Multi-sensor physical activity measurement in early childhood

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ABSTRACT

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The purpose of this dissertation was to develop, validate, and implement multi-sensor approaches for measuring physical activity and social/contextual covariates in 2-5 year-old children via wearable-, wireless communication-, and infrared-depth camera-based technologies. In Chapter 2, a three-phased study design was used to validate a method for estimating metered distances between wearable devices using accelerometer-derived Bluetooth signals. Results showed that distances, up to 20 meters, can be predicted between a single Bluetooth beacon and receiver using a Random Forest algorithm. When multiple Bluetooth beacons and receivers were used within the same environment, a moving average filter was required to recover observations lost due to noise. Overall, simulation and validation data suggest that accelerometer-derived Bluetooth signals can be used in studies of physical activity co-participation to 1) estimate metered distances between devices using a single beacon-receiver paradigm, as well as to 2) estimate the proportion of time that devices are proximal when using multiple beacons and receivers. Chapter 3 characterized the relationship between objectively measured physical activity and dyadic spatial proximities in 2 year-olds and their parents. Data revealed that the overall proportions of time that children and their parents spent in total physical activity were positively associated, and time series data revealed that this relationship remained consistent when analyzed hour-to-hour. Time spent engaged in sedentary behavior was also positively associated between children and parents; however, there was no association between child and parent moderate-vigorous physical activity volumes. Dyadic proximity results showed that girls

spent more time in joint physical activity with their mothers than boys. Furthermore, children who engaged in ≥60 minutes of daily moderate-vigorous physical activity spent an additional 30 minutes in joint total physical activity with their mothers each day, on average, when compared to children who engaged in <60 minutes of daily moderate-vigorous physical activity. Finally, boys and girls who engaged in ≥60 minutes of daily moderate-vigorous physical activity participated in joint physical activity with their mothers across wider relative distances, on average, than did boys who engaged in physical activity at closer relative distances to their mothers. In Chapter 4, an original computer vision algorithm was applied to infrared-depth camera data for the purpose of converting three-dimensional videos into triaxial physical activity signals in young children. Physical activity data were collected in 2-5 year-old children during 20-minute semi-structured, indoor child-parent dyadic play sessions. Play session video data were converted into triaxial physical activity signals using a multi-phased computer vision algorithm for each child. Computer vision-derived triaxial physical activity cut points for 2-5 year-olds were calibrated against a direct observation reference system using a machine learning algorithm. Results revealed that triaxial activity signals, as measured by a dual-sensor camera, can be used to estimate both physical activity intensities and volumes in young children without the use of wearable technology. Collectively, these studies show that multi-sensor approaches to physical activity measurement are a valid means by which to measure physical activity and social/contextual covariates in young children using either wearable sensors or computer vision.

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For the Dance

CHAPTER I

Introduction

Physical activity (PA) is defined as musculoskeletal contractions that cause increased energy expenditure (Casperson, Powell & Christenson 1985), and early childhood (ages 2-5 years) has been identified as an important age period for the development of physical activity behaviors (Kohl & Hobbs, 1998). Studies widely show that higher daily PA volumes in young children are positively associated with beneficial health outcomes (Andersen, 2006; Remmers et al., 2013). Moreover, PA behaviors developed during childhood appear to carry-forward throughout adolescence and into adulthood (Telama, 2009). Taken together, these studies suggest that daily physical activity behaviors in early childhood play a significant role in both short- and long-term health and behavioral outcomes (Timmons et al., 2012; Janz et al., 2010).

Current physical activity guidelines provide precise recommendations for the volume of physical activity minutes young children need each day in order to receive its health-enhancing benefits (AHA, 2016; IOM, 2011). Unfortunately, parental proxy reports on their children's daily physical activity appear to have limited validity (Oilver et al., 2007; Saker, 2015), which precludes their use when accurate PA estimates are required. Given the evidence of a dose-response relationship between daily minutes of activity and myriad health outcomes in young children (Ekelund et al., 2012), the need for comprehensive and accurate estimates of time spent in physical activity in early childhood is evident.

As such, public health efforts have been organized to objectively monitor childhood physical activity behaviors on a large scale (Troiano et al., 2008; Tudor-Locke et al., 2011). Among the many options for monitoring PA behavior in children (Rowlands & Eston, 2007), researchers have increasingly turned to the use of wearable technologies for the purpose of improving the validity, accuracy, and robustness in PA measurement in the young (Oliver, Schofield & Kolt, 2007). Of the available methods for objectively measuring PA (Hills, Mokhtar, & Byrne 2014), accelerometry is a feasible and popular method for quantifying daily activity volumes and activity patterns in young children (Rowlands et al., 2007; Van Cauwenberghe, Gubbels, De Bourdeaudhuij & Cardon 2011). Accelerometry research has shown that the use of such devices is a valid and reliable means by which to estimate time spent in physical activity in young children (Cliff, Reilly & Okely, 2009). Moreover, since young children tend to engage in short-burst physical activity patterns (Rowland, 2005), the time stamping feature available in accelerometers permits the analysis of activity patterns and temporal trends (Rowlands, 2007). For example, a study of 3-5 year-old low-income young children used accelerometer data and a functional data analysis approach to show associations between physical activity volumes and a diagnosis of asthma at different periods throughout a given day (Goldsmith, Liu, Jaconbson & Rundle, 2016), and another study showed that young children tend to engage in an array of qualitatively distinct episodes of short-burst activity patterns throughout the day (Ruiz, Tracy, Sommer, & Barkin, 2012). However, even as accelerometer data can provide high-resolution temporal information for pattern analyses, the use of a single triaxial accelerometer for measurement can provide only limited information about additional factors that are essential to PA behavioral patterns (Butte, Ekelund & Westerterp, 2012; Loveday, A., Sherar, Sanders, Sanderson & Esliger, 2015; Sylvia, Bernstein, Hubbard, Keating & Anderson, 2014).

More specifically, the development of PA behaviors in young children is known to be simultaneously associated with physiological, environmental, and sociocultural factors (Kohl et al., 1998). Several studies have shown the feasibility of employing multiple sensors to derive simultaneous objective estimates of PA and associated factors in order to develop more comprehensive and accurate models of PA behavior (Ellis, Godbole, Kerr & Lanckriet, 2015; Gao, Bourke & Nelson, 2014). Such integrative approaches to measurement afford researchers an opportunity to objectively assess PA using multifactorial methodological paradigms. In older children and adolescents (5-18 years), multi-sensor PA measurement approaches have been employed to objectively measure PA behavior in tandem with environmental covariates via Global Position System data, physiological correlates via indirect calorimetry, and sociocultural factors via simultaneous objective PA measurement in child-parent dyads (Duncan, Wilson, Tallis, Eyre, 2016; Fuemmeler, Andersson & Mâsse, 2011; Oreskovic et al., 2012;).

In young children, however, little is known about the application of multiple sensors to comprehensively characterize PA behavior. For example, only a small number of studies have investigated PA behaviors in parents and their young children using objective measures (Yao & Rhodes, 2015; Uitdewilligen, Müller-Riemenscheider, Lim, Brage & van Sluijs, 2017). A recent study used wearable sensors to simultaneously measure PA behaviors and spatial proximities in young children and their parents (Dlugonski, DuBose & Rider, 2017); however, the methods used in the study to objectively measure dyadic spatial proximities were not validated. Few studies have simultaneously measured PA using wearable sensors and indirect calorimetry in preschoolers when calibrating accelerometers to estimate energy expenditure (Butte et al., 2014; Pfeiffer, McIver, Dowda, Almeida & Pate, 2006; Roscoe, James & Dunan, 2017). With regard to the use of multi-sensor systems (e.g., infrared-depth sensing cameras) for remote PA measurement, only one study has applied such a method to simultaneously assess PA in children (Maile et al., 2015). However, the three-dimensional camera system was not calibrated against a criterion measure of PA. In the absence of system calibration, the interpretations that can be made from the 3D signals, with respect to PA measurement, are limited. Taken together, it appears that while multi-sensor systems have been used to uncover important association between physical activity and its correlates in older children, further methodological studies on approaches that can optimize the integrated use of multiple wearable or remote sensors in young children are needed to advance the science of PA measurement in this population (Corder, 2008).

As technological advancements extend the utility of multi-sensor activity monitoring (Liu Gao, Staudenmayer & Freedson, 2011), measurement researchers must remain at the edge of developing valid and reliable means by which to accurately estimate PA behavior, energy expenditure, and related parameters of interest (Corder, 2008). This clearly points toward the need for innovative multi-sensor studies and respective analytic models that can synthesize objectively monitored signals toward their meaningful use in characterizing early childhood PA behavior, in addition to its developmental determinants and correlates.

Significance

Objective measurement of PA behaviors has become ubiquitous in pediatric PA measurement in recent years (Chen, Janz, Zhu & Brychta, 2012). Studies investigating the quality and quantity of PA in pediatric populations have determined that these two PA behavioral attributes in particular are distinctly associated with specific health outcomes in childhood (Andersen et al., 2006; Ekelund et al., 2012). Furthermore, a host of factors, such as parental PA behaviors, are known to influence early childhood PA behaviors (Yao et al., 2015). To that end, the use of multi-sensor systems in early child PA measurement can provide deeper insights into children's PA behavior, its influences, and its associations with health outcomes during an essential developmental stage. Moreover, the use of time synchronized multi-sensor systems in early childhood PA assessments afford researchers the ability to simultaneously measure physical activity behavior and auxiliary signals, such that time-specific activity patterns can be modeled with respect to PA correlates in order to extend what is known about PA development .

By employing an integrative, multi-sensor approach to early childhood PA measurement, the findings from the studies conducted herewith may significantly impact what is known within the field of early childhood physical activity measurement in several ways. Collectively, they will:

1) propose a validated algorithm for objectively measuring interpersonal spatial proximities between young children and their parents during physical activity
2) characterize hour-to-hour physical activity behaviors and spatial proximity patterns between 2 year-old children and their parents via multiple wearable sensors
3) propose triaxial cut points for remotely monitored physical activity behaviors in young children

Overview

The three studies that comprise this dissertation series exclusively focus on 1) a social correlate of PA behavior that can be objectively measured, 2) child-parent dyadic physical activity behaviors and interpersonal spatial proximity patterns, and 3) the development of cut points for a 3D remote physical activity monitoring paradigm to assess PA intensities and volumes. Study one is a three-phased methodological study that proposes a method for objectively measuring interspatial proximities between individuals alongside physical activity data. The second study is a cross-sectional study, that applies the methods of study one, and objectively measures hour-to-hour physical activity behaviors and interspatial proximities in young children and their parents over one week in order to better understand interactive physical activity behavioral patterns in child-parent dyads. The third study is a methodological study that establishes triaxial physical activity cut points for an infrared-depth sensing camera in young children (2-5 year-olds) in order to assess physical activity intensities and volumes without the use of wearable technology.

Therefore, this dissertation series aims to:

1) validate the use of accelerometer-derived Bluetooth signals as an objective measure of interpersonal spatial proximity during physical activity
2) describe overall child-parent PA behaviors among families with young children
3) describe interactive hour-to-hour child-parent PA behavior patterns and PA inter-relationships between dyadic counterparts
4) explore the influence of spatial proximity on interactive child-parent free-living PA over several days
5) calibrate triaxial physical activity cut points for a 3D camera in 2-5 year-olds

Dissertation Structure

The series of discrete, yet interrelated, studies that follow have been organized into the following format:

Chapters II, III, and IV are three separate studies that have employed integrative, multi-sensor systems to measure physical activity behavior and proximity in young children. For each of these chapters, an abstract, introduction, methods, results, discussion, conclusions, references, and related tables and figures are presented. Appendix A includes the literature review for the dissertation. Appendices B and C are supportive, discrete studies that are associated with the primary dissertation studies. Appendix D includes information on KinetiWave, an original computer software platform for signal analyses in physical activity research. Appendix E includes all definitions and abbreviations referenced across the primary dissertation studies. Appendix F includes all data forms and questionnaires used within the primary dissertation studies. Related Institutional Review Board documents from Teachers College, Columbia University, and where applicable Columbia University Medical Center, are included for all primary dissertation studies and are provided in Appendix G.

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Analysis of accelerometer-derived interpersonal spatial proximities: A calibration, simulation, and validation study

Abstract

Purpose: To estimate distances from accelerometer-derived Bluetooth signals as a measure of interpersonal spatial proximity. **Methods:** Accelerometer-derived proximity data were collected indoors and outdoors over a 10m range to calibrate simulation models. Proximity data were simulated over 20m (indoor) and 50m (outdoor) ranges. Competing statistical and machine learning models were used to predict simulated distances; the Root-Mean-Square-Error (RMSE) was calculated. Simulation estimates were validated under conditions wherein a single beacon-receiver (SBR) and multiple beacons-receivers (MBR) collected proximity data indoors and outdoors within a ≤10m range. **Results:** Simulation data showed that a Random Forest (RF) model performed optimally. The validated RF RMSE was ≤2.7 for SBR, and ≥90% of predicted distances were accurately classified as ≤10m. For MBR, ≥67% of predicted distances were accurately classified as ≤10m. **Conclusions:** Simulation and validation data suggest that distances can be estimated from accelerometer-derived proximity data within a 20m range using a SBR.

Introduction

Physical activity (PA) behaviors appear to be interdependent among children and their parents (Yao & Rhodes, 2015; Barkin et al., 2017). Few studies of child and parent co-participation in PA have used objective measures to determine the periods of time during which child and parent were proximally engaged in PA, and the use of objective measures has been shown to mitigate biases otherwise encountered when using self-report proxy measures (Uijtdewilligen et al., 2017). In order to model child and parent co-participation in PA with good internal validity, accurate measures of the periods of time during which dyadic counterparts are engaged in simultaneous and proximal PA are required. The use of accelerometers combined with an additional sensor that can measure the distance between dyadic counterparts allows for the analysis of activity intensities patterns in tandem with dyadic spatial proximity patterns (Uijtdewilligen et al., 2017), and affords researchers the potential to comprehensively and accurately characterize interpersonal proximities and child-parent physical activity. However, further research is needed on the validity and applications of such objective methodological approaches in the measurement of child and parent PA co-participation.

The available validated objective measures of spatial proximity between family members and activity levels have largely been limited to using two separate monitors (i.e., accelerometers and Global Positioning System devices), which may be cumbersome for use in certain populations (Uijtdewilligen et al., 2017), such as in very young children. Newer accelerometer models afford researchers the capability of simultaneously collecting inter-device spatial proximity data via Bluetooth signals while measuring PA, which can be used to measure child-parent co-participation in PA (Dlugonski, DuBose, & Rider, 2017). Though the radio wave-based technology embedded within newer accelerometers has been widely used to measure inter-device spatial proximities across various devices (Botta & Simek, 2013; Oliveira, Hongbin, Almeida, & Abrudan, 2014; Seidel & Rappaport, 1992), there have been no studies that have systematically validated the use of accelerometry combined with Bluetooth-based sensors to estimate interpersonal spatial proximities as metered distances during PA measurement.

Given that an accurate measure of interpersonal distance is a requisite factor in determining simultaneous and proximal child and parent PA engagement (Uijtdewilligen et al., 2017), further research on objective measures of interpersonal spatial proximities will support future studies of familial co-participation in PA. Moreover, the use of accelerometers alone to measure activity intensity and proximities between dyadic counterparts, in contrast to the use of multiple devices, may dually afford researchers a convenient and integrated system for analyzing child-parent PA co-participation. The purpose of this study, therefore, was to validate a method for estimating interpersonal distances between dyadic counterparts using accelerometer-derived Bluetooth proximity signals. To achieve this aim, a three-phased calibration, simulation, and validation study was conducted in order to derive an accurate and robust model for estimating metered distances between accelerometers using Bluetooth data.

Calibration

As a precursor to estimating interpersonal distances from accelerometer-derived Bluetooth proximity signals, proximity calibration data were first collected, processed, and analyzed, as described below:

<u>Methods</u>

Site. Proximity calibration data were collected in various indoor and outdoor environments on a university campus located within a major urban center.

Sample & Procedure. ActiGraph wGT3X-BT accelerometers (ActiGraph Corp, Pensacola, FL) were used to sample "proximity tagging" data. The "proximity tagging" feature in the wGT3X-BT model uses Light Energy Bluetooth technology to detect relative received signal strength between ActiGraph accelerometers (ActiGraph, 2014). Two accelerometers were respectively initialized as a "receiver" and "beacon" using ActiLife software. Received Signal Strength Indicator (RSSI) signals were recorded on the receiver. Within each testing session, two accelerometers, respectively affixed to a stationary and mobile support, were placed within a given indoor or outdoor environment in and out of direct line of sight. Repeated, scheduled RSSI measurements were collected at 1m increments (from 1m to 10m) indoors and outdoors using a 10 second epoch length, and the observed distances (i.e., ground truth) were recorded by two observers. RSSI data were downloaded from the receiver using ActiLife software.

Measures. The log-distance path loss model has been used in prior research on radio signal propagations between wireless devices, while accounting for reductions in radio signal power density (i.e., path loss) due to a host of factors (e.g., signal reflection, diffraction, and absorption by environmental features) that can introduce noise into the system (Rappaport, 2002). As shown (1), the path loss at distance d is expressed as the sum of its expected value and normally distributed random error X_σ. The expected value of the path loss is modeled by a constant reference path loss (PL_0), the path loss exponent (α), and the log-transformed ratio of the observed distance (d) to the reference signal distance (d_0).

$$\begin{aligned} PL(d) &= \overline{PL}(d) + X_\sigma \\ \overline{PL}(d) &= PL_0 + 10\alpha log_{10}\left(\frac{d}{d_0}\right) + X_\sigma \end{aligned} \tag{1}$$

This study manipulated and simulated the following variables: *received signal strength (RSSI)*, the *path loss exponent* (α), and *distance (d)*. A propagation model was applied to data

(*RSSI*, *d*) collected during indoor and outdoor calibration in order to calculate α for each observation.

Received Signal Strength Indicator. RSSI data were measured in decibels (*dB*) for the indoor and outdoor calibration phase. RSSI observations (2) were calculated as shown:

$$RSSI_i = RSSI_0 - 10 \times \alpha_i \times \log_{10} d_i + \varepsilon_i \qquad (2)$$

Where i is an observation, $RSSI_i$ is the received signal strength, $RSSI_0$ is the reference signal strength, α_i is the path loss exponent, d_i is the observed distance, and ε_i is normally distributed random error for the i^{th} observation (Tateshi & Ikegami, 2008).

In order to calibrate the model, calibration data were used to determine $RSSI_0$ (Botta & Simek, 2013; Seidel & Rappaport, 1992). Results showed that $RSSI_0$ = *-55dB* for wGT3X-BT accelerometers at a reference distance d_0 = 1; therefore, a reference signal strength ($RSSI_0$= *-55dB*) and reference distance (d_0 = 1m) were used in all calculations. The path loss exponent during the reference distance calibration was α = 2—no obstructions were present, and devices were in direct line of sight in order to attain conditions wherein free-space path loss could be assumed (Botta et al., 2013; Madhavapeddy & Tse, 2005).

Path Loss Exponent. The path loss exponent was calculated for all respective $RSSI_i$ and d_i observations from the indoor and outdoor calibration results (3):

$$\alpha_i = \frac{RSSI_0 - RSSI_i}{10 \times \log_{10}(d_i)} \qquad (3)$$

Distance. Distance was measured in meters, and observed values ranged from 1m to 10m during the indoor and outdoor calibration sessions.

Statistical Analyses.

Descriptive statistics of data collected during the calibration phase were generated using MATLAB R2017a (The Mathworks Inc., Natick, MA) and are presented as *Median* (Interquartile Range) and Frequencies [%(*n*)].

<u>Results</u>

Descriptive Statistics. Table 1 shows descriptive data from indoor and outdoor device calibration. RSSI values from the indoor calibration ranged -55 to -81*dB*, and outdoor data showed an RSSI range of -54 to -75*dB*. Using a subset of the data, Figure 1 shows the variance in RSSI at each observed distance for indoor and outdoor data sets, with the cluster of weaker RSSI values at 7m illustrating an example of signal attenuation.

Simulation

Given that path loss due to noise is a highly variable and influential element of the log-distance path loss model (Seidel & Rappaport, 1992; Tateshi & Ikegami, 2008), a two-phased simulation study was conducted in order to assess the performance of competing distance estimators across a range of possible environmental noise conditions. Calibration data and results were used to parameterize the simulation model as described below:

<u>Methods</u>

Two separate simulation methods were used in this study in order to explore distance estimation under measurement conditions wherein 1) the path loss exponent is known or can be calculated for a given environment (fixed alpha), or 2) when the path loss exponent is unknown or cannot be calculated (random alpha).

Method 1— Fixed Alpha. A total of $N = 10{,}000$ cases were generated for respective indoor and outdoor data sets in MATLAB.

Distance observations for each case were simulated as a first order Markov chain, such that the simulated proximity value at a given time would be contingent only upon the single proximity value observed immediately prior. The purpose of this approach was to simulate random data as a memoryless process with scheduled, 60 second sampling intervals under free-living conditions. The Markov property has been used in prior research on physical activity behavior to good effect (Kerr et al., 2016). Data were generated for hypothetical 12 hours periods with 60 second sampling intervals for each condition (j), where each indoor (j = 1) and outdoor (j = 2) data set respectively contained i = 720 observations. According to the manufacture, the wGT3X-BT accelerometer can measure received signal strength at distances of up to 20m in indoors environments and up to 50m outdoors (ActiGraph, 2014). Therefore, distances were simulated from 1m to 20m (indoor range) and from 1m to 50m (outdoor range). The state space S_j was defined as $S_j = \{1, 2, 3, \ldots, n_j\}$, where $n_1 = 20$ and $n_2 = 50$. Simulated transition matrices of sizes 20 x 20 and 50 x 50 were used to determine state transition probabilities in their respective indoor and outdoor applications. To simulate the transition matrix:

1) Let $z_i \in \{1, 2, 3, \ldots, n_j\}$ denote the row number in the transition matrix $\boldsymbol{T}_j$, and z_i is the state of the process at time $i \in [1, 720]$. For each row vector of state transition probabilities, $\boldsymbol{s}_{jz}$, the k^{th} element in $\boldsymbol{s}_{jz} \in [P(\boldsymbol{s}_{jz1}), P(\boldsymbol{s}_{jzk})]$ was derived using the height of the Gaussian probability density function with mean $\mu_{jz} = z$ and variance $\sigma^2 = Var(S_j)$ evaluated at $k = \{1, 2, 3, \ldots, n_j\}$, such that $P(\boldsymbol{s}_{jzk}) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(k-z)^2}{2\sigma^2}}$. The Gaussian distribution was used to simulate data collected in free-living conditions under the assumptions that 1) for any state transition, the probability of observing no change in states between time steps is highest, and 2) the state transition probabilities decrease as $\left|z_i - z_{i+1}\right|$ increases. That is to say, the

probability that the devices were observed at similar distances, relative to each other at each 1 minute sampling interval, was higher than the probability that they were observed at a more extreme relative distance in either direction (i.e., closer or nearer).

