 80% of preliminary wheeling periods as well as those that are shorter than 0.8 s are also classified as a valid wheeling period. Finally, valid wheeling periods that are less than 2 s apart are fused again.

D.4.2.2 Discrimination between active and passive wheeling

As a first step, the raw data of the wrist sensor is filtered. The acceleration signal is passed through an infinite impulse response eight order elliptic low-pass filter with a cut-off frequency of 0.3 Hz, a passband ripple of 0.02 dB, and a minimum stopband attenuation of 200 dB in order to separate the static acceleration component due to gravity a_{static} from the dynamic acceleration component resulting from wrist movement $a_{dynamic}$ (Karantonis et al., 2006).

Wheeling periods lasting longer than 5.12 s are divided into segments with a window length of 5.12 s and an overlap of 75%. Each segment in which the wrist sensor is not able to communicate with the wheelchair sensor via Bluetooth Low Energy is classified as non-wheeling activity. Here, it is assumed that the wheelchair is far away from the participant. The remaining segments are either classified as active or passive wheeling. The same features of the original publication of this algorithm (Popp et al., 2016) were calculated and the feature selection process was repeated with data of children with mobility impairments. It revealed just a single relevant feature: $P_{10th}(a_{wrist,static,x})$. This feature is a surrogate for the orientation of the wrist. It is 9.81 m/s^2 if the x-axis is parallel to gravity and zero if the x-axis is perpendicular to gravity. Movement related features did not improve classification accuracy since we encouraged children to do hand activities while they were pushed around in their wheelchair. The threshold to distinguish between active and passive wheeling was trained with a decision tree by minimizing the Gini's Diversity Index. The resulting threshold is $T_{wrist} = -0.61 * 9.81\ m/s^2$. Wheeling periods with the hand facing down towards the wheel are classified as active wheeling while periods with the hand facing more horizontal or upward are classified as passive wheeling.

D.4.3 Outcome measures

The algorithm derives the total duration of active and passive wheeling separately.

D.5 Walking detection algorithm

This part of the algorithm detects walking periods and differentiates between level walking and stair climbing with data of a single ankle sensor. Further, the algorithm discriminates between free and assisted walking with data of the sensor attached to a walking aid.

D.5.1 Sensor placement

The ankle sensor is worn on the less-affected ankle. The x-axis faces toward the floor and points to the lateral malleolus (see **Figure D.4**). If applicable, a sensor is placed firmly on the walking aid of the participant. The position and orientation of this sensor are irrelevant.

D.5.2 Detection of walking bouts

D.5.2.1 Preprocessing I

As a first step, the algorithm verifies the placement of the ankle sensor. If the average acceleration signal of the x-axis is greater than zero, it is assumed that the sensor was placed upside down. In this case, the sensor is rotated 180° around its z-axis by multiplying the acceleration and gyroscope signals of the x- and y-axis by -1. Then, the bias and drift of the gyroscope signal are corrected as described in chapter D.3.2

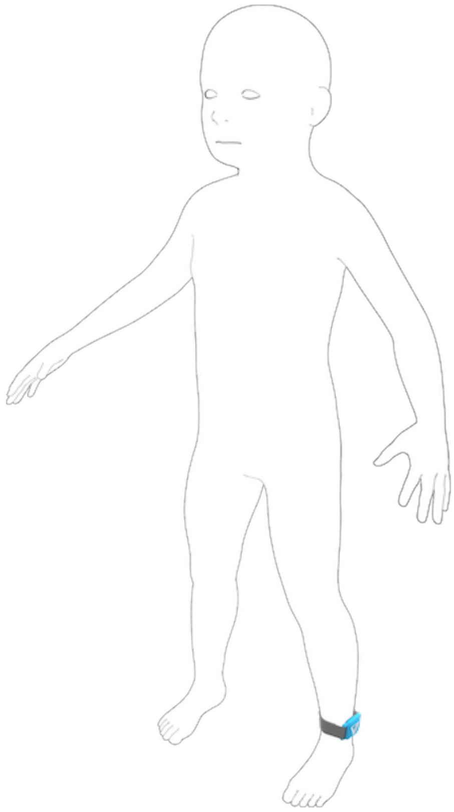


Figure D.4 – Sensor placement of the walking detection algorithm (created by Rehabilitation Engineering Laboratory, ETH Zurich).

D.5.2.2 Segmentation and preprocessing II

A 5th order low-pass filter (cut-off frequency = 3 Hz) is applied to the gyroscope signal. Then, the signal is segmented into windows of 30 s and an overlap of 15 s. In each segment, the angular rate around the mediolateral axis ω_{ml} is determined by correcting for misalignment around the x-axis of the ankle sensor and by the assumption that the majority of leg movement occurs in the sagittal plane:

$$\begin{pmatrix} \cdot \\ \omega_{ml} \end{pmatrix} = \mathbf{v} \begin{pmatrix} \omega_y \\ \omega_z \end{pmatrix},$$

with **v** being the eigenvector of $cov(\omega_y, \omega_z)$ with the largest eigenvalue. Since the eigenvector can point in both directions, the signal ω_{ml} has to be multiplied with -1 whenever it is upside down. To verify this, the algorithm uses the fact that the angular rate is larger during the swing phase compared to the stance phase. It compares the means of the upper and lower envelops of the signal and multiplies ω_{ml} with -1 whenever the mean of the lower envelop is larger than the the mean of the upper envelop. Consequently, positive values of ω_{ml} correspond to a backward rotation of the shank as during the swing phase and vice versa. An exemplary signal is shown in **Figure D.5**

