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Monitoring of child-specific activities in ambulatory children with and without developmental disabilities

Barbara Engels[1,2,3], Manon A. T. Bloemen[1,3,10*], Richard Felius[1,4], Karlijn Damen[1], Eline A. M. Bolster[1,3], Harriët Wittink[1], Raoul H. H. Engelbert[5,6,7] and Jan Willem Gorter[2,8,9]

Abstract

Background Pediatric healthcare professionals facilitate children to enhance and maintain a physically active lifestyle. Activity monitors (AM) can help pediatric healthcare professionals assess physical activity in everyday life. However, validation research of activity monitors has often been conducted in laboratories and insight into physical activity of children in their own everyday environment is lacking. Our goal was to study the criterion validity of a prototype AM (AM-p) model in a natural setting.

Methods Cross-sectional community-based study with ambulatory children (2-19 years) with and without developmental disability. Children wore the AM-p on the ankle and were filmed (gold standard) while performing an activity protocol in a natural setting. We labelled all videos per 5-second epoch with individual activity labels. Raw AM-p data were synchronized with activity labels. Using machine learning techniques, activity labels were subdivided in three pre-defined categories. Accuracy, recall, precision, and F1 score were calculated per category.

Results We analyzed data of 93 children, of which 28 had a developmental disability. Mean age was 11 years (SD 4.5) with 55% girls. The AM-p model differentiated between 'stationary', 'cycling' and 'locomotion' activities with an accuracy of 82%, recall of 78%, precision of 75%, and F1 score of 75%, respectively. Children older than 13 years with typical development can be assessed more accurately than younger children (2-12 years) with and without developmental disabilities.

Conclusion The single ankle-worn AM-p model can differentiate between three activity categories in children with and without developmental disabilities with good accuracy (82%). Because the AM-p can be used for a heterogenous group of ambulatory children with and without developmental disabilities, it may support the clinical assessment for pediatric healthcare professionals in the future.

Keywords Device-measured physical activity, Pediatric physiotherapy, Accuracy, Performance, Activity monitor

*Correspondence:
Manon A. T. Bloemen
manon.bloemen@hu.nl
Full list of author information is available at the end of the article

Background

Physical activity (PA) in children decreased over the last years, with 80% of adolescents failing to meet the WHO guidelines of 60 minutes moderate-to-vigorous PA per day [1–3]. A physically active lifestyle in early childhood is correlated with the amount of PA in adolescence and adulthood [4–6]. With regular PA, we can promote the physical, cognitive and psychosocial development as well as quality of life of children [1, 2]. Therefore, it is important to facilitate an active lifestyle in early childhood. Pediatric healthcare professionals as pediatric physiotherapists, support children and adolescents aged 0–19, both with and without developmental disabilities, to help them enhance and maintain an active lifestyle [7]. Quantification of PA of children is essential to be able to assess baseline activity patterns of individuals and evaluate intervention strategies regarding improvement of PA.

Self-report questionnaires or activity diaries can be used to quantify PA. They are a valuable method to understand the impact of PA on the lived experience, however, they are subject to recall bias, which may lead to over- or under-reporting [8–10]. Furthermore, questionnaires in children younger than 12 years seem not to correlate with device-measured PA [11]. There is also a lack of valid and reliable questionnaires for children with chronic conditions [12]. The limited applicability of existing PA questionnaires restrains the usability of questionnaires in pediatric patients. In recent years, an increasing amount of research has been dedicated to investigate psychometric properties in human activity recognition, using an activity monitor (AM) in both typically developing children and children with a developmental disability [13–16]. Existing AMs frequently struggle to correctly recognize atypical gait in children with developmental disabilities, explicitly crouch gait, toe walking, or a slow walking pace [17–20]. Furthermore, AMs encounter challenges when measuring PA in preschool aged children, due to characteristic movement patterns of short bursts of various activities, encompassing activities as crawling, being carried or riding a stroller [21, 22]. A stable gait develops around the age of six years, resulting in a gait pattern with less variation and more maturity. Nonetheless, early childhood (0–5 years of age) is a critical period for growth and development, and a time when children and their families and caregivers are most susceptible to external influences that can shape health and well-being [23]. Therefore, it is also important to assess PA in young children.

Adding to the complexity of activity assessment, numerous AMs are constructed as multi-device systems resulting in more robust results of assessments than singular AMs. Unfortunately, multi-device systems increase wearer burden and reduce adherence of children in day-to-day use [24–27]. This underscores a significant gap in the availability of a single AM that is validated with representative data and can accurately recognize specific categories of activities in children with typical development and developmental disabilities in daily life use.