2) Each row in $\boldsymbol{T}_j$ was standardized to sum to one

To derive each simulated 12hr case of distance observations, the following procedure was used:

Step 1) A random integer was drawn from the discrete uniform distribution $d_0 \sim Unif\{1, n_j\}$ and was used as the starting distance (i.e., state)

Step 2) Given z_i, the corresponding probability row vector in $\boldsymbol{T}_j$ was used to calculate the cumulative sum vector, $\boldsymbol{q}$, of the state transition probabilities as follows: $\boldsymbol{q}_N = \Sigma_{k=1}^{N} \boldsymbol{s}_{jzk}$, with $N = \{1, 2, \ \ldots, n_j\}$

Step 3) An observation was drawn from the continuous uniform distribution $x_i \sim Unif(0,1)$, and $d_i = m$, where $m = \max_N q_N \leq x_i$

Calibration results showed that $\alpha \in [1.3, 5]$ in indoor and outdoor environments, and prior studies have reported that $\alpha \in [1.8, 5.2]$ (Seidel & Rappaport, 1992; Tateshi & Ikegami, 2008). Fixed values for $\alpha \in [1, 5]$ and simulated distances were used to calculate (2) RSSI values for each complete indoor (20m range) and outdoor (50m range) data set at each respective fixed value of alpha. Calibration data also showed standard deviations of $SD(RSSI) = 5.34$ for indoor data and $SD(RSSI) = 5.65$ for outdoor data; therefore, these values were used to compute random error for respective indoor and outdoor data sets. A prior study of path loss prediction models showed that $SD \in [4.3, 16.3]$ across various indoor and multi-floored environments (Seidel & Rappaport, 1992).

The wGT3X-BT product manual (ActiGraph, 2014), and data from our device calibration confirmed, that RSSI values less than -90*dB* are not likely to be recorded by the receiver accelerometer. Accordingly, simulated RSSI observations that were less than -90*dB*, as well as corresponding distance and path loss exponent data, were removed from all cases prior to analyses. For both indoor data and outdoor data, the final training set (n = 7,000) and test set (n = 3,000) contained simulated RSSI, distance, and path loss exponent observations for each case.

Method 2— Random Alpha. Data cases (N = 10,000) were generated for respective indoor and outdoor data sets.

Distance observations were simulated using the Markov chain approach described previously. Path loss exponents in this method were allowed to vary across observations on the interval [1.3, 5]. This is because calibration results showed that at any fixed value of $d \in [1, 10]$, the variance in received signal strength observations was zero when $\alpha \in [1.3, 5]$ was fixed at any observed value. When α was not controlled, the variance in $RSSI_i$ was much higher in both environments, and in the range [0.4, 13] *dB*. These results show that the variance in $RSSI_i$ due to changes in α was high. Given calibration results, the path loss exponent was allowed to vary for each simulated *RSSI* observation since calibration data showed that α varies indoors and outdoors even when distance is constant.

Path loss exponent data were also simulated as a Markov chain with transition probabilities generated from the normal probability density function in order to account for potential external sources of signal attenuation (Baccour et al., 2012). The state space for the path loss exponents was defined as $S = \{1.3, 1.4, 1.5, \ldots, 5\}$ in agreement with calibration results as described previously. The transition matrix for α was normally distributed, as described previously, and each row was standardized to sum to one. To derive each case of path loss exponents, a random number was drawn from the discrete uniform distribution $\alpha_0 \sim Unif\{1.3,5\}$ and was used as the starting value. The cumulative sum of the state transition probabilities from the corresponding transition matrix was calculated, and the new state α_i was determined using the criteria described above (*Step 3*). The path loss exponent Markov chain procedure was reiterated for all α_i, resulting in a total of 720 path loss exponent observations for each case. Element by element distance and path loss exponent data for each case were used to calculate (2) RSSI observations, with signal strength variance controlled, *SD(RSSI)* = 1, given that the path loss exponent was allowed to vary.

Simulated RSSI observations that were less than -90*dB*, as well as corresponding distance and path loss exponent data, were removed from all cases prior to analyses. For both indoor data and outdoor data, the final training set (*n* = 7,000) and test set (*n* = 3,000) contained simulated RSSI, distance, and path loss exponent observations for each case of *n* = 720 observations.

Statistical Analyses

Statistical and Machine Learning. Distances were estimated from simulated indoor and outdoor RSSI data using several competing models: Linear Regression, regression tree using a Random Forest algorithm, Natural Cubic Spline, Artificial Neural Network, and Linear Regression with $log_{10}(d)$ as the outcome. Prior research on inter-device proximities using Bluetooth signals have shown that non-parametric methods perform optimally when compared to the use of the propagation model alone (1) to estimate distances (Zhuang, Yang, Li, Qi, El-Sheimy, 2016). Given the curvilinear relationship between RSSI and distance shown in the calibration results, in addition to potentially complex noise patterns in the signal due to various sources of RSSI attenuation, non-linear statistical and machine learning approaches were employed to predict distances from RSSI data. The Natural Cubic Spline model fits a sequence of piecewise third-order polynomials over a series of discrete segments of a signal, where the function is constrained to be linear at the signal boundary, in order to yield a continuous, smooth curve (James, Witten, Hastie & Tibshirani, 2013). The Random Forest algorithm partitions, or splits, the predictor space (i.e., RSSI) into discrete non-overlapping regions, and then assigns the mean of the response values (i.e., distance) observed within each given region as the predicted outcome for all elements within the predictor space subset. In order to determine an optimal split at each node in the tree, and to yield a tree that produces estimates with low variance, the algorithm repeats this process on a number of bootstrapped training sets using a random subset of predictors for each split to grow a forest of trees. Finally, the mean of the predicted values for each value in the predictor space is calculated across all trees in the forest to yield the final predictive model (Breiman, 2001). Neural Networks model a non-linear relationship between a response and any number of predictors. This study specified a single-layer, Bayesian regularized, feed-forward network, expressed as $y = f(f(\boldsymbol{X}\mathbf{V}^{\mathrm{T}})\mathbf{W}^{\mathrm{T}})$, where y is the predicted distance, $\boldsymbol{X}$ is a matrix comprised of a column of RSSI observations and an additional column of ones, and both $\boldsymbol{V}$ and $\boldsymbol{W}$ are arrays of model coefficients (i.e., weights). Model weights and bias values were determined using Bayesian regularization to optimize model generalization (Burden & Winkler, 2008). The "hidden layer" of unobserved variables is expressed as $\boldsymbol{H} = f(\boldsymbol{X}\boldsymbol{V}^{\boldsymbol{T}})$, where $\boldsymbol{H}$, a linear combination of the predictors to which the logistic function $f(t) = 1/[1 - e^{-t}]$ has been applied, is similarly augmented to include a column of ones. The number of hidden layers determines the flexibility of the model, with more flexible models tending to lead toward overfitting thus limiting generalization of the model to new data sets (Keller, Kim, & Steiner, 2015). In specifying the Neural Network model, we found that increasing the number of hidden layers above one had little effect on model performance, thus we specified the model with a single hidden layer. Finally, the simple linear regression and linear regression with log_{10} transformed outcome models were included as baseline comparisons to the non-parametric approaches. At each iteration (N = 1,000) in the statistical and machine learning procedure, 70% of training data cases were passed to each model, followed by 30% of test data cases which were passed to each trained model for cross-validation.

Method 1 & 2—Fixed & Random Alpha. Indoor (20m range) and outdoor (50m range) distances were predicted using each model and each respective array of fixed path loss exponents. Distance (*d*) was used as the outcome and *RSSI* was the predictor. The cross-validated Root Mean Square Error (RMSE), $RMSE = \sqrt{\frac{\sum_{i=1}^{N}(\hat{y}_i - y_i)^2}{N}}$, and Mean Absolute Error (MAE), $MAE = \frac{\sum_{i=1}^{N}|\hat{y}_i - y_i|}{N}$, for the estimated distances, $\hat{y}_i$, versus true distances, y_i, were calculated across both the fixed and random alpha conditions.

Results

Statistical and Machine Learning with Fixed Alpha. Figure 2 demonstrates the face validity of the data simulation approach when the path loss exponents were generated under the first simulation approach (i.e., fixed path loss exponents). Table 2 shows RMSE and MAE for distance estimates derived from statistical and machine learning algorithms across the range of values at which the path loss exponent was fixed. As the path loss exponent increased, the proportion of simulated distances greater than ~10m (for the 20m range) and greater than ~20m (for the 50m range) decreased given that the RSSI values were less than -90*dB* at higher distances. Thus, prediction error concomitantly decreased as the range of possible distances decreased. The Random Forest model estimated distances with the lowest RMSE and MAE for both indoor and outdoor data, and also provided estimates with marginally less variance than similarly performing models. For the 20m range (indoor), distances were predicted within 0.9m to 4.6m of the true distance, on average. Over the 50m range (outdoor), distances were predicted within 1.0m to 11.6m of the true distance, on average. Fitted values for the Random Forest model, when α was fixed at 2, are shown for both 20m and 50m ranges (Figures 3a & 3b).

Statistical and Machine Learning with Random Alpha. Fitted values for the Random Forest model, with a randomly varying α, are shown for both the 20m and 50m ranges (Figures 4a & 4b). Error for the 20m range (indoor) distance predictions was lowest for the Random Forest (Figure 4c), Natural Cubic Spline, and Neural Network models, which had an RMSE of *4.3*(<0.01)m and MAE of 3.5(<0.01)m, on average. For the remaining models, the average RMSE and MAE were respectively found to be: Linear Regression [4.4; 3.6]m, Linear Regression with $log_{10}(d)$ [4.6; 3.6]m. Error for the 50m range (outdoor) distance predictions was also lowest for the Random Forest (Figure 4d) and Natural Cubic Spline models, with an average RMSE of 11.7(0.02)m and MAE of 9.5(0.02)m. For the remaining models, the average RMSE and MAE were respectively found to be: Linear Regression [11.8; 9.7]m, Linear Regression with $log_{10}(d)$ [12.5; 9.6]m, and Neural Network [11.7; 9.6]m.

Validation

Sampling. The Random Forest model distance estimates were validated under two separate conditions: 1) a single beacon and receiver in indoor and outdoor environments, and 2) multiple beacons and receivers in indoor and outdoor environments. For the single beacon single receiver condition, data from the calibration phase, as described above, were used. For the multiple beacon and receiver condition, data were collected both indoors and outdoors at an Early Head Start (EHS) in a major metropolitan area. EHS is a nationally funded program that provides educational services for under-resourced young children (birth to 5 years) and their parents (ECLKC, 2016). Indoor data were collected within a range of 10m within various Early Head Start classrooms. Outdoor data were also collected within a range of 10m on the sidewalks of a publically accessible main thoroughfare as children walked alongside their parents or were pushed in strollers. Families (N = 34) with 24-35 month-old children attending an Early Head

Start were invited to participate. The mean age for children was *29*(4) months and parents were *32*(6) years old, on average, with 96% of families self-reporting their ethnicity as Latino/Hispanic. The study was approved by the universities' respective Institutional Review Boards, and all participating parents provided informed consent.

Measures.

Sociodemographic questionnaire. Parents completed a brief sociodemographic questionnaire and provided information on children's sex and age, as well as their own age, sex, and ethnicity, as reported above.

Physical activity. For each child-parent dyad, children and a single parent wore the ActiGraph wGT3X-BT devices at the hip for 7 days. Raw acceleration data were collected for both children and parents and were downloaded and exported using the ActiLife software in 15s and 60s epochs respectively. Data reduction was conducted in MATLAB R2017a using custom algorithms. Following, device wear time was established for children's (Cliff, Reilly, & Okely, 2009) and parents' (Choi, Lui, Matthews, & Buchowski, 2011) activity data using standard algorithms. Given that activity intensity was not required for this study, cut points were not applied to data. Finally, 30min time segments were extracted for each dyad that corresponded to the times during which they were observed to be indoors and outdoors at the EHS center.

Proximity. Data on child-parent spatial proximities were collected via direct observation (i.e., ground truth) and were simultaneously measured using ActiGraph wGT3X-BT devices. Direct observations and accelerometer-derived Bluetooth measures were collected within indoor and outdoor settings, where dyadic counterparts were within a maximum range of 10m across conditions. Bluetooth signals were collected using 60s epochs, with devices initialized as the beacon and receiver for parents and children, respectively. Only proximity data where parent and child had valid wear time data, as determined by the aforementioned physical activity wear time algorithms, were conserved. Bluetooth data (RSSI) were downloaded from children's devices using ActiLife, and were exported for further analyses in MATLAB.

Statistical Analyses

Predicted distances for proximity data were estimated from accelerometer-derived proximity signals (RSSI) using the trained 20m random alpha Random Forest model, and the proportion of epochs with missing observations were calculated. RMSE and MAE were calculated for the single beacon condition given that epoch-to-epoch metered distances between devices were known. In order to determine agreement between the directly observed distances and the predicted distances for both the single and multiple beacon conditions, the proportion of observations accurately classified as ≤10m was calculated (Birkimer & Brown, 1979). Descriptive statistics are presented as *Mean* (Standard Deviation), *Median* (Interquartile Range), and Frequencies %(*n*). Analysis of validation data from the multiple beacon and multiple receiver condition showed that the median number of missing epochs between observations was *3*(7.5), thus a 3 epoch moving average filter was applied to predicted distances in the multiple beacon scenario. The simple moving average filter is a finite impulse response filter that smooths a given signal, using the formula $x_i = \frac{x_i + x_{i-1} + \cdots + x_{i-Z}}{Z+1}$, where $Z+1$ is the length of the filter and x_i is the i^{th} observation in a given time series.

Results

Single beacon. The Random Forest model predicted distances from the original indoor calibration data with an RMSE and MAE of 2.7m and 2.5m, respectively, and a mean predicted distance of *6.9*(1.8)m. Predicted distances for the outdoor calibration data had an RMSE and

MAE of 2.3m and 2.1m, respectively, and the mean predicted distance was *7.1*(2.1)m. The majority of indoor (90%) and outdoor (100%) distances were accurately predicted as ≤10m.

Multiple beacons. Results from the validation of accelerometer-derived proximity data when multiple beacon were used showed that, for raw signals, *32*(24)% of indoor observations were missing and *25*(25)% of outdoor observations were missing. The mean predicted distances for raw signals using the regression tree model were *8.4*(3.2)m indoors and *9.2*(1.4)m outdoors, and the proportion of observations correctly predicted as ≤10m were *58*(23)% and *59*(20)% for indoor and outdoor conditions, respectively. After applying a 3 epoch moving average filter, *1*(1)% and *1*(2)% of indoor and outdoor observations were missing, respectively. The mean predicted distances for filtered signals in the respective indoor and outdoor conditions were *8.2*(3.8)m and *9.0*(2.8)m, with *69*(10)% and *67*(16)% of observations correctly predicted as ≤10m across respective conditions.

Discussion

This study intended to validate the use of accelerometer-derived proximity signals as an objective measure of interspatial proximity within interpersonal contexts and during physical activity. Results from this simulation and validation study showed that received signal strength data collected using ActiGraph wGT3X-BT accelerometers can be used to estimate the distance between devices both in and out of direct line of sight. Thus, accelerometer-derived Bluetooth signals can be used as an objective measure of child-parent interpersonal distances in studies of child-parent co-participation in PA. To our knowledge, this study is the first to predict metered distances between accelerometers using ActiGraph "proximity tagging" data.

Using a Random Forest model, simulated data showed that distances were predicted with an RMSE of 0.9 to 4.6m over a 20m range and 1.0 to 11.7m over a 50m range. Moreover, validation data showed that the RMSE for indoor and outdoor predicted distances were 2.7m and 2.3m, respectively, when proximity data were collected over a 10m range using a single beacon and receiver. A prior study on physical activity using GPS data for outdoor location estimation found that GPS data predicted subject location with an acceptable amount of error (3.02m) (Rodriguez, Brown, & Troped, 2005), so our results show that accelerometers with Bluetooth technology can be used to estimate distances with a similar accuracy as this well-accepted measurement methodology. Similarly, a study of indoor localization using smartphones and Bluetooth Low Energy devices showed estimate accuracies from < 3.1m to < 3.88m 90% of the time, across various measurement conditions (Zhuang et al., 2016). Combined, our simulation and validation results suggest that accelerometer-derived proximity data can provide acceptable estimates of the distance between devices over a 20m range, which is the maximum range that ActiGraph Corp. indicates that these devices can be used to measure proximity while indoors. However, given that the predicted distance errors for the simulated accelerometer-derived proximity data was quite high over the 50m range (i.e., the indicated maximum outdoor range for the ActiGraph proximity tagging feature), physical activity researchers might choose to use GPS data in outdoor measurement applications when more accurate estimates of interpersonal spatial distances are needed in outdoor environments. With respect to the 20m range, when the path loss exponent is known (i.e., device calibration within a given environment is feasible), the Random Forest model was able to predict distances on the range [1.0, 16.4]m; however, when the path loss exponent cannot be known, as may be the case in most free-living applications, the model predicted distances on the range [1.1, 11.8]m.

Under conditions wherein multiple beacons and receivers were used, the proportion of predicted distances that were accurately classified as ≤10m was much lower, and the number of missing observations was much higher, than in the single beacon condition. This may be attributed to higher levels of external signal interference between beacons and receivers due to the increased number of Bluetooth signals transmitted within the same environment, multiple Wi-Fi signals in the surrounding area, cellphones, and other sources of signal attenuation (Baccour et al., 2012). Therefore, a moving average filter was needed in order to recover proximity observations that would have been otherwise lost due to environmental noise. Moreover, in noisier environments, proximity data might best be used to determine the proportions of time that devices are within range, rather than to predict metered distances. We suggest the use of filtered proximity data over raw proximity signals to estimate either distances or the proportion of time that devices are within range. Finally, data from our lab (not shown) revealed that the receiver device will completely discharge within approximately 3 days when initialized with a 10s epoch sampling frequency. Therefore, we recommend using a 60s epoch sampling frequency in order to collect accelerometer-derived proximity data for greater than 3 days.

A limitation of this study is that the ActiGraph proximity tagging data file does not provide an additional wireless communication metric called the Link Quality Indicator (LQI). LQI data may provide further insight into the variance in signal strength (Baccour et al., 2012), which may improve model estimates. Another limitation of this study is that it was conducted in an urban environment, and evidence suggests that path loss exponents observed across various environments (e.g., rural and urban) may differ (Rappaport, 2002). Though the range of path loss exponents used in simulated data fell within the range of path loss exponents used in prior studies (Seidel & Rappaport, 1992; Tateshi & Ikegami, 2008), future studies should replicate the methodology of this study in other environments in order to determine if there are local differences in path loss exponents that are observed when using ActiGraph wGT3X-BT accelerometers. Within the multiple beacon condition, the precise epoch-by-epoch distances between devices were unknown and all directly observed proximities were ≤10m between dyadic counterparts. Thus, we were limited from calculating the Root Mean Square Error or more robust measures of inter-observer agreement that require instances of nonoccurrence agreement (i.e., directly observed and accelerometer-derived distances that were >10m). Finally, prior studies have suggested that the distance-dependent path loss model should subtract some constant value (*W*) for any signal observed through an outdoor wall (Durgin, Rappaport, & Xu, 1998). This study did not measure *W* during the calibration phase, nor did it include *W* during simulations. However, the range of path loss exponents tested during the simulation conducted in our study reflect the path loss exponents that have been reported in prior research when devices were separated by up to 3 walls in prior research (Seidel & Rappaport, 1992).

Physical activity researchers using ActiGraph proximity tagging data may use the methodology tested in this study in order to determine the distance between accelerometers worn by subjects under both controlled and free-living conditions. This approach may be particularly of use to researchers who are interested in measuring spatial proximities between children and parents to model child-parent PA behavior patterns. Prior studies have shown that the use of multiple static sensors may improve location estimates (Papamanthou, Preparata, Tamassia, 2008); therefore, future studies should investigate distance estimation methods using multiple stationary and non-stationary devices in order to improve distance estimates.

Conclusions

A Random Forest model can be used to predict metered distances from accelerometer-derived proximity data when devices are separated by up to 20 meters when using a single beacon and receiver. Over a range of 50 meters, however, accelerometer-derived proximity data may not be useful in providing estimates of the distance between devices, depending on the level of accuracy required. Given that proximity signals are subject to various sources of external interference and noise, we suggest the application of a moving average filter to both smooth predicted distances and recover observations that might otherwise be lost. Future research on intra-familial co-participation in physical activity can use accelerometer-derived proximity data and the methods presented in this study to estimate proportions of time that devices are within range, as well as to predict distances between devices within a 20m range.