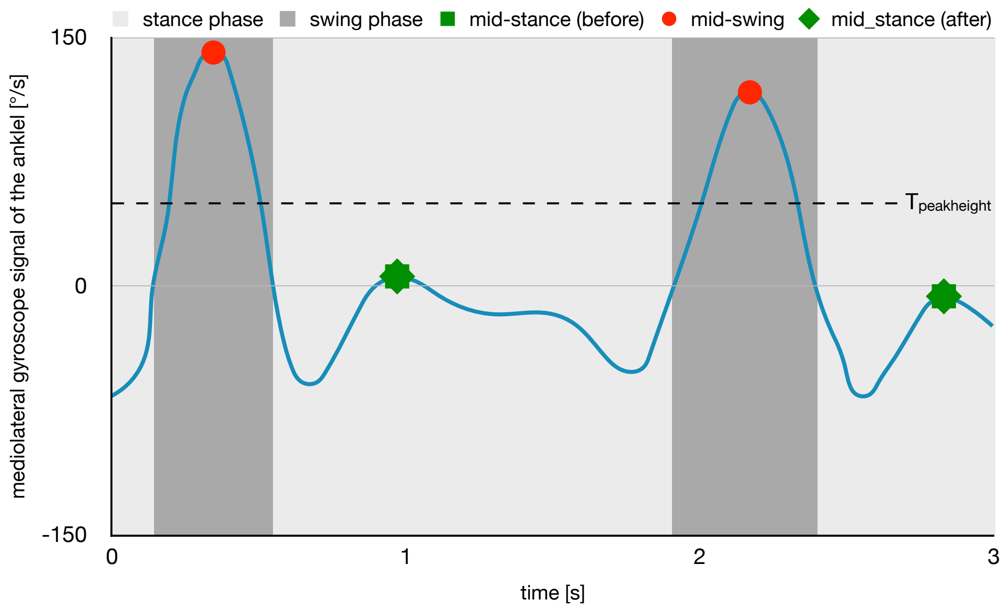


Figure D.5 – Exemplary illustration of the gyroscope signal of two steps as well as the corresponding gait phases and gait events detection.

D.5.2.3 Step detection

The algorithm detects steps by finding local maxima in ω_{ml}, corresponding to the peak angular rate during mid-swing of each step (see **Figure D.5**). The amplitude of these maxima, as well as the duration between two consecutive maxima, must exceed the thresholds $T_{peakheight}$ and $T_{peakdistance}$, respectively. These thresholds are adapted to the underlying data of each segment and, thus, to individual gait patterns.

$$T_{peakheight} = max(50^\circ/s, 0.2P_{99th}(\omega_{ml}))$$

A minimum of $50^\circ/s$ was chosen to exclude maxima of non-walking data (Salarian et al., 2004).

$$T_{peakdistance} = \frac{0.5}{\tilde{f}_{walking}}$$

with $\tilde{f}_{walking}$ being the median estimated step frequency (steps per second) of each segment. An initial step frequency $f_{initial}$ is estimated for the whole segment by applying a fast Fourier transformation to ω_{ml} and taking the first main frequency component. An adapted step frequency is estimated by repeating this step in a sliding window of $\frac{3}{f_{initial}}$ and an overlap of $\frac{2}{f_{initial}}$. Eventually, a moving average filter with a span of $\frac{9}{f_{initial}}$ is applied to determine the time-dependent step frequency $f_{walking}$. Eventually, only steps of the middle 15 s of each segment are considered to avoid duplicates in overlapping segments.

Removing unreasonable steps The swing phase of each step is defined as the time t_{swing}

between the first zero-crossings of ω_{ml} before and after mid-swing. The stance phase is defined as the time t_{stance} between the first zero-crossing of ω_{ml} after the preceding mid-swing and the beginning of the current swing phase. Steps with $t_{swing} < 100\ ms$ or $t_{stance} < 200\ ms$ are not considered valid steps (Trojaniello et al., 2014).

D.5.2.4 Mid-stance detection and classification of walking periods

The algorithm detects the mid-stance before and after each mid-swing detected above, and the period between the two mid-stance is classified as walking. During continuous gait, the mid-stance after one mid-swing is equal to the mid-stance before the subsequent mid-swing and the whole period is classified as walking. During interrupted gait, the two mid-stance do not overlap, and the period between is classified as non-walking (see **Figure D.6**). Mid-stance is defined as the time of the largest local maximum in ω_{ml} during the stance phase (see **Figure D.5** and **Figure D.6**). The occurrence of local maxima is a typical characteristic of gait. If there is no local maximum (e.g., during cycling periods), the algorithm removes the corresponding step. Moreover, the angular rate of the local maxima is usually negative which corresponds to a forward progression of the shank. However, the angular rate can reach positive values during walking on uneven surfaces or stair climbing. Still, the local maxima during the stance phases are considerably smaller than those during the swing phases. Therefore, the algorithm removes steps whenever the local maximum during the stance phase exceeds half of the maximum during the swing phase. Eventually, t_{stance} needs to be smaller than $\frac{3}{\tilde{f}_{walking}}$. Otherwise, the mid-stance after the preceding step is set to the end of the preceding swing phase, and the mid-stance before the subsequent step is set to the beginning of the subsequent step. Consequently, the stance phase will be classified as a non-walking period.

Removing unreasonable steps The algorithm determines the orientation of the ankle sensor φ_{ankle} (see chapter D.3.2) between the mid-stance before and after each step. Then, steps with unreasonable orientation and range of motion are classified as non-walking periods if one of the following criteria is fulfilled:

$$\begin{aligned} min(\varphi_{ankle}) &> -45^\circ \\ max(\varphi_{ankle}) &> 0^\circ \\ max(\varphi_{ankle}) - min(\varphi_{ankle}) &< 5^\circ \\ max(\varphi_{ankle}) - min(\varphi_{ankle}) &> 90^\circ \end{aligned}$$

D.5.2.5 Break detection

This part of the algorithm detects breaks within each walking period and classifies them as non-walking. It is assumed that the step duration between two consecutive mid-swings remains relatively constant during continuous gait. Therefore, breaks are detected with long and irregular step durations. The specific criteria depend on the number of steps within each