Our ultimate goal is to measure PA accurately with a single AM, so that pediatric healthcare professionals can use it in clinical practice in order to evaluate the PA of children with and without developmental disabilities. The purpose of this study is to evaluate the accuracy of a single ankle-worn AM-p model in identifying three activity categories in both children with and without developmental disabilities who are ambulatory in the age of 2–19 years. We hypothesized (1) that the AM-p would be able to differentiate between three predefined categories 'stationary' (lying, sitting, standing; artificial movements as being carried or pushed in a stroller, sitting in a driving car), 'cycling'(biking), and 'locomotion' (walking, running, stairclimbing, jumping) with an accuracy >70% [16, 28]. We chose the category 'cycling' because the bicycle is used for any kind of purpose in the Netherlands, and with over 1.2 bicycles per person in 2016, a very popular mobility device [29]. Additionally, the WHO recommends to increase levels of walking and cycling as regular modes of transport to address multiple global health priorities [23], and should therefore be assessed, too. We compared the accuracy between children with typical development and children with developmental disabilities. We hypothesized (2) that the accuracy would be higher for children with typical development because accuracy of AMs seems to be lower in children with developmental disabilities, due to atypical walking patterns such as crouch gait or toe walking [30]. We also analyzed potential variations in accuracy based on age: children (2 to 12 years) and adolescents (13 to 19 years). We chose this split in two sub-groups for a number of reasons, including the fact that young children show more varied movements than adolescents [23], and previous research often investigated children >13 years [31–33]. Furthermore, Baque et al. found that children aged >13 years with acquired brain injury showed less variable estimates of daily PA than younger ones [34]. Therefore, we planned for an additional analysis to explore the difference of accuracy with the data of two to five year old children included versus the analysis without the younger children. We hypothesized (3) that the accuracy would be higher for older children (>13 years old) as young children tend to have more varied movement patterns with short bursts [21].

Methods

Participants and recruitment

We recruited a convenience community-based sample of children from 2 to 19 years in The Netherlands between November 2018 and June 2019. To measure a broad variety of movement patterns within ambulant children, we included 1) children with typical development and 2) children with developmental disability. We distributed flyers, contacted rehabilitation centers, and sport clubs throughout the Netherlands, via social media, and the pediatric physiotherapist network of the research team. Participants had to be able to follow (1) simple verbal Dutch instructions, (2) walk short distances (>5 meter) independently or with a walking aid. Participants were excluded if they had (1) recent surgery (<3 months) and/or (2) were not able to perform the activity protocol due to acute illness or injury.

Procedure and data collection

The activity protocol was based on existing literature and consultation of experts in the field of motor development of children [16, 19, 33, 35–37]. The activity protocol incorporated three categories (stationary, cycling, locomotion) [38, 39] with 10 main activities, and 17 sub-activities. The main activities were 1) Sitting, 2) Standing, 3) Lying, 4) Artificial movements, 5) Cycling, 6) Walking, 7) Running, 8) Jumping, 9) Walking stairs, 10) Moving on the floor. We defined 'artificial movements' as movements where motion is detected but the child is not moving actively: being carried, being pushed in a buggy or wheelchair, sitting on the back of a bike or in a moving car. As adolescents usually do not move across the floor, we excluded main activity 10 from the activity protocol for this age group. For assessed activities, sub-activities and definitions, see Table 1. Children completed the activity protocol in a single session of maximum 60 minutes. If necessary, children were allowed to use their own walking aids such as crutches or walkers.

The assessment took place in a setting convenient for the participant and parents/caregivers, e.g., home, school, pediatric phyiotherapist practice, school for special education, or rehabilitation center. We collected demographic data of participating children with questions about age, weight, height, gender, diagnosis, and walking aids. For children with developmental disability, we explained the Functional Mobility Scale (FMS) [40] to children and caretakers, respectively, and collected their answers. The FMS is a performance measure which implies that it is important to rate what a child does, not what it can do or was able to do [41]. It has a moderate to good concurrent validity in children with neuromotor disorders [42]. For children with cerebral palsy, parents or pediatric physiotherapist informed us about the assigned Gross Motor Function Classification System (GMFCS) level [43]. Based on the walking and running abilities of children, an experienced specialist in pediatric rehabilitation medicine (JWG) and an experienced pediatric physiotherapist (BE) determined the presence

Table 1 Summary of protocol: categories, activities and sub-activities

Category		Main activity		Sub activities	Definition
Stationary	1	Sitting	1.1	Sitting	With small, incidental movements as scratching the nose
			1.2	Sitting with upper extremity activity	Writing, puzzling, building a tower from blocks (shoulder flexion <90 degrees)
	2	Standing	2.1	Standing still	Children with a disability may incidentally step aside to maintain balance
	3	Lying	3.1	Supine, prone, sides	No rolling over
	4	Artificial movement	4.1	Being carried	
			4.2	Being pushed in a buggy or wheelchair	
			4.3	Sitting on the back of a bike	
			4.4	Sitting in a (driving) car	
Cycling	5	Cycling	5.1	Cycling	Any kind of outdoor two-wheel bicycle and trike.
Locomotion	6	Walking	6.1	Straight line, with curves	Self-paced slow, normal, fast
	7	Running	7.1	Straight line, with curves	Self-paced; there must be a flight phase
	8	Jumping	8.1	Forward, on the spot	Both feet have to be off the ground
	9	Walking stairs	9.1	Up and down	
	10	Moving on the floor	10.1	Crawling	With or without holding a toy
			10.2	Walking on knees	
			10.3	Moving forward on the belly	
			10.4	Shoveling	

or absence of a typical walking pattern in children with developmental disability.