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Table 1. Characteristics of ActiGraph wGT3X-BT proximity tagging data collected within indoor and outdoor environments in a major metropolitan area

	Condition	
	Indoors	Outdoors
Variables		
Observations (n)	2,051	2,082
Missing (%)	0.004	0.002
Path loss exponent	2.00(1.46)	2.13(0.43)

Note: Table values are *Median*(IQR) or Frequencies (%). The path loss exponent was calculated from received signal strength and distance observations collected within respective indoor and outdoor environments

Table 2. Root Mean Squared Error (left) and Mean Absolute Error (right) for distance estimates derived from statistical and machine learning algorithms using simulated indoor and outdoor ActiGraph wGT3X-BT proximity tagging data and a range of path loss exponents

	α									
Error	1		2		3		4		5	
Indoor										
Linear	[4.7	3.9]	[3.6	3.0]	[3.1	2.5]	[1.9	1.5]	[1.0	0.8]
log_{10}(Y)	[4.9	4.0]	[4.1	3.2]	[3.1	2.3]	[1.8	1.3]	[1.0	0.7]
Cubic Spline	[4.6	3.9]	[3.7	3.0]	[3.0	2.3]	[1.8	1.3]	[0.9	0.7]
Neural Network	[4.6	3.9]	[3.8	3.0]	[3.0	2.3]	[1.8	1.3]	[0.9	0.7]
Random Forest	[4.6	3.9]	[3.7	3.0]	[3.0	2.3]	[1.8	1.3]	[0.9	0.7]
Outdoor										
Linear	[11.6	9.7]	[9.5	7.7]	[5.9	4.5]	[2.2	1.6]	[1.1	0.8]
log_{10}(Y)	[12.5	10.1]	[10.1	7.8]	[5.7	3.9]	[2.1	1.4]	[1.0	0.7]
Cubic Spline	[11.6	9.6]	[9.4	7.5]	[5.6	4.0]	[2.0	1.4]	[1.0	0.7]
Neural Network	[11.6	9.6]	[9.5	7.6]	[5.7	4.0]	[2.0	1.4]	[1.0	0.7]
Random Forest	[11.6	9.6]	[9.4	7.5]	[5.6	4.0]	[2.0	1.4]	[1.0	0.7]

Note: At each fixed value of alpha, Table 2 shows model RMSE (left) and MAE (right) for predicted distances over 20m (indoor) and 50m (outdoor) ranges. Abbreviations: linear regression (Linear), regression tree (Tree), linear regression with $\log_{10}(d)$ as the outcome [log_{10}(Y)], path loss exponent (α), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), distance (d)

Figure 1. Scatterplots of received signal strength as a function of distance for ActiGraph wGT3X-BT proximity tagging calibration data collected indoors (left) and outdoors (right) in a major metropolitan area

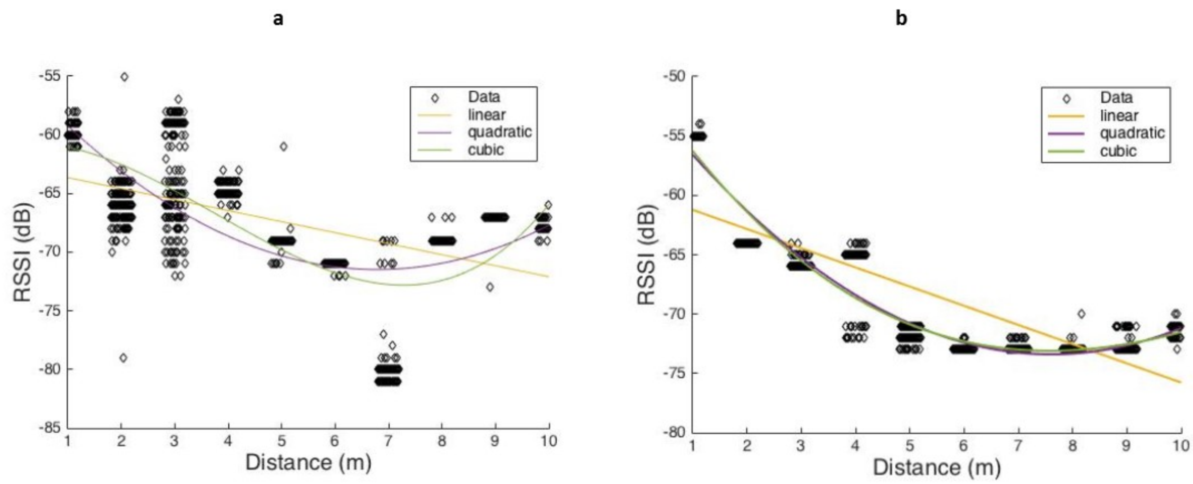


Figure 1a shows indoor RSSI variance given distance and lines of best fit. Figure 1b shows outdoor RSSI variance given distance and lines of best fit. Abbreviations: received signal strength (RSSI), decibels (dB), m (meters).

Figure 2. Simulated received signal strength indicator and distance data with random noise

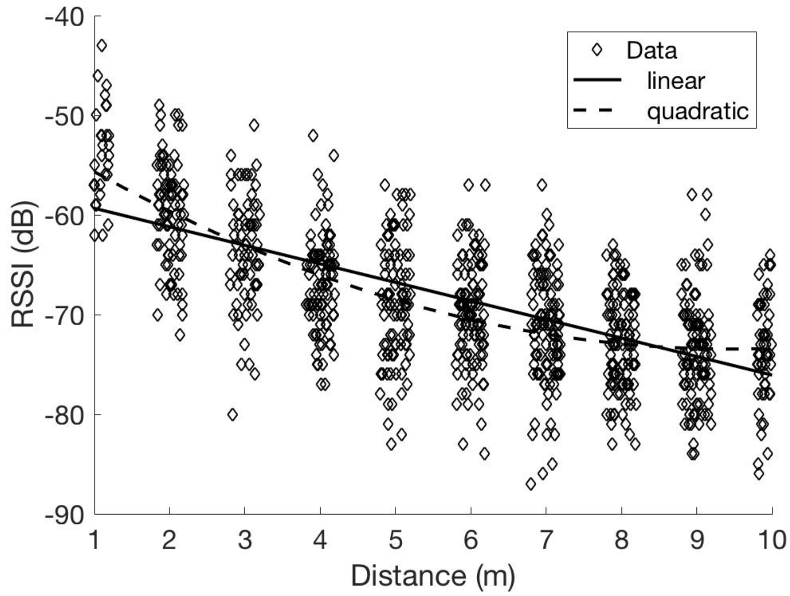
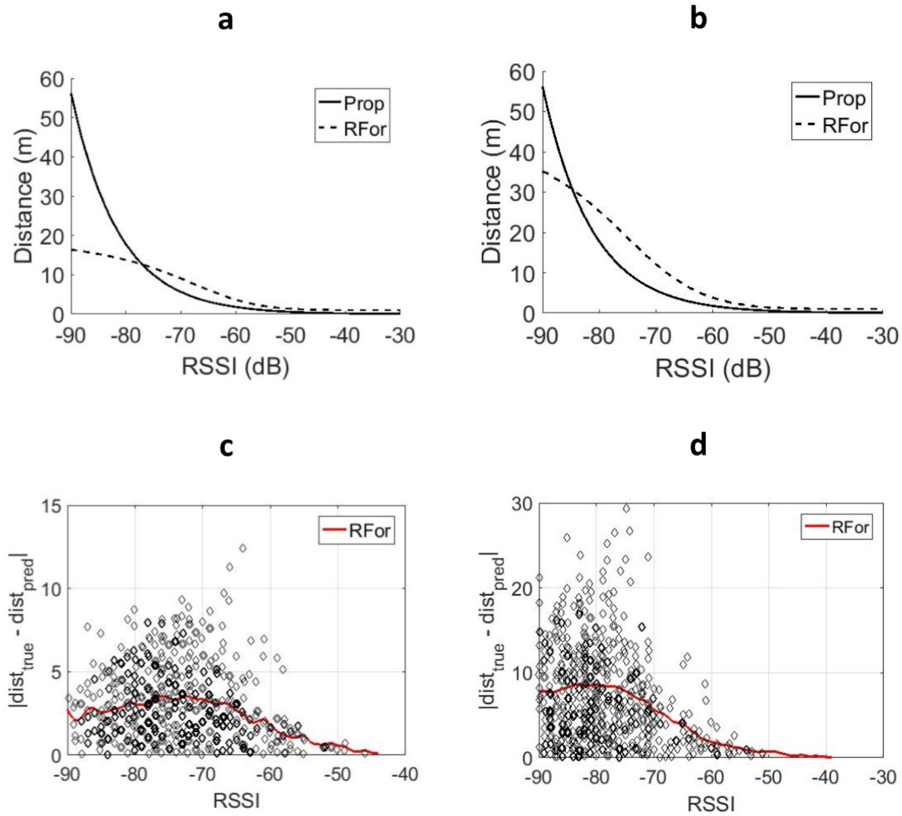


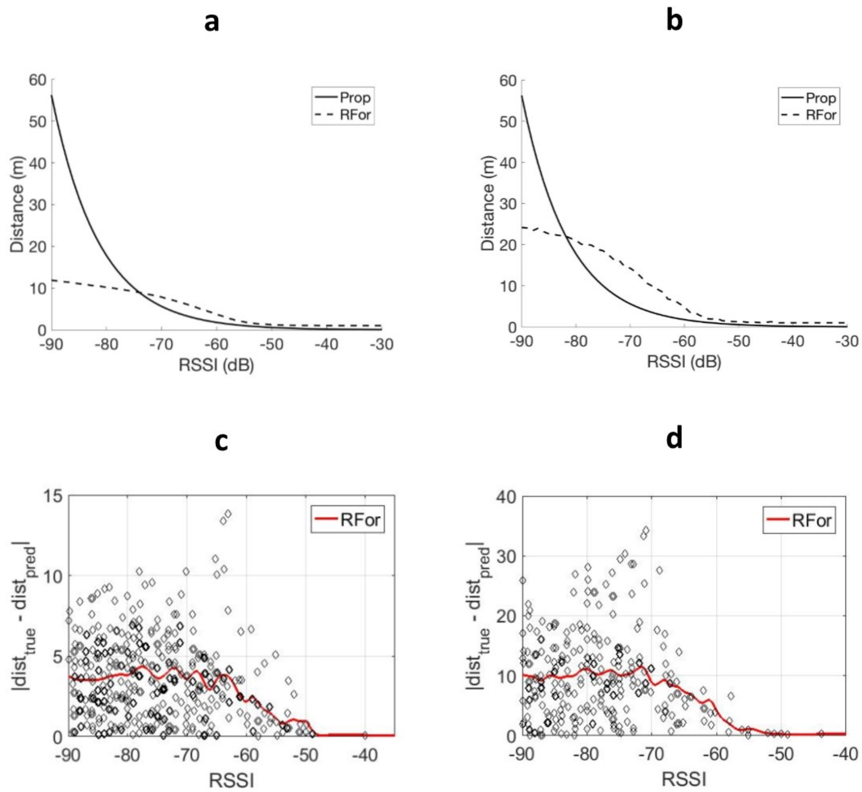
Figure 2 shows illustrates the face validity of the simulated data over the 10m range and lines of best fit. Abbreviations: received signal strength (RSSI), decibel (dB), m (meters).

Figure 3. Fixed alpha—Random Forest fitted values (above) and prediction errors (below) as a function of signal strength for simulated indoor (left) and outdoor (right) conditions



Figures 3a and 3b show the theoretical distance-RSSI relationships over the (a) 20m and (b) 50m ranges derived from the propagation model in the absence of random noise and when the path loss exponent is fixed at 2 (i.e., free-space path loss) in relationship to the Random Forest model predicted distances with simulated random noise. Figures 3c and 3d show simulated signal strength and absolute differences between the true and Random Forest predicted distances fitted with a smoothing spline for the (c) 20m and (d) 50m ranges with simulated random noise. Abbreviations: propagation model (Prop), Random Forest model (RFor), received signal strength (RSSI), distance (dist), predicted (pred).

Figure 4. Random alpha—Random Forest fitted values (above) and prediction errors (below) as a function of signal strength for simulated indoor (left) and outdoor (right) conditions



Figures 4a and 4b show the theoretical distance-RSSI relationships over the (a) 20m and (b) 50m ranges derived from the propagation model in the absence of random noise and when the path loss exponent is fixed at 2 (i.e., free-space path loss) in relationship to the Random Forest model predicted distances when the path loss exponent varied on the range [1, 5] with simulated random noise. Figures 4c and 4d show simulated signal strength and absolute differences between the true and Random Forest predicted distances fitted with a smoothing spline for the (c) 20m and (d) 50m ranges when the path loss exponent varied on the range [1, 5] and with simulated random noise. Abbreviations: propagation model (Prop), Random Forest model (RFor), received signal strength (RSSI), distance (dist), predicted (pred).

CHAPTER III

Interactive dyadic physical activity and spatial proximity patterns in 2 year-olds and their parents

Abstract

Purpose: To characterize daily physical activity (PA) behaviors in 2 year-old girls and boys and their parents, with and without an objective measure of dyadic spatial proximity. **Methods:** Urban-dwelling parent-toddler dyads (*N*=110) wore accelerometers for 7 days, and parents completed a sociodemographic questionnaire. Accelerometers were initialized to collect PA and Bluetooth-based proximity data. After applying wear time algorithms, *n*=65 dyads were further analyzed using a dyadic analysis statistical methodology. The *a priori* significance level was $p<0.05$. **Results:** Toddler-parent sedentary and light PA time were respectively interdependent, but moderate-vigorous PA (MVPA) time was not. Toddlers were significantly more active on weekdays and weekends than their parents, and no differences were found in daily PA volumes between girls and boys. In dyads with proximity data (*n*=34), analyses of joint (i.e., proximal and mutual) PA time showed that girls participated in significantly more joint PA with their mothers than boys. Children who participated in ~2hrs of joint PA/day engaged in ≥60min of MVPA/day, while children with <60min of MVPA/day engaged in ~30min less joint PA time with their mothers. Boys and girls who engaged in joint PA with their mothers across greater relative distances also participated higher daily MVPA volumes, as compared to boys who engaged in joint PA at closer relative distances to their mothers. **Conclusions:** Toddlers who participated in more joint PA with their mothers, and at greater relative distances, engaged in ≥60min of daily MVPA. Further research on the dyadic activity-proximity relationship is needed across early childhood development.

INTRODUCTION

Early childhood (2-5 years-old) is an essential period during physical activity (PA) behavior development (Kohl & Hobbs, 1998), and PA is an important predictor of health in the early years (Timmons et al., 2012). Research shows that parents play an important role in early childhood PA development and the years beyond (Booth et al., 2017; Kohl et al., 1998), with numerous reports of child and parent PA confirming positive associations between child-parent habitual daily PA volumes throughout childhood and well into adulthood (Telama, 2009; Yao & Rhodes, 2015). While a large body of evidence appears to support an interdependent child-parent PA relationship, research also shows that these dyadic PA interdependencies may not ubiquitous (Dlugonski, DuBose & Rider, 2017; Johansson et al., 2016). As such, further research is needed in order to better understand the interdependent child-parent PA relationship and contributing factors.

Studies of dyadic PA in young children and their parents have reported differential associations between child and parent PA after stratifying analyses by child and parent sex (Johansson et al., 2016; Moore, et al., 1991). However, little is known about what contributes to these differences in the dyadic PA relationship between boys, girls, and their parents. A recent review of methods for measuring child and parent co-participation in PA has suggested the use of accelerometry in tandem with an objective measure of child-parent proximity in order to provide more robust descriptions of child-parent PA (Uijtdewilligen et al., 2017). Such a multi-sensor approach captures dyadic PA in terms of both dyadic activity intensities and spatial dynamics (Uijtdewilligen et al., 2017), which in their combination may help to reveal interpersonal factors associated with the child-parent PA relationship at a key developmental stage.

Few studies, however, have used wearable technology to measure child and parent PA and dyadic proximity in early childhood (Dlugonski et al., 2017; Uijtdewilligen et al., 2017). In a sample of 1-5 year-olds and their mothers, no differences in joint child-parent PA volumes were found between mothers and their children with respect to child sex (Dlugonski et al., 2017). By contrast, a report of objectively measured child-parent PA and proximity in older children (8-14 year-olds) showed that child sex was associated with differences in joint child-parent PA volumes (Dunton et al., 2012). Given the potential influences of interpersonal proximity, child sex, and parent sex on the child-parent PA relationship, the need for further research on dyadic PA and proximity during early childhood is evident. This need is further underscored by the overall paucity of objective dyadic PA-proximity reports that are currently available to inform the developing definition of child and parent co-participation in PA (Uijtdewilligen et al., 2017).

Therefore, the aims of this study were to measure dyadic physical activity and interpersonal spatial proximity in 2 year-old boys and girls and their parents using wearable technology in order to characterize: 1) habitual daily child-parent PA interdependence, with and without a measure of dyadic proximity, 2) hour-to-hour interactive child-parent PA interdependence over a 3 day period, and 3) joint physical activity behaviors in child-parent dyads.

METHODS

Site & Sample

Study participants were recruited from an Early Head Start (EHS) in a major urban center, with a catchment area that serves under-resourced families across multiple city districts. EHS is a nationally funded program that aims to bolster the physical, cognitive, and socio-emotional development of children under 3 years and their parents. The EHS reported that 57% of its families share apartments with ≥1 families and 95% of families speak Spanish in the home. Families attend the EHS center for ~3.5 hours once per week, and also receive semi-monthly home-visits from one of their regular classroom teachers. Parents of 24-35 month-old children attending the EHS were invited to participate in this study. All children who were 24-35 months-old without exclusion criteria were eligible for the study and were invited to participate. Exclusion criteria included children with extreme developmental delays, significant sensory or behavioral concerns, or health conditions that might restrict PA. The absence of exclusion criteria were confirmed by parental or teacher report at the time of recruitment. Parents provided informed consent according to the policies and procedures of the Institutional Review Boards that approved study protocols.

Measures

Physical Activity. Child-parent dyads were asked to wear triaxial ActiGraph accelerometers (Pensacola, FL; Models: wGT3X+ or wGT3X-BT) at the hip (anterior superior iliac spine) for 7 contiguous days (Aadland & Ylvisáker, 2015; Cliff, Reilly & Okely, 2009), except while bathing or during sleep. Accelerometers were initialized to collect triaxial data at 30Hz for 8 days (Brønd & Arvidsson, 2016). ActiGraph data were exported from ActiLife software in 15s epochs for children and 60s epochs for parents. Data reduction procedures were conducted in MATLAB R2017a (The Mathworks, Inc, 2017). To yield accelerometer data with sufficient reliability ($r \geq 0.70$), the nonwear time criteria applied to children's accelerometer data were: 0cpm x 20min, <6 $h \cdot day^{-1}$, <3 days observed (Cliff, Reilly & Okely, 2009). For adults, nonwear time criteria were: 0cpm x 90min, 120s spike tolerance (bracketed by 30min spike tolerance windows), <6 $h \cdot day^{-1}$, <4 days observed (Barkin et al., 2017; Choi, Liu, Matthews & Buchowski, 2011), where cpm refers to the counts observed per minute. Accelerometer data were analyzed for N = 110 parent-child pairs, and after applying data reduction algorithms, n=65 dyads met wear time criteria and were included in further analyses. Activity intensity thresholds for sedentary behavior

(SED), light PA (LPA), and moderate-vigorous PA (MVPA) were applied to accelerometer counts for children [SED (≤25); LPA (>25 & <420); MVPA (≥420)] and adults [SED (≤99); LPA (<99 & <1952); MVPA (≥1952)] using established cut points (Freedson, Melanson & Sirard, 1998; Trost et al., 2012).The proportion of parents meeting current recommendations for MVPA of ≥150min/week were calculated (Garber et al., 2011). The proportion of children meeting current recommendations for TPA and MVPA of ≥180min/day and ≥60min/day, respectively, were also calculated (American Heart Association, 2016; Institute of Medicine, 2011). Total PA (TPA) was defined as any activity above the respective SED thresholds for children and parents.

Proximity. Proximity tagging data that are available in newer accelerometers can be used as an objective measure of dyadic proximity (Uijtdewilligen et al., 2017). ActiGraph wGT3X-BT accelerometers were additionally initialized to collect proximity data in 60s epochs, with devices respectively assigned as “receiver” and “beacon” for child-parent dyads (Dlugonski et al., 2017). Accelerometer-derived proximity data can be used to predict metered distances between devices (≤20m), as well as to yield proportions of time that devices are proximal (≤50m) (McCullough, Keller, Qiu & Garber, 2018). Proximity data were conserved for periods during which dyads had mutually valid accelerometer wear time data. Proportions of time when receivers and beacons were within range were calculated. Metered distances between dyadic counterparts were also predicted from accelerometer-derived Bluetooth signals (McCullough et al., 2018), and were then transformed into z-scores in order to derive a standardized measure of the relative distance (i.e., nearer [<0] or farther [>0]) between child and parent during activity. Of the dyads meeting wear time criteria, n=34 dyads had proximity data and were included in further proximity analyses. All dyads with proximity data were also mother-child dyads.

In light of the current recommendation for a consensus on the definition of *co-participation in PA* (Uijtdewilligen et al., 2017), we focused on a single element of the current understanding of the term—mutual and proximal engagement in activity. We use the term *joint* to describe such bouts of activity wherein child and parent activity intensities are synchronous and dyadic counterparts are oriented proximally in space.

Additional Measures. In order to compute descriptive statistics of sample characteristics and to also adjust models of child-parent activity and proximity for potentially influential covariables, parents were asked to complete a brief sociodemographic questionnaire. The questionnaire included items on children (age and sex) and parents (age, sex, country of origin, household income, education, and family size).

Statistical Analyses

A dyadic analysis methodology was employed for this study because it is expressly suited for studies wherein data have been purposively sampled in dyads (Kenny, Kahsy & Cook, 2006). Moreover, the application of a dyadic analysis methodology to child-parent PA data affords researchers an opportunity to analyze interactive child-parent PA patterns using over-time dyadic models, which can provide high-level detail on child-parent PA interdependencies at various temporal resolutions.

Data were analyzed in MATLAB and MPLUS 7 (Muthén & Muthén, 2012). Descriptive statistics are reported as Mean (Standard Deviation), Median (Interquartile Range), or Frequencies (%) for child-parent sociodemographic characteristics, activity behavior, and dyadic proximity data. In order to test for interdependence between child and parent covariates of interest, intraclass correlations (r_I) and Pearson's correlations (r) were analyzed for child and parent proportions of time spent SED, in LPA, and in MVPA.[24] Pearson's correlations were repeated after conditioning on child sex. Correlations between the proportion of time that children and parents spent in each respective activity threshold (SED, LPA, and MVPA) while proximal were also examined after conditioning on child sex.