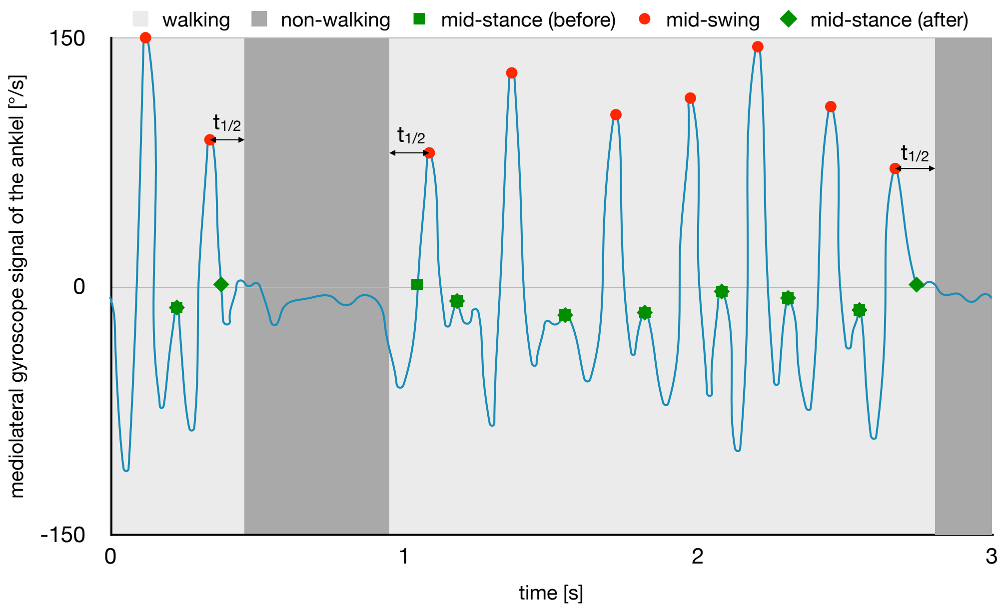


Figure D.6 – Exemplary illustration of the gyroscope signal of interrupted gait as well as the corresponding gait events detection and the resulting walking classification. $t_{1/2}$ represents half of the mean step duration of each walking period to determine the corresponding start and end points

walking period and are defined as follows:

≥4 steps First, the algorithm calculates the median step duration of four consecutive steps. If the step duration of one of these steps is greater than one and a half times the median step duration, the corresponding stance phase is classified as non-walking. This part is repeated for each set of four consecutive steps.

3 steps If one of the two step durations is more than twice as long as the other, the whole period is classified as non-walking.

2 steps If the step duration is longer than 5 s, the whole period is classified as non-walking.

1 step Walking periods with a single step are ignored and classified as non-walking.

D.5.2.6 Start and end point

At the beginning and end of each walking period, there is no typical mid-stance. Hence, each walking period begins half of the mean step duration before the mid-swing of the first step and ends at half of the mean step duration $t_{1/2}$ after the mid-swing of the last step (see **Figure D.6**).

D.5.3 Use of walking aids

The algorithm classifies each walking period as either free walking or assisted walking. If the participant does not use a walking aid and there is no data available, all walking periods are classified as free walking. Walking periods in which the ankle sensor is not able to communicate with the sensor on the aid via Bluetooth Low Energy are classified as free walking, too. Here, it is assumed that the walking aid is far away from the participant. To determine whether the walking aid was used or not, the acceleration signal of the sensor placed on the walking aid is processed with a high-pass filter and a cut-off frequency of 0.3 Hz to remove the gravity component in the signal. Then, for each walking period, the algorithm verifies if the 95th percentile of the magnitude of the filtered signal a_{aid} is above a predefined threshold $T_{aid} = 0.05 * 9.81\ m/s^2$ to determine whether the walking aid was moved around or not:

$$P_{95th}\left(\sqrt{a_{aid,x}^2 + a_{aid,y}^2 + a_{aid,z}^2}\right) \begin{cases} \leq T_{aid} & \Longrightarrow \text{free walking} \\ \\ > T_{aid} & \Longrightarrow \text{assisted walking} \end{cases}$$

D.5.4 Detection of stair climbing

The algorithm detects stair climbing periods based on the altitude change per step. Previously detected walking periods (independent of the use of walking aids) are classified as level walking, going upstairs, or going downstairs.

D.5.4.1 Altitude estimation

The pressure signal p is transformed to the altitude above sea level h with the following formula[1]:

$$h = \log \frac{1013}{p} * 7990$$

Then, a median filter with a window length of five samples is applied. The resulting signal is filtered with an 8th order decomposition, heuristic, automatic 1-D de-noising filter using a soft threshold and symlet8 wavelet (Leuenberger et al., 2014).

D.5.4.2 Expected altitude change per step

Normal step heights are between 14 and 21 cm.[2] However, the expected altitude change per step ranges from 14 to 42 cm since data of a single ankle sensor is used and participants can walk in a step-by-step or a step-over-step pattern. The algorithm adds a margin of 7 cm, which corresponds to the half of the smallest expected step height. Therefore, the lower border for discriminating between level walking and stair climbing was set to 7 $cm/step$, and the upper

[1] a simplification of the international barometric formula
[2] DIN 18065:2020-08 Stairs in buildings - Terminology, measuring rules, main dimensions

border was set to 49 $cm/step$. An upper border is needed as large altitude changes can occur when the environmental temperature changes rapidly (e.g., when walking out of a heated building).

D.5.4.3 Classification of going upstairs and going downstairs

Walking periods containing less than four steps are always classified as level walking. The remaining walking periods are segmented into windows of four consecutive steps and an overlap of three steps. For each window, the algorithm determines the altitude change and compares it to the expected altitude change described above:

$$\begin{aligned} 7\ cm/step < \tfrac{\Delta h}{4\ steps} < 49\ cm/step \quad &\Longrightarrow \quad going\ upstairs \\ -49\ cm/step < \tfrac{\Delta h}{4\ steps} < -7\ cm/step \quad &\Longrightarrow \quad going\ downstairs \end{aligned}$$

