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A Novel Mixed Methods Approach to Assess Children's Sedentary Behaviors

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Purpose: Accurately measuring sedentary behavior (SB) in children is challenging by virtue of its complex nature. While self-report questionnaires are susceptible to recall errors, accelerometer data lacks contextual information. This study aimed to explore the efficacy of using accelerometry combined with the Digitising Children's Data Collection (DCDC) for Health application (app), to capture SB comprehensively. **Methods**: 74 children (9–10 years old) wore ActiGraph GT9X accelerometers for 7 days. Each received a SAMSUNG Galaxy Tab4 (SM-T230) tablet, with the DCDC app installed and a specially designed sedentary behavior study downloaded. The app uses four data collection tools: 1) Questionnaire, 2) Take a photograph, 3) Draw a picture, and 4) Record my voice. Children self-reported their SB daily. Accelerometer data were analyzed using R-package GGIR. App data were downloaded and individual participant profiles created. SBs reported were grouped into categories and reported as frequencies. **Results**: Participants spent, on average, 629 min (i.e., 73% of their waking time) sedentary. App data revealed most of their out-of-school SB consisted of screen time (112 photos, 114 drawings, and screen time mentioned 135 times during voice recordings). Playing with toys, reading, arts and crafts, and homework were also reported across all four data capturing tools on the app. On an individual level, data from the app often explained irregular patterns in physical activity and SB observed in accelerometer data. **Conclusion**: This mixed methods approach to assessing SB adds context to accelerometer data, providing researchers with information needed for intervention design.

Keywords: accelerometers, activity classification, adolescents, context

Evidence suggests that sedentary behavior (SB) in children is a risk factor for adverse health outcomes (Martinez-Gomez et al., 2010; Saunders, Chaput, & Tremblay, 2014; Tremblay et al., 2011). Despite this, children spend the majority of their waking time engaged in sedentary activities (Carson, Tremblay, Chaput, & Chastin, 2016; Talarico & Janssen, 2018). Defined as any waking behavior characterized by low energy expenditure while in a seated, reclining, or lying posture (Tremblay et al., 2017), SB encompasses a diverse group of behaviors, and different types of SB have different associations with health indicators (Carson, Hunter, et al., 2016). Not only do researchers need an understanding of the amount of time spent sedentary, but also the types of behaviors and the context in which these behaviors occur, in order to design future interventions effectively. Accurate assessment of SB in children is notoriously difficult to achieve (Hardy et al., 2013; Lubans et al., 2011), due mainly to the complexity of the behavior itself.

Traditionally, self-report questionnaires (or in the case of young children, proxy-report by a parent/carer) have been used to measure SB (Atkin et al., 2012; Lubans et al., 2011). However, self- and proxy-report tools are known to be susceptible to recall errors, misrepresentations, and social desirability (Atkin et al., 2012; Hardy et al., 2013; Loprinzi & Cardinal, 2011). More recently, accelerometry has become a widely accepted device-based method of measuring SB (Atkin et al., 2012; Cain, Sallis, Conway, Van Dyck, & Calhoon, 2013). Researchers are now able to use population-specific raw acceleration cut-points to classify SB (Hildebrand, Hansen, van Hees, & Ekelund, 2016; Hurter et al., 2018) and/or the sedentary sphere method to predict the most likely posture from wrist-worn devices (Hurter et al., 2019). One of the limitations of accelerometry however, is its inability to provide any *context* about the type of behavior or settings in which the behaviors occur. Rich, contextual data would include type of activity (e.g., screen time, reading, homework etc.), whether children are alone or interacting with other people (e.g., friends, siblings, or parents/guardians) and the settings where the behaviors occur (e.g., home, car, school). Currently, direct observation is the only tool that can provide researchers with this type of information, and has successfully been used to report behaviors in restricted

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areas during short time periods (e.g., school playgrounds during break time [Roberts, Fairclough, Ridgers, & Porteous, 2013]). However, direct observation is labor intensive, expensive and not feasible in a free-living context. In adult studies, (e.g., Kim & Kang, 2019) wearable cameras have successfully been used as a criterion measure of a direct observation proxy; however, due to limited battery life, added participant burden and various ethical considerations (Kelly et al., 2013) this was not feasible for this study conducted involving children. Indeed, Lubans et al. (2011) recommend that a mix of methods be used to estimate SB in children. More recently, researchers investigating associations between SB and academic performance also called for studies to use both accelerometry and self-report tools in order to differentiate between academic-based (e.g., reading, homework) and screen-based SB (Lima, Pfeiffer, Moller, Andersen, & Bugge, 2019; Syväoja et al., 2013). According to Lima et al. (2019), a lack of contextual information has prevented researchers from evaluating the association between SB and academic performance. Moreover, researchers need to differentiate between different forms of screen time, as evidence suggests that television viewing for example is related to obesity (Stiglic & Viner, 2019), but there is currently insufficient evidence to conclude the same relationship exists with other forms of screen time (e.g., computers, video games, mobile phone use).

The present study aimed to explore the efficacy of using accelerometry in combination with a digitalized data capture tool called the Digitising Children's Data Collection (DCDC) for Health (Cooper & Dugdill, 2014), in order to capture SB more comprehensively. The DCDC application (app) was developed at the University of Salford to allow flexible data collection with primary school–aged children via tablets across multiple settings, using a mixed-methods approach. DCDC may therefore enable the capture of contextual data that is lacking when using accelerometry alone.

The app can be used within diverse settings and be used to collect data over a longer period of time than is currently possible with traditional self-report questionnaires which would require repeat administration by a researcher. While paper-based methods that ask children to recall their behavior over the previous week are typically used in a school setting, giving children a tablet enables them to report their behavior through photos, drawings, and voice recordings at home or wherever they go. Asking children to self-report their SB on a daily basis, as opposed to trying to remember what they did the previous week could reduce recall errors. Combining the DCDC app with accelerometry, this study aimed to explore whether the app can capture the rich, contextual data about children's SB that has been absent in the literature until now. Knowing *what* types of SB children engage in and the settings in which these behaviors occur, together with time spent sedentary (according to accelerometry), would help researchers identify specific behaviors to influence intervention design.