Before starting the activity protocol, we fixated the AM-p with flexible, padded strips and velcro tape (Fig. 1, activity monitor worn by a five year old child) on the lateral side above the lateral malleolus of the dominant leg [44].

An experienced pediatric physiotherapist (KD) and three trained students of the Master's program in pediatric physiotherapy tested all children. Students were trained in assessing the protocol and were supervised the first assessments. The researchers encouraged each participant to perform the activities described in the activity protocol. We asked participants to self-pace the velocity of walking and running.

Instrumentation

Video-recorded direct observation is considered the gold standard as reference method for observations of movements [45]. We started videorecording before attaching the AM-p to the participants' ankle and stopped after the activity protocol was finished.

The AM-p is a commercially available wireless sensor (developed by Aemics b.v., Oldenzaal, The Netherlands) [46]. It integrates a triaxial accelerometer and gyroscope, enabling comprehensive motion tracking. The sampling rate was set at 12.5 samples per second [21].

Data preparation

To synchronize the video with the AM-p data, the video recording started prior to activation of the AM-p. Next, the AM-p was flipped before being fixated to the participants' body. The flipping-procedure caused a distinctive signal in the raw data [37]. A custom-made algorithm was used to detect this distinctive point and therefore enabled synchronization of the AM-p data and the video with an error of maximally 1 second. The error range was considered during the subsequent data analysis. The AM-p data was down sampled to 10 samples/s to account for potential between-sensor differences in sampling frequency.

The categorization of activities depicted in the video was executed through annotation, based on the sub-activities listed in Table 1. The activities were labeled per 5 seconds in an Microsoft Excel Spreadsheet (Microsoft Corporation 365, Version 2409, Redmond, WA, USA). by two independent researchers. A time interval of 5-seconds was chosen because of the intermittent character in the moving pattern of children [21]. Only epochs with clear activity indicated were included in further analysis. The two Excel-files were checked for overlap. Consensus was found and in case of mismatch, a third researcher was consulted.

Following the annotating process, AM-p data were merged with the labels in the Excel files, resulting in an epoch of 50 samples across six dimensions per label. Subsequently, these labels were grouped into the three main categories described in Table 1.

To detect outliers, we calculated the mean and standard deviation of each dimension of every epoch. These values were used to calculate Z-scores per dimension resulting in 12 z-transformed values per epoch, indicating how different an epoch is from average. If the difference was larger than 4 times the typical spread in any of the dimensions, it was considered an outlier.

Availability of data and materials: human activity recognition

A Convolutional Neural Network (CNN) was used for the categorization of the raw AM-p data, i.e., human

Fig. 1 Activity monitor worn by five year old child

activity recognition [47]. To contribute to open science and potential data harmonization, the model and raw data is available via: https://github.com/RichardFel/AMVA_Normaal_afwijkend.

Model development

The model architecture consisted of three convolutional layers coupled with subsequent layers for max pooling and batch normalization. The convolutional layers were configured with 32, 64 and 128 filters and a kernel size of 3. After the convolutional layers, one dense layer was added, which was regularized using drop-out with a probability of 0.5. A rectified linear unit activation function was used in all layers [47, 48].

The models' performance was assessed using the cross-entropy loss function. Optimization was performed using the Adam optimizer with a learning rate set at 0.001. The output of the model were the three categorical groups (Table 1) [49].

During the training process, data were presented to the model using a batch size of 32 samples. To prevent overfitting, early stopping was incorporated with a patience parameter of 15. We expected the activity class distributions to be uneven as some activities were more common than others. To counteract this bias in training, sample weights were adjusted according to the relative frequency of labels within the training dataset [50].

Model evaluation

The performance of the CNN was evaluated using a Leave-5-out cross-validation, which was repeated 10 times to ensure robust evaluation. Within each cycle, a subset of five randomly-selected subjects was withheld from the dataset. The remaining data was portioned into a training and validation subset with an 80/20 ratio. The repeated cross validation was done four times. First for all children (hypothesis 1), second with only children with developmental disability in the test set (hypothesis 2), third with only children aged 2–12 years in the test set (hypothesis 3), and fourth with only children aged 13–19 years in the test set (hypothesis 3) [51].

The averaged accuracy was used as the primary outcome to evaluate the model performance, calculated with A = (TN+TP)/(TN+TP+FN+FP) [33]. TN represents true negative, TP true positive, FN false negative and FP false positive values. We considered an accuracy of >90% excellent, 80% to 90% good, 70% to 80% moderate and less than 70% poor [16]. In addition to the accuracy, we calculated recall and precision, and constructed a confusion matrix. Recall is equal to sensitivity and quantifies a model's ability to accurately identify instances of the different categories by using the formula R = TP/(TP+FN) [33]. In addition to recall, precision was calculated, employing the formula P = TP/(TP+FP) [33]. This metric equals the positive predictive value which demonstrates the model's capacity to accurately classify positive instances within each category. F1 score takes into account how the data are distributed and is a harmonic mean of precision and recall. We used the formula F1 = 2*(Precision*Recall)/(Precision + Recall) [52].