D.5.5 Outcome measures

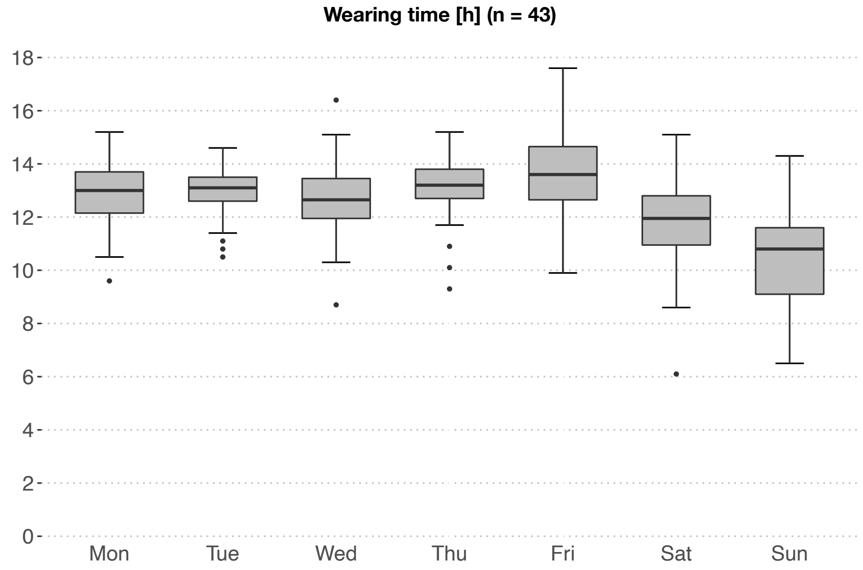
Eventually, the algorithm derives the free and assisted walking duration and estimates the covered altitude change during stair climbing periods.

D.6 Acknowledgments

This algorithm is an extension of previous algorithms developed at the Rehabilitation Engineering Laboratory, ETH Zurich (RELab). Therefore, I want to express my gratitude to three former and current members of the RELab for providing me with the codes of their work. Specifically, I want to thank Kaspar Leuenberger for providing his codes regarding the preprocessing of sensor data, Werner Popp for providing his wheeling detection algorithm for adults with a spinal cord injury, and Charlotte Werner for providing her codes regarding gait detection. Moreover, I want to thank Charlotte for revising this manuscript.

E Day-to-day variability of the motor performance measures

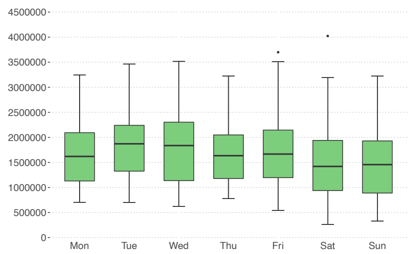
This appendix corresponds to the Supplementary file 1 of **Chapter 11**. It shows the descriptive statistics of the wearing time and the performance measures and the pairwise comparison between weekdays.



	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Mon	12.9	1.00	0.94	0.96	0.15	0.00	0.00
Tue	+0.1	13.0	0.75	1.00	0.32	0.00	0.00
Wed	-0.3	-0.4	12.6	0.36	0.01	0.02	0.00
Thu	+0.2	+0.1	+0.5	13.1	0.66	0.00	0.00
Fri	+0.6	+0.5	+0.9	+0.4	13.5	0.00	0.00
Sat	-1.1	-1.2	-0.8	-1.4	-1.8	11.8	0.00
Sun	-2.5	-2.6	-2.3	-2.8	-3.2	-1.4	10.3

n = number of participants; upper triangle: tukey adjusted p-values; diagonal: estimated marginal means; lower triangle: estimated difference between weekdays

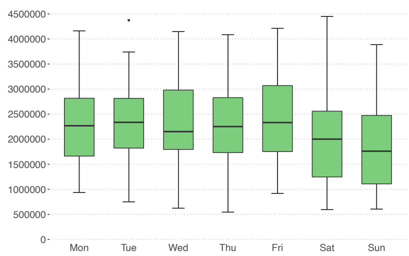
Functional activity counts (more affected hand) [counts] (n = 42)



	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Mon	1'689'003	0.96	1.00	1.00	0.72	0.65	0.06
Tue	+64'434	1'753'437	0.92	0.98	1.00	0.11	0.00
Wed	-11'295	-75'729	1'677'707	1.00	0.62	0.76	0.09
Thu	+8'578	-55'856	+19'873	1'697'581	0.75	0.50	0.03
Fri	+101'039	+36'605	+112'334	+92'461	1'790'042	0.02	0.00
Sat	-109'731	-174'165	-98'436	-118'309	-210'770	1'579'272	0.81
Sun	-205'349	-269'783	-194'054	-213'927	-306'388	-95'618	1'483'654

n = number of participants; upper triangle: tukey adjusted p-values; diagonal: estimated marginal means; lower triangle: estimated difference between weekdays

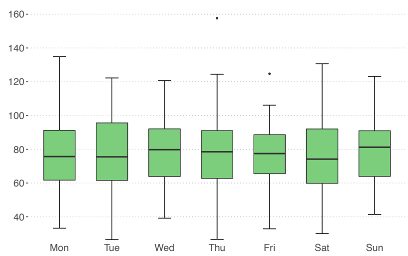
Functional activity counts (less affected hand) [counts] (n = 42)



	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Mon	2'312'892	0.99	0.99	1.00	0.85	0.17	0.00
Tue	+56'726	2'369'618	0.81	1.00	1.00	0.02	0.00
Wed	-55'031	-111'757	2'257'861	0.95	0.43	0.55	0.02
Thu	+23'997	-32'729	+79'028	2'336'888	0.94	0.05	0.00
Fri	+103'613	+46'887	+158'645	+79'617	2'416'505	0.00	0.00
Sat	-199'351	-256'077	-144'320	-223'348	-302'964	2'113'541	0.61
Sun	-342'069	-398'795	-287'037	-366'065	-445'682	-142'718	1'970'823

n = number of participants; upper triangle: tukey adjusted p-values; diagonal: estimated marginal means; lower triangle: estimated difference between weekdays

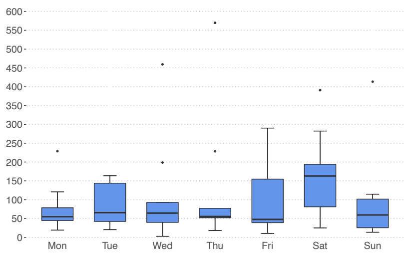
Functional activity counts (more affected/less affected hand) [%] (n = 42)