Methods

After gaining institutional research ethics approval (reference number: 17/SPS/034), 74 Year 5 children (9–11 years old, $n = 45$ girls) were recruited from four primary schools. School administration consent was obtained from the schools (e.g., school head teacher or year tutor), while parents/guardians and children signed informed consent and child assent forms respectively, prior to data collection. Parents/guardians completed demographic information forms, reporting participants' dates of birth, home postcodes, and ethnicity. The National Statistics Postcode Directory Database was used to generate UK Government 2015 Indices of Multiple deprivation (IMD) rank scores, an indication of neighborhood-level socio-economic status. IMD rank scores are reported as IMD deciles, where 1 represents the highest level of deprivation. Rolling recruitment and data collection took place between November 2017 and June 2018. The researcher had one contact session with participants in each school prior to the start of data collection, which was used for anthropometric measurements, explanation, and fitting of accelerometers and familiarization with the DCDC application on the tablet.

Anthropometrics

Body mass was measured in light clothing without shoes, to the nearest 0.1 kg using an electronic scale (Seca, Birmingham, UK). Stature and sitting height were measured to the nearest 0.1 cm using a stadiometer (Leicester Height measure; Seca, Birmingham, UK). Waist circumference was measured at the midpoint between the bottom rib and the iliac crest, to the nearest 0.1 cm using a plastic non-elastic measuring tape (Seca, Birmingham, UK). Participants self-reported their dominant hand to establish accelerometer wear site, by answering the question "Which hand do you usually write with?" Maturation were calculated using anthropometric data, participant date of birth, date of testing, and validated regression equations (Mirwald, Baxter-Jones, Bailey, & Beunen, 2002).

Sedentary Behavior

Participants wore an ActiGraph GT9X (ActiGraph LLC, Pensacola, FL) accelerometer on their non-dominant wrist, and were asked to wear it 24 $hr{\cdot}d^{-1}$ for seven consecutive days. They were instructed to remove the monitor only for water-based activities (e.g., swimming, bathing) or contact sports (e.g., rugby). Participants were given a log sheet (paper based) to record any times and reasons they removed the monitors.

Each participant also received a Samsung Galaxy Tab4 (SM-T230) tablet, with the DCDC for Health app installed (Cooper & Dugdill, 2014). Each tablet had a unique asset number, enabling the researcher to link the data captured by each tablet to the relevant participant. The DCDC for Health consists of two applications, a Supporting Server Application (SSA) and a Tablet application (TA). The SSA (a remotely installed web application) allows researchers to design and build their own studies, using a mixed-methods approach. Further, the SSA manages and stores data flowing to and from the TAs. Prior to data collection, the first author designed and built a SB study using the SSA, and downloaded the study onto the TA on each Samsung tablet. In order to prevent children from using the tablets for longer than necessary, only the DCDC app was accessible, with all other applications password protected. Internet access was also blocked, preventing children from accessing unsuitable content online.

The app uses four types of data collection tools: 1) answer some questions (a questionnaire tool), 2) take and explain a photograph, 3) draw and explain a picture, and 4) record my voice. Participants were asked to open the app once per day (suggested as towards the end of the day) and report their SB, by answering the questions in each tool. Once one of the tools were opened and answered, that tool was greyed out and the child could only access it again the next day. The first tool, "Answer some questions", consisted of six multiple-choice questions regarding behaviors outside of school time. The questions were adapted from the SB section of the Youth Activity Profile (Saint-Maurice & Welk, 2015). The second tool, "Take a photograph", asked the child "Can you take a photograph of any activities you did while sitting or lying down today?", and allowed a photo to be taken with the tablet's built-in camera. Children were instructed not to take any photographs of people, but rather of places/settings they spent time in. After taking a photo, children were given the option to save their photo and either to write something about their photo or describe their photo with a voice recording. The "Draw a picture" tool asked children the question: "Can you draw a picture of any activity you did while sitting or lying down today?" Children used their fingers to draw on the screen, and could choose between different brush sizes and colors. Once saved, they were given the opportunity to write or talk (record their voice) about their drawing. Finally, the "Record your voice" tool asked participants to answer two questions: "Can you tell us what you did this morning?" and "Can you tell us what you did this afternoon?" During the familiarization session, children were instructed to answer these questions by reflecting on their out-of-school time (i.e., in the mornings before school, and afternoons after school). A short video with a more detailed explanation of how the app works can be viewed *here.*

After seven days of data collection, all tablets, accelerometers, and log sheets were returned to school for collection. The results synchronized automatically with the SSA when connected to WiFi. Once synchronized, the study could be downloaded again for the next round of participants using the same tablets but with new participant numbers. Audio files from voice recordings were transcribed verbatim. Participant profiles were created for each participant using a template, with their photos, drawings, voice recordings, and multiple-choice answers, all of which were time and date stamped. For each tool, activities photographed, drawn, or mentioned by the participants in voice recordings were grouped into different categories for analysis (e.g., television, computer/laptop, reading, playing with toys) and reported as frequencies. Whenever a photo, drawing, or recording was unclear, researchers referred to the data from the other tools on that particular day and for most of the time, this triangulation of data clarified the uncertainty.

Accelerometer Data Processing and Analysis

The ActiGraph accelerometers were initialized to collect data at 100Hz. After each data collection session, the 7-day files were downloaded using ActiLife (version 6.13.3) software, saved in raw format as .gtx3 files and converted to time-stamped .csv files and analyzed using R package GGIR (version 1.6-7). GGIR is an open source R package developed to generate physical activity outcomes from raw accelerometer data (Migueles, Rowlands, Huber, Sabia, & Van Hees, 2019) and was used as described by Rowlands, Edwardson, et al. (2018). As the participants kept the monitors on while sleeping, researchers used GGIR to report the full 24-hour activity behavior profiles, which include the following: time in bed (sleep), time spent sedentary per day (threshold defined as waking time accumulated below 50 m*g* [Hurter et al., 2018]), moderate to vigorous intensity physical activity (MVPA) per day (defined as time accumulated above 200 m*g* [Hildebrand, Van Hees, Hansen, & Ekelund, 2014]), average acceleration across the day (ENMO, m*g*), and intensity gradient. The intensity gradient is a recently published (Rowlands, Edwardson, et al., 2018) accelerometer metric describing the intensity distribution of physical activity over the 24-hour day. All outcomes were broken down into weekdays, weekend days, and whole week data. Inclusion criteria for raw data analysis were at least 16 hours of wear time per day (Rowlands, Mirkes, et al., 2018) for at least four days (including at least one weekend day) (Trost, Pate, Freedson, Sallis, & Taylor, 2000).

Differences between boys and girls, weekday and weekend data were examined using paired *t*-tests and effect sizes calculated as Cohen's *d* (Cohen, 1988) with 0.2, 0.5, and 0.8 defined as small, medium, and large effects, respectively. Analysis was completed using IBM SPSS Statistics v.24 (IBM, Armonk, NY) with level of statistical significance set at $p < .05$ and Microsoft Excel 2016 (Microsoft, Redmond, WA).