Partial correlations were tested between the proportions of time that children and parents spent in TPA, after controlling for children's age and the mean daily proportion of time that dyads were proximal. The following linear mixed effects (LME) models were run after controlling for the random effect of dyad—Model 1: Weekday and weekend TPA ~ day (i.e., weekday and weekend), role (i.e., child and parent), day x role, child sex, and child age. Model 2: included proximity and a proximity x sex interaction as additional covariates to those in model 1. Continuous covariates were mean centered to facilitate interpretation of interaction effects. A residual maximum likelihood method was used in LME models with a sample size of $n \leq 50$, otherwise a maximum likelihood estimator was used (Snijders & Bosker, 2012). Respective models were systematically assessed for the assumptions of 1) within dyad interdependence and 2) mutually independent residuals with distribution $N \sim (0, \sigma^2)$—both of which were found to be tenable across models (Kenny et al., 2006; Snijders et al., 2012).

Interactive hour-to-hour child and parent TPA behaviors were examined in an actor-partner interdependence model (APIM) (Kenny et al., 2006). The APIM estimates cross-partner influences within dyads and the stability of a given signal within-subjects over time. Dyadic hour-to-hour proportions of time spent in TPA were randomly extracted from 3 monitored days on which children and parents mutually had valid TPA data. A total of n=63 dyads had sufficient mutual wear time data and were included in the APIM analysis. Model 3: For a given hour, child TPA time ($CHILD_t$) was regressed on lagged child ($CHILD_{t-1}$) and lagged parent ($PARENT_{t-1}$) TPA time, and parent TPA time ($PARENT_t$) was regressed on lagged child and lagged parent TPA time.

To explore the influence of hourly dyadic proximity on hourly TPA time, an additional model was fit for dyads with proximity data. Again, here the model averaged over TPA hour-to-hour, and thus does not distinguish between periods of mutual engagement versus non-mutual engagement in PA during each hour. Additionally, the proportion of time spent in proximity hour-to-hour only represents the amount time that dyadic counterparts spent together each hour, and does not distinguish between periods of activity or inactivity. Model 4: The lagged proportion of time that children's and parents' devices were within range ($PROX_{t-1}$) was added to the model, such that $CHILD_{t-1}$ and $PARENT_{t-1}$ TPA were regressed on $PROX_{t-1}$, and $PARENT_t$ and $CHILD_t$ were regressed on $PARENT_{t-1}$ and $CHILD_{t-1}$. Continuous covariates were mean centered; the grand mean of $CHILD_{t-1}$ and $PARENT_{t-1}$ was respectively subtracted from each predictor according to APIM specifications in both models (Kenny et al., 2006). Both models were also respectively adjusted for correlated errors within dyads and repeated measures within subjects. Model fit was assessed for both Model 3 [$\chi^2_1 = 0.71, p > 0.05$; CFI/TLI ≥1.0; RMSEA <0.01] and Model 4 [$\chi^2_3 = 3.64, p > 0.05$; CFI/TLI ≥0.99; RMSEA =0.01], and both were found to have good model fit.

In order to explore differences in joint TPA with respect to child sex and MVPA, two separate two-way ANOVA models were run with *post hoc* multi-comparisons using Scheffe's procedure. Model 5: Tested for differences in the proportion of time that children and parents engaged in joint TPA time, conditioning on the following dichotomous independent variables—child sex (female; male) and mean daily MVPA volume (<60min/day; ≥60min/day). Model 6: Tested for differences in the mean relative distance (z-scores) at which child and parent engaged in joint TPA, conditioning on child sex and mean daily MVPA volume. Main effects and interaction effects were assessed in each respective model. The assumptions of normality and homogeneity of variances were assessed and found to be tenable. Effect sizes are presented as partial eta squared.

Tests for differences in MVPA and TPA time between dyads with and without proximity data showed that there were no significant differences for children nor parents. All models were estimated with an *a priori* significance level of $\alpha = 0.05$.

RESULTS

Summaries of sociodemographic variables and descriptive statistics for wear time, activity, and proximity data are presented in Table 1. Of those who reported their ethnicity (n=43), >97% (42) identified as Latino/Hispanic and ~2% (1) identified as not Latino/Hispanic. Overall, children spent 52(8)% of their time SED, 38(5)% in LPA, and 10(4)% in MVPA, while parents spent 56(9)% SED, 40(8)% in LPA, and 4(2)% of their time in MVPA. Dyadic counterparts were within proximity 73(18)% of mutually monitored wear time, on average, with a relative distance z-score of -0.01(0.21). Table 2 shows activity and proximity characteristics for girls, boys, and their mothers while their respective dyadic counterpart was engaged in activity of any given intensity. With respect to overall wear time, dyads engaged in joint SED 19(7)% of the time with relative distance z-score of -0.01(0.22), in joint MVPA <0.01(0.005)% of the time with a relative distance z-score of -0.001(0.46), and in joint TPA 15(5)% of the time with a relative distance z-score of 0.14(0.54).

Dyadic Activity-Proximity Interdependencies

Without Proximity. Intraclass correlations for overall child-parent proportions of time spent SED ($r_I = 0.10$), in LPA, ($r_I = 0.22$), and in MVPA ($r_I < 0.01$) suggest that SED and LPA were interdependent within dyads. Pearson's correlations showed that the mean daily proportions of time that children and parents spent SED each day were not significantly correlated ($r = 0.20$, p

>0.05), nor were the proportions of time spent in MVPA (r = - 0.07, p >0.05); however, mean daily proportions of time spent in LPA were significantly correlated (r = 0.27, p <0.05). After stratifying by child sex, no relationship (p >0.05) was found between the overall proportions of time that girls and their parents spent in SED (r = 0.03), LPA (r = 0.09), or MVPA (r = -0.06) each day. The proportions of time that boys and their parents spent SED (r = 0.45) and in LPA (r = 0.44) were interdependent (p < 0.05), while boy-parent MVPA was not (r < 0.01, p >0.05).

With Proximity. After conditioning on dyadic proximity, intraclass correlations for the child-parent proportions of time spent SED (0.69), in LPA (0.76), and in MVPA (<0.01) showed that proximal SED and LPA behaviors were interdependent within dyads. Pearson's correlations showed that the mean proportions of time that children and their mothers spent SED were interdependent when dyadic counterparts were proximal (r = 0.78, p < 0.001). The mean proportions of time spent in LPA were also interdependent when child and mother were proximal (r = 0.75, p <0.001); however, the mean proportions of time spent in MVPA were not interdependent when child and mother were proximal (r = -0.13, p >0.05).

For girls and their mothers, the mean proportions of time spent SED were interdependent (r = 0.90, p <0.001) when proximal, LPA volumes were interdependent when proximal (r = 0.87, p <0.001), and the mean proportions of time spent in MVPA were not interdependent when proximal (r = 0.17, p >0.05). Among boys and their mothers, the mean proportions of time spent SED were interdependent when proximal (r = 0.72, p <0.01), the mean proportions of time spent in LPA were interdependent when proximal (r = 0.47, p <0.05), and the mean proportions of time spent in MVPA were not interdependent when proximal (r = -0.26, p >0.05).

Partial correlations showed that the proportions of time that child and mother spent SED while proximal remained positively associated (ρ = 0.74, p <0.001) after controlling for age and the relative distance (z-score) at which child and mother engaged in SED while their respective counterpart was proximal and engaged in any activity intensity. The proportions of time that child and mother spent in TPA while proximal ($\rho = 0.73$, p <0.001) remained positively associated after controlling for age and the relative TPA distance z-scores for mothers and their children.

Overall Daily Child-Parent PA

Without Proximity. Results from model 1 showed that children spent *7*(1)% (p <0.001) more time in weekday and weekend TPA than parents [*42*(1)%)], controlling for all other model covariates. Dyads were also 2(1)%, more active on weekdays (p <0.05) than weekends. Dyadic weekend and weekday TPA were not associated with child age nor sex (Adjusted R^2= 0.39).

With Proximity. After adjusting for the proportion of time that child-mother dyads were in proximity and the proximity x child sex interaction, there was a significant interaction between proximity and sex [$\beta_{prox} \cdot \beta_{sex}$= *0.22*(0.07), p <0.05]. For a 1% increase in the proportion of time that girls and their mothers were within proximity, there was a 0.13% decrease in the mean proportion of time that girl-parent dyads spent in TPA [*52*(6)%]. For boys and their mothers, a 1% increase in the proportion of time that dyadic counterparts spent in proximity was associated with a 0.23% decrease in the mean proportion of time that boy-mother dyads spent in TPA [*56*(7)%]. Role was also a significant covariate in the model (p <0.001), showing again that, on average, children spent additional time in TPA [*8*(2)%] above parents [*41*(2)%], controlling for all other model covariables. No other model covariates were significantly associated with dyadic weekday and weekend TPA (Adjusted R^2= 0.40).

Hour-to-Hour Interactive Child-Parent PA

Without Proximity. Model 3 showed that on average children's [β_{11}= *0.37*(0.02), p <0.001] and parents' [β_{22}= *0.47*(0.02), p <0.001] own TPA behaviors during a given hour significantly predicted their own TPA behavior in the following hour after adjusting for all other model covariates. Parents' TPA during a given hour was also positively associated with their children's TPA over time [β_{21}= 0.09(0.02), p <0.001]; however, children's lagged TPA was not significantly associated with parents' hourly TPA (p >0.05). Children's and parents' hourly TPA were also correlated from hour-to-hour [φ= 0.29(0.02), p <0.001], and the variances were also correlated for child-parent hourly TPA (p <0.001).

With Proximity. After adjusting for hourly dyadic proximity, dyadic hourly TPA remained correlated hour-to-hour (φ= 0.25, p <0.001); however, mothers' TPA no longer predicted children's PA hour-to-hour (Figure 1a). Lagged hourly dyadic proximity was significantly inversely associated (p <0.001) with lagged mothers' TPA [β= -0.31(0.03)] at a given hour, but not children's (p >0.05). Figure 1b shows dyadic mean hourly TPA and proximity signals throughout the day. The peak TPA time for parents was from 14:00 to 14:59, with parents spending [*52.7*(15.2)%] of their time in TPA on average, and was from 20:00 to 20:59 for children [*56.0*(14.1)%]. The mean proportion of time that dyads spent in proximity was lowest from 17:00 to 17:59 [*68.2*(21.0)%].

Joint Dyadic PA

Daily Activity Time. The two-way ANOVA (Figure 2a) on the daily proportion of time children and mothers spent engaged in joint TPA showed a non-significant child sex x MVPA volume interaction ($F_{1,30}$ = 0.07, p > 0.05, $\eta_p^2 < 0.01$), but significant main effects for child sex ($F_{1,30}$ = 9.14, p < 0.01, $\eta_p^2 = 0.23$) and MVPA volume ($F_{1,30}$ = 8.69, p < 0.01, $\eta_p^2 = 0.23$). *Post hoc* analyses showed that, on average, girls engaged in significantly more (p = 0.006) joint TPA time with mothers [18(1)%] than boys [13(1)%], and children who engaged ≥60min of daily

MVPA participated in significantly more ($p = 0.005$) joint TPA time with their mothers [18(1)%] than those with <60min of daily MVPA [13(1)%].

Dyadic Distance. Figure 2b shows results from the two-way ANOVA on the relative distance (z-scores) between child and mother while engaged in joint TPA. There was a significant child sex x MVPA volume interaction ($F_{1,30} = 4.37$, $p < 0.05$, $\eta_p^2 = 0.13$), a significant main effect for MVPA volume ($F_{1,30} = 14.7$, $p < 0.001$, $\eta_p^2 = 0.33$), and a non-significant main effect of child sex ($F_{1,30} = 0.9$, $p > 0.05$, $\eta_p^2 = 0.03$). Girls who engaged in ≥60min of daily MVPA participated in joint TPA at significantly ($p = 0.04$) greater distances from their mothers [0.17(0.10)] than boys with <60min of daily MVPA [-0.20(0.08)], as did boys with ≥60min of daily MVPA [0.26(0.07)] with respect to boys with less MVPA ($p = 0.001$). Girls with <60min of daily MVPA did not engage in joint TPA at significantly different distances [0.03(0.07)] than any other group ($p > 0.05$), and there were no significant differences in relative dyadic distances between boys and girls with ≥60min of daily MVPA ($p > 0.05$).

DISCUSSION

This study aimed to characterize the dyadic activity-proximity relationship in a sample of 2 year-old boys and girls and their parents. Using a dyadic analysis statistical methodology, results showed that child and parent mean daily SED and LPA, but not MVPA behaviors, were interdependent. These results remained consistent even after specifically examining the periods of time during which child and mother were proximal. Hour-to-hour dyadic PA behaviors were also interdependent after controlling for dyadic proximity, which was inversely associated with maternal hourly PA. Results also showed that children who participated in greater amounts of joint (i.e., mutual and proximal) TPA time with their mothers also engaged in higher daily MVPA volumes than children who engaged in less child-mother joint TPA. Moreover, with respect to joint TPA time, participating in dyadic PA across greater distances was associated with higher volumes of daily MVPA for children. Thus, the findings from our study suggest that interpersonal spatial dynamics between dyadic counterparts may help to explain some of the variability in early childhood PA, specifically with respect to children's daily activity volumes and intensities.

At the dyadic level, child-mother daily PA was inversely associated with the proportion of time that counterparts were proximal, and child sex was found to moderate the inverse relationship between dyadic PA and proximity. However, further analyses of hour-to-hour activity-proximity data revealed that the inverse relationship between dyadic proximity and PA was only significantly associated with maternal hourly PA, and that it had no association with children's hour-to-hour PA behaviors. It is important to note, however, that our model made no constraints on mutuality with respect to child and mother activity intensities at any given hour. As such, our data suggest that mothers were less active as they and their children spent more time in proximity, irrespective of their counterpart's level of activity, which includes proximal sedentary time. In another study of objectively measured activity and proximity in young children and their mothers, joint TPA time was inversely associated with mothers' PA at times when they were not proximal to their children (Dlugonski et al., 2017). Though direct comparisons between studies may be limited due to differences in proximity data processing (McCullough et al., 2018), both point toward inverse associations between dyadic proximity and maternal PA behaviors. Thus, further research is needed to better explain influential factors in the observed inverse relationship among mothers, as well as to confirm its presence across diverse dyadic cohorts. Additionally, child and parent hour-to-hour PA variances in our study remained correlated between counterparts after adjusting for within-subject hourly PA tracking, dyadic cross-partner interactions, and dyadic proximity. The remaining shared dyadic variance may point toward genetic, cultural, and environmental factors that were unexplained by the model (Kohl et al., 1998; Pérusse, Tremblay, Leblanc & Bouchard, 1989). As such, more research is needed in order to respectively characterize the relative contributions of learned, inherited, and environmental factors on the development of PA behavior in early childhood.

Though the hour-to-hour interactive model seemed to suggest an arbitrary relationship between dyadic proximity and children's PA behaviors, targeted evaluation of the time periods during which children and mothers were engaged in joint PA revealed that joint child-mother PA was associated with differences in toddlers' daily MVPA volumes. Specifically, children in our study who engaged in higher daily volumes of moderate-vigorous PA (≥60 min/day) also participated in ~2 hours of PA with their mothers each day, as where children with lower daily MVPA volumes (<60min/day) participated in ~1.5 hours of PA with their mothers daily. These results may provide initial evidence of a daily PA target for toddler-mother dyads; however, further study across early childhood is required to confirm suggested dyadic PA targets. Dually, these results invite research on the benefits of ~30min dyadic activity interventions in young children, particularly as they transition from age 2 years to 3 years—the age at which it is widely recommended that children participate in ≥60min of daily MVPA (American Heart Association, 2016; Institute of Medicine, 2011).

Furthermore, our novel analysis of relative distance scores between dyadic counterparts while engaged in joint PA showed that child-mother spatial dynamics were associated with differences in toddlers' daily MVPA volumes. Specifically, girls and boys who engaged in ≥60min MVPA/day also participated in joint PA at greater distances from their mothers; this particular activity-proximity dynamic was especially important for boys. Among girls with lower daily MVPA volumes, however, there were no differences in the relative distances at which they participated joint TPA when compared to any other group. Notably, girls in our study were also found to participate in more joint PA with their mothers than boys. A prior report of dyadic PA and proximity in 8-14 year-olds and their parents also showed that girls spent more time in joint MVPA with their parents than boys (Dunton et al., 2012), which similarly points towards sex-dependent differences in the dyadic activity relationship (Johansson et al., 2015). Despite differences between boys and girls with respect to child-mother joint PA time, no differences were found between the overall time that boys and girls spent in PA. While our report of no difference in overall PA volumes between girls and boys is congruent with other studies of PA in 2 year-olds (Johansson et al., 2016), these results remain striking because studies also report differences in PA between girls and boys by 3 years of age (Pate, Pfeiffer, Trost, Ziegler & Dowda, 2004). Taken together, these findings encourage especial attention toward the influence of sociocultural and interpersonal factors on the differential trajectories of PA behavior in young girls and boys. In order to better understand the contextual qualifiers that may explain these apparent sex-based differences, further research on PA behaviors in young boys and girls is needed with a particular focus to the concurrent influences of dyadic interpersonal spatial dynamics, parental support for PA, and parenting style (Beets, Cardinal & Alderman, 2010; Hennessy, Hughes, Goldberg, Hyatt & Economos, 2010).

With regard to limitations of the study, the adult sample in our study was predominantly comprised of mothers and all families in our study reported an annual income below the federal poverty level, thus our results may be more indicative of activity proximity relationships in mother-toddler dyads. Finally, the use of dyadic analysis limits the direct comparison of these findings to other studies that have used a dyadic analysis approach to study child-parent PA beahviaors (Uijtdewillgen et al., 2017). Findings from our study may, therefore, be generalizable to other under-resourced toddler-parent dyads living in areas of pronounced need within a major urban center.

To our knowledge, this study is the first to use a dyadic analysis statistical methodology to analyze dyadic physical activity (Uijtdewillgen et al., 2017; Yao et al., 2015), as such parameter estimates were appropriately and necessarily adjusted for interdependent relationships between child and parent outcomes (Kenny et al., 2006). Along with the recent recommendation to include objective measures of dyadic proximity in studies of child-parent PA (Uijtdewillgen et al., 2017), we add that studies of dyadic PA and proximity should consider the use of dyadic analysis in the treatment of their dyadic data. Results from our study show its utility in analyzing correlated dyadic data, but also reveal its potential to uncover additional layers of information with regard to cross-partner and within-subject PA behavior patterns. For example, an unintended, albeit notable, artifact of employing the hour-to-hour actor-partner interdependence model was the discovery that toddlers' hourly PA volumes were stable over time. Thus, while it is well-established that young children characteristically engage in random "short burst" PA patterns (Cliff et al., 2009), our data show that toddlers' activity patterns also appear to exhibit a significant degree of consistency throughout the day.

In conclusion, we found that child sex moderated the relationship between dyadic activity and proximity, and that differences in joint child and mother PA time were associated with children's daily moderate-vigorous activity volumes. Girls engaged in more joint PA time with their mothers than boys, and relative distances between dyadic counterparts during joint PA were also associated with differences in children's daily moderate-vigorous activity volumes. For boys in particular, engaging in bouts of joint PA that maximized relative dyadic distances was associated with participating in higher daily volumes of moderate-vigorous PA. These findings show that relative dyadic distance may be an important explanatory factor in characterizing dyadic PA. Results from our study invite further investigation of sex-based differences in the dyadic activity-proximity relationship across diverse samples of young children and parents.

