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A Clustering Approach for Modelling and Analysing Changes in Physical Activity Behaviours from Accelerometers

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ABSTRACT To evaluate the impact of Health interventions promoting physical activity, researchers typically conduct pre- and post-assessments using accelerometers. While aggregated metrics such as daily counts, daily steps and time spent at various intensity levels are commonly used, very few studies exploit the richness of the data often collected with a very fine granularity. We investigate the benefit of a deeper analysis of wrist accelerometry data to understand physical activity behaviours throughout the day, as well as how these may change overtime. To analyse physical activity behaviour changes, we propose a methodology that extracts bouts of physical activity characterised by their activity levels and duration, and uses these as features to cluster participants' daily and hourly behaviours. We then compare these clusters to assess changes following an intervention promoting physical activity in children. We demonstrate that this approach provides a more insightful analysis of the physical activity behaviours because it highlights the nature and the timing of behaviour changes, when present. We illustrate this methodology using data from research-grade activity trackers (GENEActiv) and explain the insights discovered in the context of an intervention aimed at educating school children about healthy behaviours.

INDEX TERMS Accelerometer, Activity Trackers, Behaviour Change, Clustering, Data Mining, Health Education, Physical Activity, Exercise, Children

I. INTRODUCTION AND BACKGROUND

Evidence shows that children worldwide are not sufficiently physically active. A recent global health study [1] revealed that only 9% of boys and 2% of girls meet the World Health Organisation daily recommendations of 60-min of moderate to vigorous physical activity (MVPA). This is concerning because physical activity (PA) plays an important protecting role against many metabolic diseases. To tackle this issue, a growing number of health interventions are deployed, especially in schools. However, only 56% of school-based interventions have reported a significant, yet very small change in PA behaviour [2]. This points to the need to improve the design of interventions and gain better understanding of their impact on PA. Having the capacity to precisely assess the effectiveness of interventions, health

promotion or health education programs is critical both from a public health perspective and from an economical perspective.

The use of technology in health promotion or education interventions has shown great potential to improve health behaviours and provides insights on how to improve their effectiveness [3], in particular where PA is concerned. With increasingly available wearable technologies, researchers now routinely use activity trackers with 3-axial accelerometers to assess physical activity unobtrusively, objectively and continuously [4] [5]. These can capture daily activity occurring in real life, replacing or complementing self-reported data which is often inaccurate and coarse, especially in children where self-reported data and/or parental reports are found to be very inaccurate [6]. Activity trackers provide a better mea-

sure of achievement of public health recommended guidelines such as performing 12,000 daily steps [7] and 60 min of daily MVPA [8]. In addition, the richness and objectiveness of accelerometer sensor data opens the way to deeper analysis of PA, in terms of occurrence and distribution, and in relation to currently established health guidelines. Researchers can investigate more effectively and accurately research questions such as whether the continuity and duration of PA bouts (e.g. frequent, shorts bouts vs less frequent, longer bouts) play an important role in achieving healthy guidelines, or gaining insights into how PA is distributed during the day, for instance in relation to a child's typical schedule. In addition this can help build evidence for researching the optimal way to accumulate PA and MVPA [9] in the longer term and informing policies and recommendations.

Whilst the most frequent use of accelerometers is to quantify daily physical activity, particularly in response to intervention promoting PA, much more detailed information is captured from their data, enabling deeper analysis such as activity recognition [10] and changes in everyday PA [11]. Extracting behaviour changes in response to learning, and investigating the evolution of knowledge or skills from user data is of course not new: Specialised data science fields such as Educational Data Mining [12] and Learning Analytics [13] have been developing techniques making use of various types of learner data. These recently expanded to using physical movement data captured by accelerometers. There is now an emerging interest in using sensors to capture fine-grained physical behaviours in education: for example, for learning kinaesthetic skills like martial arts [14], dance [15], using clinical equipment [16], or precise hand movements for engineering activities [17]. Generally, these education domains are focused on learning specific movements where a known gold standard (or expert) movement pattern exists, making supervised learning techniques appropriate to use.

However, assessing the impact of health education interventions is open-ended, thus requiring to analyse data using unsupervised learning methods [18] in order to discover, at a meaningful granularity level, the shape and patterns of physical activity and to detect PA behaviour changes after intervention, especially in relation to what has been learned. We tackle here the problem of modelling and comparing PA behaviours between two sets of accelerometer data, captured before and after the learning and behavioural change intervention, in order to understand the extent and the nature of its impact. For instance, an important question is whether any additional MVPA observed after an intervention occurs in longer bouts of activity (which would suggest more sustained intentional activity), or scattered in minuscule amounts throughout the day (which is more likely to be just incidental)? And if so, when did it occur? during school time, when the children are within their school environment or after school when they are may be supported by family and friends?

The contribution of this paper is a clustering-based approach for a more insightful analysis of the physical activity

behaviour of the participants, and of the nature of physical activity behaviour changes, if present. Our two research questions are:

- (RQ1) Can we extract daily changes of PA behaviour from accelerometer data, at an appropriate granularity to meaningfully assess the impact of health interventions with regards to the daily recommended targets?
- (RQ2) What technique can be used to further the analysis of PA behaviour change in relation to the part of the day it occurred?

This paper builds on our earlier work [19] to understand the impact of a learning intervention by analysing physical activity behaviour changes at a daily level. We propose a more comprehensive approach that enables a deeper analysis of both daily and hourly behaviours, and we apply it to a larger dataset.

The paper is structured as follows. Section 2 presents existing work in mining sensors data for extracting health related behaviours. Section 3 introduces the health education program, its data and rationale. In section 4 we describe our methodology and apply it to extract daily and hourly behaviours. Section 5 describes the resulting clusters of physical activity behaviours. In section 6 we analyse the behaviour change using these behaviour clusters to answer the research questions. Finally section 7 concludes the paper.

II. RELATED WORK

A. NON DATA MINING APPROACHES

Evaluating PA changes after health interventions is traditionally done through statistical techniques, on data aggregated over the test period. For example, [20] reports the daily average amount of MVPA (min/day), Light PA (min/day), accelerometer counts (counts/min) and step counts (steps/day). [21] use accelerometers, questionnaires and a series of fitness tests (Eurofit) to evaluate PA and fitness. The authors compare pre- and post-intervention data by computing the percentage of time spent at various intensities per day and their mean values, standard deviations and main effects (F-values). Whilst such analysis is useful to provide a big picture of changes, these measures are highly aggregated and do not provide information about the patterns of PA, and whether/how these may have evolved.

B. SUPERVISED TECHNIQUES

Supervised data mining of activity tracker data has been essentially used to assess quality of movement or to identify activities, however this type of analysis does not provide insight into PA patterns and characteristics. Nevertheless, relevant accelerometer features and data mining techniques can be found in these works. For example, [22] assesses the quality of physical exercise movements using smartphone accelerometer data features such as acceleration average, standard deviation and distance between acceleration peaks in a decision trees to classify them. For activity recognition, [23] used tri-axial acceleration data from smartphones to

generate acceleration data features such as average, standard deviation, difference and average. These were used to build classifiers for six pre-labelled activities (walking, jogging, upstairs, downstairs, sitting, standing) using decision trees (J48), logistic regression and multilayer neural networks models with up to 90% accuracy. With 5 bi-axial accelerometers, [24] used mean, energy, entropy, and correlation features as input to recognise 20 different pre-labelled activities with over 80% accuracy. For accelerometers combined with other sensors, [25] used light, temperature sensor and microphone data features to classify 6 different activities (sitting, standing, walking, ascending stairs, descending stairs and running) using a C4.5 Decision Tree classifier with over 80% accuracy.

