applied sciences

Systematic Review

Machine Learning Applications for Physical Activity and Behaviour in Early Childhood: A Systematic Review

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Featured Application: Machine learning algorithms applied to accelerometer data can enhance physical activity and sleep pattern assessment in preschool children, enabling more accurate and automated monitoring for educational and health interventions.

Abstract: This systematic review evaluated machine learning applications for analysing physical activity and behaviour in preschool children using accelerometer data. Following the PRISMA guidelines, we systematically searched PubMed, FECYT, and ProQuest Central databases. Fourteen studies implementing machine learning approaches for preschool accelerometry data were identified and assessed using the MINORS scale. Studies focused on two primary domains: physical activity analysis (n = 10) and sleep monitoring (n = 4). The ActiGraph GT3X+ was predominantly used, with placement varying between the hip and wrist. Random Forest algorithms proved most effective, achieving accuracy rates up to 86.4% in activity classification and 96.2% in sleep prediction. Sampling frequencies (0.25–100 Hz) and epoch lengths (1–60 s) varied considerably across studies. Machine learning applications show promising results for preschool physical activity assessment. However, small sample sizes and methodological inconsistencies limit generalizability. Future research should prioritise larger cohorts, explore multiple sensor integrations, and develop standardised protocols to enhance practical applications.

Keywords: technology; preschool; prediction; computer science; education

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1. Introduction

The early childhood years represent a critical period for establishing healthy physical activity patterns that can influence lifelong health outcomes. Physical activity is crucial for children's health and development, affecting their physical growth, cognitive development, and social skills [1]. Furthermore, research has identified physical activity as a significant protective factor against mental health challenges, including depressive symptoms and suicidal behaviour in later developmental stages [2]. Understanding their activity level can provide valuable information for designing public health interventions, school physical activity programmes, and disease prevention strategies [3]. By improving the accuracy of these assessments, we can obtain a clearer and more detailed picture of children's physical activity, which can lead to more effective interventions to promote healthy lifestyles from an early age [4].

Historical approaches to measuring children's physical activity have relied heavily on subjective methods. Traditionally, studies aimed at measuring children's physical activity were based on questionnaires or parental reports [5]. These methods lack objective measurement capabilities and introduce significant reporting biases, as parents may unconsciously project their behavioural patterns onto their assessments. This limitation has driven the need for more objective measurement tools.

In response to these methodological challenges, the use of accelerometry has become increasingly prevalent for collecting objective data in physical activity and sport research, both for adults and children. This technology provides continuous, unbiased measurement of movement patterns throughout the day. In the case of children, accelerometry has proven particularly valuable as it offers an objective method to validate questionnaire responses and provide accurate activity measurements [6].

The data collected from accelerometers enables the application of advanced analytical approaches, particularly Machine Learning (ML) or Deep Learning (DL) algorithms, which offer several key advantages: (1) real-time monitoring of children's physical activity with automated alert systems, (2) personalised evaluation frameworks that account for age and gender differences, (3) identification of sedentary patterns to inform intervention strategies, and (4) detection of complex movement patterns that might be missed by traditional analysis methods [7–9].

Significant progress has been made in applying various ML algorithms (such as Random Forest and Support Vector Machine) and DL approaches (including Artificial Neural Networks and ensemble models) to accelerometer data. Several reviews have examined different aspects of this field, specifically focusing on wearable technology for measuring physical activity in children [10,11]. Petersen et at. [12] have contributed valuable insights on physical activity measurement in children with neuromotor disorders, and the broader application of artificial intelligence in children's education has been systematically reviewed [12].

This review aims to critically evaluate the effectiveness of machine learning applications in improving physical activity measurements in preschool children, specifically focusing on accelerometer-based data collection methods. By synthesising current evidence and identifying key trends, this review seeks to provide a comprehensive understanding of how machine learning can enhance our ability to measure and analyse physical activity patterns in young children.

2. Materials and Methods

2.1. Experimental Approach to the Problem

This systematic review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [13] and adhered to established guidelines for performing systematic reviews in sports sciences [14]. The review protocol was developed to ensure comprehensive coverage of relevant literature while maintaining methodological rigour. This systematic review has been registered in PROSPERO (ID: CRD420251062269).

2.2. Information Sources

A comprehensive search was conducted across three databases: PubMed, FECYT (including Web of Sciences, CCC, CIDW, KJD, MEDLINE, RSCI, and SCIELO), and ProQuest Central. The search encompassed all published literature before 20 March 2024. This combination of databases was selected to ensure broad coverage of both medical and sports science literature.

2.3. Search Strategy

The PICO (Patient, Problem, or Population—Intervention or Exposure—Comparison, Control, or Comparator—Outcome[s]) framework was implemented to structure the search strategy and ensure systematic coverage of relevant literature. To maintain transparency, the authors were not blinded to journal names or manuscript authors. Language filters were applied to include English and Spanish publications only. The search terms were carefully selected to capture all relevant literature on accelerometry and machine learning in preschool settings. The final search string was as follows:

> *(Preschool OR kindergarten OR "early childhood") AND ("machine learning" OR "deep learning" OR forecast* OR predicti*) AND ("microelectromechanical system*" OR MEMS OR accelerometer* OR wearable*)*

2.4. Eligibility Criteria

The authors introduced the search string to databases and downloaded the titles, authors' names, journals, and dates of all the articles that appeared in the search. Once the Excel spreadsheet was organized, all duplicates were removed, and the remaining articles were evaluated for their eligibility. If the authors found articles that did not appear in the search, they included them in the Excel document as "included from external sources". Table 1 represents the inclusion and exclusion criteria in the systematic review.

Table 1. Inclusion and exclusion criteria.