	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Mon	75.7	0.93	1.00	1.00	1.00	1.00	0.93
Tue	+2.0	77.6	0.99	0.99	0.89	0.92	1.00
Wed	+0.7	-1.2	76.4	1.00	1.00	1.00	0.99
Thu	+0.6	-1.3	-0.1	76.3	1.00	1.00	0.98
Fri	-0.2	-2.1	-0.9	-0.8	75.5	1.00	0.89
Sat	+0.0	-1.9	-0.7	-0.6	+0.2	75.7	0.93
Sun	+2.1	+0.1	+1.4	+1.5	+2.2	+2.1	77.7

n = number of participants; upper triangle: tukey adjusted p-values; diagonal: estimated marginal means; lower triangle: estimated difference between weekdays

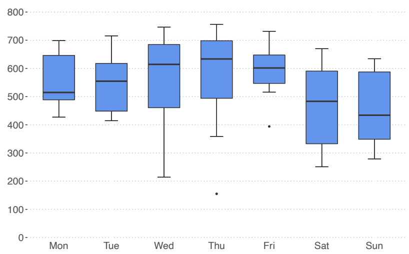
Duration in lying position [min] (n = 10)



	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Mon	87.2	1.00	0.98	0.87	1.00	0.49	0.94
Tue	+1.7	88.8	0.99	0.909	1.00	0.57	0.96
Wed	+33.1	+31.5	120.3	1.00	1.00	0.93	1.00
Thu	+50.0	+48.3	+16.8	137.1	1.00	0.99	1.00
Fri	+24.0	+22.3	-9.2	-26.0	111.2	0.88	1.00
Sat	+74.1	+72.5	+41.0	+24.1	+50.1	161.3	0.99
Sun	+45.8	+44.2	+12.7	-4.2	+21.8	-28.3	133.0

n = number of participants; upper triangle: tukey adjusted p-values; diagonal: estimated marginal means; lower triangle: estimated difference between weekdays

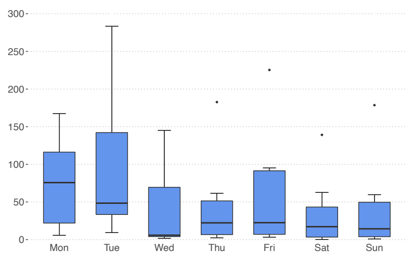
Duration in sitting position [min] (n = 10)



	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Mon	539.0	1.00	1.00	1.00	0.99	0.70	0.56
Tue	+11.8	551.0	1.00	1.00	1.00	0.60	0.47
Wed	+7.0	-4.8	546.0	1.00	1.00	0.57	0.46
Thu	+14.3	+2.6	+7.4	553.0	1.00	0.46	0.38
Fri	+38.9	+27.1	+31.9	+24.6	578.0	0.28	0.20
Sat	-74.1	-85.9	-81.1	-88.5	-113.0	465.0	1.00
Sun	-96.6	-108.4	-103.6	-111.0	-135.5	-22.5	443.0

n = number of participants; upper triangle: tukey adjusted p-values; diagonal: estimated marginal means; lower triangle: estimated difference between weekdays

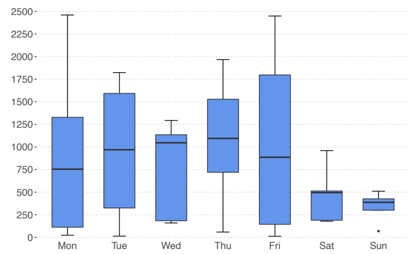
Duration in standing position [min] (n = 10)



	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Mon	68.7	0.92	0.44	0.62	0.98	0.24	0.29
Tue	+18.1	86.8	0.06	0.12	0.54	0.02	0.04
Wed	-30.5	-48.6	38.2	1.00	0.95	1.00	1.00
Thu	-26.7	-44.8	+3.8	42.0	0.98	1.00	0.99
Fri	-13.7	-31.8	+16.8	+13.0	55.0	0.80	0.79
Sat	-35.9	-53.9	-5.3	-9.1	-22.2	32.9	1.00
Sun	-38.8	-56.8	-8.3	-12.1	-25.1	-2.9	30.0

n = number of participants; upper triangle: tukey adjusted p-values; diagonal: estimated marginal means; lower triangle: estimated difference between weekdays

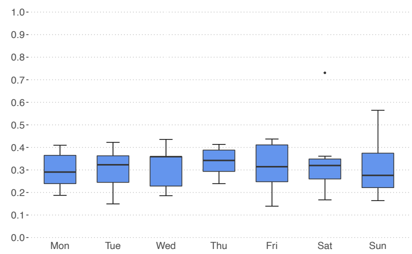
Active wheeling, distance [m] (n = 10)



	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Mon	833.0	1.00	0.96	1.00	0.97	0.44	0.58
Tue	+45.9	879.0	0.92	1.00	0.99	0.35	0.49
Wed	-284.1	-330.0	549.0	0.75	0.52	0.96	0.98
Thu	+142.5	+96.6	+426.6	975.0	1.00	0.14	0.28
Fri	+242.6	+196.7	+526.7	+100.2	1075.0	0.06	0.15
Sat	-562.7	-608.6	-278.6	-705.2	-805.3	270.0	1.00
Sun	-565.0	-610.9	-280.9	-707.5	-807.6	-2.3	268.0

n = number of participants; upper triangle: tukey adjusted p-values; diagonal: estimated marginal means; lower triangle: estimated difference between weekdays

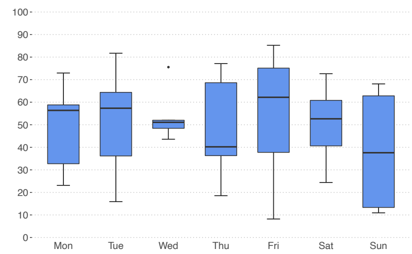
Active wheeling, speed [m/s] (n = 10)