Free living health monitoring assistance and support make use of such combinations of various sensor devices into a wireless body area network (WBAN). [26] proposed a decision support system using classification and regression analysis with Support Vector Machine, extracting features from accelerometers, global positioning system (GPS), heart rate, blood pressure and weight data. [27] used a range of data sources (electrocardiogram (ECG), electromyography (EMG), electroencephalography (EEG), blood pressure, tilt, breathing, movement and a "smart sock") combined with external data such as forecast data to classify user states and activities in the domain of computer-assisted physical rehabilitation. Such techniques have been used for educational purposes. For instance, [28] created a decision-making algorithm to optimize a reinforcement learning system for a weight loss intervention program using pre-classified data from Fitbit sensors, together with intervention responses. [29] created a gamified intervention to motivate children to increase every-day physical activity where Support Vector Machine and Random Forests (RF) data mining techniques were applied to smartphone accelerometer data in order to (i) classify children's PA into activities (sitting, standing, walking, jogging, walking upstairs, walking downstairs and intense physical activity) and (ii) calculate a score based on the amount of time spent in these activities.

C. UNSUPERVISED TECHNIQUES

Unsupervised data mining has been used to detect changes and analyse physical activity. For the detection of change in PA behaviours, time window-based techniques have been developed. For example [11] created a Physical Activity Change Detection algorithm (PACD), an adaptation of Permutation-based Change Detection in Activity Routine algorithm (PCAR) [30], which uses the distance between PA time series windows to detect a significant change in PA. They found that the PACD algorithm detected more changes than other window-based change detection algorithms (RuLSIF, texture-based, PCAR and a virtual classifier) using synthetic and PA data (Fitbit data). While this work aims to detect PA changes in accelerometer data, it focuses on detecting changes in daily activity-based routines to identify and quantify changes from those routines, rather than comparing two different sets of data. Furthermore, the physical

activity data is represented by a single characteristic (sum of steps time series), leaving aside other important and relevant characteristics, such as the PA intensity which is important to meaningfully assess the impact of a health intervention.

For the analysis of PA, [31] used kmeans clustering algorithm to group people according to their physical activity levels from uni-axial hip accelerometer data in an observational study of family health, happiness and harmony. Once transformed to Moderate to MVPA and Light Physical Activities (LPA), datapoints were separated into weekday and weekend, and averaged by hour. This generated 48 hourly counts of MVPA and LPA, which were used as features for clustering in order to be able to extract participants' weekday and weekend behaviours. Two clusters were found, one active and one much less active. Through these clusters, the authors analysed demographic, lifestyle, PA level and health characteristics. [32] used three accelerometers and a heart rate monitor, and clustered the data using Hierarchical Clustering Analysis (HCA) and k-means algorithms with time and frequency domain as features to provide patients and caregivers with a more accurate overview of their physical activities. Whilst [31] and [32] are the most related works to ours, their focus was to highlight general temporal PA patterns in their population without addressing the needs of an intervention context, and in particular to evaluate pre- and post- intervention behaviour changes, assessing both changes in PA and sedentary time.

Recently, [5] analysed the data from wrist activity trackers that children wore during a school-based health education intervention (iEngage) by creating daily behaviour clusters. These clusters were built using features such as the sum of minutes spent on different levels of PA (Light, Moderate and Vigorous), the number of daily steps, and the weekly consistency by which children adhered to international recommendation guidelines as the program progressed. The resulting clustering enabled deeper analysis of progress in PA throughout the educational intervention showing us that children improved PA behaviours along the program, and in particular those who were the least active at the beginning of the study.

In conclusion, while data mining techniques have been successfully applied to identify activities, to characterise daily patterns or to assess behavioural change during intervention, there is a lack of methods to analyse the data at fine granularity in order to 1) characterise fine patterns of engagement in PA, 2) identify changes in behaviours that are hidden in current analyses. This is important because it may help detect early changes, predict trajectory and help tailor interventions.

III. CONTEXT AND BACKGROUND

A. IENGAGE STUDY

The accelerometry data was collected before and after a 5-week school-based digital health education intervention (iEngage) [33]. The experimental group of children (N=61) followed the iEngage learning sessions over 5 weeks, whilst

the control group (N=26) did not. The iEngage program aims to develop health knowledge and skills to empower 9-11 year old school children achieve healthy behaviours, with a focus on reaching recommended levels of daily PA (at least 60 mins per day of MVPA [34]) and decreasing sedentary time.

B. ACCELEROMETER DATASETS

Pre- and post-tests were carried out, measuring unobtrusively and continuously the children's PA with research grade activity trackers (GENEActiv [35]) for five consecutive school days, hence generating two five-day long datasets per child. The GENEActiv accelerometers were placed on the wrist of their non-skilled hand and captured acceleration in three axes (x,y,z) with a sample frequency of 60 Hz.

To ensure that all daily records had the same length, we excluded records with missing data. The result of this filtering is summarised in Table 1.

TABLE 1: Dataset after filtering. Total Hours = Number of hours recorded. Total Days = Number of days with records. N 5-days = Number of children with five-day datasets. N Complete = Number of children with five-days datasets after filtering. N Pairs = Number of children with matching pre-post datasets pairs, after filtering.

Group		Total Hours	Total Days	N 5-days	N Complete	N Pairs
Experimental	Pre	7080	295	59	54	45
	Post	6360	265	53	50	
Control	Pre	3120	130	26	26	24
	Post	3000	125	25	25	

C. RATIONALE

A high-level analysis of the total time spent daily in PA between the control and the experimental group from the first iEngage study [36] showed that pre-intervention, both groups spent similar time in each PA intensity (p-values of 0.63, 0.62, 0.76, 0.29 for Sedentary, Light, Moderate and Vigorous intensities respectively). In contrast, the post intervention data showed a significant increase in PA in the experimental group, especially in MVPA levels (p-values of 0.003, 0.017 respectively for Moderate and Vigorous), compared to no change in the control group. While this is consistent with the intervention reaching the overall desired effect (at least short term) on this population, we sought more insights on how this activity is distributed throughout the day, and how it evolved (RQ1 and RQ2). To answer these questions, we must analyse finer-grained information about the salient structure of PA with regards to intensity, duration and frequency of PA bouts. This led us to explore bouts of PA in terms of intensity level, length and frequency. Considering bout duration is necessary to provide meaningful analysis of data because very short bouts will contain lots of noise and longer bouts may dilute MVPA time if mixed with lighter PA. Furthermore, it has been shown that PA sessions of at least 5 min including at least 80% of MVPA bouts were probably required for effective positive health outcomes [37]. The next important aspect was to enable meaningful comparison between PA behaviours: for instance, a period of mostly sedentary time

followed by a mostly MVPA period is no different to a period of mostly MVPA period followed by sedentary time. In contrast, a period with very scattered MVPA among otherwise sedentary time is different to a grouped period of MVPA occurring within light activity for instance. This led us to model behaviours over a certain period of time to absorb meaningless differences yet conserving the overall shape of the activity over that period of time. Once these behaviours are modelled, we can then compare them.

IV. METHODOLOGY FOR EXTRACTING PHYSICAL ACTIVITY BEHAVIOURS

The methodology is summarised in Figure 1. Both datasets (pre- and post-intervention) were pre-processed and transformed into sequences of PA intensity levels vectors. Then we compressed these into bouts of PA per intensity level and used characteristics of these bouts as features to cluster the data and identify types of PA behaviours during the relevant period (day or hour). The next sub-sections will detail these steps.