Item	Inclusion	Exclusion
Population	Children attending preschools or kindergartens.	Children who do not attend preschools or kindergartens.
Intervention or Exposure	The data were extracted from accelerometers. The data was processed using machine learning or deep learning algorithms.	The data were not extracted from accelerometers. The data were not processed or not was processed using machine learning or deep learning methods. Study protocols.
Comparation	Not applicable	Not applicable
Outcome[s]	Any result about machine learning application (validity or reliability studies, predictions, etc.).	Results non-related to machine learning/deep learning applications or machine learning/deep learning validation.
Other criteria	Peer-reviewed full-text studies published in original journal articles written in English or Spanish.	Non-peer reviewed journal articles. Non-original full-text studies (conference papers, etc.). Studies written in another language.

2.5. Data Extraction

A standardized data extraction process was implemented using an Excel spreadsheet developed in accordance with the Cochrane Consumers and Communication Review Group's data extraction template. The spreadsheet facilitated a systematic assessment of inclusion and exclusion requirements for all selected studies. Two authors independently conducted the extraction process, with any disagreements resolved through discussion until consensus was reached. Full documentation was maintained for excluded articles, including specific reasons for exclusion. All data were systematically recorded and stored in the spreadsheet.

2.6. Assessment of Study Methodology

The methodological quality assessment was conducted using the methodological index for non-randomized studies (MINORS) [15]. While the complete MINORS scale contains 8 essential points and expands to 12 points for comparative studies, in this review, nine items were assessed (out of 18 points) due to the non-applicability of three items to the included studies (see items in the study by Rico-González et al. [16]). Each item was scored on a scale of 0 to 2 (0 = Low quality; 1 = Medium quality; 2 = High quality), based on the quality of reporting for each criterion. The assessment maintained rigorous evaluation standards while acknowledging the specific characteristics of accelerometry and machine learning studies in preschool settings.

3. Results

3.1. Identification and Selection of Studies

After analysing all databases (PubMed: 43; Web of Science: 50; ProQuest Central: 37; External sources: 1), the contents of 131 articles were checked, detecting, at the initial stage, 72 duplicate articles. Then, the authors analysed if each of the remaining 59 articles meet all inclusion criterion, resulting on the elimination of 45 articles by exclusion criteria number one (n = 6), exclusion criteria number two (n = 23), exclusion criteria number four (n = 3), and exclusion criteria number five (n = 13). The remaining 14 articles were included in the qualitative synthesis of the systematic review (Figure 1).

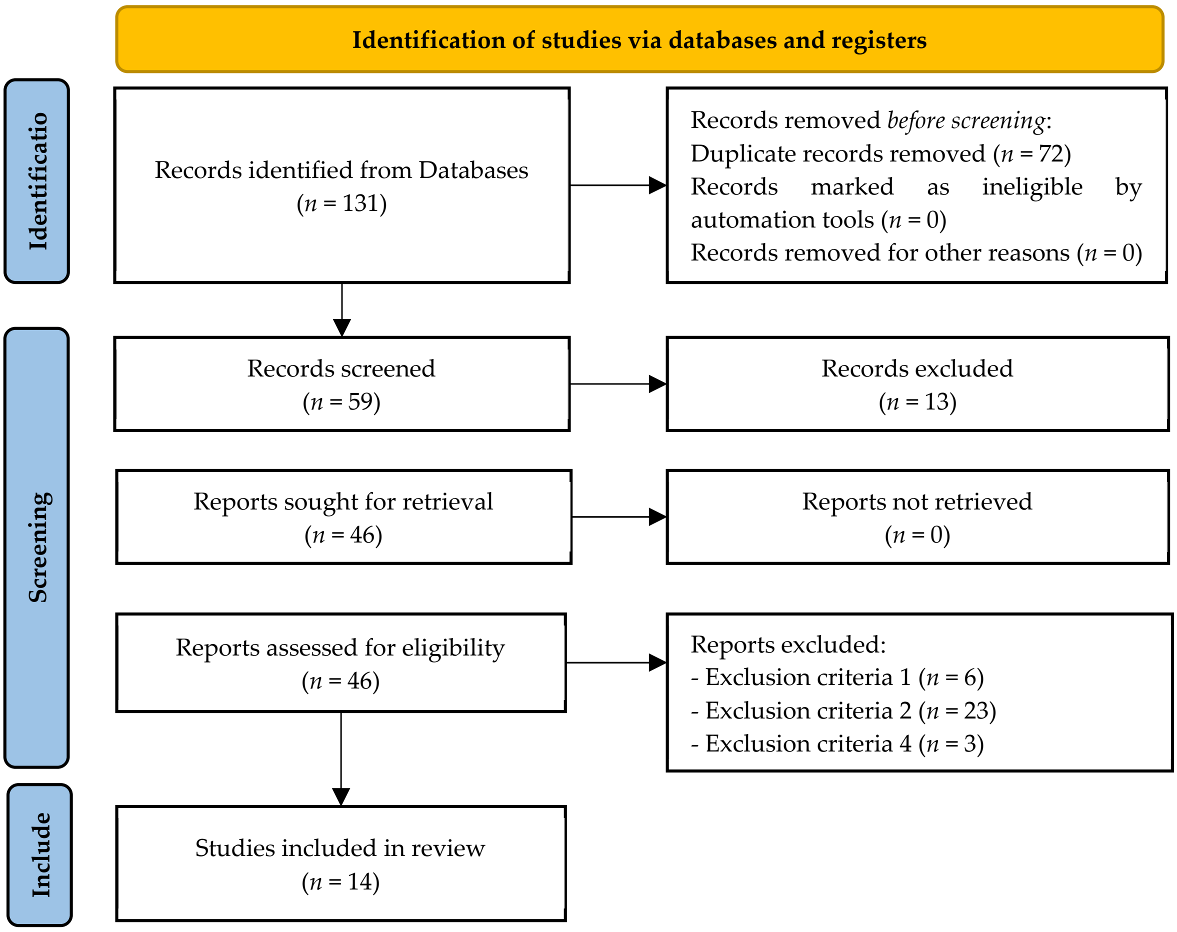

Figure 1. PRISMA flowchart of the systematic review.