Results

Descriptive characteristics of all participants are presented in Table 1, while Figure 1 is a flow diagram showing participants included and excluded from each step of the analysis. Compliance from the 65 participants included in the raw acceleration data analysis was high with 52 (80%) full datasets (i.e., seven valid days), nine consisting of six valid days, three with five valid days each and one dataset of four valid days. Children mostly removed the monitors when taking a bath or shower, swimming, or for sports like rugby, gymnastics, or martial arts.

Table 2 shows results from the accelerometer data analysis, separated into weekdays and weekend days, while Table 3 shows differences between boys and girls. Participants spent, on average, 629 min (almost 10.5 hours) of their waking time per day sedentary. Time spent sedentary on weekend days was significantly higher than weekdays (652 min ± 78.27 vs 619.88 min ± 57.11; $p <= .001$; Cohen's $d = 0.47$). There were no significant differences found between boys' and girls' sedentary times (weekdays: $p = .58$,

Table 1 Descriptive Characteristics for All Participants Expressed in Means (*SD*)

	Boys ($n = 29$)	Girls ($n = 45$)	All ($n = 74$)
Age (years)	9.9 (0.4)	10 (0.4)	10 (0.4)
Height (cm)	140.8 (9.6)	139.8 (6.9)	140.2 (8.1)
Body mass (kg)	37.8 (12.5)	36.6 (8.5)	37.1 (10.2)
BMI (kg/m^2)	18.6 (4.0)	18.6 (3.2)	18.6 (3.5)
Overweight* (*n*, %)	6 (20.7%)	10 (22.2%)	16 (21.6%)
Obese* (*n*, %)	4 (13.8%)	3 (6.6%)	7 (9.5%)
Waist circumference (cm)	65.7 (10.2)	65.5 (8.2)	65.6 (8.9)
APHV† (years)	13.5 (0.6)	11.7 (0.4)	12.5 (0.9)
Maturity offset	−3.6 (0.7)	−1.7 (0.5)	−2.5 (1.1)
Ethnicity (*n*, %)			
White (UK)			53 (71.6)
Mixed			13 (17.6)
White (other)			3 (4.1)
Chinese			4 (5.4)
Asian (Indian)			1 (1.4)
SES¥			3 (2.6)

Note. BMI indicates body mass index; SES = socio-economic status. *Age and sex-specific BMI cut points used to classify children as overweight / obese (Cole, Bellizzi, Flegal, & Dietz, 2000). †Age at Peak Height Velocity. ¥SES is measured by the Index of Multiple Deprivation decile score, where 1 is the most deprived and 10 the least deprived.

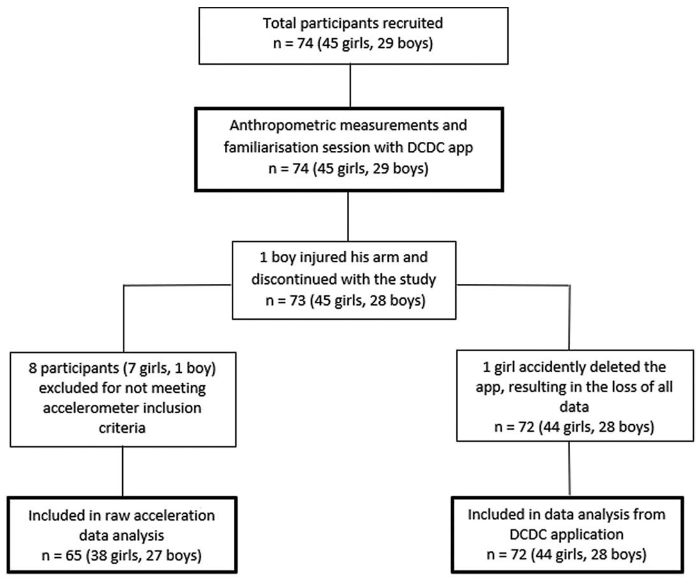

Figure 1 — Flow diagram of participants.

weekends: $p = .78$). Results from the intensity gradient metric showed a significantly lower (steeper) gradient over weekends compared to weekdays ($p < .001$, $d = 0.96$). On average, girls had significantly lower (steeper) intensity gradients than boys (whole week: $p = .001$, $d = 0.9$; weekdays: $p = .001$, $d = 0.88$; weekend days: $p = .009$, $d = 0.7$).

Contextual data provided by 72 participants via the app were included in the analysis. Only nine children had full datasets (i.e. their results included seven photos, seven drawings, 14 voice recordings, and the multiple choice questionnaire answered on all seven days). One of the full datasets, however, had 10 blank audio files (from the "Record my voice" tool).

The first data capturing tool, "Answer some questions", was the preferred option of the four methods, with participants answering at least some of the questions on average 5.3 ($SD = 1.7$) days during the 7-day period of data collection. The different questions were answered between 377 and 383 times by the participants (out of a possible 504). The app allows participants to go to the next question without answering the one on their screen; therefore, not all questions were answered the same number of times.

Results from this tool are displayed in Supplemental Tables S1–S3 (available online). Supplemental Table S1 (available online) shows the number of days each answer was given, broken down into weekdays and weekend days, while Supplemental Table S2 (available online) shows the differences between boys' and girls' answers (in number of days). Supplemental Table S3 (available online) shows only the answers from screen-based behaviors, specifically how many participants chose each answer, and its weekly average. Results indicated an increased amount of television viewing on weekend days compared to weekdays (Supplemental Table S1 [available online]), with a 10% reduction in the number of children reporting not watching any TV during weekend days (25%) as opposed weekdays (35%). The same trend was observed for playing video games, with all answers indicating an increased amount of time playing video games during weekend days. Children reported not using a computer at all on 244 days (63.9%) and not using a mobile phone at all on 242 (63.4%) of days (Supplemental Table S3 [available online]). There was limited active travel on school days with the majority of participants in this study traveling to school by car (59.9% of days reported). The biggest difference between boys and girls was observed in playing video games (Supplemental Table S2 [available online]). Boys reported on 12.2% of days (17/139) to have spent more than three hours playing video games, as opposed to girls reporting the same behavior on only 2.5% of days (6/243).