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Table 1. Demographics, activity, inactivity, and spatial proximity in toddler-parent dyads attending an Early Head Start Program in a major metropolitan area

	Dyads (*n* = 65)	
Variables	Children	Parents
Sex		
Female (*n*)	34	63
Male (*n*)	31	2
Age	*29* (4) months	*32* (6) years
Income below Federal Poverty Level (%)		100
Family Size (*n*)		*4.1*(1.2)
Country of Origin (%) (*n* = 58)		
Mexico		66.7%
Dominican Republic		6.8%
Ecuador		10.0%
USA		8.3%
Other		8.1%
Education (%) (*n* = 55)		
Less than High School		50.9%
High School Diploma/GED		29.1%
Associates Degree/Some College		10.9%
College Degree/Graduate Degree		9.1%
Accelerometer Wear time		
Days	*5.5* (1.5)	*6.4* (1.0)
Weekend days (*n* = 53)	*1.4* (0.8)	*1.6* (0.7)
Hours/day	*10.1* (1.3)	*12.3* (1.5)
Daily Minutes by Activity Intensity		
SED	*312.6* (61.3)	*415.2* (84.0)
TPA	*293.7* (60.1)	*356.1* (83.2)
MVPA	*61.3* (27.6)	27.2 (15.9)
Meeting PA Guidelines (%)		
MVPA	44.6[a]	40.0[b]
TPA	98.5[c]	
Proximity Wear Time (*n* = 34)		
Days		*6.4*(1.1)
Hours/day		*12.4(*1.4*)*

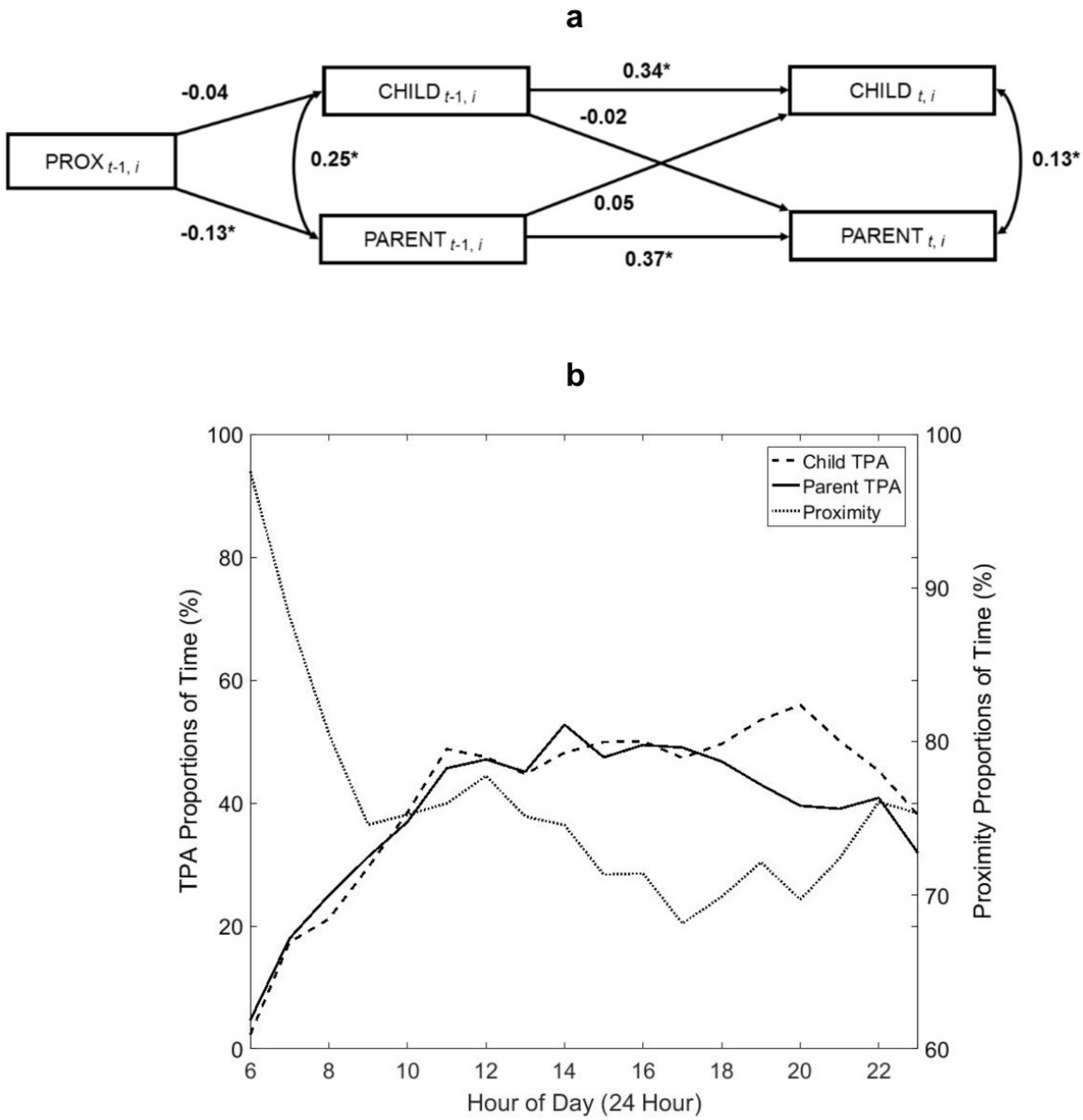
Note**:** Table values are *Mean* (Std. Deviation) or Frequencies (%). Abbreviations: physical activity (PA), Sedentary Behavior (SED); Moderate-Vigorous Physical Activity (MVPA); Total Physical Activity (TPA). Activity Guidelines are: a) American Heart Association,[28] b) American College of Sports Medicine,[29] c) Institute of Medicine[30]

Table 2. Mother-child activity and dyadic proximity characteristics stratified by child sex

	Girl-Mother Dyads (*n* = 15)		**Boy-Mother Dyads** (*n* = 19)	
	Girls	Mothers	Boys	Mothers
Time (%) spent in each intensity while proximal				
SED	38(21)%	40(19)%	35(13)%	46(11)%
LPA	32(13)%	34(15)%	28(5)%	28(9)%
MVPA	5(4)%	3(3)%	7(4)%	3(3)%
Relative distance (z-scores)				
SED	0.07(0.17)	-0.13(0.33)	0.11(0.29)	-0.07(0.48)
LPA	0.23(0.16)	0.18(0.15)	0.12(0.29)	0.15(0.31)
MVPA	0.12(0.18)	0.24(0.19)	0.27(0.36)	-0.17(0.41)

Note: Table values are Median(IQR). All values are interpreted with respect to the indicated dyadic counterpart, as their dyadic partner was proximally engaged in activity of any intensity. Relative distances (z-scores) for dyadic counterparts: Nearer <0; Farther >0. Abbreviations: sedentary (SED), light physical activity (LPA), moderate-vigorous physical activity (MVPA).

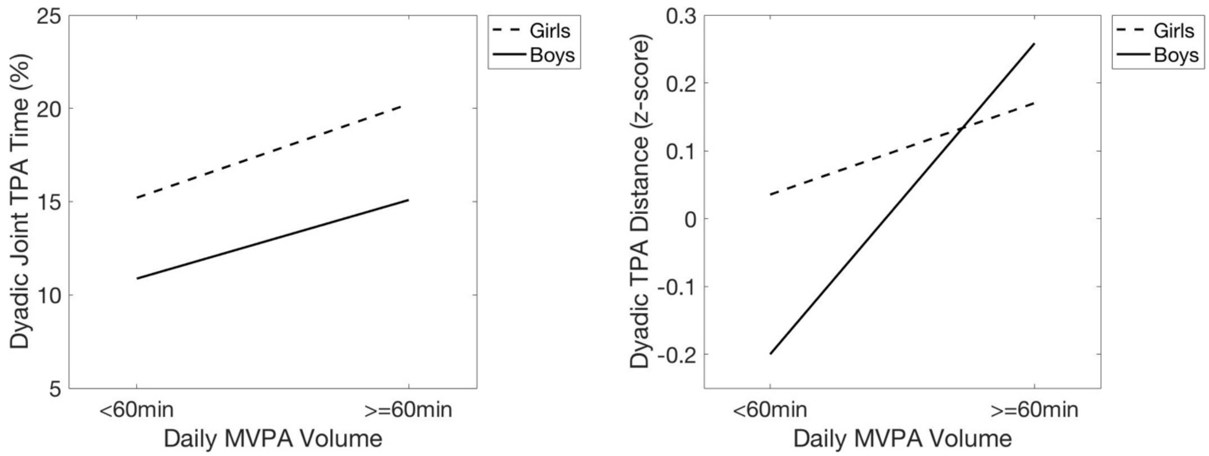
Figure 1. Associations between toddler-mother hourly physical activity time and dyadic proximity over 72hrs among urban-dwelling families



Note: Figure 1a shows that children's and mothers' time spent in total physical activity (TPA) during a given hour significantly predicted ($p < 0.01$) their respective time spent in TPA during the following hour after controlling for dyadic proximity. The model also shows an inverse relationship between hour-to-hour dyadic proximity and maternal PA. Figure 1b illustrates hourly proximity-activity signals for child-parent dyads. Asterisk (*) indicates $p < 0.01$. Abbreviations: prox (proximity).

Figure 2. Differences in child-mother joint physical activity time (left) and relative distances (right)

a **b**



Note: Figure 2a shows that girls spent more time in joint PA with their mothers than boys, and children who engaged in ≥60min MPVA/day participated in more joint PA than those with <60min MVPA/day. Figure 2b shows that girls and boys who participated in joint PA with their mothers across wider relative distances participated in >60min MVPA/day, compared to boys with <60min MVPA day who participated in joint PA at closer relative distances. Abbreviations: physical activity (PA), moderate-vigorous PA (MVPA), minutes (min).

CHAPTER IV

Calibration of a dual-sensor camera for detecting triaxial physical activity signals in young children

Abstract

Objective measures of physical activity (PA) are important for accurately assessing PA behaviors in early childhood. Remote sensors, such as 3D cameras, can provide additional contextual and group-based data that can enhance what is known about PA in young children; however, no physical activity cut points exits for PA data collected using a 3D camera. **Purpose:** To develop triaxial physical activity cut points, as measured by an infrared-depth sensing camera, in young children. **Methods:** Families with children (2-5 years-old) were recruited and invited to participate in semi-structured 20 minute play sessions that included activities such as quiet play, walking, running, etc. while indoors. During the play session, children's PA was recorded using an infrared-depth sensing camera, Microsoft's Kinect (MSK). PA video data were analyzed via direct observation using the Children's Activity Rating Scale (CARS), and infrared-depth PA video data were processed and converted into triaxial PA accelerations using computer vision. PA data from children (n = 10) were analyzed, and the Receiver Operating Characteristic Area Under the Curve (AUC) was calculated in order to determine triaxial cut points for infrared-depth sensor-derived PA data. **Results:** Children were *45*(12) months-old on average, 6 were girls, and 4 were boys. A CART algorithm accurately predicted the proportion of time that children spent sedentary (AUC = 0.89), in light PA (AUC = 0.87), and moderate-vigorous PA (AUC = 0.92) during the play session, and there were no significant differences ($p > 0.05$) between observed and CART predicted proportions of time spent in each activity intensity. **Conclusions:** Results from this study showed that a computer vision algorithm and 3D camera can be used to estimate the proportion of time that children spend in all activity intensities without the use of wearable technology.

INTRODUCTION

The health-enhancing benefits of physical activity (PA) in early childhood (ages 2-5 years) have been widely reported (Ekelund et al., 2012; Janz et al., 2010), and evidence suggests that social and contextual factors, such as proximity to others, may influence PA behaviors in young children (Knuth et al., 2017; Uijtdewilligen et al., 2017). To date, multiple wearable sensors (e.g., accelerometers and GPS devices) have been used simultaneously to provide social and contextual information alongside objective estimates of children's daily PA volumes (Rowlands & Eston, 2007; Uijtdewilligen et al., 2017). However, the cost of such a multi-sensor measurement approach may be a limitation, and the use of multiple wearable sensors during free-living activities may increase participant burden especially in young children.

As an alternative method for dynamically measuring PA and social-contextual signals, studies have shown that video data can be processed using computer vision algorithms to extract information about physical activity behaviors within a given context (Carlson et al., 2017). Computer vision uses an array of techniques from fields such as engineering and machine learning to extract meaningful information (e.g., facial features and hand gestures) from digital images including video (Han, Ling, Shao, Xu, Shotton, 2013). While a small number of studies have used custom computer vision algorithms to convert video-recorded PA behaviors into quantifiable PA signals (Silva et al., 2015, Maile et al., 2015; Carlson et al., 2017), no study has validated such a method for estimating PA volumes and intensities in young children.

Of the available studies that have used computer vision to estimate PA volumes (Silva et al., 2014; Carlson et al., 2017), only one has calibrated an algorithm to measure PA in children from a camera (Silva et al., 2015). This study of 10 year-old children was the first to establish that a ceiling-mounted 2D camera could be used to automatically derive estimates of PA velocities in bi-dimensional space (Silva et al., 2015). Concurrently, a feasibility study demonstrated the potential application of three-dimensional (3D) cameras to measure PA (Maile et al., 2015); however, PA was only analyzed in one of the available three dimensions and the algorithm was not calibrated for activity intensity estimation. A recent report in adults revealed that computer vision algorithms can also accurately estimate time spent in PA outdoors when compared to acceleroemtery (Carlson et al., 2017), but direct application of their findings may be limited to use in adults alone given that energy expenditure profiles, as they relate to physical activity, change over time due to maturation (Rowland, 2005).

While the feasibility and validity of using computer vision to estimate activity volumes and intensities has been shown (Maile et al., 2015; Carlson et al., 2017), little is known about the use of computer vision to measure PA in young children. Given the lack of available methods to measure young children's PA from video data using an automated process, the need for a validated computer vision algorithm for estimating PA in young children is clear. Therefore, the purpose of this study was to calibrate triaxial physical activity cut points for a three-dimensional camera in a sample of 2-5 year-old children.

METHODS

Sample. Families with 2-5 year-old children were recruited from community centers, preschools, early childhood centers, day cares, and a hospital located within a major urban center via flyers, emails, and word-of-mouth. Children for whom engaging in moderate-vigorous physical activity would present any concerns for safety due existing medical conditions were excluded from participating in the study. The presence of exclusion criteria were confirmed via parental report at the time of recruitment and were confirmed during an orientation session. Informed consent was obtained by one or both parents for $N = 11$ children, and the study was approved by the Institutional Review Board at both Columbia University Medical Center and Teaches College, Columbia University.

Play Session Protocol. After providing informed consent, families were scheduled to attend a 20 minute indoor play session. The play session took place on a 100 square foot padded play area located within our laboratory. Prior to beginning the play session, parents were informed that the target physical activity behaviors for children to perform were: quiet play, climbing, walking, running, and jumping. Children and their parents were then invited to play freely with various affordances for movement (e.g., toy cars, blocks, risers, bubbles, etc.) for the first 10 minutes of the play session. If all of the target behaviors were performed within the first 10 minutes of the play session, families were invited to continue engaging in semi-structured play for the remaining 10 minutes. Otherwise, if a given behavior was not performed within the first 10 minutes of the play session, a member of the research team introduced various games (e.g., "tag") and pretend play scenarios into the play session in order to encourage children to perform the target physical activity behavior.

Measures

Sociodemographic. Parents were asked to complete a questionnaire that included items on children's sex and age.

Anthropometric. Children's height was measured in meters (m) using a stadiometer, and weight was measured in kilograms (kg) using a calibrated scale. Body Mass Index (BMI) was calculated as kg/m^2, and children's BMI percentiles were determined according to the reference values provided by the Centers for Disease Control (CDC, 2012).

Physical Activity. In order to validate triaxial physical activity intensity cut points for an infrared-depth camera, physical activity was concurrently measured during the play session using Microsoft's Kinect for Windows and also by direct observation (i.e., the ground truth).

Microsoft's Kinect (MSK). Children's physical activity behaviors were measured remotely during the play session using Microsoft's Kinect for Windows (v1). MSK is a low-cost, portable 3D camera fit with a color and infrared-depth sensor (Han et al., 2013). During the 20 minute play session, infrared and depth sensor data were collected via MSK using Kinect Connect (Appendix E). Kinect Connect was initialized to simultaneously collect infrared and depth image frames with a 480 x 640 pixel resolution as 16-bit unsigned integers at 30Hz, and frames were iteratively stored as *.bin files on a specified end point. Triaxial physical activity counts for all persons (i.e., children, parents, and research team members) who entered the frame during the recording were respectively extracted and processed from *.bin files using Kinect Analyze (Appendix E). Kinect Analyze converts infrared-depth image data into an array of unique triaxial acceleration signals for each moving object (e.g., person) that enters the frame using a computer vision algorithm that is described in detail elsewhere (Appendix C; Appendix E). Triaxial video-derived activity data for children were exported in 5s epochs as vector magnitude activity counts from Kinect Analyze for further analyses. Review of the data showed that the infrared-depth sensor signal was severely corrupted by noise in one child's play session, thus this case was removed from the data set. For the remaining children (n = 10), triaxial acceleration data that corresponded to the first 5 minutes of the play session were extracted and used for comparison to direct observation.

Children's Activity Rating Scale (CARS). Unprocessed 2D play session video data that were collected using the infrared camera were converted from *.bin files into 16-bit, 480 x 640 pixel images. Following, each frame was processed in the spatial and frequency domains using an image restoration algorithm, and then exported as *.avi video files for direct observation analyses using the KinetiWave toolbox, Kinect Share (Appendix E). From the restored video recordings, children's physical activity behaviors were coded using a second-by-second CARS protocol (Van Cauwenberghe, Labarque, Trost, De Bourdeaudhuij. & Cardon, 2011; Puhl, Greaves, Hoyt & Baranowski, 1990). CARS activity intensity categories (i.e., 1 = lying down or sitting, 2 = standing, 3 = walking, 4 = walking, moderate, 5 = running, strenuous activity) were modified to reflect the following four categories: 1) lying down or sitting, 2) standing, 3) walking, 4) running or jumping (Puhl et al., 1990; Trost et al., 2012). Two trained coders applied the CARS protocol to play session *.avi files using a computer-based direct observation system, Visual Movement Analysis Platform (Appendix E). After coding all videos, the second-by-second data were reintegrated into 5s epoch data using a standard weighted average formula (Trost et al., 2012). For every 5s, each activity code within the epoch was multiplied by the frequency of its occurrence in the epoch, and the mean was calculated iteratively. Following, the weighted CARS scores were recoded into the standard physical activity intensity classifications using the following thresholds: sedentary behavior (SED) >2; light physical activity (LPA) 2 to 2.99; and moderate-vigorous physical activity (MVPA) ≥ 3 (Trost et al., 2012). In order to assess inter-rater reliability between coders, the intraclass correlation (ICC) was calculated for $n = 4$ randomly selected 20min play session videos that were coded by both raters. The ICC for the weighted mean CARS scores ($r_{ICC} = 0.95$) showed acceptable agreement between raters.

Statistical Analyses

Data were analyzed using MATLAB R2017b (The MathWorks, Inc., Natick, MA). Descriptive statistics are presented as Mean (Standard Deviation), Median (Interquartile Range), and Frequencies [%(n)]. In order to determine optimal early childhood physical activity cut points for an infrared-depth camera, the Receiver Operating Characteristic Area Under the Curve (AUC) and its bootstrapped 95% confidence interval were computed using several competing non-parametric classifiers. The boundary between SED and LPA/MVPA combined, as well as the boundary between MVPA and SED/LPA combined, were estimated using separate logistic regression models (Trost et al., 2012). This serial approach to determining physical activity cut points was repeated using a Classification and Regression Tree (CART) algorithm. Given a binary or multiclass categorical outcome variable, the CART algorithm iteratively partitions a given predictor space into a cascade of binary decisions (i.e., a decision tree) toward predicating classes for new data set while simultaneously reducing the overall model classification error (Breiman, Friedman, Olshen & Stone, 1984). Additionally, both a multinomial regression and a multiclass CART algorithm, wherein all classes were simultaneously modeled, were used in order to explore the results of calibrating activity cut points in parallel. The model with the highest AUC was identified as the model with optimally performing physical activity cut points for remotely sensed triaxial acceleration data in 2-5 year-old children. The difference between the observed and estimated proportions of time spent in each activity intensity were calculated using a Wilcoxon Signed Rank test, and the significance level was established *a priori* at $\alpha = 0.05$.

RESULTS

Children were *45*(12) months-old, on average, 60% (6) were girls and 40% (4) were boys. BMI percentiles showed that 70% (7) of children were normal weight, 20% (2) were at risk of overweight, and 10% (1) were overweight. Table 1 shows the performance of each of activity intensity classifier in comparison to direct observation. Overall, the CART algorithm outperformed all other classifiers, as it had the highest AUC across all activity intensities. The CART algorithm underestimated the proportion of time spent SED, and overestimated LPA and MVPA time;

however, CART predicted values did not significantly differ from the observed activity volumes for any activity intensity. The logistic regression model performed poorly for all activity intensity estimates, and significantly overestimated the proportion of time spent in all three intensities. While the multinomial model performed slightly better than the logistic regression model, it significantly overestimated MVPA and under estimated LPA. The multiclass CART algorithm performed similarly to the CART model; however, the mean difference between the observed and predicted proportions of time spent in LPA was lower for the multiclass model.

DISCUSSION

This study aimed to calibrate a computer vision algorithm to estimate physical activity behavior intensities in young children using an infrared-depth camera. To our knowledge, this is the first study to use computer vision to objectively measure PA in young children. Results showed that triaxial physical activity acceleration signals derived from a 3D camera can be used to accurately estimate children's physical activity and the relative proportions of time spent in each activity intensity without the use of a wearable sensor. Of the competing activity intensity classifiers, the CART algorithm predicted the proportion of time that 2-5 year-olds spent in activity during an indoor play session with good to excellent accuracy and without significant over- or underestimation.

Proportions of time spent in each activity intensity were estimated at the individual-level in our study of 10 children, and participants were allowed to engage in their choice of physical activity during the semi-structured play session with their parents. A prior study in 8 children (10 years-old) calibrated a computer vision algorithm to estimate group-level PA intensities using a low frequency sampling method (i.e., periodic 10s observations) while children played basketball indoors (Silva et al., 2015). In a study of 9 adults, activity intensities were estimated at the group level while participants were asked to sit, stand, walk, and jog while outdoors using an ecological assessment measurement approach that took periodic activity samples (Carlson et al., 2017). Comparatively, a continuous sampling approach was used during our semi-structured and dyadic play session protocol, and the large volume of data used to calibrate the computer vision algorithm was highly variable across all sessions and participants with respect to physical activity intensity and spatial patterning. Thus, our cut points were specifically calibrated to capture the short-burst, multiplanar physical activity behaviors that young children typically exhibit. Our study contributes evidence of both the feasibility and validity of using computer vision to analyze individual PA behaviors within dyadic contexts to an emerging area of physical activity measurement research.

A strength of our study is that 3000s of data were used to calibrate the computer vision algorithm across ten 2-5 year-old children. The only other study using computer vision to measure PA in children used a total sample of 1000s for algorithm calibration. Thus, the findings presented herewith comprise the largest study of computer vision–based methods to measure physical activity in children to date. At the same time, a limitation of this study was that the sample size precluded the inclusion of additional covariates that may help to improve cut point performance, such as age. Though studies using accelerometers have shown that activity intensity cut points may be similar for toddlers (2-3 year-olds) and preschool-aged (3-4 year-olds) children (Trost et al., 2012) at higher activity intensities, research also shows that age-specific cut points may improve activity estimates for accelerometer-derived data (Sirard et al., 2005). As such, further research is needed to determine if 3D camera-derived activity intensity classifiers would dually benefit from the inclusion of age as a model covariate in young children in much larger samples. Additionally, these cut points were developed using a computer vision algorithm that was tuned for indoor physical activity measurement. Therefore, the algorithm and cut points may be specific to indoor physical activity measurement. Future studies should continue to develop methods for measuring physical activity in young children across a broader range of contexts using computer vision.

CONCLUSIONS

Computer vision methods can be used to accurately predict the proportions of time that 2-5 year-old children spend in activity from a 3D camera. Future studies should investigate the use of 3D camera-based sensors and computer vision to remotely measure physical activity behaviors in children across various developmental age periods and environmental contexts.