3.2. Quality Assessment

The MINORS scale assessment revealed consistent methodological quality across studies, with scores ranging from 20/24 to 24/24 points (Table 2). Nine studies scored 20/24, three achieved 22/24, and one received 24/24 points. The studies uniformly demonstrated maximum scores for critical methodological components: objective definition, patient inclusion, data collection methodology, assessment protocols, evaluation procedures, follow-up design, and statistical approach. However, eleven of the fourteen studies received zero points in two areas: dropout rate documentation and prospective sample size calculation.

Table 2. Methodological assessment of the included studies.

Reference	1	2	3	4	5	6	7	8	9	10	11	12	Score
Hagenbuchner et al. [17]	2	2	2	2	2	2	0	0	NA	NA	NA	2	20/24
Ahmadi et al. [18]	2	2	2	2	2	2	0	0	NA	NA	NA	2	20/24
Ahmadi et al. [19]	2	2	2	2	2	2	0	0	NA	NA	NA	2	20/24
Ahmadi et al. [7]	2	2	2	2	2	2	0	0	NA	NA	NA	2	20/24
Zhao et al. [20]	2	2	2	2	2	2	0	0	NA	NA	NA	2	20/24
Clark et al. [21]	2	2	2	2	2	2	2	2	NA	NA	NA	2	24/24
Ahmadi and Trost [8]	2	2	2	2	2	2	0	0	NA	NA	NA	2	20/24
Trost et al. [22]	2	2	2	2	2	2	0	0	NA	NA	NA	2	20/24
Kwon et al. [23]	2	2	2	2	2	2	2	0	NA	NA	NA	2	22/24
Kuzik et al. [24]	2	2	2	2	2	2	2	0	NA	NA	NA	2	22/24
Li et al. [25]	2	2	2	2	2	2	0	0	NA	NA	NA	2	20/24
Li et al. [26]	2	2	2	2	2	2	0	0	NA	NA	NA	2	20/24
Hammam et al. [27]	2	2	2	2	2	2	0	0	NA	NA	NA	2	20/24
Abdollahi et al. [28]	2	2	2	2	2	2	2	0	NA	NA	NA	2	22/24

Note: NA = not applicable. (see items in Rico-González et al. [16]).

3.3. Study Characteristics

This section presents the key characteristics of studies implementing machine learning with accelerometer data in preschool children, as summarized in Table 3. The analysis is organized into four categories: Sample characteristics, detailing participant demographics; Data Collection Methods, outlining accelerometer specifications and protocols; Study Settings and Research Focus, describing measurement contexts and research objectives; and Machine Learning Implementation, summarizing algorithms, feature extraction approaches, and performance metrics used to classify physical activity behaviors in this age group.

Table 3. Main characteristics and findings of machine learning applications using accelerometer data in preschool children.