Participants took 300 photos during the study. 142 of the photos had written text attached, while 37 had voice recordings, explaining what the photo was about. Despite being instructed not to take photos of people, 29 photos had to be subsequently "blurred", as faces were recognizable. However, 10 of these were useable within the analysis as their comments explained the context of the photo, resulting in 281 photos used in the analysis. On average, participants took photos on four of the seven data collection days. Even though the question clearly asked to take a photo of an activity they did while *sitting* or *lying down*, participants often chose to take photos of any activity they did during the day, not only sedentary activities. However, the majority of photos (68%) were taken of various sedentary activities, with screen time the most frequently photographed behavior. A total of 110 photos (39%) were taken of different screens including televisions (35 photos by 14 girls and 8 boys), video game consoles like an Xbox or PlayStation (27 photos by 6 girls and 9 boys), tablets (21 photos by 7 girls and 3 boys), computers / laptops (13 photos by 6 girls and 1 boy), and mobile phones (12 photos by 11

Table 2 Sedentary Behavior and Physical Activity Outcomes for Weekday and Weekend Data ($n = 65$)

	Weekday Data		Weekend Data		Whole Week (Weighted Week)	
	Mean Minutes (*SD*)	95% CI	Mean Minutes (*SD*)	95% CI	Mean Minutes (*SD*)	95% CI
Mean ENMO [m*g*]	49.73 (15.47)	45.89–53.56	36.58 (17.56)	32.23–40.94	45.91 (15.23)	42.14–49.69
Sleep	563.17 (40.98)	553.02–573.33	556.36 (55.26)	542.67–570.05	561.19 (37.77)	551.84–570.56
Sedentary time*	619.88 (57.11)	605.73–634.03	652.0 (78.27)†	632.61–671.4	629.19 (51.28)	616.49–641.90
LPA	172.64 (29.65)	165.28–180.0	155.36 (46.65)	143.8–166.92	167.63 (30.01)	160.19–175.07
MPA	48.18 (14.63)	44.56–51.81	41.74 (22.97)	36.05–47.44	46.31 (15.56)	42.46–50.17
VPA	13.05 (7.49)	11.19–14.90	8.56 (9.33)	6.25–10.87	11.74 (7.64)	9.85–13.64
MVPA	61.24 (20.74)	56.1–66.38	50.29 (30.96)	42.63–57.97	58.06 (22.03)	52.61–63.52
Intensity regression line						
Intensity gradient	-1.96 ± 0.14		-2.11 ± 0.17		-2.01 ± 0.13	

Note. 95% CI indicates 95% confidence interval; ENMO = average acceleration across the day; LPA = low physical activity; MPA = moderate physical activity; VPA = vigorous physical activity; MVPA = moderate to vigorous physical activity. *Threshold = <50m*g*. †Significantly higher than weekday data.

Table 3 Sedentary Behavior and Physical Activity Outcomes for Boys (27) and Girls (38)

	Weekday data, *M* (*SD*)		Weekend data, *M* (*SD*)		Whole week (weighted week), *M* (*SD*)	
	Boys	**Girls**	**Boys**	**Girls**	**Boys**	**Girls**
Mean ENMO [m*g*]	57.56 (16.86)	43.95 (11.63)	42.4 (22.22)	32.45 (12.0)	53.08 (17.64)	40.62 (10.71)
Sleep	560.5 (35.9)	565.07 (44.62)	548.46 (50.43)	561.97 (58.46)	557.01 (31.35)	564.17 (41.9)
Sedentary time*	614.45 (40.38)	623.03 (66.88)	655.43 (86.24)	649.57 (73.18)	627.04 (43.96)	630.72 (56.44)
LPA	172.52 (33.86)	172.73 (26.83)	155.63 (49.82)	155.18 (44.95)	167.62 (32.82)	167.64 (28.31)
MPA	53.99 (14.59)	44.06 (13.37)	48.28 (27.6)	39.09 (18.0)	52.34 (16.67)	42.04 (13.36)
VPA	17.23 (8.28)	10.08 (5.19)	11.64 (12.51)	6.37 (5.38)	15.61 (9.07)	9.0 (4.94)
MVPA	71.23 (21.02)	54.13 (17.59)	59.91 (38.27)	43.47 (22.66)	67.95 (24.17)	51.04 (17.52)
Intensity regression line						
Intensity gradient	−1.89 (0.11)†	−2.01 (0.14)	−2.05 (0.18)†	−2.16 (0.15)	−1.94 (0.12)†	−2.05 (0.12)

Note. M (*SD*) indicates mean (standard deviation); ENMO = average acceleration across the day; LPA = low physical activity; MPA = moderate physical activity; VPA = vigorous physical activity; MVPA = moderate to vigorous physical activity. *Threshold = <50m*g*. †Significantly lower than girls.

girls). Often the voice recordings or written text attached to the photos provided more detail, like a photo of a TV screen with the following attached: "While eating my breakfast I watched YouTube" (P28).

Other types of SBs photographed include playing with toys (24 photos by 11 girls and four boys), reading books (17 photos by seven girls and eight boys), followed by 13 photos from eight girls and two boys of a bed/couch, arts and crafts (13 photos by nine girls and one boy), and homework (nine photos from six girls). As stated earlier, sometimes children reported other non-sedentary types of behaviors. Most notably were 19 photos (by five girls and five boys) related to physical activities they participated in during that day (e.g. swimwear, a bicycle, a park or a garden with a football).

From the "Draw a picture" tool, 333 drawings were downloaded, with written text attached to 174 and voice recordings attached to 24 drawings. Twenty-five of the drawing files were blank, leaving 308 drawings for analysis. As with the photos, participants often chose to ignore the question and drew any activity they took part in, including 40 drawings (by seven girls and six boys) related to physical activity. Again, screen time was the most reported sedentary activity, with 114 (37%) drawings depicting screen-based behaviors. These included 43 drawings of television viewing (by 17 girls and seven boys), 27 drawings of playing video games (by three girls and nine boys), 17 drawings of spending time on a mobile phone (by seven girls and two boys), 14 drawings of playing with a tablet (by six girls and two boys), and 13 drawings of a computer/laptop (by seven girls and one boy). Other after-school sedentary activities included reading (10 by eight girls and one boy), playing with toys (11 by six girls and two boys), arts and crafts (11 by eight girls and one boy), spending time on the bed/couch (six by six girls), playing a musical instrument (four by four girls), sitting in the car (three by two girls and one boy) or church (three by two girls and one boy), and doing homework (three by two girls and one boy). Figure 2 shows some examples from the "Take a photo" and "Draw a picture" tools.