Results

Demographics and characteristics

Out of 105 children included and tested in the study, we identified 93 to be eligible for full analysis: 12 could not be included in the analysis due to technical problems with the AM-p (n=10) or undetectable flips (n=2). The analyses are based on data from 93 children of which 65 children with typical development, and 28 children with developmental disability. Of the children with developmental disability, seven were diagnosed with cerebral palsy (CP), 11 with a syndrome (genetic) disorder, two with acquired brain injury, and eight with another developmental disability. Demographic data of participants is displayed in Tables 2, 3 and 4.

Table 2 Demographics and characteristics of all included children

	Age (years) Mean (SD)	Gender Girls (n)	Weight (kg) Mean (SD)	Height (cm) Mean (SD)	Regular sport (>1x/week; n)
Children with DD (2–12 years); *n*=28	9.0 (2.3)	18	34.7 (11.4)	135.9 (15.2)	16
Children with TD (2–12 years); *n*=31	7.6 (2.8)	14	26.5 (8.9)	127.6 (16.8)	25
Children with TD (13–19 years); *n*=34	16.3 (1.8)	19	68.7 (15.9)	176.3 (10.5)	33
Total *n*=93	11.3 (4.5)	51	44.7 (22.6)	148.4 (26.1)	74

DD developmental disability, *TD* typical development, *cm* centimeter, *SD* standard deviation, *n* number

Table 3 Mobility characteristics of children with developmental disabilities (*n*=28)

Diagnosis	n	Orthotics	Atypical gait	Regular sport (>1x/week; n)
CP GMFCS I (3) GMFCS II (4)	7	3	7	5
Syndromes (genetic)	11	6	9	5
ABI	2		2	2
DCD	1			1
Congenital heart disease	1			
Microcephaly	1			1
Clubfoot	1		1	1
Not diagnosed DD	4		2	1

CP Cerebral Palsy, *GMFCS* Gross Motor Classification System (I = walks without limitations; II = walks with limitations), *ABI* acquired brain injury, *DCD* developmental coordination disorder, *DD* developmental disability

Model evaluation

In total, 12 726 epochs of AM-p data were collected. These consisted of 6 883 epochs of stationary activities; 746 epochs of cycling, and 5 097 epochs of locomotion activities. Respectively, 275, 24, and 90 epochs were identified as outliers and excluded from further analysis. The distribution of included categories per group is provided in Table A1 in the Supplemental Digital Content.

The repeated Leave-5-out cross-validation was calculated for the group of all included children. Regarding hypothesis 1, the model achieved a good averaged accuracy (81–85%) for identifying the pre-defined categories among all children and sub-group analyses (Fig. 2A. All children 2–19 years). Recall and precision were moderate to good (71%–82%) for all analyses, and the F1 score with 75% moderate (Table 5). Overall, the model can recognize stationary activities best (Fig. 2A-D). Analysis of hypothesis 2 shows that the prediction of activities is with 82% accuracy slightly better for children (2 to 12 years) with developmental disability than for children with typical development (80% accuracy, 2 to 12 years; Fig. 2B and D). Recall, precision and F1 score are moderate for all children aged 2–12 years. The variation (standard deviations, Table 2) is higher in both the groups of children (2 to 12 years) with typical development and developmental disability compared to the variation in the group of children with typical development 13–19 years. Regarding hypothesis 3 is the prediction of activities with 85% accuracy and 80% F1 score is better in older (13–19 years) than young children (80% accuracy with 71% F1 score for children with typical development and 82% accuracy with 75% F1 score for children with developmental disabilities). Figure 3 shows a positive relation where the accuracy of the model is better in older children than in younger ones. Exploratory analysis of children > 6 years of age (Figure 4A in Appendix. All children 6–19 years) shows the same accuracy in all children for stationary activities (87%), 1% less accuracy for cycling and 3% more for locomotion (79%). The highest difference within the subgroup of children when excluding 2–5 year old participants is with developmental disabilities who show 5% less accuracy in stationary activities than the same group with children from 6–12 years (Fig. 2D. Children with DD 2–12 years; Figure 4C in Appendix. Children with DD 6–12 years).

Discussion

In this study, we evaluated the criterion validity through estimation of accuracy of our single ankle-worn AM-p in identifying three activity categories in both children with typical development (2 to 19 years), and children with developmental disabilities (2 to 13 years). The accuracy for all children is good (82%), with moderate to good precision, recall, and F1 score. The accuracy is 85% with and F1 score of 80% for adolescents with typical development (13–19 years), compared to an accuracy of 81% for children with (F1 score 75%) and without (F1 score 71%) a developmental disability (2 to 12 years).