Ref.	Participants	Activity Registration				Aim of Prediction	ML/DP Accuracy		Conclusions	Practical Application from Predicting
		Accelerometer	Hz and Epoch	Place	Attributes/Features/ Variables		Algorithm	%		
Machine Learning and Physical Activity										
Hagenbuchner et al. [17] Year: 2015	N° children: 11 Country: Australia Age: 3–6 years (4.8 ± 0.87)	Branch: ActiGraph GT3X+ (ActiGraph, Pensacola, FL, USA) Placement: right hip	Hz: 100 10 s 15 s 20 s 30 s 60 s	Laboratory	Participants completed 12 standardised activity trials (TV, reading, tablet game, quiet play, art, treasure hunt, cleaning up, active game, obstacle course, bicycle riding) over two laboratory visits. Activities were categorized into five activity classes: sedentary activities, light activities, moderate to vigorous activities, walking, and running.	Activity type	Standard feed-forward ANN	ANN: 69.7% (sedentary 82%, light 79%, MVPA 64%, walking 36%, running 46%)	Compared to the accuracy of a standard feed-forward ANN for recognizing and accurately predict activity type, a DL-inspired ensemble neural network provided the best accuracy among preschool children.	It can contribute to addressing important questions such as: (i) how much and which types of activity are important for health, (ii) how active are preschool children, (iii) what are the key determinants of physical activity, and (iv) which strategies are most effective for promoting physical activity in young children?
							SOM	-		
							DL Ensemble Network	DL: 82.6% (sedentary 84%, light 91%, MVPA 79%, walking 73%, running 73%)		
Ahmadi et al. [18] Year: 2020	N° children: 31 Country: Australia Age: 3–5 years (4.0 ± 0.9)	Branch: ActiGraph GT3X+ accelerometer (ActiGraph Corporation; Pensacola, FL, USA) Placement: right hip and non-dominant wrist.	Hz: 100	Free-living	Five activity classes: sedentary, light-intensity activities and games, walking, running, and MVPA.	To evaluate the accuracy of the automatic recognition of five activity classes	RF	Hip: 69.4% Wrist: 59.1%	ML activity classification models for preschool-aged children trained on laboratory-based activity trials do not generalize well to free-living conditions.	To improve the performance of activity classification models under free-living conditions, future studies should: (1) train models with free-living data; (2) use smaller sliding windows to accommodate the sporadic activity patterns of preschool children; and (3) explore the utility of temporal features, and feature fusion approaches from multiple sensors.
							SVM	Hip: 66.4% Wrist: 59.3%		
							General data	In comparison with laboratory, accuracy decreases 11–21%. Classification accuracy for sedentary 72–78%, light 58–79%, MVPA 71–84%, walk 9–15%, and run 66–75%.		
Ahmadi et al. [19] Year: 2020	N° children: 25 Country: Australia Age: 3–5 years (4.1 ± 1.0)	Branch: ActiGraph GT3X+ accelerometer (ActiGraph Corporation; Pensacola, FL, USA) Placement: right hip and non-dominant wrist.	Hz: 100	Laboratory Free-living	Two variations in the LAB models were evaluated: - Laboratory (LAB): an "off the shelf" model without additional training. - Retrained laboratory (retrained LAB): models retrained on free-living data, replicating the methodology used in the original calibration study.	Energy expenditure	RF, SVM, ANN	General RMSE for the free-living and retrained LAB models ranged from 0.63 to 0.67 kcals/min. Hip RMSE's for the hip LAB (0.62–0.71), retrained LAB (0.58–0.62) and free-living models (0.61–0.65) were similar. Wrist Free-living SVM had a significantly higher RMSE (0.73 ± 0.29 kcals/min) than the retrained LAB SVM (0.63 ± 0.30 kcals/min) and LAB SVM (0.64 ± 0.18 kcals/min). RF The LAB (0.64 ± 0.28), retrained LAB (0.64 ± 0.25), and FL (0.62 ± 0.26) RF exhibited comparable accuracy.	ML energy expenditure prediction models trained on LAB and free-living data had similar accuracy under free-living conditions. Although the laboratory-based models generalized well to a free-living environment and exhibited acceptable accuracy at the group level of measurement, the strong evidence of proportional bias and wide prediction limits exhibited by all the models suggests that they may be inappropriate for predicting EE in individuals.	To improve predictive accuracy, future studies should train models using accelerometer data with enough training instances of physical activity with low and high energy expenditure for accurate prediction over the complete PA intensity continuum. The inclusion of physiological sensor data such as heart rate or person-level features such as height and weight may improve accuracy.
Ahmadi et al. [7] Year: 2020	N° children: 31 Country: Australia Age: 3–5 years (4.0 ± 0.9)	Branch: ActiGraph GT3X+ accelerometer (ActiGraph Corporation; Pensacola, FL, USA) Placement: right hip and non-dominant wrist.	Hz: 100	Free-living	Five activity classes: sedentary, light-intensity activities and games, walking, running, and MVPA.	PA classification	RF	62.6–86.4% depending on prediction window of 1, 5, 10 or 15 s, with only minimal improvements beyond the 10 s windows.	RF activity classification models trained with free-living accelerometer data provide accurate recognition of young children's movement behaviours under real-world conditions. The RF activity classifiers with prediction windows of 10 or 15 s provided the accurate recognition of five activity classes representative of young children's movement behaviours.	Future studies should train models using accelerometer data collected over extended time periods and a wider range of settings to provide more movement diversity in the training data. Such studies should explore the inclusion of additional temporal features, such as the ratio of the dominant frequency for the current and adjacent windows or information/features from additional sensors such as heart rate monitors, gyroscopes, barometric pressure sensors, and GPS trackers.
Zhao et al. [20] Year: 2013	N° children: 69 Country: USA Age: 3–5 years	Branch: ActiGraph GT3X+ activity monitor (ActiGraph, Pensacola, FL) Placement: right hip	Hz: 0.25–2.5 60 s	Free time under supervision	Sleep, watching TV, colouring, video games, puzzles, kitchen/toys, ball toss, active video games, dance, aerobics, running in place	PA classification	SVM	With sleep CVER: 24.70% Without sleep CVER: 20.16% Overall CVER: 15.56%	The SVM classifiers have a smaller 10-fold CV error rate than them SVM supersedes the classical classifier (multinomial logistic regression) in categorizing physical activities in preschool-aged children.	Using accelerometer data, SVM can be used to correctly classify physical activities typical of preschool-aged children with an acceptable classification error rate.