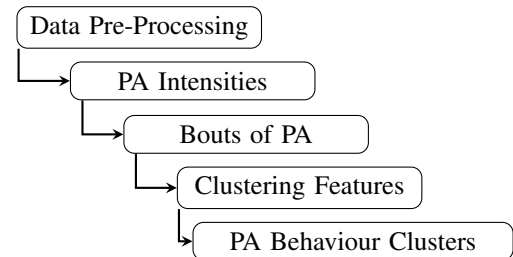


FIGURE 1: Methodology for extracting PA behaviours

A. DATA PRE-PROCESSING

The data was pre-processed using R [38], which has a specific library to manipulate GENEActiv trackers data [39]. We converted the accelerometer binary files to accelerometer data frames and applied the data cleaning explained in section III. Then we translated the three-dimensional 60 Hz acceleration data frame into gravity-subtracted Signal Vector Magnitudes (SVMgs) [40] quantities within a 1 second epoch (see Formula 1). Each data is timestamped.

$$SVMgs = \sum_{i=1}^{60} |\sqrt{x_i^2 + y_i^2 + z_i^2} - g| \quad (1)$$

The 1 second epoch was chosen because children engage in moderate to vigorous activities mostly in very short bouts. For example, it has been reported that 80% of MPA and 93% of VPA are performed in bouts lasting less than 9s and 4.7s respectively [41] [42]. This indicates that children behaviour, in particular PA patterns, maybe incorrectly assessed and that smaller epochs are needed to detect accurate activity.

B. FROM SVMGS TO PA INTENSITY LEVELS

We categorised each 1-sec SVMgs into a PA intensity level according to cut-offs scientifically validated for assessment of PA intensity in children [43] (Table 2).

TABLE 2: SVMgs Cut Off Levels

Physical Activity Intensity Levels	SVMgs Cut Off
Sedentary	[0, 4.5[
Light	[4.5, 16.5[
Moderate	[16.5, 42[
Vigorous	≥ 42

Using the above cut-offs each second was coded with a letter as follows: S for sedentary time, L for light PA, M for moderate PA and V for vigorous PA (Figure 2). As an example, a piece of 5 seconds length of this string can be LLLMVV, which can be read as 3 seconds of light activity followed by 1 second of moderate activity and followed by 2 seconds of vigorous activity.

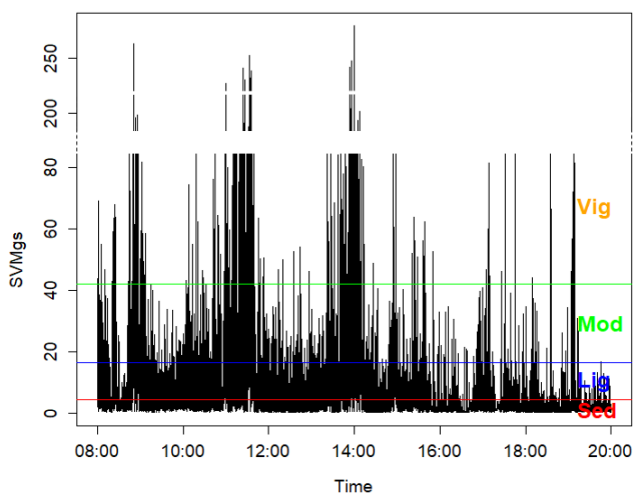


FIGURE 2: SVMgs time series of one child over one day (the figure is truncated between 80-200 SVMgs for a better display). The red horizontal line represents the cut-off from sedentary to light, the blue line the cut-off from light to moderate, and the green line the cut-off from moderate to vigorous

C. BOUTS OF PA

As mentioned earlier, we analysed the data through the notion of bouts with a focus on MVPA and sedentary time (SED) bouts during daytime. Let us first introduce some definitions.

- A *bout* is a continuous episode of PA at a specific range of intensity level.
- The *length of a bout* is the number of seconds spent during that bout.
- The *bout frequency* is the number of occurrences of all bouts of a certain length during a day.

As the daily recommendations are expressed in terms of MVPA (combining moderate and vigorous PA), we merged M and V into one category "MVPA". For instance, a sequence of 11 seconds spent in M, 8 seconds in V, and 12 seconds in M preceded and followed by L's would generate one bout of MVPA that would be 31 seconds long. This is pictured in Figure 3.

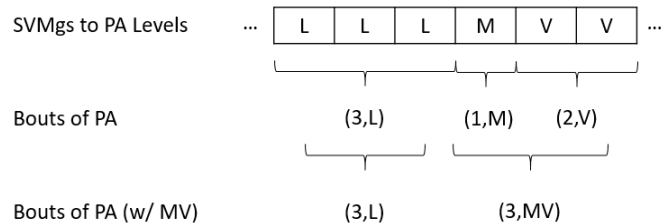


FIGURE 3: From PA levels to bouts (and merging Moderate and Vigorous levels)

Before using these bouts as features for the clustering, we conducted a quick analysis of their distribution, by computing the total time spent in MVPA done in bouts of at least x seconds. Formula 2 shows the reverse cumulative sequence, where t is the bout length and b is the number of seconds spent in bouts of length of at least t . For $t=1$, this is equivalent to the total number of seconds spent in MVPA bouts of 1 second. For $t=2$, the total number of seconds spent in bouts of at least 2 seconds (therefore excluding the time spent in bouts only 1 second long), and so on.

$$Bouts\ Cum\ Sum_t = \sum_{i=t}^n b_i \quad (2)$$

Figure 4 shows a sample of the result of these calculations, where every line shows the average daily MVPA cumulative bout length for a particular child. Over 10 seconds the lines start to flatten as bout length increases.

This figure shows a lot of potential noise in the 1-2 seconds bout, and an exponentially decreasing function that flattens after 30 seconds for MVPA. The same method was applied to SED bouts showing that the curve flattens after 300 seconds (not shown).

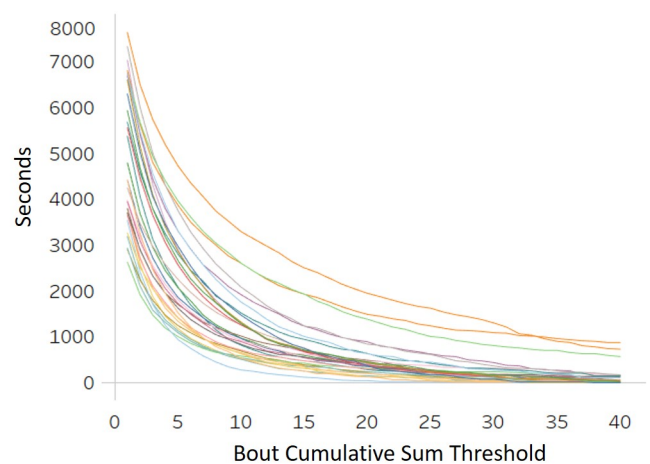


FIGURE 4: Reverse Cumulative Bout Lengths

We ran a paired T-Test on the before and after cumulative series which reveals that overall, children in the experimental group increased MVPA bouts length (p -value= $6.883e-10$), increased MVPA bout frequency (p -value= 0.008), decreased SED bout length (p -value= $2.2e-16$) and decreased SED bout

frequency (p -value= $2.2e-16$). Such analysis thus brings new information to characterise how the intervention impacted behaviours.

D. CLUSTERING FEATURES

We selected various thresholds of bout length following the established literature [44] and empirically, based on the exploration above. In particular, meaningful MVPA detected by GENEActivs was found to start from 3 seconds, as any shorter activity is likely to be agitation rather than physical activity. For MVPA we selected bout lengths of at least 3, 10 and 30 seconds, and for SED at least 60, 120, 300 seconds. Then, for each length and each PA Intensity Level, we calculated two indicators: the frequency of bouts, and the accumulated time spent (in seconds). The resulting 12 clustering features are summarised in Table 3.