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Table 1. Performance of activity intensity classifiers for the infrared-depth sensing camera as compared to direct observation

	Median (IQR)	AUC (95% C.I.)	Mean Difference	p-value
SED (% time)				
Direct Observation	*25* (20)%			
Logistic Regression	*17* (25)%	0.69 (0.64 to 0.72)	5%	> 0.05
CART	*33* (27)%	0.89 (0.87 to 0.91)	-8 %	> 0.05
Multinomial Regression	*24* (25)%	0.70 (0.66 to 0.74)	0.8%	> 0.05
Multiclass CART	36 (24)%	0.86 (0.82 to 0.88)	-11%	> 0.05
LPA (% time)				
Direct Observation	*37* (28)%			
Logistic Regression	*4* (10)%	0.53 (0.50 to 0.60)	34%	< 0.01
CART	*29* (13)%	0.87 (0.85 to 0.90)	8%	> 0.05
Multinomial Regression	69 (32)%	0.55 (0.49 0.59)	-24%	< 0.05
Multiclass CART	40% (10)	0.83 (0.78 to 0.86)	2%	> 0.05
MVPA (% time)				
Direct Observation	28 (18)%			
Logistic Regression	0 (0)%	0.69 (0.65 to 0.72)	26%	< 0.01
CART	24 (15)%	0.92 (0.89 to 0.93)	4%	> 0.05
Multinomial Regression	8 (10)%	0.69 (0.65 to 0.74)	18%	< 0.01
Multiclass CART	25 (17)%	0.88 (0.85 to 0.91)	4%	> 0.05

Note: Table shows differences between proportions of time in each activity intensity as determined by direct observation and each respective classifier. Abbreviations: sedentary (SED), light physical activity (LPA), moderate-vigorous physical activity (LPA), proportion of time (% time), receiver operating characteristic area under the curve (AUC), bootstrapped 95% Confidence Interval (95% C.I).
Mean difference overestimates are indicated by positive values, and negative values suggest underestimation. Wilcoxon Signed Rank Test p-values show significant differences ($p < 0.05$) between directly observed and estimated proportions of time in each activity intensity.

Appendix A

Literature Review

Introduction

Physical activity is defined as any bodily movement caused by musculoskeletal contraction that results in increased energy expenditure (Casperson, Powell & Christenson, 1985), and physical activity (PA) is essential for health in young children (2-5 year-olds) (Andersen et al., 2006). Given that parental reports of young children's PA behaviors are typically of limited validity (Oliver, Schofield & Kolt, 2007; Sarker et al., 2015), objective methods of physical activity measurement are preferred in estimating pediatric energy expenditure (Eston & Rowlands, 1998). Of the available objective methods, accelerometry is a feasible and valid means by which to measure physical activity behaviors in young children (Van Cauwenberghe, Gubbels, De Bourdeaudhuij & Cardon, 2011; Oftedal, Bell, Davies, Ware & Boyed, 2014; Eston et al., 1998). Newer triaxial accelerometers are light-weight and small devices, most commonly worn at the hip or wrist (Migueles et al., 2017), that are well-tolerated in diverse samples of young children (Costa Barber, Cameron & Clemes, 2014; Oftedal et al., 2014).

The use of triaxial accelerometers in particular affords researchers the ability to measure physical activity in three orthogonal planes of motion (Welk, 2005), which enables researchers to better measures the characteristically multiplanar physical activity behaviors of young children (Gabbard, 2012; Oftedal et al., 2014). Additionally, the time sampling capabilities available in accelerometers allow researchers to analyze physical activity and intensity patterns in light of diurnal rhythms (Rowlands & Eston, 2007), while the use of traditional pedometers do not. Furthermore, research shows that, in place of pedometers, accelerometers can be used to determine daily step volumes in young children (Pagels, Bolderman & Raustorp, 2011), and that accelerometer-derived step counts can be paired with timestamp data to produce metrics on time-dependent cadence patterns (Barreira, Katzmaryk, Johnson & Tudor-Locke, 2012). In light of the multiplanar, short burst, and Brownian motion-like nature of physical activity in young children (Gabbard, 2012; Rowland, 2005), the benefits of using triaxial accelerometry to objectively measure physical activity behavior in early childhood is clear (Oftedal et al., 2014).

Methodological studies in accelerometry and wearable sensor data analytics have shown that data processing considerations are multifactorial (i.e., sampling frequency, cut-points, epoch length, data reintegration, number of monitoring days, etc.), and that each factor respectively affects accelerometer-derived estimates of physical activity, sedentary behavior, and overall estimate reliability (Banda et al., 2016; Brønd & Arvidsson, 2015; Cliff et al., 2009; Welk, 2005; Trost et al., 2000). Moreover, differences in any of the aforementioned accelerometer specifications limit the generalizability of the findings (Banda et al., 2016; Smith et al., 2017). As such, recent studies have suggested that a consensus be reached on accelerometer data processing techniques in order to facilitate comparisons between studies, and that studies should apply and report on many data processing techniques simultaneously until the field reaches consensus (Kerr et al., 2017; Smith et al., 2017).

Relatedly, some PA measurement studies have investigated the use of remote sensors and multi-sensor systems as a means to objectively measure activity in tandem with contextual and group-based data (Dlugonski, DuBose & Rider, 2017; Maile et al., 2015). However, no consensus statements exist with regard to device specifications nor data analysis protocols in remote sensor and multi-sensor systems in physical activity measurement, which clearly mirrors the cluster of current issues faced broadly within the field of objective physical activity monitoring (Banda et al., 2016, Kerr et al., 2017; Smith et al., 2017). For example, a recent study employed a multi-sensor measurement system, comprised of a wearable accelerometers and Bluetooth sensors, to objectively measure child-parent physical activity and spatial proximity (Dlugonski et al., 2017); however, the validity of the method the study used to estimate dyadic proximity is unknown. Thus, the findings of that study may not be generalized to any other population with any modicum of certainty. A recent remote sensor study pioneered the use of a 3D camera to measure children's PA in addition to contextual information (Maile et al., 2015). However, the study did not calibrate their method against a gold-standard criterion method, thus no cut points exist that can be used to interpret the activity signals meaningfully. In order to align remote sensor and multi-sensor physical activity research with the recommended trajectory for wearable activity monitoring, further research is needed to test the validity and reliability of these novel applications of remote and multi-sensor devices within physical activity measurement.

Given these nontrivial measurement considerations, in addition to those specific to measuring short-burst, multiplanar physical activity behaviors in young children, the goals of this review of the literature were to: 1) briefly describe the nature of physical activity behavior in young children, 2) provide an overview of the health-benefits of PA in young children, 3) describe accelerometry and measurement in young children, 4) discuss the state of remote and multi-sensor physical activity measurement in young children, and 5) consider how remote and multi-sensor measurement might be more closely aligned with current measurement and analysis recommendations in wearable activity monitoring.

Early childhood PA behavior

Early childhood is a critical period for the development of physical activity behaviors (Kohl & Hobbs, 1998). Rowland (2005) describes physical activity behaviors in children as short bouts of intense activity, mixed with moderate and low intensity movement—reminiscent of Brownian motion. In a study of children age 6-10, conducted using direct observational techniques, researchers found that 95% of the intense activity bouts recorded did not last beyond 15s, and that intense movement generally lasted no longer than 3s (Bailey et al., 1995). These short-burst activities in children appear to utilize both aerobic and anaerobic metabolic substrates (Rowland, 2005).

Since the sporadic, short-burst nature of PA in young children is inextricably linked to metabolic substrate utilization (Rowland, 2005), it follows that higher-resolution and temporally sophisticated measurement approaches are well-suited for modeling early childhood PA behaviors. Studies that have applied higher-resolution analytical approaches have revealed the importance of higher sampling frequencies, as well as the benefit of considering temporal-dependence in pediatric PA measurement and analyses (Baquet, Stratton, Van Praagh & Berthoin, 2007; Berman, Bailey & Cooper, 1998; Obeid, Nguyen, Gabel & Timmons, 2011). As an example, Baquet and colleagues (2007) used brief measurement episodes (i.e, 2s epochs) to analyze physical activity behaviors in 8-10 year-olds, and showed that ≥80% of the time a bout of moderate-vigorous activity lasted less than ten seconds. Relatedly, in a study of 6-10 year-olds, Berman (1998) reported that time spent in episodes of higher intensity activity, while brief, accounted for 40% of energy expenditure in a study that used spectral analysis to analyze PA direct observation and indirect calorimetry data in 3s epochs. In young children (3-5 years-old), Ruiz (2013) used 15s epoch accelerometer data to reveal that children’s PA patterns might be characterized along two dimensions—isolated and clustered; sustained or occurring in spurts.

Research on these activity patterns and wellness in young children also show, for example, that the PA temporal patterns may be associated with respiratory health (Goldsmith, Lui, Jacobson & Rundle, 2016). Few studies, however, have blended high-resolution analyses of physical activity with patterns and clustering methods to better understand how these unique features of early childhood PA are associated with health outcomes.

As it is known that early childhood is a critical period with regard to lifelong health and behavioral outcomes (Janz et al., 2010; Telama, 2009), more research is needed on the development PA behaviors in young children. More specifically, studies that employ higher resolution analyses, which can be better tailored to model the intermittent and seemingly-random nature of early childhood PA, are required. These studies will be able to provide the requisite level of detail in the analysis of short-burst PA behaviors and its temporally dependent associations with health outcomes in young children (Goldsmith et al., 2016).

Benefits of PA in young children

Cardiometabolic risk factors in children (e.g., higher levels of fasting glucose, higher blood pressure, insulin resistance, triglycerides, overweight/obesity) place children at higher risk of developing cardiovascular disease and/or diabetes throughout the lifespan (Camhi & Katzmarzuk, 2010). While, higher volumes of daily physical activity are known to improve cardiometabolic outcomes in children (Ekelund, 2012), a majority of young children appear to be insufficiently active (Hnatiuk, 2012; Spittaels, 2012; Hinkley, 2012). Moreover, PA behaviors, anaerobic power, and aerobic fitness levels appear to carry-forward over time during early childhood years (Caldwell et al., 2016; Gabel et al., 2011), and PA behaviors patterns from childhood track forward into adolescence and adulthood (Telama, 2009). Thus, the volumes of daily PA in which young children engage can inform what is known about key health outcomes such as adiposity, bone health, motor development, psychosocial health, and cardiometabolic health indicators (Timmons, 2012), and also point toward health and behavioral outcomes throughout the lifespan (Janz et al., 2010; Telama, 2009).

Furthermore, there appear to be differences in the associations between PA and various cardiometabolic risk factors in boys and girls, across ages, across physical activity intensities, as well as differences in children who are healthy weight and overweight/obese (Jiménez-Pavón et al., 2013; Laguna et al., 2013; Remmers et al., 2013; Collings et al., 2013). These apparent moderators suggest the need for further research on associations between physical activity and cardiometabolic risk in children with specific focus on the number and severity of cardiometabolic risk factors at the time of measurement, sociodemographic and anthropometric differences, in addition to intensities of physical activity.

Associations

Accelerometry data in childhood physical activity research shows that physical activity shares a positive collinear relationship with aerobic fitness, as measured by treadmill endurance time or cycle ergometer predicted $\dot{V}O_{2max}$ (Andersen et al., 2006; Rowlands, Eston & Ingledew, 1999). Higher levels of daily physical activity also appears to be inversely associated with BMI, body fat, insulin resistance, fasting blood glucose, systolic and diastolic blood pressure, triglycerides, and cholesterol in children (Andersen et al., 2006; Remmers et al., 2013, Rowlands et al., 1999, Timmons et al., 2012). Notably, moderate-vigorous PA in particular has been shown to be inversely associated with cardiometabolic risk factors independent of sedentary time in children (Ekelund, 2012), which suggests that PA behavior in itself plays a critical role in predicting risk for disease and early markers of the same in young children. Similarly, irrespective of dietary behaviors, children with an unhealthy diet who engaged in sufficient volumes of daily activity had lower abdominal adiposity when compared to children who had an unhealthy diet and were insufficiently active (Loprinzi, Lee, Andersen, Crespo & Smit 2015). In a study of 16,224 children ages 2-9 years-old, physical inactivity was associated with higher odds of having clustered CVD risk factors (Jiménez-Pavón, 2013).

Objectively measured physical activity behaviors in children also appear to be associated with gross motor development and fundamental movement skills in young children (Barnett et al., 2016; Williams et al., 2008). In particular, physical activity appears to be positively correlated with motor coordination, object control skills, and locomotor skills in early childhood. Evidence dually suggests that PA in the early years (age 5) predicts bone health at later developmental stages (ages 8 and 11 years) (Janz et al., 2010), and also that childhood PA is associated with bone health in adulthood (Gunter, Almstedt & Janz, 2012). Across several of these studies, however, important moderators in the relationship between PA and health outcomes have also been identified such as children's age, sex, weight status, and even the level of physical activity intensity in which they engage.

Potential Moderators

In a study investigating associations between physical activity and BMI, Remmers and colleagues (2013) showed that physical activity was not associated with changes in BMI among normal weight girls across the ages of 5-9 years, but that it was inversely associated with BMI in boys of the same age. Further, higher daily volumes of light physical activity were associated with decreases in BMI for overweight/obese boys, but not for girls. Jiménez-Pavón (2013) showed that total physical activity (and vigorous PA in particular) was associated with CVD risk scores in 2-6 year-old boys but not in girls. The study also showed that among older children (6-9 years), PA was associated with CVD risk scores irrespective of gender, and across activity intensity thresholds.

Loprizni (2015) revealed that children who engaged in sufficient physical activity and healthy eating habits had lower cardiometabolic risk than those who did not; however, there were no differences between groups of adolescents with various combinations of healthy lifestyle behaviors (i.e., sufficient physical activity and/or health eating habits). Thus, physical activity had differential cardiometabolic protective effects across developmental periods. In a study of preschoolers, conducted by Collings (2013) and colleagues, vigorous physical activity was inversely associated with BMI, but not moderate intensity exercise. Not surprisingly, time spent in PA also appears to differ among normal weight children and healthy weight children, with normal weight children spending more time in physical activity than those who are overweight/obese (Laguna, 2013). Moreover, the relationship between bone mineral content and physical activity may also be moderated by sex (Janz et al., 2010), with positive associations reported between PA behavior and bone health over time (ages 5 to 11) in boys but not in girls.

Across all of these studies using accelerometers to measure PA and health in children, however, different devices, data reduction algorithms, activity intensity cut points, and methods of analyses were used to estimate activity volumes. Therefore, the interpretability and generalizability of each report on the dose-response between PA minutes and health are extremely limited outside of any case wherein precisely the same methods are used (Banda et al., 2016). Given the critical role that accelerometer specifications play in interpreting the associations between PA and crucial health outcomes in children, such bone health and cardiometabolic risk factors, each aspect of designing an accelerometer-based measurement study should be thoroughly considered.

Accelerometry

Within the context of physical activity measurement, accelerometers are used in the form of wearable activity monitors that quantify volumes of physical activity after being calibrated (Rowlands et al., 2007; Welk, 2005). Currently, the underlying hardware within these devices are typically differential capacitance accelerometers or piezoelectric/piezoresistive compressive integrated chips that measure perturbations from a semi-static state (Chen, Janz, Zhu & Brychta 2012). These particular types of acceleration transducers record signals that are caused by both gravitational acceleration and also those caused by human movement. Moreover, these acceleration signals are measured in up to three orthogonal planes (vertical, antero-posterior, and mediolateral) depending upon the available degrees of freedom within the inertial measurement unit (Sasaki, John & Freedson, 2011).

The choice of device plays a significant role in physical activity measurement and activity estimate interpretation across studies, as data suggest that activity counts registered across devices differ (Rowlands, 2015). When comparing the GENEActiv and ActiGraph triaxial accelerometers with a concurrent hip-worn placement protocol in adults, Rowlands (2015) and colleagues found that, after processing raw acceleration data from both devices in both the time and frequency domains, activity counts from the ActiGraph accelerometer were consistently lower than those recorded by the GENEActiv. Interestingly, a recent study has proposed a new algorithm that allows researchers to transform raw acceleration signals from a alternative accelerometer models into the popularly used ActiGraph activity counts (Brønd, Andersen &

Arvidsson, 2017). As such, the former problem of device specific cut points may become moot as physical activity measurement research progresses. In order to validate this new algorithm for inter-device cut point transformations and calculations in young children, specifically, further research is needed.

Accelerometry in Early Childhood

As an alternative to the use of parental proxy reports for measuring young children's physical activity, given their limited validity (Oliver et al., 2007; Sarker et al., 2015), researchers commonly use accelerometry to measure physical activity behavior in children (Rowlands et al., 2007). Furthermore, while pedometers provide useful objective estimates of daily activity volumes in young children (Pagel et al., 2011), accelerometers afford researchers additional temporal and multidimensional details that are especially pertinent to PA measurement in young children. Specifically, accelerometers timestamp physical activity signals (Rowlands et al., 2007, which allows researchers to conduct higher resolution analyses of PA behavior (Goldsmith et al., 2016), whereas pedometers typically do not timestamp discrete observations. Given the intermittent and pulsatile nature of PA in young children (Rowland, 2005), additional temporal specificity during the measurement process extends the ability for researchers to characterize these short burst PA behaviors in early childhood (Ruiz et al., 2013).

Additionally, young children typically engage in multiplanar physical activity behaviors (Gabbard, 2012), which suggests the use of monitors that measure physical activity in three-space (i.e., triaxial accelerometers) (Oftedal, Bell, Davies, Ware & Boyd 2014). Thus, while both uniaxial and triaxial accelerometers have been validated in young children (Ott, Pate, Trost, Ward & Saunders, 2000), research shows that triaxial accelerometers may more sensitively estimate physical activity behaviors in young children (Oftedal et al., 2014).

Beyond selecting an appropriate monitor for an early childhood population, the devices must be initialized using the correct sampling frequency (i.e., the number of raw accelerations sampled per second), given that differences in sampling frequency can significantly impact data analysis and estimation when data are converted from raw accelerations (*g*) to activity counts (Brond, 2015; Chen, Janz, Zhu & Brychta, 2012). Furthermore, the placement of the device must be considered for both practical (i.e., ease of use by the participating population) and measurement reasons (i.e., cut points used must be placement specific) (Welk, 2005). When accelerometers are placed at the hip in young children, evidence suggests that contralateral placement (i.e., whether the device is consistently placed on the dominant or non-dominant side) is not important (Cliff et al., 2009). Finally, data should be collected over several contiguous days in order to meet sufficient reliability ($r \geq 0.70$) requirements (Trost et al., 2000).

Prior to applying validated cut points to accelerometer signals, data must first be cleaned by distinguishing non-wear time from sedentary time using validated algorithms (Cliff et al., 2009; Oliver et al., 2011). Data sets meeting and not-meeting established wear time criteria (which include the number of minutes/hour, hours/day, and day/week) are determined, and cut points are applied to cleaned data sets meeting wear time criteria. Epochs, or discrete sampling intervals over which data are summarized, are an important feature of measurement that can also affect analysis and estimation (Cliff et al., 2009; Kim et al., 2013; Banda et al., 2016).

After data have been cleaned, age- and population-appropriate cut points must be applied to physical activity counts (i.e., arbitrary values that serve as a proxy for physical activity intensity) in order to classify counts into various activity intensities (i.e., sedentary behavior, light PA, moderate PA, and vigorous PA) (Welk, 2005; Costa et al., 2014; Oftedal et al., 2014). Cut points should be epoch specific, and data should be directly summarized in the epoch length of interest from raw accelerations (Banda et al., 2016). The development of physical activity cut points are often determined using indirect calorimetry as a measure to establish its criterion validity (Welk, 2005); however, in younger children (~2 years-old), direct observation has been used given the apparent impracticability of requiring children to wear apparatuses that measure gas exchange during physical activity (Costa et al., 2014). Given that young children typically move in short-burst physical activity patterns (Bailey et al., 1995; Berman et al., 1998), shorter epochs (≤5 seconds) may more sensitively characterize PA behaviors in children (Oftedal et al., 2014; Baquet et al., 2007). Finally after data are classified into different activity intensities, time spent in respective activity intensities are estimated.

Owing to the fact that differences in accelerometer specifications may affect physical activity estimates (Banda et al., 2016), further discussion of each parameter is warranted. Moreover, given that population characteristics should be carefully considered when designing an accelerometer study, each discrete aspect of accelerometer measurement design will be interpreted in light of the short-burst, multiplanar physical activity behavior patterns that are characteristic of young children.

Placement

Studies of young children show that differences in device placement affect accelerometer-derived estimates of daily activity volumes (Cliff et al., 2009). In young children, uniaxial and triaxial accelerometers have been worn at either the hip, wrist, ankle, umbilicus, or sacrum to measure physical activity behaviors (Oftedal et al., 2014; Trost et al., 2012; Kelly et al., 2004; Toschke, von Kries, Rosenfield, & Toschke, 2007). A recent report of current trends in accelerometer methods showed that among studies using newer triaxial accelerometers, 92%

used a hip-worn protocol and the remaining 8% used a non-dominant wrist-worn protocol (Migueles et al., 2017). While there are currently no guidelines with regard to device placement (Welk, 2005), some research suggests that wrist-worn placements may be best for measuring PA in young children (Johansson, Larisch, Marcus & Hagströmer, 2015). Given that recent recommendations aim to improve interpretability of findings across studies (Kerr et al., 2017), further research on differences in device placement in very young children is needed.

Differences in placement also directly affect accelerometer-derived activity intensity counts (Kerr et al., 2017). In a sample of 5-6 year-olds, Tochke (2007) and colleagues found that uniaxial accelerometer-derived activity counts were significantly higher when devices were worn at the umbilicus rather than at the anterior superior iliac crest. In 4 year-old children, wrist-worn activity counts were also found to be higher than those recorded while devices were worn at the anterior superior iliac crest (Johansson et al., 2015). It is possible that these differences are explained by the differential relationships between the device placement and center of mass at each wear location (Chen et al., 2012). Thus, while device placement is a matter of preference in studies using accelerometry to measure PA (Welk, 2015), the impact of placement on the interpretability of findings across studies suggests the need for some consensus on device placement in early childhood physical activity research.

Sampling Frequency

Broadly, accelerations in human movement are $\leq$10Hz (Welk, 2002), and when measured proximally (e.g., at the hip) accelerations are in the range [0.3,3.5]Hz—at the head [-0.2,0.2]g, upper-body [-0.3,0.8]g, and up to 8.1g at the ankle when walking down stairs (Mathie, Coster, Lovell & Celler, 2004). In running, the dominant frequency can reach up to 18Hz using a hip-worn device protocol, and heel strikes during walking can reach 60Hz when measured by ankle-worn accelerometers (Chen et al., 2012). Given the Nyquist principle, in order for a signal to be properly recovered without aliasing, a sampling rate of twice the highest expected observed frequency is needed (Gonzalez & Woods, 2008). In most cases, a sampling frequency of 30Hz is sufficient to capture human physical activity when using a hip-worn accelerometer protocol (Chen et al., 2012). However, when attempting to capture the braking and propulsive phases of running, for example, evidence suggests the need for sampling rates up to 100Hz when using hip-worn accelerometers (Vähä-Ypya, Vasankari, Husu, Suni & Sievänen, 2016).