Table 3. *Cont.*

Ref.	Participants	Activity Registration				Aim of Prediction	ML/DP Accuracy		Conclusions	Practical Application from Predicting
		Accelerometer	Hz and Epoch	Place	Attributes/Features/ Variables		Algorithm	%		
Clark et al. [21] Year: 2020	N° children: 125 Country: - Age: 3–5 years (4.3 ± 0.5)	Branch: ActiGraph GT3X+ accelerometer (Actigraph, Pensacola, FL, USA) Placement: waist, above the right hip,	Hz: 100 1 s	24 h activity	Anthropometrics, motor competence, PA at different intensities	Profiles of motor competence and movement behaviours	*k-means* cluster SOM	Non-specified	The SOM analysis indicated five different profiles according to motor competence and PA. The results show that whilst differences in movement behaviours are already manifest in young children, resultant changes in adiposity are not clear, highlighting that basic anthropometric screening is insensitive, inadequate.	The authors of the present study assert that the focus should change from obesity monitoring, to one of "moving well". Given the importance of this stage of life for future health, activity engagement and MC, it is of critical importance accurate profiles, particularly of relative low competence children, be ascertained, so that nuanced, early, interventions may be implemented.
Li et al. [25] Year: 2019	N° children: 34 Country: USA Age: 3–5 years	Branch: ActiGraph GT3X+ accelerometer (Actigraph, Pensacola, FL, USA) Placement: wrist and hip	Hz: 30 15 s epoch and thereafter col-lapsed to 60 s epochs	Non-free-living setting	Sedentary behaviour, light PA, moderate PA, vigorous PA, MVPA	Establishing cut-points for wrist-worn accelerometry to assess PA	ROC OLR *k-means* cluster	*k-means* cluster had the highest classification accuracy, with more than 70% of the total epochs being classified into the correct PA categories as examined by the hip reference. *K-means* cut-points also exhibited the most accurate estimates on SED, LPA, and VPA as the hip reference, whereas none of the three wrist methods were able to accurately assess MPA.	This study demonstrated that ML techniques have potential to distinguish PA intensity levels with the exception of moderate PA in preschool-aged children.	This study demonstrates the potential of ML approaches on establishing cut-points for wrist-worn accelerometry to assess PA in pre-schoolers
Ahmadi and Trost [8] Year: 2022	N° children: 31 Country: Australia Age: 3–5 years (4.0 ± 0.9)	Branch: ActiGraph GT3X+ accelerometer (Actigraph, Pensacola, FL, USA) Placement: wrist and hip	Hz: 0.25–5.0 15 s	Free-living	Sedentary activity, light intensity, and MVPA	PA intensity	RF	Sedentary and light: 83–88% MVPA: 68–78%	RF exhibited significantly higher agreement with ground truth PA intensity than other traditional methods such as cut-point methods. ML classification models showed equivalence (within ±0.5 SD) with directly observed time in sedentary, light, and MVPA. None of the cut point's exhibited evidence of equivalence.	The authors encourage researchers to use the random forest physical activity classification models evaluated in this study.
Trost et al. [22] Year: 2018	N° children: 31 Country: Australia Age: 3–6 years (4.8 ± 0.9)	Branch: ActiGraph GT3X+ accelerometer (Actigraph, Pensacola, FL, USA) Placement: wrist, hip, and combined wrist and hip	Hz: 0.25–5.0 15 s	Free-living	Sedentary activity, light intensity, MVPA, walking, and running	Activity class	RF SVM	RF: Hip: 0.80 (95% CI, 0.79–0.82) Wrist: 0.78 (95% CI, 0.77–0.80) Combined: 0.82 (95% CI, 0.80–0.83) SVM: Hip: 0.81 (95% CI, 0.80–0.83) Wrist: 0.80 (95% CI, 0.79–0.80) Combined: 0.85 (95% CI, 0.84–0.86)	Recognition accuracy was consistently excellent for sedentary (>90%); moderate for light activity games, MVPA, and running (69–79%); and modest for walking (61–71%).	ML algorithms such as RF and SVM are useful for predicting PA class from accelerometer data collected in preschool children. Although classifiers trained on hip or wrist data provided acceptable recognition accuracy, the combination of hip and wrist accelerometer delivered better performance. Compared with sample-specific cut points for the hip or wrist, the ML algorithms provided higher classification accuracy for absolute PA intensity.
Kwon et al. [23] Year: 2022	N° children: 301 Country: USA Age: 3–5 years	Branch: ActiGraph GT3X+ accelerometer (Actigraph, Pensacola, FL, USA) Placement: wrist	Hz: 80 1 s 5 s 10 s 15 s	24 h	Five activity classes: run, walk, other MVPA, LPA, and sedentary.	Daily time spent at MVPA (MVPA; the sum of minutes spent in running, walking, and other MVPA) and total PA (the sum of MVPA and light-intensity PA).	RF	Non-detailed	The study found that preschool-aged children engaged in 28 min/day of MVPA and 361 min/day of total PA. However, the authors do not centre their findings and conclusions on ML.	No practical applications about the use of ML in preschool was detailed

Table 3. *Cont.*

Ref.	Participants	Activity Registration				Aim of Prediction	ML/DP Accuracy		Conclusions	Practical Application from Predicting
		Accelerometer	Hz and Epoch	Place	Attributes/Features/ Variables		Algorithm	%		
Machine Learning and Sleep										
Kuzik et al. [24] Year: 2021	N° children: 89 Country: Canada Age: 4.5 years	Branch: ActiGraph wGT3X-BT Placement: waist	Hz: 30 15 s	24 h	Nap, sleep, and wake	Sleep duration	RF	96.2%	This study demonstrated almost perfect agreement between free-living visual inspection ground truth measurements and several techniques for predicting sleep in preschool-aged children wearing waist-worn ActiGraph accelerometers. This is the first study to create a technique to classify sleep duration in this age group using this device.	A simplified formula to predict sleep was created that can greatly reduce computational demands. Hence, RF and Hidden Markov Modelling technique appears best for sleep classification; however, the simplified formula is optimal if computing power is limited.
Li et al. [26] Year: 2020	N° children: 262 Country: USA Age: 0–2 years	Branch: Actiwatch-2 (Phillips Respironics Mini-Mitter) Placement: ankle	Hz: 0.35–7.5 1 min	24 h	Activity rhythm	Sleep activity rhythms	PML	Non-detailed	The proposed PML algorithm can effectively conduct circadian rhythm analysis using time-series wearable device data.	Application of the method effectively characterized sleep–wake rhythm development and identified the association between daily rhythm formation and motor development during early childhood. PML can be extended to other types of circadian studies using information such as body temperature, heart rate, and hormone data. Therefore, the PML algorithm can be widely applied to other wearable device studies to help characterize periodic information.
Hammam et al. [27] Year: 2020	N° children: 634 Country: Age: 3–5 years	Branch: ActiGraph GT3X-BT accelerometer (Actigraph, Pensacola, FL, USA) Placement: wrist	Hz: 30 60 s	24 h	Activity	Sleep period	HMM	Non-detailed	This study utilized an ML approach to examine associations between objectively assessed childhood sleep duration and behaviour problems. We found significant associations between ML-derived sleep states and behavioural problems among preschool children. Children with longer sleep without movement had lower behavioural problems scores. Associations between sleep and behaviour problems were stronger among children with sleep-disordered breathing.	The findings highlight that the associations between sleep problems and behaviour problems may vary depending on how sleep problems are processed (actigraphy-algorithms or ML–sleep states) and the child's medical history (SDB vs. no SDB). Also, we hope that our work will stimulate other researchers to examine (or re-examine) their own feature-rich datasets to identify additional sleep patterns or states.
Abdollahi et al. [28] Year: 2022	N° children: 638 Country: Finland Age: 3–6 years (4.76 ± 0.89)	Branch: ActiGraph GT3X-BT accelerometer (Actigraph, Pensacola, FL, USA) Placement: wrist	Non-detailed	24 h	Six variables were formed from actigraphy-measured sleep: (1) night time sleep onset, (2) morning wake-up, (3) sleep duration, (4) time spent asleep within sleep duration, (5) wake after sleep onset, (6) sleep efficiency, (7) sleep midpoint, and (8) weekend–weekday differences in sleep midpoint.	Sleep timing in association with weight status	HMM	HMM has been validated previously against polysomnography with 85.7% overall accuracy. Not detailed in this study.	Though the sleep estimation methods were consistent and correlated, actigraphy measures should be favoured as they are more objective and sensitive to identifying associations between sleep timing and weight status compared with parent reports.	Most commonly used actigraph sleep estimation methods are often heuristic, commercialized, and require the input of reported sleep times, which may make sleep research cumbersome and expensive in large study populations. This study highlights the potential of an openly accessible data-driven, unsupervised algorithm used to estimate nighttime sleep from actigraph data. Further studies are needed to better understand the associations with sleep timing and weight status.