	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Mon	0.29	1.00	1.00	0.97	1.00	0.96	1.00
Tue	0.00	0.29	1.00	0.98	1.00	0.98	1.00
Wed	0.00	0.00	0.29	0.99	1.00	0.98	1.00
Thu	+0.04	+0.04	+0.04	0.33	1.00	1.00	1.00
Fri	+0.03	+0.02	+0.02	-0.01	0.31	1.00	1.00
Sat	+0.05	+0.04	+0.04	0.00	+0.02	0.33	1.00
Sun	+0.01	+0.01	+0.01	-0.03	-0.02	-0.03	0.30

n = number of participants; upper triangle: tukey adjusted p-values; diagonal: estimated marginal means; lower triangle: estimated difference between weekdays

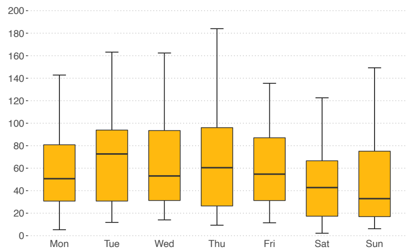
Active wheeling distance / total wheeling distance [%] (n = 10)



	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Mon	46.9	1.00	1.00	1.00	1.00	1.00	0.67
Tue	+2.5	49.4	1.00	1.00	1.00	1.00	0.53
Wed	-0.0	-2.5	46.9	1.00	1.00	1.00	0.70
Thu	-2.8	-5.3	-2.8	44.1	0.97	1.00	0.80
Fri	+4.7	+2.3	+4.8	+7.5	51.6	0.99	0.36
Sat	-1.7	-4.2	-1.7	+1.1	-6.4	45.2	0.76
Sun	-17.6	-20.1	-17.6	-14.8	-22.3	-15.9	29.3

n = number of participants; upper triangle: tukey adjusted p-values; diagonal: estimated marginal means; lower triangle: estimated difference between weekdays

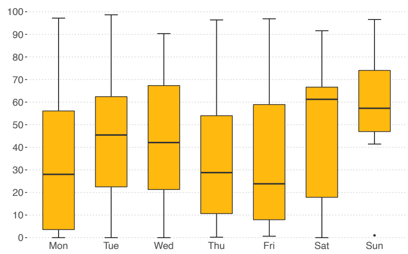
Walking duration [min] (n = 29)



	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Mon	60.4	0.29	1.00	0.94	1.00	0.69	0.45
Tue	+12.0	72.4	0.33	0.89	0.61	0.00	0.00
Wed	-0.1	-12.1	60.3	0.94	1.00	0.74	0.50
Thu	+5.7	-6.3	+5.8	66.1	1.00	0.10	0.04
Fri	+3.1	-8.9	+3.2	-2.6	63.5	0.29	0.14
Sat	-8.8	-20.8	-8.7	-14.5	-11.9	51.6	1.00
Sun	-11.0	-23.0	-10.9	-16.7	-14.1	-2.2	49.4

n = number of participants; upper triangle: tukey adjusted p-values; diagonal: estimated marginal means; lower triangle: estimated difference between weekdays

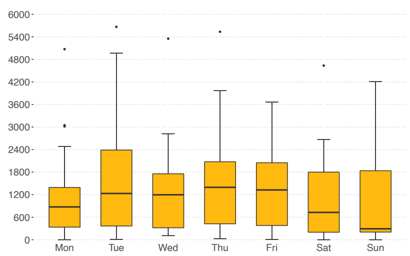
Assisted walking duration / total walking duration [%] (n = 9)



	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Mon	63	0.74	0.99	1.00	0.95	0.93	1.00
Tue	-14.7	48.2	0.99	0.53	1.00	1.00	0.59
Wed	-7.5	+7.2	55.4	0.95	1.00	1.00	0.95
Thu	+2.6	+17.3	+10.1	65.5	0.83	0.78	1.00
Fri	-9.2	+5.5	-1.7	-11.8	53.7	1.00	0.85
Sat	-10.1	+4.7	-2.5	-12.6	-0.8	52.9	0.81
Sun	+3.3	+18.0	+10.8	+0.7	+12.6	+13.4	66.3

n = number of participants; upper triangle: tukey adjusted p-values; diagonal: estimated marginal means; lower triangle: estimated difference between weekdays

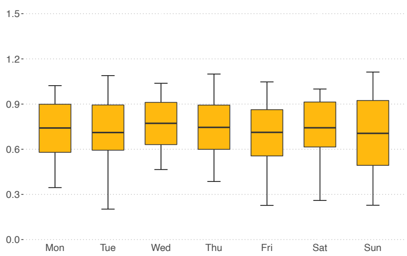
Walking distance [m] (n = 29)



	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Mon	1322	0.49	1.00	0.99	1.00	0.97	0.98
Tue	+343.6	1665	0.22	0.90	0.72	0.08	0.11
Wed	-106.0	-449.6	1216.0	0.85	0.97	1.00	1.00
Thu	+137.4	-206.1	+243.4	1459	1.00	0.62	0.69
Fri	+71.4	-272.2	+177.4	-66.0	1393	0.84	0.89
Sat	-168.2	-511.8	-62.2	-305.7	-239.6	1154	1.00
Sun	-152.7	-496.3	-46.7	-290.2	-224.1	+15.5	1169.0

n = number of participants; upper triangle: tukey adjusted p-values; diagonal: estimated marginal means; lower triangle: estimated difference between weekdays

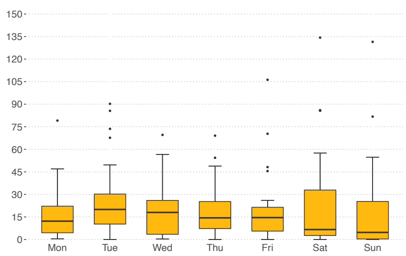
Average walking speed [m/s] (n = 29)