Studies have shown that differences in the sampling rate used to collect accelerometer data affect the activity counts derived from the raw acceleration data (Brønd et al., 2015). As such, careful attention must be given to the sampling rates used to initialize devices prior to data collection. In young children, the majority of recent studies using accelerometers initialized devices with a 30Hz sampling frequency (Migueles et al., 2017), with the two next common sampling rates being 60Hz, followed by a tie between 80Hz and 100Hz. As with device placement, differences in sampling frequency protocols limit the comparisons that can be made between studies.

For example, Costa (2014) and colleagues calibrated triaxial accelerometer cut points to measure physical activity in 2-3 year-olds using data collected at 80Hz with a manipulated data collection filter (i.e., low frequency extension). In order to compare the newly calibrated cut points to existing ones, several sets of early childhood physical activity cut points that were originally developed for data collected at 30Hz were applied to the 80Hz accelerometer data. Results from the comparison showed that triaxial cut points in toddlers did not outperform the existing uniaxial cut points. By contrast, Oftedal et al., 2014 showed that, for data collected at

30Hz, triaxial accelerometer cut points were able to achieve a higher sensitivity and specificity in distinguishing physical activity in young children than 30Hz uniaxial cut points. Given the evidence of an effect of sampling frequency on the derived activity estimates, it is possible that the difference between these two studies using triaxial accelerometers in young children is due to the sampling frequency protocols. Oftedal (2014) appropriately kept the sampling frequency at 30Hz which is in alignment with the original sampling rate for the uniaxial cut points, whereas Costa (2014) applied cut points intended for 30Hz data to 80Hz data that additionally used a low frequency extension filter. It is possible that the Costa (2014) cut points would have performed optimally if calibrated using data collected at 30Hz and then compared to the uniaxial cut points originally designed for data collected at 30Hz.

Since sampling frequency appears to play a key role in deriving estimates of time spent in physical activity, further research on the optimal sampling rates for capturing the short burst PA patterns of young children, using a range of accelerometer placement protocols, is needed.

Signal Filtering

Few studies of young children have reported on the signal filtering method used during the data collection and processing phases (Migueles et al., 2017). Moreover, a small number of studies have reported collecting data using a low frequency extension filter; however, little is known about the effects of a low frequency extension filter versus a normal filter on accelerometer signals in early childhood PA measurement. A study in adults showed that the addition of a low frequency extension filter during the data collection process, in comparison to a normal filter, affects activity estimates (Cain, Conway, Adams, Husak & Sallis, 2013). In light of filter specific differences in activity counts, Cain (2013) and colleagues suggest that cut points and nonwear time algorithms may need to be not only device specific but also specific to the filtering methods used during data collection. Studies are needed to determine the extent to which the inclusion of a low frequency extension filter, versus a normal filter, affects activity estimates in young children. Moreover, in agreement with the current recommendations for more detailed reporting of wearable data collection and processing procedures across all studies (Kerr et al., 2017; Smith et al., 2017), research in young children should consistently report on the type of signal filtering methodology employed during data collection.

A methodological study on the comparative effects of an array of signal filtering techniques, all aimed at removing the gravitational component present within raw accelerometer signals, showed that variability in energy expenditure was differentially explained by filter selection (van Hess et al., 2013). In particular, the use of a Euclidean Norm Minus One (ENMO) [$||k|| - 1g$] or a High-Pass Filtered Euclidean Norm ($HFEN_+$) [the Euclidean Norm of the high-pass 4th order Butterworth filtered raw accelerations with cut-off frequency $\omega_0 = 0.2$Hz; plus the Euclidean norm of the low-pass 4th order Butterworth filtered raw acceleration with cut-off frequency $\omega_0 = 0.2$Hz minus $1g$], where $||k||$ is the vector magnitude of raw triaxial accelerations ($\mathbf{x}$, $\mathbf{y}$, $\mathbf{z}$), explained the most variability in adult PA energy expenditure as measured by both indirect calorimetry and doubly labeled water methods. Studies investigating the effects of signal filtering on variability explained in pediatric PA energy expenditure are limited. As the current recommendations point toward the analysis of raw accelerometer signals for better interpretability between studies (Smith et al., 2017), more specific criteria on the signal filtering specifications that are most appropriate for measuring physical activity in young children are required.

Epoch Length

The majority of recent studies using objective measures to quantify early childhood physical activity have analyzed accelerations 15s episodes, or epochs (Migueles et al., 2017). Several studies show that the choice of epoch length, like other accelerometer specification, can drastically change the results derived from these wearable activity monitors (Banda et al., 2016; Kim, Beets, Pate, & Blair, 2013). Studies investigating the effect of epoch length on activity estimates show that the use of shorter epochs (2s) in measuring physical activity in young children may provide additional detail on physical activity patterns in this population, especially within the higher activity thresholds (Baquet et al., 2007). Research also discourages reintegrating shorter epochs into larger epochs, as this may lead to biased estimates of activity volumes (Kim et al., 2013).

Physical activity measurement researchers have argued for the use of shorter epochs in early childhood physical activity analyses given the short-burst nature of physical activity at this age (Costa et al., 2014; Oftedal et al., 2014). Methodological studies have shown that shorter epochs (≤5s) provide a sufficient level of detail by which to assess and characterize daily activity volumes in young children (Costa et al., 2014; Johansson et al., 2015; Oftedal et al., 2014). Given that few studies have analyzed children's physical activity data in ≤2s epochs (Migueles et al., 2017), additional higher-resolution studies of early childhood physical activity using very brief epoch lengths will provide useful data on the short-burst nature of early childhood physical activity. Moreover, in order to align early childhood measurement research with the prevailing recommendations (Kerr et al., 2017), further research is needed to determine the optimal epoch length for measuring physical activity behaviors in young children.

Wear Time Criteria

Distinguishing between device nonwear time and observed sedentary behavior is an important consideration in studies using wearable activity monitors (Cliff et al., 2009). In young children, the added layer of day time naps must also be factored into the analysis of physical activity signals since parents may or may not remove the activity monitors during these brief periods of time. While a recent review of studies using triaxial accelerometers reports that no current definitions of wear time are available for young children (Migueles et al., 2017), earlier studies suggest that 20min periods of 0cpm were sufficient for discriminating non-wear time and sedentary time in young children (Cliff et al., 2009). Studies in young children have used nonwear periods of 10, 20, 30min strings of zeros (Migueles et al., 2017);

Research on nonwear time algorithms in adults have proposed that the use of a spike tolerance can improve nonwear time estimation by filtering artifact out of the signal when devices are in an otherwise semi-static state (Choi, Lui, Matthews & Buchowski, 2011; Oliver et al., 2011). No studies in young children, however, appear to report on the use of a spike tolerance during non-wear time estimation (Migueles et al., 2017). Further research on the utility of applying spike tolerance criteria to nonwear time algorithms in young children is needed. Additionally, there appear to be no available algorithms to determine when young children are being carried or pushed in a stroller. Thus, studies that can begin to help separate volitional physical activity time from those periods when children are in passive translocation should be conducted.

In light of the variable nature of human PA behaviors, studies have shown that protocols using multiple accelerometer wear days improve activity estimate reliability (Addy, Trilk, Dowda, Bryun & Pate, 2015; Trost et al., 2000). The definition of a valid observation day, however, is contingent upon the minimum number of observation hours required for a given 24hr period to be included in further analyses (Migueles et al., 2017), and differences in the number of hours required to constitute an observation day may affect activity estimates (Ruiz et al., 2013). In terms of the number of hours required, a study of ~5 year-olds showed that increasing the observation hours per day from 3hr/day to 10hr/day had only a small effect on estimate reliability (Penpraze et al., 2006). With regard to the number of days, $\geq$3 days led to satisfactory reliability ($r \geq 0.60$); however, 7 days of contiguous measurement resulted in very good reliability ($r \geq 0.80$). Similarly, a study of 3-5 year-olds conducted by Addy (2013) and colleagues showed that an accumulation of $\geq$5 observation days led to satisfactory reliability ($r \geq 0.75$). In a sample of ~7 year-old children, Trost (2000) and colleagues reported that physical activity data acquired over ~4.7 observation days resulted in reliability estimates of $\geq$0.80, and that the number of days required to reach 0.80 reliability ranged from 4.2 to 8.8 days depending on the children's age group. Since young children engage in short burst PA, more studies are needed on PA estimate reliability in children younger than 3 years-old in order to develop evidence-based consensus statements inclusive of physical activity monitoring in the very young.

Cut points

Estimates of the amount of time that children spend in various intensities of activity are contingent upon the cut points used to classify the accelerometer activity counts (Welk, 2005). Accelerometer counts are arbitrary values that are the product of signal processing and data reduction procedures. Physical activity cut points are typically developed by calibrating accelerometer-derived activity counts against a criterion measure, usually either direct or indirect calorimetry or direct observation, for the purpose of determining meaningful movement intensity thresholds for accelerometer data (Welk, 2005). These movement intensities respectively relate to energy expenditure (from low to high), and are widely known as sedentary behavior (SED), light physical activity (LPA), moderate physical activity (MPA), and vigorous physical activity (VPA). Time spent in each of these activities are used as predictors of short- and long-term health outcomes in children (Andersen et al., 2006; Janz et al., 2010). Notably, PA estimates derived from any given set of cut points do not appear to be generalizable to activity estimates derived using another (Banda et al., 2016). Thus, the precision of reported associations between accelerometer-derived activity estimates and health may be cut point biased to a degree. The recent recommendation that researchers apply multiple analytic approaches to accelerometer data may help to overcome the cut point specificity conundrum (Smith et al., 2017).

Since 2010, more than 12 sets of physical activity cut points have been recently reported in the early childhood triaxial accelerometer-based PA measurement literature (Migueles et al., 2017), and the most commonly used set of cut points in young children (2-5 year-olds) appear to be the Evenson 2008 values calibrated in 5-8 year-olds. This is interesting, given that anaerobic power and speed have been reported to increase with age and body size in young children (Gabel et al., 2011; Rowland, 2005) and energy expenditure levels (i.e., the accelerometer criterion measure during calibration) measured during PA in older children are likely to be significantly lower in young children (Schmelzle. Schröder, Armburst, Unverzagt & Fusch, 2004). An example of cut points that clearly take age into account are the Sirard (2005) values, which adjust physical activity intensity cut point equations for age in 3-5 year-old children. Early childhood physical activity researchers in particular should consider the rapid changes in metabolic substrate utilization during the early childhood years throughout the measurement process in order to move toward the most robust measures of activity in this age group.

Butte (2014) and colleagues calibrated activity intensity cut points for both uniaxial and triaxial accelerometers in ~4 year-old children against room calorimetry. When compared against such a precise measure of energy expenditure, confusion matrices showed that sedentary behavior was correctly classified ≥81% of the time using accelerometry, and that light and moderate PA were correctly classified ≥64% and ≥62% of the time, respectively. Using indirect calorimetry as the criterion measure in 3-5 year-olds, Pfeiffer (2006) and colleagues reported that 73% and 85% of moderate and vigorous activity observations agreed, respectively, between accelerometer- and calorimeter-derived estimates of energy expenditure. The difference in accuracy for children of roughly the same age, may potentially be explained by differences in the criterion measures that were respectively used, accelerometer models, age of the children being measured, or data analysis specifications (Banda et al., 2016; Gabel et al., 2011). Regardless of the source of variance between cut points, the fact remains that cut point selection will affect energy expenditure estimates—showing again that consensus statements on accelerometer-data analyses are required in order for the field to advance (Kerr et al., 2017).

While, like other accelerometer specification domains, cut point selection is a matter of choice, recommendations on which cut points should be used in early childhood will allow for broader interpretation of early childhood activity estimates across studies. This need is especially underscored by the significant role that cut points play in determining estimates of daily activity volumes that are used as predictors of pediatric health (Andersen et al., 2006; Ekelund et al., 2012). Thus, newer studies have begun to investigate the use of accelerometer data analysis methods that can decouple accelerometer estimates from these specific constraints—toward universal triaxial activity cut points (Brønd et al., 2017; Vähä-Ypyä et al., 2015).

Classification & Pattern Recognition

Recently, the field of PA measurement has moved toward the analysis of raw triaxial accelerations so as to make use of the granular level of detail available in accelerometer signals for pattern recognition, and also to address practical issues such interpretation of findings across studies (Brønd et al., 2017; Rowlands et al., 2015; Vähä-Ypyä et al., 2015). Accelerometer signal features from the time and frequency domains (e.g., peak power, signal entropy, mean amplitude deviations, power spectral density, etc.) have been explored as predictors of physical activity mode (e.g., walk, jog, sprint) in classification problems (Vähä-Ypyä et al., 2015). Time and frequency domain traits have also been used to calibrate activity cut points that can be used across activity monitors and using data sampled at [10, 30, 100] Hz (Vähä-Ypyä et al., 2015). Moreover, raw acceleration data from wrist-worn protocols has been used to classify sedentary behavior modes (e.g., sitting, lying, etc.) in classification analyses (Rowlands et al., 2016). With the recent release of an algorithm that can generate a common set of activity counts across a range of devices using raw acceleration signals (Brønd et al., 2017), it seems the analysis of raw acceleration data will become an essential feature of wearable activity monitor research moving forward (Smith et al., 2017).

Similarly, studies using advanced statistical treatments of accelerometer data have been able to solve physical activity classification and pattern recognition questions (Witowski et al., 2014; Ruiz et al., 2013; Pober et al., 2006). Berman et al., (1998) used spectral analysis to determine patterns, intensities and frequencies of physical activity bouts in 6-10 year-old boys and girls. Researchers found that boys engaged in slightly longer bouts of physical activity than girls; however, girls engaged in slightly more bouts of PA than boys. Ruiz (2013) and colleagues, devised a system of rules (i.e., fuzzy logic) to determine patterns in the way that short burst physical appear in young throughout the day using accelerometer data. The team identified four patterns of physical activity behaviors in young children: isolated and clustered episodes; spurts and sustained bouts of movement. Using Quadratic Discriminant Analysis and Hidden Markov Models (HMM), Pober and colleagues (2006) were able to classify various activities (e.g., vacuuming, sitting, walking) with the HMM correctly classifying activity mode >80% of the time. Witowski (2014) and colleagues also explored the use of several HMMs to classify activity mode and bouts using a simulation approach, and further supported the use of HMM in future PA research interested in PA mode classification.

A recent study in adults applied a text mining approach to develop and test bigram analyses in physical activity phenotyping (Millard, Tilling, Lawlor, Flach & Gaunt, 2017). Millard et al, 2017 and colleagues showed that examining couplets of epoch level activity classifications may provide a promising means by which to correlate PA traits and health outcomes. The combined use of machine learning and signal feature extraction to classify movement features from the Laban Movement Analysis repertoire (e.g., sudden, sustained, bound, free) have also been explored (Kikhia et al., 2014). Using a Laban-based approach, researchers were able to discern qualitative differences in movement effort-states (i.e. bound—free, sustained—sudden, strong—light) in adults, which may be useful in further phenotyping more subtle physical activity traits in healthy and clinical populations. However, little work of this nature has been explored in children.

Ellis, Kerr, Godbole, Staudenmayer & Lancriet (2015) applied a multi-step machine learning approach to develop physical activity intensity cut points for adults. A Random Forest algorithm was trained to predict activity mode (i.e., in a vehicle, sitting, standing, walking/running) from triaxial wrist- and hip-worn accelerometer data. Ellis and colleagues used a wearable video camera to determine activity class labels for the machine learning algorithm. Results showed that hip and wrist placement yielded very good overall classification accuracies of >89% and >84%, respectively. Artificial Neural Networks (ANN) have also been used to predict energy expenditure from accelerometer activity counts (Montoye, Mudd, Biswass & Pfeiffer, 2015; Staudenmayer, Pober, Crouter, Bassettm Freedson & 2009). Montoye (2015) and colleagues trained an ANN to predict energy expenditure from accelerometer-derived activity counts using a simulated activities of daily living protocol in adults. The group reported high correlations (r >0.89) between the ANN calibrated activity cut points, using a thigh-worn protocol, and the observed energy expenditure as measured by indirect calorimetry. Similarly, Staudenmayer et al., (2009) trained an ANN to predict energy expenditure in METs (Metabolic Equivalents) and also to predict activity mode in adults, using indirect calorimetry as the criterion measure. The ANN was able to predict METs with an RMSE of 1.1, and activity mode was predicted correctly >88% of the time. Taken together, these findings suggest that the application of advanced statistical analyses to accelerometer data can yield useful layers of insight to physical activity measurement, which are needed in order to better characterize PA behavior and its associations with health outcomes. As with other aspects of wearable PA monitoring, more research is needed in young children using these advanced statistical techniques, so that pediatric physical activity measurement continues to progress in stride with PA studies conducted at other periods across the lifespan.

Toward Remote & Multi-Sensor Systems

New frontiers in PA measurement have introduced the use of 3D cameras as a feasible measure of PA in children, though further research is needed in order to determine the criterion validity of this technology to measure PA (Maile et al., 2015). At the same time, Silva et al.,

(2015) presented a method for converting physical activity data collected via 2D camera into velocities to which MET related speed thresholds could be applied for energy expenditure estimation. Authors report that the use of a 2D camera in PA measurement research is a promising tool that requires further study. While there are few studies using remote sensors to measure physical activity behavior in children, this new area of the literature begs further investigation given its ability to provide contextual and group-based information about PA behaviors. These applications may be of especial interest in research on dyadic and family-based physical activity patterns.

Dyadic PA research, where two dyadic counterparts simultaneously and respectively wear activity monitors, may be considered a multi-sensor measurement approach. Though studies applying such an approach to measure child-parent PA in the young are few (Yao & Rhodes, 2015), insights gleaned from the available studies confirm that child-parent physical activity behaviors are interdependent even in early childhood (Yao et al., 2015). In light of these findings, a recent study has tasked the field with developing valid objective measures of child-parent co-participation in PA, as there currently appear to be few studies employing such methods (Uijtdewilligen et al., 2017). For example, a study of maternal-child PA using accelerometers, with simultaneous dyadic spatial proximity measurement via Bluetooth sensors, reported no validation study for the use of Bluetooth signals to measure dyadic proximity (Dlugonski et al., 2017). Thus, while the approach was a novel application of a multi-sensor system, the validity, and thereby also the generalizability, of the approach is uncertain.

Multi-sensor PA measurement studies have also used multiple sensors for a single person for the purpose of better capturing physical activity behavior from a multi-dimensional perspective (Ojiambo et al., 2012; Duncan, Badland & Schofield, 2009; Roudpoushti, Dias, Peixoto, Metsis & Nunes, 2017). Ojiambo (2012) and colleagues compared the use of a uniaxial accelerometer with simultaneous heart rate measurement to triaxial accelerometry in young children, and showed that uniaxial accelerometers plus heart rate monitors combined provided similar information about energy expenditure to a triaxial accelerometer. Duncan et al., (2009) showed the feasibility of the combined use of heart rate monitors and GPS data to characterize relationships between physical activity intensities and the environment in children. Using a multi-sensor system comprised of 17 inertial measurement units embedded within a suit and a multilevel Bayesian program, Roudpoushti (2017) and colleagues recently showed that an integrated sensor system can be used to determine contextual, human-to-human interactive, and activity modality in adults.

The applications of multi-sensor systems to measure physical activity in young children, their parents, and families is largely untapped. Moreover, there appear to be no consensus statements on the use of multi-sensor or remote sensor systems on standards of measurement in physical activity research. Further research is needed to inform the filed on best practices in early childhood physical activity measurement with respect to the use of multi-sensor and remote sensor systems.

Future Directions

Physical activity is essential for children's health, and accurate measurement of physical activity is needed to predict important short- and long-term health outcomes in children with certainty. Wearable activity monitor research, while able to provide objective insights into PA behavior, is fraught with limitations, especially with regard to generalizability of findings across studies. While current research efforts are aimed at addressing these limitations through novel analysis techniques and filed wide statements on best practices in measurement reporting, the lack of studies in early childhood research prevent informed recommendations for PA measurement in this population group. Furthermore, the recent application of remote sensors to measure PA dually requires inclusion within future guidelines on objective activity measurement. The potential benefits of objective PA measurements to accurately classify, predict, and characterize human behavior and associations with health continue to emerge. Further work is needed to explore the uses of available novel techniques for signal processing and data analyses in children in order to extend what is known about physical activity and health in the early years.

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Appendix B

Validity of a novel objective screening test for risk of physical inactivity in toddlers

INTRODUCTION

Physical activity (PA) behavior in early childhood (2-5 years-old) is positively associated with short- and long-term health outcomes in children (Ekelund et al., 2012; Janz et al., 2010). Evidence suggests, however, that <41%of young children may be receiving the health-enhancing benefits of PA due to insufficiently volumes of daily PA (Bai et al., 2016). In order to identify young children who may require PA interventions in order to meet current recommendations for early childhood PA (AHA, 2016; IOM, 2011), efficient and accurate screening tests for physical inactivity in young children are needed. Parental proxy reports of children's PA are a widely available, time efficient instrument for estimating daily PA volumes in children; however, the validity of these questionnaires in young children is limited (Oliver, 2007; Sarker, 2015). It follows that the use of parental proxy reports as a screening tool for physical inactivity in young children is dubious.

Alternatively, accelerometers are widely used to accurately estimate daily activity volumes in young children (Butte et al., 2014; Rowlands & Eston, 2007), and thus identify those at risk of daily physical inactivity (Bai et al., 2016). Standard accelerometery protocols in young children typically include continuous measurement over periods of ≥3 days (Van Cauwenberghe et al., 2011), which may be a limitation of their application across various contexts especially when few devices are available for use in large samples. To our knowledge, brief accelerometer data segments (≤ 1 hour) have not been explored as a means by which to identify children at risk of insufficient daily activity. Thus, toward effectively hybridizing the brevity of parent questionnaires with the accuracy of accelerometry, this study aimed to evaluate the accuracy and reliability of PHIT (Physical Inactivity Test)—a brief (15-60min) accelerometer-based protocol and algorithm for identifying risk of daily physical inactivity in 24-35 month-olds.