Note: ANN: artificial neural network; CI: confidence interval; CVER: cross-validity error rate; DL: deep learning; HMM: Hidden Markov Model algorithm; ML: machine learning; OLR: ordinal logistic regression; RF: Random Forest; RMSE: Root mean square error; ROC: receiver operating characteristic curve; PML: Penalized Multi-band Learning; SOM: the Self-Organizing Map; SVM: Support Vector Machine; PA: physical activity.

3.3.1. Sample

The reviewed studies encompassed a diverse population of preschool children, with mean ages ranging from 4.0 to 4.8 years when reported. Sample sizes demonstrated considerable variation, from small-scale studies with 11 participants to large cohorts of 638 children. Small samples (<100 participants) characterized nine studies (n = 9; [7,8,17–20,22,24,25]), while four studies included larger cohorts (>250 participants) (n = 4; [23,25,27,28]). Geographic distribution showed concentration in Australia (n = 6; [7,8,17–19,22]) and the United States (n = 4; [20,23,25,26]), with additional research conducted in Finland (n = 1; [28]), and Canada (n = 1; [24]). Finally, two research studies, conducted by Clark et al. [21] and Hammam et al. [27], did not specify their geographical locations. Finally, the studies were published between 2013 and 2022, being six published in 2020.

3.3.2. Data Collection Methods

Data collection methodology showed strong consistency in device selection, with thirteen studies employing the ActiGraph GT3X+ accelerometer (ActiGraph LLC, Pensacola, FL, USA) and one study using the Actiwatch-2 (Philips, Eindhoven, The Netherlands) [26]. Accelerometer placement varied across studies, with hip placement (n = 4; [17,20,21,24]), wrist placement (n = 3; [23,27,28]), both locations simultaneously (n = 5; [7,18,19,22,25]), and ankle (n = 3; [26]). Technical specifications of data collection displayed considerable variation, with sampling frequencies ranging from 0.25 to 100 Hz. Epoch lengths were similarly diverse, spanning from 1 to 60 s, with several studies employing multiple epoch lengths to evaluate optimal measurement intervals.

3.3.3. Study Settings and Research Focus

The research settings demonstrated significant methodological diversity. Twenty-four-hour monitoring was conducted in six studies [21,23,24,26–28], while five studies focused on free-living conditions [7,8,18,19,22]. Laboratory settings were used in two studies [17,19], and one study implemented supervised free-time observation [20].

Research objectives clustered into two primary domains: (a) physical activity analysis (n = 10; [7,8,17–23,25]) encompassing activity classification, intensity prediction, motor competence evaluation, and energy expenditure estimation; and (b) sleep analysis (n = 4; [24,26–28]) concentrated on sleep analysis, investigating duration prediction, pattern characterization, and relationships with behaviour and weight status.

3.3.4. Machine Learning Implementation

The implementation of machine learning algorithms revealed a preference for established classification methods. Random Forest was the most frequently employed algorithm (RF, n = 7; [7,8,20,21,25,26]), followed by Support Vector Machine (SVM, n = 4; [18–20,22]). More specialized approaches included Hidden Markov Models (HMM, n = 2; [27,28]) and Artificial Neural Networks (ANN, n = 2; [17,19]), alongside clustering techniques such as K-means (n = 2; [21,25]) and Self-Organizing Maps (S-OM, n = 2; [17,21]).

Prediction accuracy varied considerably based on the specific application. Physical activity classification achieved accuracy rates ranging from 59.1% to 86.4% [7,18,19], while sleep prediction demonstrated higher accuracy rates, reaching up to 96.2% [24]. Activity type recognition showed moderate success rates between 69.7% and 82.6% [17].

4. Discussion

The accurate assessment and understanding of physical activity and sleep patterns in preschool children represents a crucial area of research with significant implications for public health interventions and child development. This systematic review examined 14 studies implementing machine learning approaches to analyse accelerometer data in preschool settings, revealing important insights into both methodological considerations and practical applications. Our findings demonstrated two primary research trajectories: physical activity analysis and sleep monitoring, with consistent methodological approaches centred on the ActiGraph GT3X+ accelerometer. The results highlight both the significant potential and current limitations in applying machine learning to early childhood activity monitoring.

4.1. Physical Activity

The implementation of machine learning algorithms for physical activity analysis has demonstrated significant potential in revolutionizing how we measure and understand preschool children's movement patterns. Random Forest algorithms have emerged as particularly effective, achieving accuracy rates up to 86.4% in free-living conditions [7]. This superior performance can be attributed to the algorithm's sophisticated handling of complex, non-linear relationships in movement data while maintaining robust protection against overfitting. The effectiveness of Random Forest algorithms aligns with findings from both laboratory and free-living studies in preschool settings [19,22].