Firstly, we hypothesized that the AM-p would be able to differentiate between the three pre-defined categories with an accuracy >70%. Based on the results, we can accept the hypothesis. Literature shows that the use of a single AM is less accurate with a loss of accuracy up to 33% compared to wearing a combination of two or more AMs [33, 53]. Goodlich et al. (population: children with CP; mean age 11 years) and Narayanan et al. (population: typically developing children; mean age 10 years) found that a combination of two AMs achieved excellent accuracy of 92%, whereas single placements dropped to 59–79% accuracy [53, 54]. In those studies,

Table 4 Functional Mobility Scale (FMS) of children with developmental disabilities (*n*=28)

FMS [40]	5m		50m			500m			
FMS score	6	5	6	5	2	6	5	2	1
n	8	20	23	4	1	3	18	1	6

FMS Functional Mobility Scale (6 = independent on all surfaces; 5 = independent on level surfaces; 2 = uses walker of frame; 1 = uses wheelchair), *m* meter

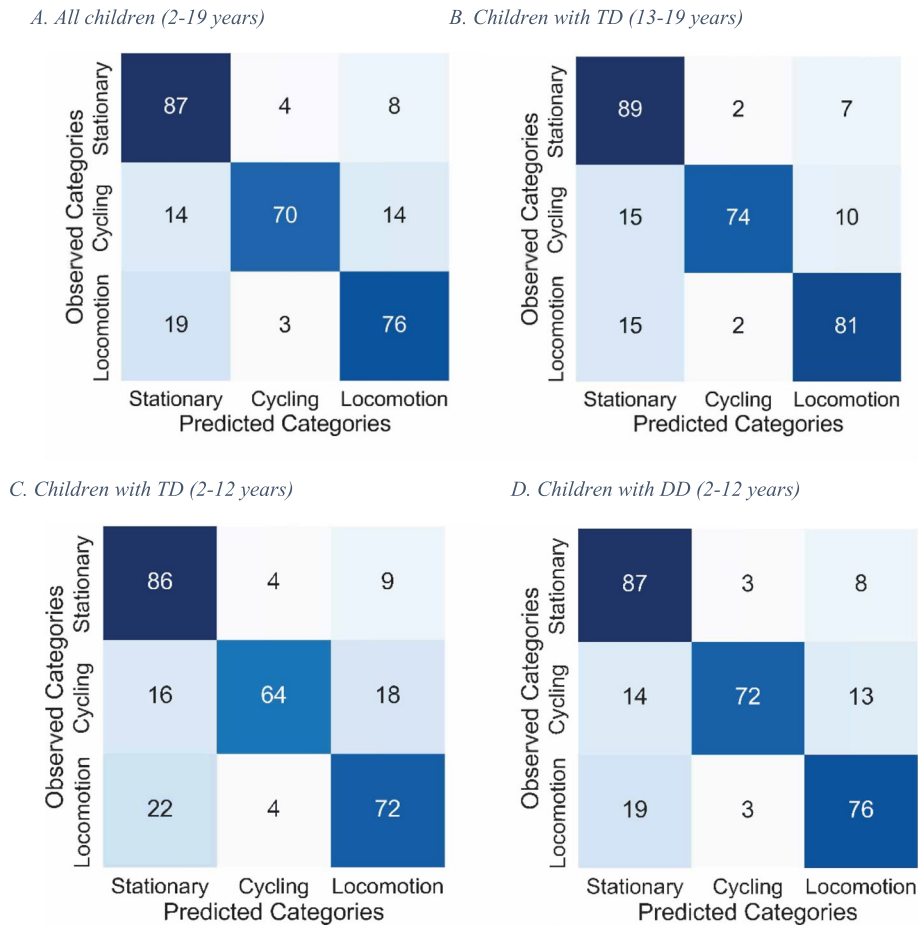

Fig. 2 Confusion matrices of the convolutional neural networks trained to categorize activities in three categories 'stationary', 'cycling', 'locomotion'. All true positive values are along the diagonal. Numbers are percentages. Panel **A** is the average confusion matrix of all participants. Panel **B** is the confusion matrix of children with typical development (TD) (2–12 years). Panel **C** is the confusion matrix of children with TD (13–19 years). Panel **D** is the confusion matrix of children with developmental disabilities (DD) (2–12 years)

Table 5 Model results for all children and sub-groups

	All Children Average (SD) [min, max]	Children with TD (2-12y) Average (SD) [min, max]	Children with TD (13-19y) Average (SD) [min, max]	Children with DD (2-12y) Average (SD)[min, max]
Accuracy	82.2 (6.4), [40.0,91.0]	80.2 (7.0), [44.2,88.4]	85.2 (2.5), [78.3,89.4]	82.2 (6.3), [46.7,89.6]
Recall	78.0 (7.5), [44.4,91.4]	73.8 (9.0), [51.5,90.5]	82.0 (4.2), [68.7,88.7]	78.4 (7.4), [50.8,93.0]
Precision	75.0 (7.6), [52.6,88.6]	71.3 (8.7), [50.2,85.5]	79.8 (3.6), [66.6,85.9]	75.2 (7.4), [44.1,86.0]
F1-score	75.3 (8.2), [36.7,87.0]	71.1 (9.6), [38.0,86.0]	80.4 (3.5), [68.4,86.9]	75.4 (8.5), [31.1,86.9]