TABLE 3: Clustering Features

Feature Number	Measure
1	Total Time of MVPA over or equal 3 seconds length
2	Total Time of MVPA over or equal 10 seconds length
3	Total Time of MVPA over or equal 30 seconds length
4	Number of bouts MVPA over or equal 3 seconds length
5	Number of bouts MVPA over or equal 10 seconds length
6	Number of bouts MVPA over or equal 30 seconds length
7	Total Time of SED over or equal 60 seconds length
8	Total Time of SED over or equal 120 seconds length
9	Total Time of SED over or equal 300 seconds length
10	Number of bouts SED over or equal 60 seconds length
11	Number of bouts SED over or equal 120 seconds length
12	Number of bouts SED over or equal 300 seconds length

E. BEHAVIOUR CLUSTERING

After feature normalisation and Principal Component Analysis dimensionality reduction, K-means algorithm was applied.

We selected this algorithm as a first step because it is a widely used, well-rounded algorithm, relatively easy to implement and suited given the reduced number of dimensions. We also attempted using a non-spherical clustering technique, DBSCAN [45], but it generated a less cohesive cluster model. We acknowledge other clustering methods could nevertheless be explored [46], especially more complex, state-of-the-art algorithms that may be better suited since the ratio between the amounts of MVPA and sedentary behaviours may require different distance metrics, such as ensembles [47], weighting [48] or alternative clustering models [49].

The resulting clusters are expected to capture PA behaviours of all children pre- and post-intervention, helping to understand the whole cohort behaviour changes.

V. PHYSICAL ACTIVITY BEHAVIOURS: RESULTS

Our methodology characterises behaviours of PA at a coarse enough level, yet captures essential elements of how the PA is distributed throughout the day. The idea is to identify the types of distributions of activity that are present in the cohort data, and to distinguish these distributions. We investigated two approaches:

- The Daily approach (subsection V-A), looking for daily activity patterns: Indeed, two days (for 2 different children, or 2 days for the same child) can show the same total quantity of MVPA (e.g. 40 minutes), but one will contain a lot of sedentary time and long sessions of MVPA, whilst another can show more broken down MVPA but less sedentary time (hence more light activity).
- The Hourly approach (subsection V-B), dwelling down on the hourly patterns, and allowing a more fine-grained analysis of when, during the day, activity occurs and evolves.

A. PA DAILY BEHAVIOURS CLUSTERING

For the daily PA behaviours analysis we only considered awake time from full school days, hence we excluded days where bracelets were installed and removed and filtered out sleeping times. As can be seen in Table 4 this resulted in 104 PA records of length of up to 45 hours of daytime activity (three 15-hour days from 7:00 to 21:59 hrs.).

TABLE 4: Daily records post filter

Group	Days			Total
	3	2	1	
Pre	44	10	0	54
Post	46	4	0	50

We computed daily behaviour vectors using the 12 daily features shown in Table 3 and averaging daily values over the three days. The resulting 104 (54 pre- and 50 post-) vectors would thus characterise a child's average daily PA, either pre- or post-intervention.

The 12 daily features were standardised and passed through Principal Components Analysis (PCA) to reduce the number of features and maximise their variance. We retained the first three Principal Components (PCs) based on three criteria [50]: cumulative percentage of total variation $\leq 80\%$, size of variances of PCs (eigen value of > 1.0 criterion) and a scree graph (see Figure 5).

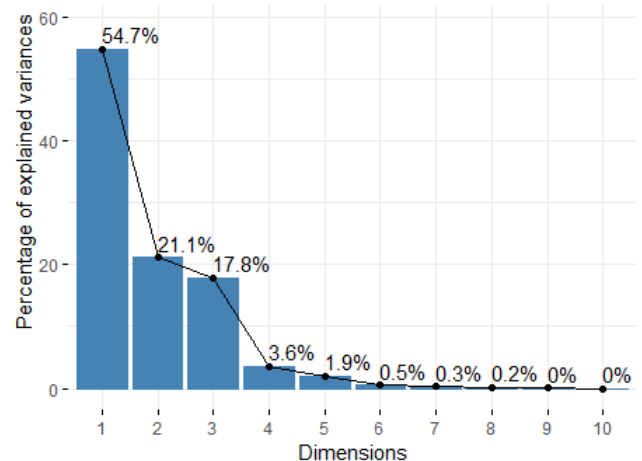


FIGURE 5: PCs scree graph

K-means unsupervised algorithm [51] with $k=6$ was applied. This number of clusters was determined by analysing when including another cluster did not improve enough the total within-cluster sum of square.

Behaviour clustering identified six types of daily PA behaviours (Table 5). Daily cluster 1 (D1) contains days with the smallest number of bouts spent in MVPA and the highest number of bouts spent in SED while D6 shows the highest number of bouts spent in MVPA and the second lowest number of bouts spent in SED. Other clusters present intermediate characteristics. It is clear that the most active daily clusters (D4, D5, D6) are also the least sedentary ones. Across all clusters, the time spent in bouts of MVPA over 30 seconds and their number is drastically less than the MPVA occurring in shorter bouts, which can be explained by the spontaneous activity of children at this age. Indeed, most of the spontaneous activity is below 30 seconds with a high recovering capacity [52]. This is also consistent with studies showing that young children fatigue less during one or several repeated high-intensity exercise bouts than adults [53].

TABLE 5: Daily Clusters Centroids

SED Intensities	Measure	1 (N=14)	2 (N=22)	3 (N=11)	4 (N=17)	5 (N=25)	6 (N=15)
≥ 60 Secs	Tot. Time (min)	354.4	247.5	455.6	263.4	160.1	184.8
	Num. of Bouts	129.1	89.7	57.2	104.7	66	68.7
≥ 120 Secs	Tot. Time (min)	247.1	165.9	406.4	171.7	96.7	120.9
	Num. of Bouts	51.2	29.4	21	37.4	19	21.9
≥ 300 Secs	Tot. Time (min)	132.9	100.3	369.2	86	53.2	71.6
	Num. of Bouts	12.5	6.6	8.1	8.1	3.4	5
MVPA Intensities	Measure	1 (N=14)	2 (N=22)	3 (N=11)	4 (N=17)	5 (N=25)	6 (N=15)
≥ 3 Secs	Tot. Time (min)	29.8	35.3	37.5	54.6	68	92.4
	Num. of Bouts	251.9	370.1	351.2	448.2	655.1	729.7
≥ 10 Secs	Tot. Time (min)	14.1	11.1	14.9	26.7	25.4	47
	Num. of Bouts	38.3	39.6	49.4	77.6	89.2	136.8
≥ 30 Secs	Tot. Time (min)	6	2.1	4	9.9	5.5	17.1
	Num. of Bouts	6.7	3	5.2	11	7	20

Given these observations, we ordered the clusters in increasing level of MVPA amounts, from the lowest activity daily cluster (D1) to the highest activity one (D6), and characterised them as seen in Table 6 using 3 seconds bouts.

TABLE 6: Daily Cluster Descriptions (Those meeting the daily recommendation of MVPA are flagged with *, and borderline with +).

Daily Cluster	Summary Description
D1	Less active cluster (Half of MVPA recommended amount) and frequent bouts of SED time.
D2	Not very active cluster (Around half of MVPA recommended amount) combined with average amount of SED time.
D3	Low MVPA (Around half of MVPA, but in slightly longer bouts) and highest SED time, including in longest bouts.
D4+	Borderline active cluster (centroid 5 min short of MVPA recommended levels, but with longer and more frequent bouts than the previous clusters) combined with frequent short SED time.
D5*	Active cluster (meets the recommended amounts of MVPA), frequent number of short MVPA bouts with the lowest SED times and frequencies.
D6*	Active cluster, with highest amount of MVPA but with slightly longer SED times and bouts than the other active cluster.

B. PA HOURLY BEHAVIOURS CLUSTERING

For the hourly PA behaviours analysis, the entire cleaned dataset was used. This included nights and the days where the bracelets were installed and removed, resulting in 10496 hours of data for the 104 PA records. The detail for each group can be seen in Table 7.