The "Record your voice" tool yielded 550 recordings made over a total of 278 days. Thirteen files were blank and one corrupted, leaving 536 recordings used in the analysis. This was the least preferred method for the participants to use, recording their voices on average 3.79 ($SD = 2.45$) days per week. As with the other data collection tools, screen time was the most frequently reported activity, with participants mentioning it 154 times. While

Figure 2 — Examples of photos taken and drawings made by participants.

these were mainly reported in the afternoon (92 instances), except for one incidence of homework, screen time was also the only sedentary activity mentioned on weekday mornings (66 instances). Children reported watching television a total of 68 times, while other forms of screen time (video games [29], computer / laptop [29], tablet [21], and mobile phone [7]) were mentioned 86 times. As with the photos and drawings, girls reported these activities more often than boys, except for playing video games, which was mentioned 29 times by 12 boys and only three girls.

The question "Can you tell us what you did this morning?", as expected, produced little variety during weekdays, with participants talking about their morning routines which included getting up, having breakfast, getting dressed and ready for school, brushing their teeth, and going to school. Thirteen participants reported screen time on weekday mornings, with two of them mentioning it on all five weekday mornings and one on four weekday mornings. For these participants, the screen time seemed part of their morning routines. For example: "This morning I had breakfast while on my laptop, got changed while on the laptop. Then I got off the laptop to brush my teeth . . ." (P59). The "Record your voice" tool often provided the researchers with rich, contextual information. A discrete case study demonstrating this type of data from the app, adding context to sedentary time according to the accelerometer, is presented below.

Case Study 1: Participant 7 (Girl, P7)

On a Saturday evening at 20:12, P7 answered the question "Can you tell us what you did this afternoon?" with the following voice recording: "When I came back from ballet, I played Minecraft. Then [Participant 4] came to visit. We played IQ puzzler, Dobble, and I showed her my ballet. Then when she went home I played on my computer for a little while, bathed, ate dinner, and played Minecraft a little. Then brushed my teeth and went to bed." In this one recording, there is evidence of physical activity (ballet), video games (Minecraft), games/toys (IQ puzzler and Dobble), and computer time all within one afternoon. Accelerometer data revealed that despite an hour's ballet lesson, P7 only engaged in 50 minutes of MVPA that day, while 652 min were spent sedentary. Not all children, however, gave such detailed accounts of their day. Participant 4's voice recording from the same afternoon simply stated: "I went to [P7's] house."

The combination of accelerometer data, log sheets, as well as the different data capturing tools via the app allowed the researcher to triangulate data, resulting in a clearer picture of the participants' behavior across the whole week. Following are two case studies, chosen to show how the app sometimes provided clarity around 'irregular' accelerometer data.

Case Study 2: Participant 32 (Boy, P32)

Accelerometer data showed high levels of sedentary time on most weekdays (around 720 min, or 12 hours per day) and even higher on weekend days (818 min, or 13.6 hours per day). Data from the app showed that he spent almost all of his free time playing video games, with six photos of his laptop, accompanied by written descriptions of the games he played as well as one photo of a games console. He also drew five pictures of himself sitting in front of his laptop and all 14 voice recordings were about his games, for example "This afternoon I was also playing games, which means I'm a gamer" and "This afternoon I was also playing games, you know, I am always playing games." Despite this, he still managed to meet the recommended guidelines for physical activity (60 minutes of MVPA per day) on all four weekdays included in the analysis (mean of 72.2 minutes per day), but his MVPA levels dropped significantly over the weekend (mean of only 16 minutes per day). On Friday, however, his sedentary time dropped to 467 min (7.7 hours) per day, with 82.75 minutes of MVPA according to the accelerometer. That evening he drew a picture of four stick men and a bicycle lying next to them and wrote: "I was going with my friends outside and I had a great time!" As he meets the recommended guidelines for physical activity, without the contextual data from the app, we would not have understood how much time he spent in screen-based sedentary pursuits. In this case, intervention design should focus on replacing some of his video gaming time with more opportunities to play outside with friends.

Case Study 3: Participant 2 (Girl, P2)

On most days, P2 exceeded the government guidelines for physical activity with a mean MVPA of 70 minutes/day, except for Wednesday and Thursday when her activity levels dropped to 30 minutes of MVPA per day, together with an increase in sedentary time. On Wednesday she drew a picture of herself in bed and wrote "I was lying in my bed." On Thursday she took a photo of her bed and wrote "I was in my bed." She also drew a picture of herself in front of the television and wrote "I was watching the TV at my Nanna's house." Voice recordings revealed how she started feeling ill on Wednesday morning (". . . felt a little bit achy . . .") before going to school. Wednesday evening she reported how she felt worse: "This afternoon I got home from school and I got my pajamas on because I was feeling a lot achy. . . ." On Thursday, she reported that they dropped her siblings off at school after which she went home and watched television. In the afternoon, she went to her Nanna's and watched television until her mum came to pick her up. Without the context from these photos, drawings and recordings, data from the accelerometer alone would have led the researchers to identify P2 as a child not meeting the recommended government guidelines for physical activity (as on two days her MVPA fell well below the recommended 60 minutes per day). When we exclude the two days she was ill, her mean MVPA level was 70 minutes per day and her sedentary time only 542 min per day (i.e., 87 minutes less than the group mean). Thus, contextual data from the app allowed us to classify her as a typically sufficiently active child spending much less time than her peers in sedentary pursuits.

Discussion

The aim of the study was to explore whether a digitalized data capture tool in combination with accelerometry could capture SB more comprehensively, by adding contextual data to sedentary time derived according to accelerometers. Results from this study showed that on average, the participants spent more than 10 hours per day (629 min) in sedentary pursuits. This result, however, is according to an intensity threshold (50m*g*) unable to distinguish between postures. Therefore, it is likely to overestimate sedentary time by about 5% (Hurter et al., 2019) as it will likely include time spent standing still. It has recently been suggested that the term *stationary time* is more accurate when describing time spent below this threshold (Freedson, 2018). According to data from the app, most of our participants' out of school SB was spent using a variety of screens. The observed increases in television viewing and video gaming over weekends could explain the increased amount of sedentary time observed in the accelerometer data during this period. On weekend days, the participants engaged in these behaviors long enough to exceed the equivalent time spent sitting in school on weekdays.

Participants' increased sedentary time and decreased MVPA observed over weekends is consistent with findings from previous studies (Biddle, Gorely, Marshall, & Cameron, 2009; Brooke, Corder, Atkin, & van Sluijs, 2014). While boys engaged in significantly higher levels of MVPA compared to girls (also consistent with previous literature [Hallal et al., 2012]), there were no significant differences found in their sedentary times. The steeper intensity gradient observed in girls indicates that they have a poorer intensity profile, with less time spent across the intensity range compared with boys. A recent study showed that a higher (shallower) intensity profile, as observed in the boys, is associated with favorable changes in health indicators (Fairclough, Taylor, Rowlands, Boddy, & Noonan, 2019).