	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Mon	0.74	0.95	1.00	1.00	0.94	0.99	0.43
Tue	-0.03	0.71	0.99	0.80	1.00	1.00	0.94
Wed	-0.01	+0.02	0.73	1.00	0.98	1.00	0.60
Thu	+0.01	+0.04	+0.01	0.75	0.75	0.90	0.19
Fri	-0.03	0.00	-0.02	-0.04	0.71	1.00	0.95
Sat	-0.02	0.00	-0.02	-0.03	+0.01	0.72	0.89
Sun	-0.05	-0.03	-0.05	-0.06	-0.03	-0.03	0.68

n = number of participants; upper triangle: tukey adjusted p-values; diagonal: estimated marginal means; lower triangle: estimated difference between weekdays

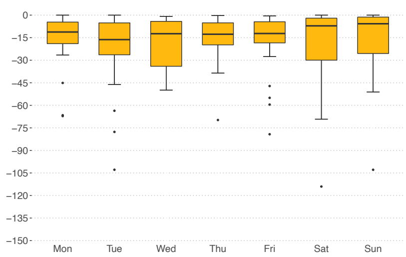
Going upstairs [m] (n = 26)



	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Mon	18.4	0.77	1.00	1.00	1.00	0.92	1.00
Tue	+8.6	27.0	0.82	0.77	0.91	1.00	0.96
Wed	+0.1	-8.4	18.5	1.00	1.00	0.94	1.00
Thu	+0.4	-8.2	+0.3	18.8	1.00	0.92	1.00
Fri	+2.1	-6.5	+1.9	+1.7	20.4	0.98	1.00
Sat	+6.8	-1.8	+6.7	+6.4	+4.8	25.2	0.99
Sun	+2.7	-5.8	+2.6	+2.4	+0.7	-4.1	21.1

n = number of participants; upper triangle: tukey adjusted p-values; diagonal: estimated marginal means; lower triangle: estimated difference between weekdays

Going downstairs [m] (n = 26)



	Mon	Tue	Wed	Thu	Fri	Sat	Sun
Mon	-18.3	0.95	1.00	1.00	1.00	0.98	1.00
Tue	-5.1	-23.4	0.92	0.63	0.94	1.00	0.71
Wed	+0.8	+5.9	-17.5	1.00	1.00	0.97	1.00
Thu	+2.9	+8.0	+2.1	-15.3	1.00	0.78	1.00
Fri	+0.0	+5.1	-0.8	-2.9	-18.2	0.98	1.00
Sat	-4.1	+1.0	-4.9	-7.0	-4.1	-22.4	0.83
Sun	+2.9	+8.0	+2.1	-0.1	+2.8	+7.0	-15.4

n = number of participants; upper triangle: tukey adjusted p-values; diagonal: estimated marginal means; lower triangle: estimated difference between weekdays

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Curriculum vitae

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Address	Pfruendmattstrasse 15, 8932 Mettmenstetten, Switzerland
Date and place of birth	19th of April in 1988, Frauenfeld, Switzerland
Nationality	Swiss (CH)

Current position

2017 – present	**Doctoral student, Research Department, Swiss Children's Rehab**, *University Children's Hospital Zurich – Eleonore Foundation.*

Academic qualifications

2017 – present	**Doctoral student, Health Science and Technologies**, *Swiss Federal Institute of Technology ETH, Zurich.*
2009 – 2011	**Master of Science, Human Movement Sciences (Biomechanics)**, *Swiss Federal Institute of Technology ETH, Zurich.*
2006 – 2009	**Bachelor of Science, Human Movement Sciences**, *Swiss Federal Institute of Technology ETH, Zurich.*

Working experience

2012 – 2017	**Research Associate**, *Institute of Physiotherapy IPT, Zurich University of Applied Sciences ZHAW, Winterthur.*
2011 – 2012	**Research Assistant**, *Institute of Physiotherapy IPT, Zurich University of Applied Sciences ZHAW, Winterthur.*
2010 – 2011	**Internship**, *Gait analysis, Children's Hospital St. Gallen.*

2010	**Internship**, *Institute for Biomechanics, Swiss Federal Institute of Technology ETH, Zurich.*

Awards

Creativity-Prize 2021	**“Validity of a novel algorithm to monitor everyday life motor activities in children with mobility impairments”**, *Children’s Research Center CRC,University Children’s Hospital Zurich*
Anna Müller Grocholski Award 2019	**”And what do families really want? A systematic overview of pediatric rehabilitation goals”**, *Anna Müller Grocholski Foundation, Zurich*
Research Award 2016	**”Measuring lumbar reposition accuracy in patients with unspecific low back pain – a systematic review and meta-analysis”**, *Reha Rheinfelden*

Research Grants

2020 – 2022	**Children’s Research Center CRC, University Children’s Hospital Zurich “Does context matter?”**, 60’000 CHF (main applicant).

Publications

Journal publications (peer reviewed)

Rast, F. M., & Labruyère, R. (2022). Concurrent validity of different sensor-based measures: Activity counts do not reflect functional hand use in children and adolescents with upper limb impairments. *Archives of Physical Medicine and Rehabilitation*, In Press. (Impact factor 2019: 3.1)

Rast, F. M., & Labruyère, R. (2020). ICF mobility and self-care goals of children in inpatient rehabilitation. *Developmental Medicine & Child Neurology*, 62(4), 483–488. (Impact factor 2019: 4.4)

Rast, F. M., & Labruyère, R. (2020). Systematic review on the application of wearable inertial sensors to quantify everyday life motor activity in people with mobility impairments. *Journal of NeuroEngineering and Rehabilitation*, 17(1), 148. (Impact factor 2019: 3.5)

Näf, O. B., Bauer, C. M., Zange, C., & **Rast, F. M.** (2020). Validity and variability of center of pressure measures to quantify trunk control in stroke patients during quiet sitting and reaching tasks. *Gait & Posture*, 76, 218–223. (Impact factor 2019: 2.3)

Pürckhauer, H., **Rast, F. M.**, Nicoletti, C., & Ernst, M. J. (2020). Joint position error after neck protraction-retraction movements in healthy office workers: A cross-sectional study. *Human Movement Science*, 72, 102633. (Impact factor 2019: 2.1)