TABLE 7: Hourly records post filter

Group	Total children	N Hours
Pre	54	5386
Post	50	5110

We computed hourly behaviour vectors using again the 12 daily features from Table 3. The resulting 10496 vectors (up to 121 hours x 104 participants pre- and post-intervention) would thus characterise a child's PA over that specific hour.

After feature normalisation, the first three Principal Components were retained (see Figure 6).

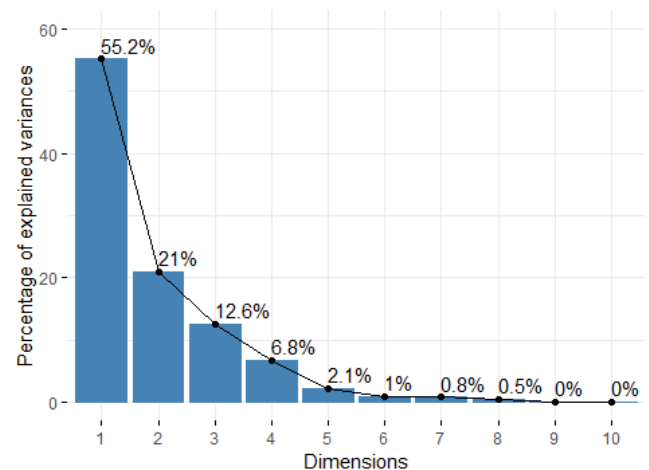


FIGURE 6: PCs scree graph

We ran k-means unsupervised algorithm with $k=4$. The number of clusters was again determined using the total within-cluster sum of square method.

Table 8 shows the centroids of the hourly clusters. In the hourly cluster 1 (H1), children spent the whole hour on long sedentary bouts with negligible MVPA, while in H4, children spent almost a quarter of an hour doing high bursts of MVPA, with hardly any sedentary time in between. H2 and H3 features were intermediate.

TABLE 8: Hourly Clusters Centroids

SED Intensities	Measure	1 (N=4340)	2 (N=2359)	3 (N=3268)	4 (N=529)
>= 60 Secs	Tot. Time (min)	57.6	26.9	5.6	5
	Num. of Bouts	4.8	11.4	3.2	2.6
>= 120 Secs	Tot. Time (min)	56.6	17.2	2.1	2.5
	Num. of Bouts	4.1	4.4	0.6	0.7
>= 300 Secs	Tot. Time (min)	52.6	6.6	0.6	0.8
	Num. of Bouts	2.9	0.8	0.1	0.1
MVPA Intensities	Measure	1 (N=4340)	2 (N=2359)	3 (N=3268)	4 (N=529)
>= 3 Secs	Tot. Time (min)	0.1	0.9	4.1	15
	Num. of Bouts	0.6	10	41.7	95.5
>= 10 Secs	Tot. Time (min)	0	0.2	1.4	9.3
	Num. of Bouts	0	0.7	5.1	24.3
>= 30 Secs	Tot. Time (min)	0	0	0.2	4.2
	Num. of Bouts	0	0	0.3	4.6

Given these observations, we ordered the clusters in increasing amounts of MVPA, from the lowest activity hourly cluster (H1) to the highest activity one (H4), and characterise them as seen in Table 9.

TABLE 9: Hourly Cluster Descriptions

Hourly Cluster	Summary Description
H1	Sedentary cluster/Sleep. Long bouts of SED time, negligible MVPA. These are mostly the sleeping hours.
H2	Not very active cluster. Infrequent brief bouts of MVPA (1 min long) and almost half of the hour (26 min) spent on SED bouts of various length.
H3	Lightly active cluster. Occasional short bouts of MVPA combined with infrequent and brief bouts of SED, implying most of the time is spent on light activity.
H4	Active cluster. High amount of MVPA bouts of various length combined with infrequent and short bouts of SED time.

VI. ANALYSING PA BEHAVIOUR CHANGE

This novel clustering approach, focusing either on day or hour offers a unique opportunity to zoom in and out a typical day or hour and to analyse individual and cohort data. This provides new insight into how participants (here children) respond to the knowledge and skills they learn about healthy physical activity behaviours because we can characterise individuals, days or hours not only based on PA descriptor but also on sedentary behaviour.

Complementary to a previous study, the daily and hourly clusters capture salient characteristics of the children’s PA behaviours such as intensity, duration of bouts of various intensities, frequency of PA engagement as well as time of the day. This approach brings new insights on PA behaviour since previous studies on PA including with children (e.g.

[20], [21]) present cumulative and sectorised analyses of the PA, making difficult a global interpretation of the results.

This novel cluster analysis enables an analysis of each salient characteristic of the behaviour, showing differences at the cohort level, as well as at an individual level, and with regards to international recommendations (with the daily clusters) and the distribution of activity throughout the day (with the hourly clusters). Let us illustrate how these clusters can help answer the initial research questions.

A. CAN WE EXTRACT DAILY CHANGES OF PA BEHAVIOUR FROM ACCELEROMETER DATA, AT AN APPROPRIATE GRANULARITY TO MEANINGFULLY ASSESS THE IMPACT OF HEALTH INTERVENTIONS WITH REGARDS TO THE DAILY RECOMMENDED TARGETS?

The **daily behaviour clusters** can help determine whether and to which extend the experimental population changed behaviours by comparing the clusters they belong to before and after the intervention. Especially, behaviour can be described in different ways, according to the structure of the PA (Table 6). This is highly relevant since this structure can have different impact on children health according to personal objectives, physical fitness level and other environmental factors associated to PA [54].

In the case of iEngage program, the analysis of accelerometry in both periods pre- and post-intervention revealed the nature and importance of the changes in relation to the minimum daily recommendations (Table 6). In particular, the Daily Cluster movement matrix (Table 10) permits to analyse each salient characteristic simultaneously as captured by the four clusters: it shows that 47% of children already belonged to an active cluster and remained in the same cluster or moved to a more active cluster; 13% of them were in a cluster below the recommended guidelines of MVPA and moved to a more active cluster; 35% of them were in a cluster that did not meet the recommended guidelines of MVPA and remained in the same or moved to another cluster that was slightly less active but also less sedentary; 4% of the children were in an active cluster and moved to a cluster that is not.

TABLE 10: Daily cluster movement matrix

		To Daily Cluster					
		1	2	3	4	5	6
From Daily Cluster	1	4	2	0	1	0	0
	2	2	3	2	1	2	0
	3	0	2	1	1	0	1
	4	0	1	0	4	0	1
	5	0	0	1	1	7	2
	6	0	0	0	0	2	4

We can visually observe behaviour changes according to various elements of the PA structure. For instance in Table 10 (movement matrix between before and after) the behaviour changes in relation to MVPA and international guidelines: the green area shows desirable movements (moves or stays in a cluster that fulfils the recommendation) and blue indicates no

improvement (stays in the same cluster that do not fulfils the MVPA recommendation) and red shows negative movements (moves from a cluster that fulfils the recommendation to one that not). If we are interested in the sedentary times, a slightly different ordering of the clusters would yield a slightly different matrix (D3 would become the most sedentary cluster). This method can be a new and reliable method to interpret globally the impact of an intervention at the scale of a cohort as well as at the individual level and help answer other research questions. Although the clusters are ordered in increasing level of MVPA and a movement from one cluster to a higher one is generally better, it is not always the case. For instance, a movement from D2 to D3 seems to be better at first glance because children in D3 spent more a little more time in longer MVPA than D2, but children in D3 also had longer bouts of SED. Given this, clusters may not be always comparable by numbers and partial order may exist. Despite the above, we know that D4 (borderline), D5 and D6 fulfil the MVPA recommendations, so we coloured the behaviour changes based on this. The green area shows desirable movements (moves or stays in a cluster that fulfils the recommendation) and blue indicates neutral changes (stays clusters that do not fulfils the MVPA recommendation, but each one with different amount of MVPA and SED) and red shows undesirable movements (moves from a cluster that fulfils the recommendation to one that not).