Data from the DCDC app added context to the accelerometry results, illustrating various forms of screen time as the main behavior reported across all four data capturing tools. These include television viewing, video game consoles, tablets, computers/laptops, and mobile phones. Results from the multiple choice questionnaire revealed that on 64% of days, the participants reported not using a computer at all, suggesting that for participants within this age group, SB does not comprise of much computer time. From the amount of days children reported not using a mobile phone at all (63%), it can perhaps be assumed that most participants did not yet own their own mobile phones. However, 45 (62.5%) participants reported that on at least one day that they had used a mobile phone. It is unknown whether they used their own, or parent's/carer's/other adult's phone.

Photos, drawings, and voice recordings revealed that, for these participants, television viewing was not children's main screen-based activity. Watching YouTube videos, playing online games like Roblox or Fortnite, watching movies (on tablets or laptops), and talking with friends (online via social media) were activities most frequently reported by participants. This trend, showing a decreased amount of TV viewing with increasingly higher usage of other screen-based devices is consistent with results from a recent review of studies (Schaan et al., 2019). Across all photos, drawings, and voice recordings, girls reported using these devices more frequently than boys, except for playing video games, suggesting that for boys video gaming was their preferred screen-based activity. A recent study by Perrino, Brincks, Lee, Quintana, and Prado (2019) confirms this gender-based difference, with girls engaged in types of screen time more likely to involve social contact and communication. This is an important finding, suggesting that interventions aiming to reduce screen use should be targeted differently for boys and girls. Furthermore, Suchert, Hanewinkel, Isensee, and läuft Study Group (2015) found that screen-based SBs had different associations with mental health indicators in boys versus girls. For example, higher screen-based SBs were associated with lower self-esteem in girls, but higher self-esteem in boys. This finding is likely the result of boys mainly playing video games (as observed in the present study), during which they master new challenges accompanied by a sense of achievement, while girls spend time on social media, often comparing themselves to unrealistic images of female body ideals (Suchert et al., 2015). Interventions designed to reduce some of the time boys spend playing video games, should aim to replace the behavior with PAs that might have a similar outcome (e.g., an obstacle course that increases in levels of difficulty). Girls, on the other hand, might benefit from PA interventions that allow them to socialize with their friends, therefore replacing their time spent on social media by spending time with peers in real life, who are less likely to portray unrealistic body ideals.

Playing with toys, reading, arts and crafts, and homework were the only other sedentary activities reported across all data capturing tools. However, these behaviors would probably not be targeted during interventions aiming to reduce SB due to their positive association with academic achievement (Carson, Hunter, et al., 2016). While summarizing the results from the app on group level proved to be difficult, the main strength of the method lies on the individual level. Despite not having full compliance by way of full datasets, most participants still provided the researchers with contextual data beyond what the accelerometer alone can offer. The app allowed participants to choose their preferred method of reporting their behavior. While some children mainly took photos, others chose to draw pictures or record their voices. The app often complemented the objective data, by helping to explain the patterns of sedentary behavior and physical activity observed.

One of the strengths of the app is that children only have to recall their behavior from that specific day, which should minimize recall errors. Self-report use-of-time tools like MARCA or PDPAR (Foley, Maddison, Olds, & Ridley, 2012) have successfully been used to report *previous* day behaviors of children; however, most focus on PA with limited information gathered regarding SB. Children might be able to choose from a selection of screen time activities (TV, video games, computer use, etc.), but with the fast-paced technological advances and children's increased access to screen-based devices, more details are required. For example, data from the app showed the current popularity of watching YouTube videos and playing Fortnite, which provides useful information when attempting to understand children's SBs and when designing interventions targeting reductions in SB.

Another strength of the app was that the four tools complemented each other. For example, sometimes a photo in itself was not clear, but the recordings clarified it or the other way around. Using only one or two of the four tools would not have given the same amount of depth and would most likely have resulted in unclear photos or drawings being discarded. This type of data triangulation, together with the direct measurement of sedentary time using accelerometers is effective in more comprehensively describing individual children's physical behavior over the seven days of data collection. This, however, is only possible in cases where the child complies with the task. For example, P4's account of her afternoon ("I went to [P7's] house") is far less comprehensive than P7's description of the same period, highlighting the individual variation in reporting.

The method also has other limitations that require consideration. Typically, the researchers were given between 40 and 60 minutes with the participants to complete anthropometric measurements, fit and explain accelerometers, as well as familiarize the participants with the app. Classrooms were busy, with both participants and non-participants in attendance. This limited the time available for children to be familiarized with the app and to ask questions. While the questions on the app asked about sedentary activities only (except for the "Record your voice" tool), children often chose to ignore the question, giving an unrelated answer. Most often, these answers were related to physical activity and while that was not the main purpose, it still provided the researcher with contextual information about the 24-hour movement profile and highlights the potential of the app to be used in future studies to add context to both physical activity and SB. Some data collection sessions took place close to Christmas, which resulted in a lot of photos, drawings and voice recordings about things like Christmas trees and festive activities. Though participants were engaging with the tool, this generated a considerable amount of irrelevant data. Future studies may wish to develop an online video explaining the tool and study that could also be shown in class detailing the necessary information. We also recommend that in future, software developers consider adding an interactive feature to the app, making it possible for the researcher to communicate with participants (via the app) during the data collection period, specifically in cases where a participant is not complying with the task. However, for the researcher to monitor incoming results from the Tablet Application to the Supporting Server Application, an internet connection would be needed and there are a number of ethical considerations to take into account. While we are confident that this method reduced recall errors, we acknowledge that some degree of recall is required, and that especially the question regarding their time spent in the mornings before school, might have been affected by recall errors. Finally, our aim was not to specifically assess the validity of the app or sections of the app for measuring SB; however, future studies may investigate this.

Conclusions

This study combined accelerometry with a mixed-method digitalized self-report data capturing tool (app), and captured children's SB comprehensively. Various forms of screen time were identified as activities that need to be targeted in future interventions, with a distinct difference observed between boys' and girls' preferences. Gender-specific interventions are needed when aiming to reduce children's SB. On an individual level, the app added context to accelerometer data, often explaining irregular physical activity and SB patterns. It might be used in studies prior to intervention, in order to identify specific behaviors to be targeted or during evaluation to observe any changes in reported behaviors. The app can potentially be used in future studies to add rich, contextual information about the whole 24-hour movement continuum, that has been absent in the literature until now.