Sommer, B. B., Weisenhorn, M., Ernst, M. J., Meichtry, A., **Rast, F. M.**, Kleger, D., Schmid, P., Lünenburger, L., & Bauer, C. M. (2019). Concurrent validity and reliability of a mobile tracking technology to measure angular and linear movements of the neck. *Journal of Biomechanics*, 96, 109340. (Impact factor 2019: 2.3)

Aegerter, A. M., Latif, S. N., Weishaupt, M. A., Gubler, B. E., **Rast, F. M.**, Klose, A., Pauli, C. A., Meichtry, A., & Bauer, C. M. (2019). An investigation into the association of the physical fitness of equestrians and their riding performance: A cross-sectional study. *Comparative Exercise Physiology*, 1–10. (Impact factor 2019: 0.4)

Rast, F. M., & Labruyère, R. (2018). Protocol of a systematic review on the application of wearable inertial sensors to quantify everyday life motor activity in people with mobility impairments. *Systematic Reviews*, 7(1), 174. (Impact factor 2019: 2.5)

Bauer, C. M., **Rast, F. M.**, Böck, C., Kuster, R. P., & Baumgartner, D. (2018). Determination of a sagittal plane axis of rotation for a dynamic office chair. *Applied Ergonomics*, 72, 107–112. (Impact factor 2018: 2.6)

Matheve, T., De Baets, L., Rast, F., Bauer, C., & Timmermans, A. (2018). Within/between-session reliability and agreement of lumbopelvic kinematics in the sagittal plane during functional movement control tasks in healthy persons. *Musculoskeletal Science and Practice*, 33, 90–98. (Impact factor 2018: 1.7)

Bauer, C. M., **Rast, F. M.**, Ernst, M. J., Meichtry, A., Kool, J., Rissanen, S. M., Suni, J. H., & Kankaanpää, M. (2017). The effect of muscle fatigue and low back pain on lumbar movement variability and complexity. *Journal of Electromyography and Kinesiology*, 33, 94–102. (Impact factor 2017: 1.6)

Rast, F. M., Graser, J. V., Meichtry, A., Ernst, M. J., & Bauer, C. M. (2017). Reproducibility of a new signal processing technique to assess joint sway during standing. *Journal of Biomechanics*, 51, 133–136. (Impact factor 2017: 2.4)

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Bauer, C. M., **Rast, F. M.**, Ernst, M. J., Kool, J., Oetiker, S., Rissanen, S. M., Suni, J. H., & Kankaanpää, M. (2015). Concurrent validity and reliability of a novel wireless inertial measurement system to assess trunk movement. *Journal of Electromyography and Kinesiology*, 25(5), 782–790. (Impact factor 2015: 1.5)

Bauer, C. M., **Rast, F. M.**, Ernst, M. J., Oetiker, S., Meichtry, A., Kool, J., Rissanen, S. M., Suni, J. H., & Kankaanpää, M. (2015). Pain intensity attenuates movement control of the lumbar spine in low back pain. *Journal of Electromyography and Kinesiology*, 25(6), 919–927. (Impact factor 2015: 1.5)

Rausch Osthoff, A.-K., Ernst, M. J., **Rast, F. M.**, Mauz, D., Graf, E. S., Kool, J., & Bauer, C. M. (2015). Measuring lumbar reposition accuracy in patients with unspecific low back pain: Systematic review and meta-analysis. *Spine*, 40(2), E97–E111. (Impact factor 2015: 2.4)

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Schelldorfer, S., Ernst, M. J., **Rast, F. M.**, Bauer, C. M., Meichtry, A., & Kool, J. (2015). Low back pain and postural control, effects of task difficulty on centre of pressure and spinal kinematics. *Gait & Posture*, 41(1), 112–118. (Impact factor 2015: 2.3)

Ernst, M. J., **Rast, F. M.**, Bauer, C. M., Marcar, V. L., & Kool, J. (2013). Determination of thoracic and lumbar spinal processes by their percentage position between C7 and the PSIS level. *BMC Research Notes*, 6, 58. (Impact factor 2013: 1.5)

Oral presentations & poster presentations

Rast, F. M., & Labruyère, R. (2021). The influence of personal and environmental factors on translating rehabilitation progress into daily life. *31st Annual Meeting of the EACD*. [**video presentation**]

Rast, F., Aschwanden, S., & Labruyère, R. (2020). Accuracy and comparison of sensor-based gait speed estimations under laboratory and daily life conditions in children undergoing rehabilitation. *ESMAC 2020, Gait & Posture*, 81, 291–292. [**video presentation**]

Rast, F., Jucker, F., & Labruyère, R. (2020). Accuracy of sensor-based classification of clinically relevant motor activities in daily life of children with mobility impairments. *ESMAC 2020, Gait & Posture*, 81, 293–294. [**video presentation**]

Rast, F. M., & Labruyère, R. (2019). Bringing assessments into daily life: Opinions of health professionals, children & parents. *31st Annual Meeting of the EACD*. [**poster presentation**]

Rast, F. M., & Bauer, C. M. (2016). Between-day reliability of a marker based polynomial approach to assess spinal angles. *ESMAC 2016, Gait & Posture*, 49, 54–55. [**oral presentation**]

Graf, E. S., Schelldorfer, S., **Rast, F. M.**, Stamm, D., & Bauer, C. (2014). Influence of Marker Misplacement on the Calculation of a Multi-Segment Foot Model—A Simulation Study. *1st Clinical Movement Analysis World Conference*. [**poster presentation**]

Bauer, C., Ernst, M., **Rast, F.**, Schelldorfer, S., Meichtry, A., Kool, J., Suni, J., & Kankaanpää, M. (2014). FRI0570-HPR Lumbar Repositioning is Influenced by Nonspecific Low Back Pain, Test Setup and Body Mass Index. *Annals of the Rheumatic Diseases*, 73, 1201. [**poster presentation**]

Schelldorfer, S., Ernst, M. J., **Rast, F. M.**, Bauer, C. M., Meichtry, A., & Kool, J. (2014). Low back pain and postural control, effects of task difficulty on centre of pressure and spinal kinematics. *Swiss Physiotherapy Congress*, 41, 112–118. [**poster presentation**]