B. WHAT TECHNIQUE CAN BE USED TO FURTHER THE ANALYSIS OF PA BEHAVIOUR CHANGE IN RELATION TO THE PART OF THE DAY IT OCCURRED?

For RQ2, the **hourly behaviour clusters** provide more specific insights into the period of the day where such potential behaviour changes occurred.

We examined the distribution of time spent on each hourly cluster throughout their school day. Figure 7 displays the proportion of time spent in each of the four clusters during a typical day pre-intervention.

It is very informative to see that most children (90%) spend time in active clusters (H3 and H4) between 8am and 3pm. After 3pm, only about 25% of children remain active. The data also clearly show that the time before class start (8-9am) morning and afternoon recess times (10am and 2pm) are characterised by the highest proportion of children in the more active cluster (H4). Only a very small proportion (less than 5%) spend time in H4 after school. This shows that schools remain the place where children engage in active behaviours compared with outside school hours.

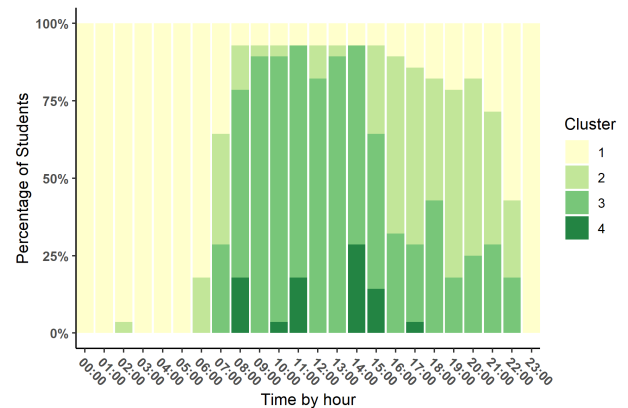


FIGURE 7: Distribution of hourly clusters during one particular pre-intervention day (24 hours). The x axis shows the day and hour, in 1-hour long intervals, and y axis shows the percentage of children present in each cluster. Clusters numbers are ordered from less active (H1) to more active (H4).

To address RQ2 and analyse the PA during specific periods of time, we used the following windows of time: *Before School* (7-9am), *During School* (9am-3pm), *After School* (3-7pm), *Evening* (7-9pm) and *Night* (9pm-7am). For each, we calculated the proportion of time participants spent in the relevant activity clusters, both pre- and post-intervention. In Table 11 we observe a general shift towards higher activity clusters and less time spent in the low activity clusters.

Notably, we observe a drop in the most sedentary clusters (H1 and H2) *Before School*, *After School* and *Evening*, whilst the time spent in the very active cluster (H4) more than doubled *After School*. We also observe that the time spent across the activity clusters *During School* is similar, although slightly more active. This suggests that the participants were more likely to engage in more active behaviour in their own time, outside school hours, especially after school.

TABLE 11: Percentage of time spent on each hourly cluster by period of time

Period of Time	Intervention	H1	H2	H3	H4
Before School	Pre	28.2	24.4	40	7.3
	Post	20.5	30.4	38.6	10.5
During School	Pre	7	14.4	67.9	10.7
	Post	6.7	11.4	68.8	13.2
After School	Pre	10.8	42.2	43	3.9
	Post	7.4	39.8	44.4	8.4
Evening	Pre	16.7	52.5	26.6	1.3
	Post	10.2	56.3	31.3	2.3
Night	Pre	85.9	11.3	2.8	0.1
	Post	83.7	11.5	4.6	0.2

Analysing in more detail the *After School* period we found a significant (Mann Whitney U test, p-value <0.05) increase of time spent in H4 evenly distributed between 16:00 to 19:00, in a magnitude of four folds, and that most of these

changes occurred by spending less time on H1 and H2 especially after 17:00 (see Table 12).

While this increase of time spent in the most active cluster (H4) post-intervention indicates a more active behaviour, the cluster centroids (refer to Table 8) allow us to examine in more details the change in PA of the cohort. It suggests that these children had a behaviour with few sedentary bouts, in particular almost none over long periods (≥ 300 secs bouts) and frequent bouts of MVPA, not only the short ones (≥ 3 secs), which are at least 4 times more frequent in H4 than in any other cluster, but also the longer ones (≥ 30 secs), which are mostly only present in H4 and indicate a sustained, purposeful period of MVPA such as exercise or physical games.

TABLE 12: Percentage of time spent on each hourly cluster *After School* time

Time	Intervention	H1	H2	H3	H4
15:00	Pre	4.4	16.6	68.3	10.7
	Post	3.4	18.9	65.5	12.3
	p-value	0.64	0.48	0.56	0.68
16:00	Pre	10	48	40.3	1.9
	Post	8	45.8	38	8.2
	p-value	0.80	0.76	0.67	0.02
17:00	Pre	13.6	54.8	29.9	1.7
	Post	8.9	47.5	36.9	6.8
	p-value	0.87	0.28	0.20	0.04
18:00	Pre	15.2	49.6	33.6	1.6
	Post	9.5	47	37.3	6.2
	p-value	0.90	0.62	0.42	0.02

The result of this analysis suggests that children became progressively active after school until dinner time. This increase is consistent with research showing that the child's environment, including parental/community support, access to facilities and feeling of security, is a positive factor for engaging in PA [55]. Indeed, each child in iEngage was assigned missions involving family, friends or support persons.

VII. CONCLUSION

We presented a methodology to extract salient aspects of children's PA behaviour and how these changed before and after a Health education intervention. We model the PA into bouts of PA intensities, using their length and frequency, as features to cluster the daily and hourly PA behaviour in relation to international recommendations. These clusters are then used to examine the differences between before and after the intervention.

This approach is complementary to using descriptive statistics to measure overall behaviour changes between pre and post- intervention data (via ANOVA or similar): It provides an aggregated analysis (via clusters), yet capturing important and essential aspects of the activity (the length and frequency of bouts of PA). It also enables a smaller grained analysis to understand the impact of the intervention at a general and individual level, starting from a high level and

zooming into more specific parts of the day, as we illustrated with the *After School* time example.

Such analysis may also help refine Health guidelines with regards to PA as the current recommendations are mostly based on the health outcomes of exercise intervention studies. The novel PA analysis approach proposed here allows experts to extract a different type of information, which considers the structure of free-living activities. This could pave the way for adopting new methodologies, particularly where physical fitness and markers of cardiovascular or metabolic health are also available.

Our methodology can easily be adapted to other types of time aggregation than day and hour, and include a wider range of relevant features such as sleeping. Cluster movements (Table 10) can be interpreted in relation to different guidelines as well, such as minimal recommended daily minutes spent on VPA or maximal amounts and lengths of sedentary behaviours bouts. This flexibility of our work is highly relevant since the guidelines for physical activity and sedentary behaviours evolve over the years as evidence grows of links between specific physical activity behaviours and health. Future work could also explore whether the use of other clustering algorithms and distance metrics (e.g. [47] [48] [49]) could further improve the quality of the physical activity clusters, hence of patterns discovery.