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References

Atkin, A.J., Gorely, T., Clemes, S.A., Yates, T., Edwardson, C., Brage, S., . . . Biddle, S.J. (2012). Methods of measurement in epidemiology: Sedentary behaviour. *International Journal of Epidemiology, 41*(5), 1460–1471. PubMed ID: 23045206 doi:10.1093/ije/dys118

Biddle, S.J., Gorely, T., Marshall, S.J., & Cameron, N. (2009). The prevalence of sedentary behavior and physical activity in leisure time: A study of Scottish adolescents using ecological momentary assessment. *Preventive Medicine, 48*(2), 151–155. PubMed ID: 19046984 doi:10.1016/j.ypmed.2008.10.025

Brooke, H.L., Corder, K., Atkin, A.J., & van Sluijs, E.M. (2014). A systematic literature review with meta-analyses of within- and between-day differences in objectively measured physical activity in school-aged children. *Sports Medicine, 44*(10), 1427–1438. PubMed ID: 24981243 doi:10.1007/s40279-014-0215-5

Cain, K.L., Sallis, J.F., Conway, T.L., Van Dyck, D., & Calhoon, L. (2013). Using accelerometers in youth physical activity studies: A review of methods. *Journal of Physical Activity and Health, 10,* 437–450. PubMed ID: 23620392 doi:10.1123/jpah.10.3.437

Carson, V., Hunter, S., Kuzik, N., Gray, C.E., Poitras, V.J., Chaput, J.P., . . . Tremblay, M.S. (2016). Systematic review of sedentary behaviour and health indicators in school-aged children and youth: An update. *Applied Physiology, Nutrition and Metabolism, 41*(6 Suppl. 3), S240–S265. doi:10.1139/apnm-2015-0630

Carson, V., Tremblay, M.S., Chaput, J.P., & Chastin, S.F. (2016). Associations between sleep duration, sedentary time, physical activity, and health indicators among Canadian children and youth using compositional analyses. *Applied Physiology, Nutrition, and Metabolism, 41*(6 Suppl. 3), S294–S302. PubMed ID: 27306435 doi:10.1139/apnm-2016-0026

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed., p. 413). Hillsdale, NJ: Lawrence Erlbaum Associates.

Cole, T.J., Bellizzi, M.C., Flegal, K.M., & Dietz, W.H. (2000). Establishing a standard definition for child overweight and obesity worldwide: International survey. *British Medical Journal, 320,* 1240–1243. PubMed ID: 10797032 doi:10.1136/bmj.320.7244.1240

Cooper, A.M., & Dugdill, L. (2014). *DCDC: Digitising children's data collection (version 2.x)* [mobile application software]. Salford, UK: University of Salford.

Fairclough, S.J., Taylor, S., Rowlands, A.V., Boddy, L.M., & Noonan, R.J. (2019). Average acceleration and intensity gradient of primary school children and associations with indicators of health and well-being. *Journal of Sports Sciences, 37*(18), 2159–2167. PubMed ID: 31156048 doi:10.1080/02640414.2019.1624313

Foley, L., Maddison, R., Olds, T., & Ridley, K. (2012). Self-report use-of-time tools for the assessment of physical activity and sedentary behaviour in young people: Systematic review. *Obesity Reviews, 13*(8), 711–722. PubMed ID: 22429291 doi:10.1111/j.1467-789X.2012.00993.x

Freedson, P. (2018). Can sedentary and stationary time be accurately assessed with wrist- and hip-worn accelerometers? *Journal for the Measurement of Physical Behaviour, 1,* 157–158. doi:10.1123/jmpb.2018-0072

Hallal, P.C., Andersen, L.B., Bull, F.C., Guthold, R., Haskell, W., & Ekelund, U. (2012). Global physical activity levels: Surveillance progress, pitfalls, and prospects. *The Lancet, 380*(9838), 247–257. doi:10.1016/S0140-6736(12)60646-1

Hardy, L.L., Hills, A.P., Timperio, A., Cliff, D., Lubans, D., Morgan, P.J., . . . Brown, H. (2013). A hitchhiker's guide to assessing sedentary behaviour among young people: Deciding what method to use. *Journal of Science and Medicine in Sport, 16*(1), 28–35. PubMed ID: 22749939 doi:10.1016/j.jsams.2012.05.010

Hildebrand, M., Hansen, B.H., van Hees, V.T., & Ekelund, U. (2016). Evaluation of raw acceleration sedentary thresholds in children and adults. *Scandinavian Journal of Medicine & Science in Sports, 27,* 1814–1823. PubMed ID: 27878845 doi:10.1111/sms.12795

Hildebrand, M., Van Hees, V.T., Hansen, B.H., & Ekelund, U. (2014). Age group comparability of raw accelerometer output from wrist- and hip-worn monitors. *Medicine & Science in Sports & Exercise, 46*(9), 1816–1824. PubMed ID: 24887173 doi:10.1249/MSS.0000000000000289

Hurter, L., Fairclough, S.J., Knowles, Z.R., Porcellato, L.A., Cooper-Ryan, A.M., & Boddy, L.M. (2018). Establishing raw acceleration thresholds to classify sedentary and stationary behaviour in children. *Children, 5*(12), pii: E172. doi:10.3390/children5120172

Hurter, L., Rowlands, A.V., Fairclough, S.J., Gibbon, K.C., Knowles, Z.R., Porcellato, L.A., . . . Boddy, L.M. (2019). Validating the Sedentary Sphere method in children: Does wrist or accelerometer brand matter? *Journal of Sports Sciences, 37*(16), 1910–1918. PubMed ID: 31012798 doi:10.1080/02640414.2019.1605647

Kelly, P., Marshall, S.J., Badland, H., Kerr, J., Oliver, M., Doherty, A.R., & Foster, C. (2013). An ethical framework for automated, wearable cameras in health behavior research. *American Journal of Preventive Medicine, 44*(3), 314–319. PubMed ID: 23415131 doi:10.1016/j.amepre.2012.11.006

Kim, H., & Kang, M. (2019). Validation of sedentary behavior record instrument as a measure of contextual information of sedentary behavior. *Journal of Physical Activity & Health, 16*(8), 623–630. PubMed ID: 31310998 doi:10.1123/jpah.2018-0645