Sensor placement has emerged as a critical factor influencing measurement accuracy, with notable variations between hip-mounted (69.4–81%) and wrist-mounted (59.1–80%) accelerometers [19,22]. This variation reflects broader challenges in pediatric activity monitoring, where movement patterns are typically more sporadic and varied than in adults [5,29]. Research in preschool populations has demonstrated the importance of considering these placement effects when designing physical activity monitoring protocols [20,25].

The evolution of activity classification methodology demonstrates a clear trajectory of improvement. Hagenbuchner et al. [17] established initial benchmarks with accuracy rates of 69.7–82.6% using neural networks, while subsequent studies by Ahmadi et al. [7,18] achieved enhanced performance through refined algorithms and improved data processing techniques. This progression aligns with recent advances in machine learning applications for childhood physical activity assessment [12,30].

4.2. Sleep Monitoring

The application of machine learning to sleep analysis in preschool children represents a particularly promising development in early childhood research. The achievement of 96.2% accuracy using Random Forest algorithms for sleep duration prediction [24] establishes a significant benchmark in automated sleep assessment. This high accuracy rate is particularly noteworthy given the challenges of traditional sleep monitoring approaches in young children [26].

The implementation of Hidden Markov Models has enabled more sophisticated analysis of sleep patterns and their relationships with behavioural outcomes [27,28]. These probabilistic approaches have shown particular promise in analysing complex sleep patterns [11]. The ability to detect subtle patterns in sleep behaviour holds significant implications for understanding early childhood development and health outcomes [10].

Despite these promising advances, the relatively small number of studies (n = 4) in sleep analysis indicates an emerging field with considerable room for growth. The high accuracy rates achieved thus far suggest that machine learning approaches could provide valuable alternatives to traditional sleep assessment methods, particularly in naturalistic settings where conventional sleep studies are impractical [26,28].

4.3. Methodological Considerations

Sample size emerged as a critical methodological consideration across the reviewed studies. The prevalence of small sample sizes (n < 50) in seven studies [7,17–19,22–24] raises important questions about statistical power and generalizability. This limitation is particularly significant in machine learning applications, where larger datasets typically yield more robust and generalizable models [6]. While these studies provided valuable proof-of-concept results, their limited participant numbers may restrict the broader applicability of their findings, especially given the heterogeneous nature of preschool movement patterns [21].

The variation in data collection protocols, particularly regarding sampling frequencies (0.25–100 Hz) and epoch lengths (1–60 s), presents significant challenges in result comparison and protocol standardization [11]. This methodological heterogeneity, while allowing exploration of optimal measurement parameters, complicates the establishment of standardized protocols for preschool activity monitoring. Recent studies suggest that these variations in data collection parameters can significantly impact algorithm performance and reliability [9]. Figure 2 indicates the methodological heterogeneity in epoch length, sampling frequency and placement site of the devices between studies.

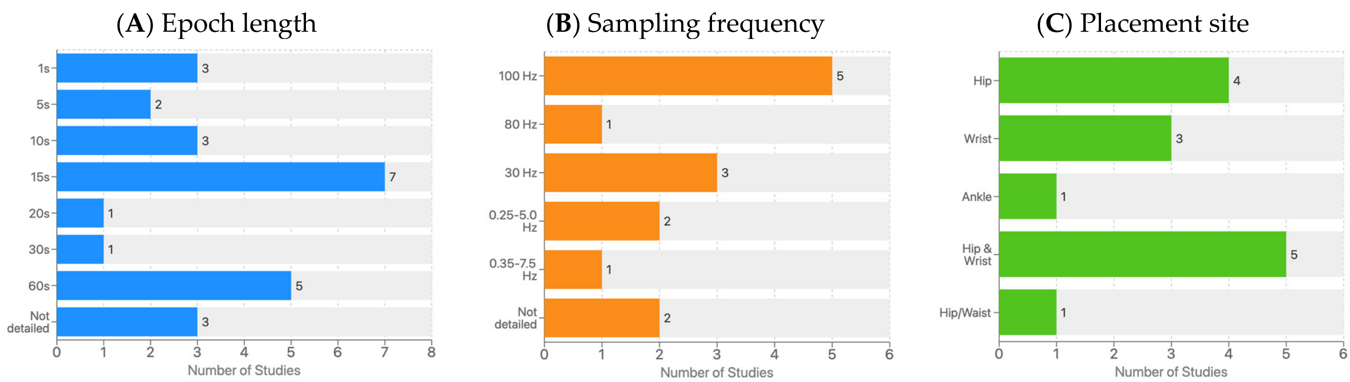

Figure 2. Methodological heterogeneity in accelerometer-based data collection: distribution of epoch lengths, sampling frequencies, and placement sites across studies.

The consistent use of ActiGraph GT3X+ across 13 studies presents both advantages and limitations. While this uniformity enables direct comparison of results and methodological approaches [8], it potentially limits our understanding of how different accelerometer types might influence machine learning performance. This standardization, though beneficial for consistency, may not capture the full range of measurement possibilities available with other accelerometer technologies [24,26].

Several factors support the predominant use of the GT3X+ in research settings. First, its reliability and validation across multiple studies ensure measurement consistency [31,32]. Second, its three-axis measurement capability provides comprehensive movement data essential for accurate activity classification. Third, its versatility in measuring multiple variables (acceleration, energy expenditure, steps, intensity) makes it suitable for diverse research applications. Additionally, its substantial memory capacity and extended battery life (approximately 30 days) facilitate long-term data collection without active supervision.

Alternative devices like Axivity AX3, GENEActiv, and SenseWear offer different measurement capabilities and might provide complementary insights (Table 4). For instance, while GT3X+ focuses on acceleration-based measurements, SenseWear incorporates multiple physiological variables that could enhance activity classification accuracy. However, the standardization around GT3X+ has facilitated result reproducibility and enabled more direct comparisons across studies, contributing to a more coherent body of evidence in preschool activity monitoring.

Table 4. Comparison of key features among common accelerometer devices used in physical activity research.