REFERENCES

- [1] A. R. Cooper, A. Goodman, A. S. Page, L. B. Sherar, D. W. Esliger, E. M. van Sluijs, L. B. Andersen, S. Anderssen, G. Cardon, R. Davey, K. Froberg, P. Hallal, K. F. Janz, K. Kordas, S. Kreimler, R. R. Pate, J. J. Puder, J. J. Reilly, J. Salmon, L. B. Sardinha, A. Timperio, and U. Ekelund, "Objectively measured physical activity and sedentary time in youth: The International children's accelerometry database (ICAD)," *International Journal of Behavioral Nutrition and Physical Activity*, vol. 12, no. 1, pp. 1–10, 2015. [Online]. Available: <http://dx.doi.org/10.1186/s12966-015-0274-5>
- [2] Y. Demetriou and O. Höner, "Physical activity interventions in the school setting: A systematic review," *Psychology of Sport and Exercise*, vol. 13, no. 2, pp. 186–196, 2012. [Online]. Available: <http://dx.doi.org/10.1016/j.psychsport.2011.11.006>
- [3] P. Krebs, J. O. Prochaska, and J. S. Rossi, "Defining what Works in Tailoring: A Meta-Analysis OF Computer Tailored Interventions for Health Behavior Change," *Prev Med*, vol. 51, no. 3–4, pp. 214–221, 2010.
- [4] G. Plasqui, A. G. Bonomi, and K. R. Westerterp, "Daily physical activity assessment with accelerometers: New insights and validation studies," *Obesity Reviews*, vol. 14, no. 6, pp. 451–462, 2013.
- [5] O. Galy, K. Yacef, and C. Caillaud, "Improving pacific adolescents' physical activity toward international recommendations: Exploratory study of a digital education app coupled with activity trackers," *JMIR mHealth and uHealth*, vol. 7, no. 12, p. e14854, 2019.
- [6] L. A. Kelly, J. J. Reilly, D. M. Jackson, C. Montgomery, S. Grant, and J. Y. Paton, "Tracking physical activity and sedentary behavior in young children," *Pediatric exercise science*, vol. 19, no. 1, pp. 51–60, 2007.
- [7] M. A. Adams, W. D. Johnson, and C. Tudor-Locke, "Steps/day translation of the moderate-to-vigorous physical activity guideline for children and adolescents," *International Journal of Behavioral Nutrition and Physical Activity*, vol. 10, no. 1, p. 49, 2013.
- [8] W. L. Haskell, I.-M. Lee, R. R. Pate, K. E. Powell, S. N. Blair, B. A. Franklin, C. A. Macera, G. W. Heath, P. D. Thompson, and A. Bauman, "Physical activity and public health: updated recommendation for adults from the american college of sports medicine and the american heart association," *Medicine & science in sports & exercise*, vol. 39, no. 8, pp. 1423–1434, 2007.
- [9] W. H. Organization et al., *Global recommendations on physical activity for health*. World Health Organization, 2010.