Lima, R.A., Pfeiffer, K.A., Moller, N.C., Andersen, L.B., & Bugge, A. (2019). Physical activity and sedentary time are positively associated with academic performance: A 3-year longitudinal study. *Journal of Physical Activity & Health, 16*(3), 177–183. PubMed ID: 30696322 doi:10.1123/jpah.2017-0587

Loprinzi, P.D., & Cardinal, B.J. (2011). Measuring children's physical activity and sedentary behaviors. *Journal of Exercise Science & Fitness, 9*(1), 15–23. doi:10.1016/S1728-869X(11)60002-6

Lubans, D.R., Hesketh, K., Cliff, D.P., Barnett, L.M., Salmon, J., Dollman, J., . . . Hardy, L.L. (2011). A systematic review of the validity and reliability of sedentary behaviour measures used with children and adolescents. *Obesity Reviews, 12*(10), 781–799. PubMed ID: 21676153 doi:10.1111/j.1467-789X.2011.00896.x

Martinez-Gomez, D., Eisenmann, J.C., Gomez-Martinez, S., Veses, A., Marcos, A., & Veiga, O.L. (2010). Sedentary behavior, adiposity and cardiovascular risk factors in adolescents. The AFINOS study. *Revista Española de Cardiología, 63*(3), 277–285. doi:10.1016/S0300-8932(10)70086-5

Migueles, J.H., Rowlands, A.V., Huber, F., Sabia, S., & Van Hees, V.T. (2019). GGIR: A research community-driven open source R package for generating physical activity and sleep outcomes from multi-day raw accelerometer data. *Journal for the Measurement of Physical Behaviour, 2,* 188–196. doi:10.1123/jmpb.2018-0063

Mirwald, R.L., Baxter-Jones, D.G., Bailey, D.A., & Beunen, G.P. (2002). An assessment of maturity from anthropometric measurements. *Medicine & Science in Sports & Exercise, 34*(4), 689–694. PubMed ID: 11932580

Perrino, T., Brincks, A., Lee, T.K., Quintana, K., & Prado, G. (2019). Screen-based sedentary behaviors and internalizing symptoms across time among U.S. Hispanic adolescents. *Journal of Adolescence, 72,* 91–100. PubMed ID: 30877842 doi:10.1016/j.adolescence.2019.02.014

Roberts, S.J., Fairclough, S.J., Ridgers, N.D., & Porteous, C. (2013). An observational assessment of physical activity levels and social behaviour during elementary school recess. *Health Education Journal, 72*(3), 254–262. doi:10.1177/0017896912439126

Rowlands, A.V., Edwardson, C.L., Davies, M.J., Khunti, K., Harrington, D.M., & Yates, T. (2018). Beyond cut points: Accelerometer metrics that capture the physical activity profile. *Medicine & Science in Sports & Exercise, 50*(6), 1323–1332. PubMed ID: 29360664 doi:10.1249/MSS.0000000000001561

Rowlands, A.V., Mirkes, E.M., Yates, T., Clemes, S., Davies, M., Khunti, K., & Edwardson, C.L. (2018). Accelerometer-assessed physical activity in epidemiology: Are monitors equivalent? *Medicine & Science in Sports & Exercise, 50*(2), 257–265. PubMed ID: 28976493 doi:10.1249/MSS.0000000000001435

Saint-Maurice, P.F., & Welk, G.J. (2015). Validity and calibration of the youth activity profile. *PLoS ONE, 10*(12), e0143949. PubMed ID: 26630346 doi:10.1371/journal.pone.0143949

Saunders, T.J., Chaput, J.P., & Tremblay, M.S. (2014). Sedentary behaviour as an emerging risk factor for cardiometabolic diseases in children and youth. *Canadian Journal of Diabetes, 38*(1), 53–61. PubMed ID: 24485214 doi:10.1016/j.jcjd.2013.08.266

Schaan, C.W., Cureau, F.V., Sbaraini, M., Sparrenberger, K., Kohl Iii, H.W., & Schaan, B.D. (2019). Prevalence of excessive screen time and TV viewing among Brazilian adolescents: A systematic review and meta-analysis. *Jornal de Pediatria, 95*(2), 155–165. PubMed ID: 29859903 doi:10.1016/j.jped.2018.04.011

Stiglic, N., & Viner, R.M. (2019). Effects of screentime on the health and well-being of children and adolescents: A systematic review of reviews. *BMJ Open, 9*(1), e023191. PubMed ID: 30606703 doi:10.1136/bmjopen-2018-023191

Suchert, V., Hanewinkel, R., Isensee, B., & läuft Study Group. (2015). Sedentary behavior, depressed affect, and indicators of mental well-being in adolescence: Does the screen only matter for girls? *Journal of Adolescence, 42,* 50–58. PubMed ID: 25910467 doi:10.1016/j.adolescence.2015.03.014

Syväoja, H.J., Kantomaa, M.T., Ahonen, T., Harto, H., Kankaanpää, A., & Tammelin, T.H. (2013). Physical activity, sedentary behavior, and academic performance in Finnish children. *Medicine & Science in Sports & Exercise, 45*(11), 2098–2104. doi:10.1249/MSS.0b013e318296d7b8

Talarico, R., & Janssen, I. (2018). Compositional associations of time spent in sleep, sedentary behavior and physical activity with obesity measures in children. *International Journal of Obesity, 42*(8), 1508–1514. doi:10.1038/s41366-018-0053-x

Tremblay, M.S., Aubert, S., Barnes, J.D., Saunders, T.J., Carson, V., Latimer-Cheung, A.E., . . . Chinapaw, M.J.M. (2017). Sedentary Behavior Research Network (SBRN) - Terminology Consensus Project process and outcome. *International Journal of Behavioral Nutrition and Physical Activity, 14*(1), 75. PubMed ID: 28599680 doi:10.1186/s12966-017-0525-8

Tremblay, M.S., LeBlanc, A.G., Kho, M.E., Saunders, T.J., Larouche, R., Colley, R.C., . . . Gorber, S.C. (2011). Systematic review of sedentary behaviour and health indicators in school-aged children and youth. *International Journal of Behavioral Nutrition and Physical Activity, 8,* 98. PubMed ID: 21936895 doi:10.1186/1479-5868-8-98

Trost, S.G., Pate, R.R., Freedson, P.S., Sallis, J.F., & Taylor, W.C. (2000). Using objective physical activity measures with youth: How many days of monitoring are needed? *Medicine & Science in Sports & Exercise, 32*(2), 426–431. PubMed ID: 10694127 doi:10.1097/00005768-200002000-00025