Features	GT3X+	Axivity AX3	GENEActiv	SenseWear
Measurements	Acceleration in three axes, other variables such as energy expenditure, intensity of physical activity	Acceleration in three axes, high temporal resolution	Acceleration in three axes, high temporal resolution	Multiple variables including physical activity and energy expenditure
Primary Use	Scientific and clinical research	Scientific research	Scientific and clinical research	Clinical applications and personal wellness
Connectivity	Data transfer to mobile devices or computers	Data transfer via USB	Data transfer via USB or Bluetooth	Data transfer via USB or Bluetooth
Applications	Scientific and clinical research	Scientific research	Scientific and clinical research	Clinical applications and personal wellness

4.4. Technical Implementation and Algorithm Selection

The predominance of Random Forest (n = 7) and Support Vector Machine (n = 4) algorithms reflects a well-established trend in activity recognition research. These algorithms have demonstrated consistent reliability across various studies [7,20,22], with Random Forest showing particular promise in handling the complex, non-linear patterns characteristic of preschool physical activity. The success of these approaches builds on foundational work in machine learning applications for movement analysis [17].

External validation of machine learning models emerged as a significant methodological gap across studies. Despite the promising accuracy rates reported, most studies conducted only internal validation using techniques such as cross-validation within the same population. Few studies have performed independent testing with new participants or in different settings, limiting our understanding of how these models would perform across diverse preschool populations [7,18,19]. This lack of external validation is particularly concerning given the heterogeneous nature of preschool movement patterns [21] and the potential influence of environmental and demographic factors on physical activity and sleep behaviours [10,11].

The emergence of more sophisticated approaches, such as Hidden Markov Models [27,28] and deep learning techniques, represents a significant evolution in analytical capabilities. These advanced methods have shown particular promise in capturing temporal dependencies and complex patterns in both activity and sleep data. The varying success rates across different algorithms and applications underscore the importance of careful algorithm selection based on specific research objectives and data characteristics [21].

4.5. Limitations and Future Research Directions

The present systematic review reveals several key limitations in the current body of research. The predominance of small sample sizes (n < 50) in half of the analysed studies [7,17–19,22–24] limits the generalisability of findings and the robustness of machine learning models. Additionally, the heavy reliance on a single accelerometer type (ActiGraph GT3X+) across studies, while providing methodological consistency, restricts our understanding of how different sensor technologies might influence algorithm performance. The variation in data collection protocols, particularly in sampling frequencies and epoch lengths, further complicates the establishment of standardised assessment procedures.

These methodological limitations have significant implications for machine learning applications in this field. Small sample sizes (n < 50) not only limit statistical power but also increase the risk of overfitting, particularly when using complex algorithms with numerous parameters. This overfitting risk is especially pronounced in models trained on laboratory data that may not generalise well to free-living conditions, as demonstrated by the reduced accuracy (11–21% decrease) observed by Ahmadi et al. [18] when laboratory-trained models were tested in real-world settings. The inconsistency in sensor placement further complicates cross-study comparisons and practical implementation, as the substantial performance variations between hip and wrist placements (10–20% accuracy differences) make it difficult to establish universal recommendations for optimal sensor positioning. Additionally, the heterogeneity in data collection protocols, particularly in sampling frequencies and epoch lengths, introduces methodological inconsistencies that may lead to variable algorithm performance across different studies and settings. These technical variations, combined with the inherent challenges of capturing sporadic movement patterns in preschool children, create significant barriers to widespread implementation of these technologies in educational or clinical environments.

Future research should prioritise larger-scale validation studies with diverse populations to enhance the generalizability of machine learning approaches in preschool settings. As highlighted by recent advances [21,28], there is a need to explore more sophisticated algorithms while maintaining practical applicability. Researchers should prioritise rigorous external validation of machine learning models across diverse preschool populations and settings. Studies should specifically test model performance with new participants from different demographic backgrounds, educational environments, and geographical locations to significantly enhance our understanding of model generalizability. Finally, the integration of multiple sensor types and locations to potentially improve classification accuracy, as suggested by the varying success rates between hip and wrist placements, should also be investigated [19,22]. The development of standardised protocols for data collection and processing would facilitate better comparison across studies and implementation in real-world settings.

5. Conclusions

The systematic analysis of machine learning applications in preschool accelerometry reveals significant progress in both physical activity and sleep monitoring, while highlighting important areas for development. The high accuracy rates achieved across studies, particularly in sleep detection (96.2%) and activity classification (up to 86.4%), demonstrate the viability of machine learning approaches for automated assessment in early childhood settings. Random Forest algorithms have emerged as particularly effective tools, showing robust performance across various applications and contexts.

These findings have several important practical implications for both researchers and practitioners working with preschool children. For researchers, the demonstrated success of machine learning approaches provides a foundation for more sophisticated analysis of movement patterns and sleep behaviours, potentially enabling more nuanced understanding of early childhood development. The consistent performance of specific algorithms, particularly Random Forest and Support Vector Machine, offers clear direction for future research design and implementation.

For practitioners in early childhood education and health settings, these results suggest practical possibilities for implementing automated activity and sleep monitoring systems. The high accuracy rates achieved with hip-mounted accelerometers (69.4–81%) provide a feasible approach for classroom-based activity monitoring, while the success in sleep analysis offers new opportunities for understanding sleep patterns in educational and clinical contexts. The findings support the use of machine learning-enhanced accelerometry as a viable tool for assessing and monitoring preschool children's physical activity and sleep patterns in real-world settings.

However, implementation should carefully consider the methodological constraints identified in this review. Practitioners should prioritise consistent sensor placement and standardized data collection protocols to ensure reliable results. The selection of appropriate algorithms should be guided by specific monitoring objectives, with consideration given to the trade-offs between accuracy and computational complexity. These considerations will be particularly important as these technologies are increasingly integrated into early childhood education and health monitoring programmes.

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