- [10] N. Ravi, N. Dandekar, P. Mysore, and M. M. L. Littman, "Activity Recognition from Accelerometer Data," in Proceedings of the Seventeenth Conference on Innovative Applications of Artificial Intelligence (IAAI). AAAI, 2005, vol. 5518 LNCS, pp. 1541–1546. [Online]. Available: <http://www.aaai.org/Papers/IAAI/2005/IAAI05-013>
- [11] G. Sprint, D. J. Cook, and M. Schmitter-Edgecombe, "Unsupervised detection and analysis of changes in everyday physical activity data," *Journal of Biomedical Informatics*, vol. 63, pp. 54–65, 2016. [Online]. Available: <http://dx.doi.org/10.1016/j.jbi.2016.07.020>
- [12] R. S. Baker and K. Yacef, "The State of Educational Data Mining in 2009: A Review and Future Visions," *Journal of Educational Data Mining*, vol. 1, no. 1, pp. 3–16, 2009.
- [13] G. Siemens, "Learning Analytics: The Emergence of a Discipline," *American Behavioral Scientist*, vol. 57, no. 10, pp. 1380–1400, 2013.
- [14] O. C. Santos, "Education still needs Artificial Intelligence to support personalized motor skill learning: Aikido as a case study," *CEUR Workshop Proceedings*, vol. 1432, pp. 72–81, 2015.
- [15] A. Dias Pereira dos Santos, K. Yacef, and R. Martinez-Maldonado, "Forró trainer: Automated feedback for partner dance learning," in Adjunct Publication of the 25th Conference on User Modeling, Adaptation and Personalization, ser. UMAP '17. New York, NY, USA: ACM, 2017, pp. 103–104. [Online]. Available: <http://doi.acm.org/10.1145/3099023.3099032>
- [16] R. Martinez-Maldonado, K. Yacef, A. D. P. D. Santos, S. B. Shum, V. Echeverria, O. C. Santos, and M. Pechenizkiy, "Towards Proximity Tracking and Sensemaking for Supporting Teamwork and Learning," in Proceedings - IEEE 17th International Conference on Advanced Learning Technologies, ICALT 2017. IEEE, 2017, pp. 89–91.
- [17] M. Worsley, "Multimodal learning analytics as a tool for bridging learning theory and complex learning behaviors," 3rd Multimodal Learning Analytics Workshop and Grand Challenges, MLA 2014, pp. 1–4, 2014.
- [18] R. M. Leech, S. A. McNaughton, and A. Timperio, "The clustering of diet, physical activity and sedentary behavior in children and adolescents: a review," *International Journal of Behavioral Nutrition and Physical Activity*, vol. 11, no. 1, p. 4, 2014.
- [19] C. Diaz and K. Yacef, "Detecting behaviour changes in accelerometer data," in *CEUR Workshop Proceedings*, vol. 2148, 2018, pp. 21–26.
- [20] W. Robertson, S. Stewart-Brown, E. Wilcock, M. Oldfield, and M. Thorogood, "Utility of accelerometers to measure physical activity in children attending an obesity treatment intervention," *Journal of obesity*, vol. 2011, 2010.
- [21] S. J. Verstraete, G. M. Cardon, D. L. De Clercq, and I. M. De Bourdeaudhuij, "Effectiveness of a two-year health-related physical education intervention in elementary schools," *Journal of Teaching in Physical Education*, vol. 26, no. 1, pp. 20–34, 2007.
- [22] L. De Moura Carvalho, V. Furtado, J. E. de Vasconcelos Filho, and C. M. G. F. Lamboglia, "Using Machine Learning for Evaluating the Quality of Exercises in a Mobile Exergame for Tackling Obesity in Children," in Proceedings of SAI Intelligent Systems Conference. Springer, 2016, pp. 373–390.
- [23] J. R. Kwapisz, G. M. Weiss, and S. A. Moore, "Activity recognition using cell phone accelerometers," *ACM SigKDD Explorations Newsletter*, vol. 12, no. 2, pp. 74–82, 2011.
- [24] L. Bao and S. S. Intille, "Activity recognition from user-annotated acceleration data," in *International Conference on Pervasive Computing*. Springer, 2004, pp. 1–17.
- [25] U. Maurer, A. Smailagic, D. P. Siewiorek, and M. Deisher, "Activity recognition and monitoring using multiple sensors on different body positions," in *Wearable and Implantable Body Sensor Networks, 2006. BSN 2006. International Workshop on*. IEEE, 2006, pp. 4–pp.
- [26] H. Zheng, C. Nugent, P. McCullagh, Y. Huang, S. Zhang, W. Burns, R. Davies, N. Black, P. Wright, S. Mawson et al., "Smart self management: assistive technology to support people with chronic disease," *Journal of Telemedicine and Telecare*, vol. 16, no. 4, pp. 224–227, 2010.
- [27] E. Jovanov, A. Milenkovic, C. Otto, and P. C. De Groen, "A wireless body area network of intelligent motion sensors for computer assisted physical rehabilitation," *Journal of NeuroEngineering and Rehabilitation*, vol. 2, 2005. [Online]. Available: <https://jneuroengrehab.biomedcentral.com/articles/10.1186/1743-0003-2-6>
- [28] E. M. Forman, S. G. Kerrigan, M. L. Butryn, A. S. Juarascio, S. M. Manasse, S. Ontañón, D. H. Dallal, R. J. Crochiere, and D. Moskow, "Can the artificial intelligence technique of reinforcement learning use continuously-monitored digital data to optimize treatment for weight loss?" *Journal of behavioral medicine*, pp. 1–15, 2018.
- [29] H. Schäfer, J. Bachner, S. Pretschner, G. Groh, and Y. Demetriou, "Study on motivating physical activity in children with personalized gamified feedback," in *Adjunct Publication of the 26th Conference on User Modeling, Adaptation and Personalization*. ACM, 2018, pp. 221–226.
- [30] P. N. Dawadi, D. J. Cook, and M. Schmitter-Edgecombe, "Modeling patterns of activities using activity curves," *Pervasive and mobile computing*, vol. 28, pp. 51–68, 2016.
- [31] P. H. Lee, Y.-Y. Yu, I. McDowell, G. M. Leung, and T. Lam, "A cluster analysis of patterns of objectively measured physical activity in hong kong," *Public health nutrition*, vol. 16, no. 8, pp. 1436–1444, 2013.
- [32] K. Dobbins and R. Rawassizadeh, "Clustering of physical activities for Quantified Self and mhealth applications," *Proceedings - 15th IEEE International Conference on Computer and Information Technology, CIT 2015, 14th IEEE International Conference on Ubiquitous Computing and Communications, IUCC 2015, 13th IEEE International Conference on Dependable, Autonomic and Secure Computing, DASC 2015 and 13th IEEE International Conference on Pervasive Intelligence and Computing, PICom 2015*, no. October, pp. 1423–1428, 2015.
- [33] K. Yacef, C. Caillaud, and O. Galy, "Supporting Learning Activities with Wearable Devices to Develop Life-Long Skills in a Health Education App," in *Artificial Intelligence in Education Conference*, 2018.
- [34] I. Janssen and A. G. LeBlanc, "Systematic review of the health benefits of physical activity and fitness in school-aged children and youth," *International Journal of Behavioral Nutrition and Physical Activity*, vol. 7, no. 1, p. 40, 2010. [Online]. Available: <http://ijbnpa.biomedcentral.com/articles/10.1186/1479-5868-7-40>
- [35] Activinsights Ltd., "GENEActiv Original - Wrist-Worn Actigraphy Device | GENEActiv Accelerometers," 2017. [Online]. Available: <https://www.activinsights.com/actigraphy/geneactiv-original/>
- [36] K. Yacef, C. Caillaud, and O. Galy, "Supporting learning activities with wearable devices to develop life-long skills in a health education app," in *International Conference on Artificial Intelligence in Education*. Springer, 2018, pp. 394–398.
- [37] A. E. Mark and I. Janssen, "Influence of Bouts of Physical Activity on Overweight in Youth," *American Journal of Preventive Medicine*, vol. 36, no. 5, pp. 416–421, 2009. [Online]. Available: <http://dx.doi.org/10.1016/j.amepre.2009.01.027>
- [38] R. Ihaka and R. Gentleman, "Interface Foundation of America R: A Language for Data Analysis and Graphics R: A Language for Data Analysis and Graphics," *Source Journal of Computational and Graphical Statistics*, vol. 5, no. 3, pp. 299–314, 1996.
- [39] Z. Fang and M. J. Langford, "Package 'GENEAread'," 2013.
- [40] D. W. Esliger, A. V. Rowlands, T. L. Hurst, M. Catt, P. Murray, and R. G. Eston, "Validation of the GENEActiv accelerometer," *Medicine and Science in Sports and Exercise*, vol. 43, no. 6, pp. 1085–1093, 2011.
- [41] R. C. Bailey, J. Olson, S. L. Pepper, J. Porszasz, T. J. Barstow, and D. M. Cooper, "The level and tempo of children's physical activities: An observational study," *Medicine and Science in Sports and Exercise*, vol. 27, no. 7, pp. 1033–1041, 1995.
- [42] G. Baquet, G. Stratton, E. Van Praagh, and S. Berthoin, "Improving physical activity assessment in prepubertal children with high-frequency accelerometry monitoring: A methodological issue," *Preventive Medicine*, vol. 44, no. 2, pp. 143–147, 2007.
- [43] L. R. S. Phillips, G. Parfitt, and A. V. Rowlands, "Calibration of the GENEActiv accelerometer for assessment of physical activity intensity in children," *Journal of Science and Medicine in Sport*, vol. 16, no. 2, pp. 124–128, 2013. [Online]. Available: <http://dx.doi.org/10.1016/j.jsams.2012.05.013>
- [44] C. A. Schaefer, C. R. Nigg, J. O. Hill, L. A. Brink, and R. C. Browning, "Establishing and evaluating wrist cutpoints for the GENEActiv accelerometer in youth," *Medicine and Science in Sports and Exercise*, vol. 46, no. 4, pp. 826–833, 4 2014. [Online]. Available: <https://insights.ovid.com/crossref?an=00005768-201404000-00024>
- [45] M. Ester, H.-P. Kriegel, J. Sander, and X. Xu, "A Density-Based Algorithm for Discovering Clusters in Large Spatial Databases with Noise," in *Proceedings of the 2nd International Conference on Knowledge Discovery and Data Mining*, 1996.
- [46] L. Rokach and O. Maimon, "Chapter 15 Minkowski : Distance Measures for Numeric Attributes," *Data Mining and Knowledge Discovery Handbook*, pp. 322–352, 2005.
- [47] H. Parvin and B. Minaei-Bidgoli, "A clustering ensemble framework based on selection of fuzzy weighted clusters in a locally adaptive cluster

- tering algorithm,” *Pattern Analysis and Applications*, vol. 18, no. 1, pp. 87–112, 2014.
- [48] A. Nazari, A. Dehghan, S. Nejatian, V. Rezaie, and H. Parvin, “A comprehensive study of clustering ensemble weighting based on cluster quality and diversity,” *Pattern Analysis and Applications*, vol. 22, no. 1, pp. 133–145, 2019. [Online]. Available: <https://doi.org/10.1007/s10044-017-0676-x>
- [49] B. Gupta, M. Tiwari, and S. Singh Lamba, “Visibility improvement and mass segmentation of mammogram images using quantile separated histogram equalisation with local contrast enhancement,” *CAAI Transactions on Intelligence Technology*, vol. 4, no. 2, pp. 73–79, 2019.
- [50] I. Jolliffe, “Principal Component Analysis,” in *International Encyclopedia of Statistical Science*. Berlin, Heidelberg: Springer Berlin Heidelberg, 2011, pp. 1094–1096. [Online]. Available: http://link.springer.com/10.1007/978-3-642-04898-2_455
- [51] J. Macqueen, “Some methods for classification and analysis of multivariate observations,” *Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability*, vol. 1, no. 233, pp. 281–297, 11 1967.
- [52] S. Ratel, C. Williams, J. Oliver, and N. Armstrong, “Effects of age and recovery duration on performance during multiple treadmill sprints,” *International journal of sports medicine*, vol. 27, no. 01, pp. 1–8, 2006.
- [53] S. Ratel, P. Duché, and C. A. Williams, “Muscle fatigue during high-intensity exercise in children,” *Sports Medicine*, vol. 36, no. 12, pp. 1031–1065, 2006.
- [54] J. Dollman, K. Norton, and L. Norton, “Evidence for secular trends in children’s physical activity behaviour,” *British Journal of Sports Medicine*, vol. 39, no. 12, pp. 892–897, 2005.
- [55] S.-J. Salvy and J. C. Bowker, “Peers and obesity during childhood and adolescence: a review of the empirical research on peers, eating, and physical activity,” *Journal of obesity & weight loss therapy*, vol. 4, no. 1, 2014.



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