TD typical development, *DD* developmental disability, *y* years, *SD* Standard deviation, min minimum, max maximum

the combination of AMs were placed at back and thigh [54] and hip and wrist [53], respectively. We chose to validate the ankle as the preferred location because it allows for wearing the AM-p under clothing and above shoes or orthotics, and therefore seems a feasible option for children, also for those with hyper- or hyposensitivity who are prone to develop pressure injuries [55]. The use of a single AM can have positive influence on the clinical use because, besides children who are ambulatory, pediatric healthcare professionals support children using (partly) a manually driven wheelchair in daily life. When using a device on the lower back or waist, children in a wheelchair are more prone to pressure points which could influence the feasibility for those children. In

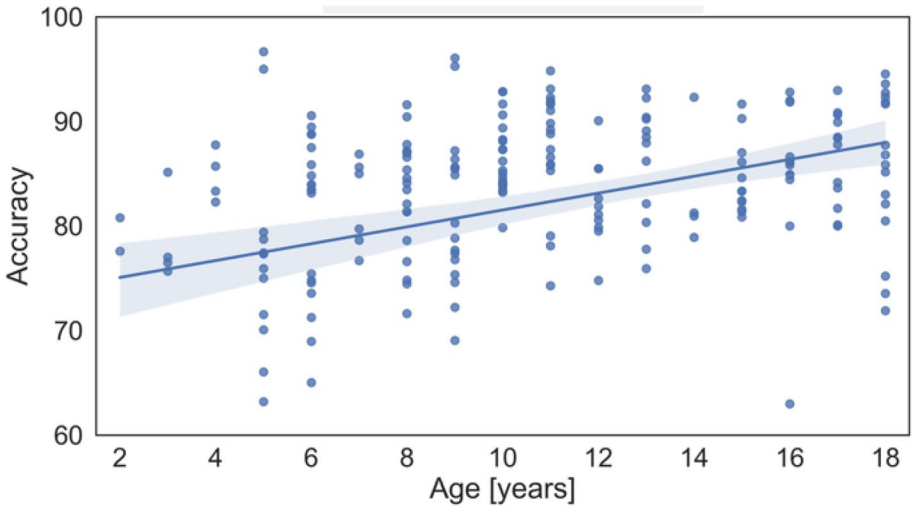

Fig. 3 Model accuracy per age. Scatter plot with regression line (multiple data points per child), showing accuracy % on the y axis and age in years on the x-axis. Results derive out of validation data, then calculated per child (leave-one-out-cross validation)

future research, we aim to expand the validation process for children who (partly) use a manually driven wheelchair in daily life, to investigate if a single AM is robust enough to detect PA in this group. Additionally, feasibility and acceptance of wearing a single AM is expected to be higher than a system with multiple AMs. This is very important, because children should wear an AM three to nine days for an accurate assessment, depending on the diagnosis [26, 56, 57].

Secondly, we hypothesized that the accuracy would be higher for children with typical development than for children with developmental disabilities. Although the difference between the accuracy was small (2%, Table 5), our findings indicate that children included in our study with developmental disabilities can be classified slightly better in the categories 'cycling' and 'locomotion' than children with typical development. This is controversial to our second hypothesis, as we expected the accuracy to be lower in children with developmental disabilities due to difficulties in detecting atypical gait [17, 18, 30]. We think that children with a developmental disability show a broader variation in movements as a group, but less when repeating one activity. For example, when walking, children with a developmental disability can show a different walking pattern or slower pace but maintain the style of walking. Children without a developmental disability show more stable walking patterns but vary more often, e.g. walking on the sidewalk or making some jumps. We analyzed the data exploratory to see if there was a difference in accuracy when excluding children aged 2 to 5 years: typically developing children achieved for 'stationary' a 5% higher accuracy in the group from 2–12 years, but 7% less accuracy for 'cycling' (Figure 4B in Appendix. Children with TD 6–12 years). As differences between the averaged accuracy among children with and without developmental disabilities are at most 10%, we recommend to use the same model for both groups. This would save time in clinical practice as pediatric healthcare professionals would have less work to prepare the software before an assessment with the AM-p, and therefore make it more feasible in daily clinical practice. There must be noted that the children in our study with developmental disabilities had relatively minor movement impairments, or were from a diagnostic group with little or no mobility impairments. Previous work has shown that accelerometer output from children with cerebral palsy from different GMFCS levels differs significantly when performing the same task [58]. We therefore recommend for future studies to preselect more children with major movement impairments and gait abnormalities, e.g. children with cerebral palsy GMFCS level III.

We accept our third hypothesis that the accuracy would be higher for older children (>13 years) than younger children (2 to 12 years). Our study contributes to an existing knowledge gap based on missing evidence of device-measured PA in young children or children with a developmental disability [23].

There are several strengths and limitations in our study. Due to time restrictions and challenges during inclusion because of COVID-19 restrictions, we were not able to validate the AM-p for children with developmental disabilities >13 years old. However, we suspect that the accuracy for 13–19 year old children with developmental disabilities is similar to the results we found in children of the same age with typical development, because the prediction improves when age increases (Fig. 3, model

accuracy per age) and there was only 5% difference in accuracy between younger children (2 to 12 years) and older children (13–19 years; Table 5).

While we have not investigated the reliability of the AM-p, we know from the literature that this psychometric property of device-measured PA in children with and without developmental disabilities is good [20, 59].

Accuracy calculates the number of correct predictions divided by the total number of predictions and scores often higher than the F1 score in imbalanced data sets. We addressed this issue by reporting the accuracy, precision, recall, and F1 score. In balanced classes, the difference between accuracy and F1 score is low, and the choice of outcome parameter is of less consequence. When analyzing a dataset with imbalanced classes, the F1 score is a better outcome parameter because it takes into account both false positives and false negatives. In our study, we see differences between F1 scores and accuracy (less than 10%) in all children, and children aged 2–12 years. The difference in older children is less than 5%, and therefore this group can be predicted the best. To our knowledge, there are no guidelines available for a correct interpretation of the F1 score. Therefore, we assume that 70% is fine, and the higher, the better.

We have three pre-determined categories, which may be rather low compared to the number of activities from the protocol. Combining the activity standing with sitting and lying activities in one category 'stationary' activities can be criticized because among children with more severe mobility impairments, standing and transitions represent significant movement targets in therapy [60]. After careful consideration, we chose to combine those activities, because the AM-p does not change position when comparing sitting to standing. We acknowledge that grouping standing with sitting and lying is a major limitation, as standing is generally recognized as a distinct activity with clinical importance—particularly for encouraging more standing time in children with disabilities. Unfortunately, our current setup does not allow us to separate these activities accurately. While adding multiple sensors could address this issue, it would reduce feasibility. Exploring alternative sensor combinations could provide a viable approach in future studies. We recommend considering this option for improved accuracy and clinical relevance moving forward. However, in our present study, we show that the AM-p is able to detect 'stationary' activities very well (87% accuracy). This is very important, because it involves artificial movements such as being carried, sitting in a riding car, sitting on the back of a bike, or sitting in a stroller. Those specific movement variations in very young children still lack in many device-measured PA protocols [22, 61]. A recently published study about PA and sedentary patterns states that an increase of >10 minutes of continuous sedentary time is unfavorably associated with changes in cardiometabolic outcomes in children aged 8 to 13 years [62]. If pediatric healthcare professionals are able to detect longer periods of stationary activities correctly, including they can inform children and caregivers and develop individually tailored approaches for an active lifestyle.

At the moment, the AM-p is not yet available for practical use. Nevertheless, the promising results of our validation study show potential for the future. As soon as we are able to develop the AM-p to an end-user accepted device, pediatric healthcare professionals have the possibility to monitor stationary behavior, cycling, and locomotion during daily activities of an ambulatory child, regardless of the presence or absence of a developmental disability. With insight into the daily device-measured PA routines, pediatric healthcare professionals can investigate PA patterns and develop individual advice or guidance. PA monitoring during school time could also be beneficial when aiming to structurally change school policies for more PA during the day. Studies show that it is possible to monitor PA trends during school hours with accelerometry children with typical development and CP [63, 64]. Being able to monitor potential changes in PA trends in the broad group of children we included in our study would be beneficial for pediatric healthcare professionals, children and parents. If solid evidence could be collected to support a more active lifestyle, policy makers would have a broader fundament to lean on and initiate changes beneficiary for children with and without developmental disabilities.

The main strength of this study is that we collected data in the natural environment of included children. Literature shows that validations in laboratory settings are not representative for real world measurements [30, 65]. The broad variation of activities in our protocol gives valuable information about different child-specific movements in daily living as well as potential misrepresentation of artificial movement (being carried, sitting on the back of a bike, riding in a car or being pushed in a stroller). Recent reviews state that there is a lack of measuring different child-specific variations of postures as different types of lying or sitting [22, 61]. The inclusion of 93 children for overall analysis with more than 25 participants per subgroup, including children with and without developmental disabilities, is rare [61]. Although the groups of children with and without disabilities were not equally distributed, we believe that our study contributes significantly to literature, as we included children starting at 2 years of age. Another strength is the use of the gold standard to measure criterion validity in PA [45]. We analyzed each 5-second epoch with a unique label to get as precise information as possible. Combined with state-of-the art

analyses, the leave-5-out-cross-validation is a widely used technique in machine learning to assess the performance of a predictive model. This technique helps in assessing how well a model generalizes to unseen data and can provide a robust estimate of its performance [51].

The accuracy of our model might be inflated, given that it has not been tested in true free-living situations. We chose for this approach, because we first wanted to explore the single AM-ps' ability to distinguish physical behavior. Therefore it needs to be able to recognize clearly defined activity frames. In a recent study, children with GMFCS I-III were tested in structured individual activity trials as well as a simulated free-living evaluation [66]. A substantially lower accuracy (>30%) was reported for the wearing location of the ankle when after evaluating the models in free-living conditions [66]. Before using the AM-p in the future, we recommend to assess the validity of the AM-p in free-living environments as well, including transfers and combined activities.

In conclusion, our single ankle-worn AM-p shows good criterion validity for ambulatory children with typical development and developmental disabilities with an accuracy of 82% for categories 1) stationary, 2) cycling, and 3) locomotion. A single AM that is suitable for ambulant children regardless of age or presence of a developmental disability can support the work of pediatric healthcare professionals in clinical practice when objectifying PA in daily living. Future research will show if the AM-p is also able to detect movement categories in children who self-propel a wheelchair.

Appendix

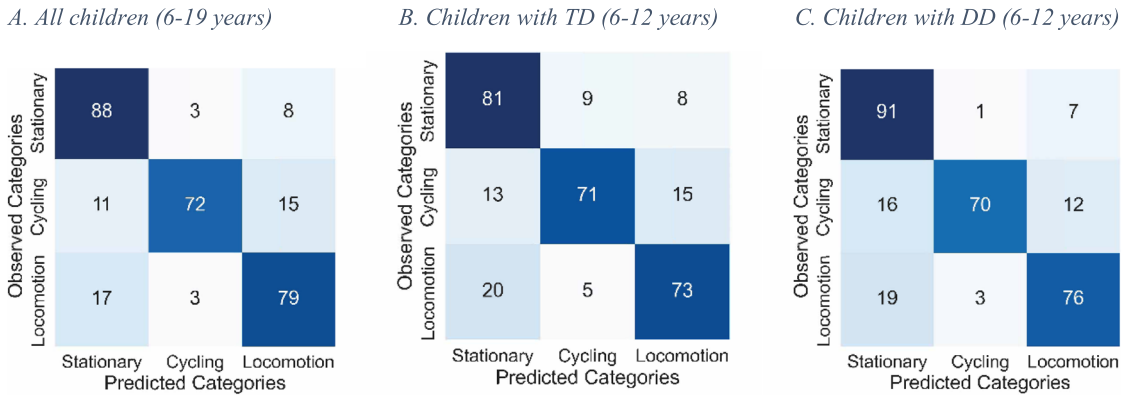

Fig. 4 Confusion matrices of the convolutional neural networks for children aged 6-19 years. All true positive values are along the diagonal. Numbers are percentages. Panel **A** is the average confusion matrix of all participants. Panel **B** is the confusion matrix of children with typical development (TD) (6-12 years). Panel **C** is the confusion matrix of children with developmental disability (DD) (6-12 years)

Abbreviations

PA	Physical Activity
AM	Activity Monitor
AM-p	Activity Monitor prototype
CP	Cerebral Palsy
FMS	Functional Mobility Scale
GMFCS	Gross Motor Function Classification System
CNN	Convolutional Neural Networks
TN	true negative
TP	true positive
FN	false negative
FP	false positive
DD	Developmental Disability
TD	Typical Development

Supplementary Information

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Supplementary Material 1.

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Authors' contributions
BE analyzed and interpreted the data, wrote the manuscript and prepared the tables. MB and KD made substantial contributions to the conception and design of the study, acquisition and data collection. MB analyzed and interpreted the data, and substantively revised the manuscript. JWG analyzed and interpreted data and substantively revised the manuscript. RF created the algorithm for Machine Learning, and was a major contributor in writing the methodological technical part of the manuscript, interpretation of data, and preparing the figures. EB and HW made contributions to the conception and analysis of the study and revised the drafted work. EB supervised analyses of data and substantively revised the manuscript. RE contributed to the interpretation of data and substantively revised the manuscript. All authors read and approved the final manuscript.

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Data availability
https://github.com/RichardFel/AMVA_Normaal_afwijkend Model and raw data.

Declarations

Ethics approval and consent to participate
The Ethical Screenings Committee for the Health Domain of the University of Applied Sciences Utrecht, the Netherlands, approved the study (reference number 77_000_2018) granted it exempt from the scope of the Medical Research Involving Human Subjects Act (WMO). Prior to testing, children aged 12 years and older, and parents of children aged less than 16 years, gave written informed consent.

Consent for publication
We obtained written informed consent of the guardians for the individual images of the child wearing our AM-p.

Competing interests
The authors declare no competing interests.

Author details
[1]Research Centre for Healthy and Sustainable Living, Research Group Lifestyle and Health, Utrecht University of Applied Sciences, Utrecht, The Netherlands. [2]UMC Utrecht Brain Center and Center of Excellence for Rehabilitation Medicine, Utrecht, the Netherlands. [3]Present Address: Research Centre for Healthy and Sustainable Living, Research Group Moving, Growing, and Thriving Together, Utrecht University of Applied Sciences, Utrecht, The Netherlands. [4]Association for Quality in Physical Therapy (SKF), Zwolle, Netherlands. [5]Centre of Expertise Urban Vitality, Faculty of Health, Amsterdam University of Applied Sciences, Amsterdam, The Netherlands. [6]Department of Rehabilitation Medicine, Amsterdam UMC, Location University of Amsterdam, Amsterdam, The Netherlands. [7]Amsterdam Movement Sciences, Rehabilitation and Development, Amsterdam, The Netherlands. [8]Department of Rehabilitation, Physical Therapy Science and Sports, UMC Utrecht Brain Center, University Medical Center Utrecht, Utrecht, The Netherlands. [9]Canchild, Department of Pediatrics, McMaster University, Hamilton, Ontario, Canada. [10]HU University of Applied Sciences Utrecht, Heidelberglaan 7, Utrecht 3584 CJ, The Netherlands.

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