METHODS

Site & Sample. Families (N = 119) with 24-35 month-old children were recruited from an Early Head Start located within a major urban center. Each week, families attended the Early Head Start center for approximately 3.5 hours on a single day, and they also received semi-monthly visits in the home from one of their regular classroom teachers. The study protocol was approved by the Institutional Review Boards (IRB) of Teachers College, Columbia University and Columbia University Medical Center, and parents provided informed consent according to IRB procedures and policies.

Measures

Sociodemographic. Parents completed a questionnaire that included items on child age and sex.

Physical Activity. ActiGraph wGT3X-BT triaxial accelerometers (ActiGraph Corp., Pensecola, FL) were used to measure daily PA volumes in children, and devices were initialized to collect raw triaxial accelerometer signals at 30Hz. Parents were asked to place the hip-worn activity monitor on their child for 1 week, and to remove the activity monitor before bedtime or water-based activities (e.g., bathing, swimming, etc.). Accelerometer data were downloaded from activity monitors in ActiLife v6 as both raw triaxial signals and in 15s epochs, and then were exported for further analyses in MATLAB R2017b (The MathWorks, Inc., 2017). Cliff (2009) wear time criteria of (0cpm x 20min; < 6 hr·day^{-1}; < 3 days observed) were applied to 15s epoch data. Following, Trost (2012) uniaxial cut points (Sedentary [≤25], total PA (TPA) [>25], moderate-vigorous PA (MVPA) [≥420]) were applied to 15s epoch data in order to calculate the total minutes spent in each activity intensity per day.

PA Guidelines. Using the 7-day accelerometer wear time data, children were respectively classified as meeting or not meeting current daily moderate-vigorous PA (MVPA) and total PA (TPA) activity guidelines for 24-35 month-olds. Children participating in daily volumes of MVPA <60min were classified as not meeting MVPA guidelines (AHA, 2016). For TPA, children who participated in <180min daily were classified as not meeting guidelines (IOM, 2011). The term "daily" was conservatively defined as any day with valid observation data (Beets et al., 2011). That is to say, children with ≥1 day(s) of insufficient PA time in a given intensity were classified as not meeting respective guidelines.

PHIT. Children were also screened for risk of daily physical inactivity using brief (≤ 1 hour) segments of triaxial accelerometer data. From the full 7-day wear period, segments [15, 30 45, 60min] were randomly extracted from the period during which children were in the Early Head Start classroom. The brief raw triaxial accelerometer data segments of each length were respectively analyzed using a novel physical inactivity screening tool, Physical Inactivity Test (PHIT). PHIT is a custom signal processing algorithm for raw triaxial accelerometer data that rates brief signals for risk of daily physical inactivity. Ratings for a brief signal are determined based upon a number of signal features and covariates including the mean amplitude deviation, signal autocorrelation, peak power from the frequency domain, children's age, and interactions between terms. Signal ratings (PHIT scores) for each case are represented as a positive scalar that dually reflects activity intensity and volume. Lower PHIT scores, relative to a given activity intensity, represent lower levels of physical activity at the indicated activity intensity. For each child in our study with valid wear time data, PHIT scores were calculated separately for each activity intensity of interest (i.e., MVPA and TPA) across respective accelerometer data segments of each length.

Statistical Analyses

A binary classification decision tree (CART) machine learning algorithm was used to respectively fit MVPA and TPA PHIT scores as predictors of children not meeting PA guidelines during the 7-day wear period. The CART algorithm determines optimal partitions of the predictor space for all variables entered into a model in order to build a decision tree that ultimately returns the class of a given vector of data based upon the partitions within the tree (Breiman, 1984). CART algorithm receiver operating characteristic area under the curve (AUC) and bootstrapped 95% confidence intervals were evaluated across n = 1,000 iterations for each respective observation length. For the optimally performing observation length, cut points for both MVPA and TPA PHIT scores are respectively presented as decision tree equations. Optimal performance was defined as the observation length with the highest PHIT score AUC and the narrowest 95% confidence intervals. PHIT scores were also used to classify children at risk of daily physical inactivity using a custom 2-step algorithm (Figure 1). The bootstrapped sensitivity, specificity, positive and negative predictive values for the 2-step PHIT decision tree were calculated across n = 1,000 iterations. All data were analyzed in MATLB R2017b, and descriptive statistics are presented as Mean (Standard Deviation), Median (Interquartile Range) and Frequencies [%(n)]. In order to assess reliability for PHIT, raw accelerometer data for two non-overlapping 15min segments were randomly selected across all cases, and the 2-step PHIT algorithm was applied. The intraclass correlation (ICC) between PHIT results for each segment was calculated, and the Spearman-Brown Prophecy Formula was used to determine the requisite length of the test in order to achieve sufficient (≥0.70) reliability.

RESULTS

Children (n = 60) with valid 7-day wear time data were *29*(4) months-old on average, and 53%(32) were girls. On average, children wore the activity monitors for *5*(1) days and 10.*1*(1.3) hours/day. Analysis of 7-day wear time data showed that 75%(45) and 32%(19) of children did not meet MVPA and TPA guidelines, respectively. Validation results for PHIT scores are shown in Table 1. For the optimally performing observation length (15min), children's median PHIT scores were *10.05*(1.30) and *3.92*(0.44) for MVPA and TPA, respectively. For the 15min observation length, the following PHIT score cut point equations (Eq. 1, Eq. 2) were derived for identifying 24-35 month-olds who did not meet activity guidelines:

$$\begin{aligned} MVPA\ RISK = {} & 1 * I(PHIT \leq 11.20) * I(PHIT \leq 10.52) + \cdots \\ & 0 * I(PHIT \leq 11.20) * I(PHIT > 10.52) * I(PHIT \leq 10.54) + \cdots \\ & 1 * I(PHIT \leq 11.20) * I(PHIT > 10.52) * I(PHIT > 10.54) + \cdots \\ & 0 * I(PHIT > 11.20) \end{aligned} \tag{1}$$

$$\begin{aligned} TPA\ RISK = {} & 1 * I(PHIT \leq 3.86) * I(PHIT \leq 3.43) + \cdots \\ & 0 * I(PHIT \leq 3.86) * I(PHIT > 3.43) * I(PHIT \leq 3.56) + \cdots \\ & 1 * I(PHIT \leq 3.86) * I(PHIT > 3.43) * I(PHIT > 3.56) + \cdots \\ & 0 * I(PHIT > 3.86) * I(PHIT \leq 4.07) + \cdots \\ & 1 * I(PHIT > 3.86) * I(PHIT > 4.07) * I(PHIT \leq 4.11) + \cdots \\ & 0 * I(PHIT > 3.86) * I(PHIT > 4.07) * I(PHIT > 4.11) \end{aligned} \tag{2}$$

where, the conditional $I(x)$ is 1 if x is true and 0 if x is false, PHIT is the PHIT score, and the outcome (risk of insufficient activity at a given intensity) is binary [0,1], with 0 indicating low risk and 1 indicating high risk.

Validation results for the 2-step PHIT decision tree (shown in Figure 1) are presented in Table 2. Across all iterations of the bootstrap procedure, 0%(0) of the screening tests were rendered invalid by the 2-step algorithm. Of the children who received a preliminary positive screening, and would be asked to wear the monitor for an additional 7 days, 94.4% would be identified as insufficiently active during the 7-day wear period. Thus, the 5.6% of children who received a false preliminary positive screening would wear the activity monitor for an additional 7 days unnecessarily. Of the children who were both insufficiently activity during the 7-day wear period and did not receive a preliminary positive screening, 91% received a positive screening (see Figure 1). Across the entire cohort, <4% of children would have received a false negative screening, and no children would have received a physical activity prescription in error.

The intraclass correlation between PHIT results for the two non-overlapping 15min samples was [r_I = 0.56]. After applying the Spearman-Brown prophecy formula, the PHIT algorithm reliability was [r_I = 0.73] using 2 fifteen minute samples, [r_I = 0.80] for 3 fifteen minute samples, [r_I = 0.84] for 4 fifteen minute samples.

DISCUSSION

The aim of this study was to determine the accuracy of Physical Inactivity Test, a novel method for objectively screening for risk of physical inactivity in 24-35 months-old using brief accelerometer data segments. Results showed that PHIT scores for raw triaxial accelerometer signals (15min), collected while children were in an Early Head Start, were valid and reliable predictors of children meeting activity guidelines at both the MVPA and TPA intensities. Moreover, using the 2-step PHIT algorithm, toddlers at risk of daily physical inactivity were accurately triaged into high and low physical inactivity risk groups. PHIT can be used within an Early Head Start setting to efficiently identify 24-35 month-olds at high risk of daily physical inactivity and who are in need of physical activity interventions.

To date, parent questionnaires are widely used as a time efficient means of estimating young children's daily physical activity volumes (Oliver et al., 2007; Sarker et al., 2015). These proxy reports, however, appear to have limited validity (Oliver et al., 2007). By contrast, the 2-step PHIT algorithm was able to identify ≥91% of children at high risk of daily physical inactivity using brief (15min) objective PA measures and without the need for 7-day activity monitoring. Furthermore, >94% of children who received a preliminary positive PHIT screening were observed to be insufficiently active during the 7-day accelerometer wear time period. Additionally, the reliability of the 2-step cascaded PHIT algorithm was found to be ≥0.80 when 2 or more 15min samples of activity data were sampled. The need for more than one period of data to improve daily activity volume estimate reliability is common in accelerometer-based studies of physical activity (Trost et al., 2000); however, the current standard in young children is >3 days of continuous measurement with several hours per day (Cliff et al., 2009). Thus, our results suggesting that at least two brief (15min) measurement periods are required for reliable physical activity estimation is consistent with studies using longer measurement periods. Taken together, these results point toward the use of PHIT as a valid, reliable, and time efficient alternative to parental proxy reports for identifying toddlers at risk of daily physical inactivity.

To our knowledge, this is the first study to identify toddlers at risk of failing to meet current activity guidelines using brief accelerometer data segments. For 15-30min data segments, the sensitivity, specificity, and positive predictive value of the 2-step PHIT decision tree were excellent (≥90%), and the negative predictive value was very good (≥86%). While the 45-60min data segments performed well, both segments had lower AUC values for PHIT scores than the 15-30min segments. This could be due to the fact that the data segments were randomly selected, and the longer monitoring periods were liable to capture more discretionary sedentary activities (e.g., circle time, lunch, etc.) during the 3.5hr Early Head Start class time. In comparing the 15min and 30min segment, the PHIT score AUC value was more stable for the 15min segment. As such, we recommend the use of a 15min segment of raw triaxial accelerometer data to calculate PHIT scores for use within the 2-step PHIT algorithm.

Accelerometer data used in this study were specifically sampled from a period of time when children were within an Early Head Start classroom setting. A prior study of highly active versus less active children showed that highly active children engaged in greater volumes of activity than their less active counterparts while indoors, but that the groups were not significantly different outdoors (Howie, 2013). Additionally, the PHIT cut point equations for 24-35 month-old were determined using a hip-worn triaxial accelerometer (ActiGraph wGT3X-BT). Therefore, the use the PHIT cut point equations from this study may limited to use within indoor classroom settings for 24-35 month-olds using similar accelerometer specifications. Further research is needed to determine which classroom periods are the most reliable testing times for using PHIT in young children.

CONCLUSION

Within an Early Head Start setting, Physical Inactivity Test accurately identified toddlers at risk of daily physical inactivity from a brief period (15min) of objectively measured PA. These findings suggest that relatively short data segments that capture indoor physical activity behaviors can be used as a proxy for daily activity volumes observed over longer periods of time. Future studies should determine which classroom periods are optimal for using the PHIT algorithm

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Table 1. Accuracy of PHIT scores in identifying toddlers at risk of insufficient daily activity according to current physical activity recommendations

Accuracy Indices	**Observation Length**			
	15min	30min	45min	60min
	n = 53	n = 60	n = 58	n = 55
PHIT Scores[†]				
(AUC [95% C.I.])				
Not Meeting MVPA[a]	0.96 [0.89, 0.99]	0.97 [0.91, 0.99]	0.92 [0.77, 0.99]	0.95 [0.86, 0.99]
Not Meeting TPA[b]	0.95 [0.87, 0.98]	0.94 [0.84, 0.98]	0.92 [0.81, 0.97]	0.90 [0.78, 0.97]

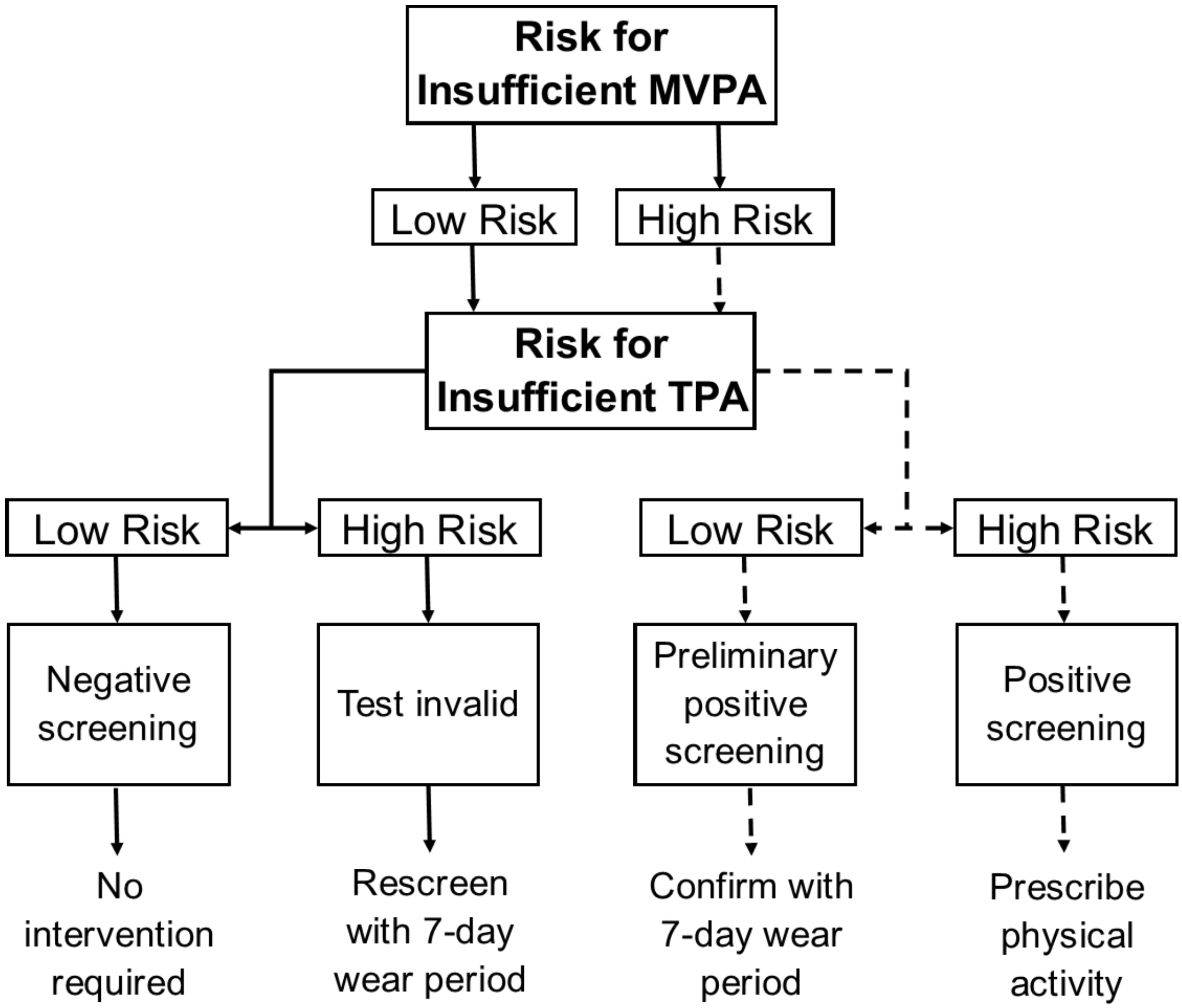
[a]American Heart Association. The AHA's Recommendation's for Physical Activity in Children
[b]Institute of Medicine. Early Childhood Obesity Prevention Policies
[†]Receiver Operating Characteristic Area Under the Curve and Bootstrapped 95% Confidence Intervals

Table 2. Accuracy of the 2-step cascaded PHIT in 24-35 month-olds

Accuracy Indices	Observation Length			
	15min	30min	45min	60min
	n = 53	n = 60	n = 58	n = 55
PHIT Screening Test† (%)				
Sensitivity	90%	93%	96%	96%
Specificity	92%	93%	92%	70%
Positive Predictive Value	94%	96%	96%	86%
Negative Predictive Value	86%	88%	92%	90%

†All values were bootstrapped

Figure 1. Cascaded 2-step PHIT decision tree for identifying toddlers (24-35 months-old) at risk of daily physical inactivity



Note. Figure 1 shows the 2-step decision tree employed by the Physical Inactivity Test (PHIT), a screening test for identifying toddlers at risk of participating in insufficient volumes of daily physical activity from brief periods (≤1 hour) of accelerometer-derived physical activity data

Appendix C

Quantizing three-dimensional physical activity videos: A dual-sensor algorithm for Microsoft's Kinect

Physical activity has known known cardiometabolic benefits (Andersen et al., 2006) and the measurement of physical activity is useful for determining individual- and population-level health-related behaviors of the same (Cliff, Reilly & Okely, 2009). Respective intensities of physical activity, namely, sedentary, light-lifestyle, moderate, vigorous, activity behaviors, have known associations with various health factors, and are based upon intensity cut points (Anderson et al., 2006; Bai et al., 2016; Cliff, Reilly, & Okely). Historically, physical activity has been measured using wearable sensors, and most recently with the use of triaxial accelerometers and device specific cut points. While there are some studies that have employed remote sensors to analyze physical activity behavior (Silva et al., 2015), these studies have only used 2D and thus are limited when compared to 3D (Maile et al., 2015). Thus, the need for objective cut points for 3D remote sensors remains.

Thus, as a precursor to developing physical activity cut points for a remote sensor, this study aimed to develop an algorithm to convert remotely sensed physical activity videos acquired using Microsoft's Kinect for Windows (v1) into triaxial accelerations.

METHODS

Site & Sample

Physical activity data were collected on video using Microsoft's Kinect for Windows (v1) in the Applied Physiology Laboratory at Columbia University Teachers College. The Kinect is equipped with both a depth sensor and color sensor, and the reliability of the device has been established in prior research (Stone et al., 2013). The color sensor was initialized to collect infrared data, images, $f(x, y, t)$, were quantized as 16-bit unsigned integers, and each video frame was sampled at a resolution of 480 x 640 pixels, where x and y represent respective row and column pixel coordinates and t represents the time of image acquisition for each frame. Sampling and quantization parameters were identical for the depth sensor; however, pixel values at a given coordinate (x, y) represent the distances from the sensor in mm. One subject ($N = 1$) participated in the study presented herewith. The subject engaged in two separate 60s measurement conditions in order to generate comparative data for algorithm performance analyses. The two conditions were as follows: 1) the subject performed low-level intensity (i.e., sedentary and light intensities) physical activity behaviors (e.g., walking and standing), and in the second segment performed 2) higher-level intensity (i.e., moderate to vigorous intensities) physical activity behaviors (e.g., running and jumping). Video data capturing the physical activities performed across the respective conditions were collected using both the infrared and depth sensors, with a frame rate of 30Hz. All acquired frames were directly stored in MATLAB R2016a at the time of acquisition using a custom algorithm. The image acquisition algorithm collected $f(x, y, t)$ for both infrared and depth sensors simultaneously, where time was measured in milliseconds using the local CPU time.

Analysis

In studies of wearable physical activity monitors, triaxial acceleration data simultaneously reflect perturbations (i.e., movements) in the frontal, vertical, and sagittal planes over time (Sasaki, John & Freedson, 2012). It follows that pixel values acquired from the infrared sensor were used to provide information about physical activity in the frontal (x) and vertical (y) planes, and the depth sensor intensity values were used for the sagittal (z) plane.

The analysis of physical activity images was conducted in MATLAB across several stages that included: 1) image acquisition, 2) image processing, 3) image representation & description, 4) calibration, and 5) Fourier motion analysis. At each stage of the analysis, custom algorithms were implemented in order to ultimately convert the three-dimensional video signals into triaxial physical activity accelerations.

To evaluate algorithm performance, triaxial accelerations results derived from physical activity video data were compared between the lower- and higher-level physical activity conditions described previously. Descriptive statistics [*Mean* (Standard Deviation)] of the triaxial vector magnitudes were calculated for each respective condition.

RESULTS

Image Acquisition

As shown in Fig 1, the image acquisition algorithm captured physical activity data from both the infrared (Fig 1A) and depth (Fig 1B) sensors. Data frames were visually inspected to determine the performance of each of the sensors in capturing physical activity data at various locations in the environment. While the infrared camera consistently collected data across all frames, the depth sensor was unable to quantize object depth when the subject was flush against the wall (Fig 1C). Given that sagittal values are required in order to compute triaxial acceleration values, frames lacking depth data for the object of interest required further consideration at later steps in the algorithm.

Image Processing

For the purposes of image segmentation, difference images (shown in Fig 2A) between consecutive infrared video frames were calculated (1),

$$d_{ij}(x, y) = \begin{cases} 1 & \text{if } |f(x, y, t_i) - f(x, y, t_i)| > 1500 \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

where, $d_{ij}(x, y)$ is the resultant image, t_i denotes the image frame to be differenced, and $t_j = t_{i-1}$ *as* the reference image frame (Gonzalez & Woods, 2008). Assuming, that the sum of pixels representing a single human object in the frame was no larger than threshold $T_1 = 6000$ pixels (as determined by iterative analyses), any differenced frames with total number of foreground pixels greater than T_1 were deemed unevaluable given that they were too noisy to extract the object of interest. In order to enhance object boundary information for each difference image d_{ij} a Sobel edge detector was applied in both the horizontal and vertical directions (Fig 2B). Following, the edge detected image was convolved with a kernel of size 3 x 3, where the origin in the output image $g(x, y)$ was equal to 1 when the sum of the kernel in $f(x, y) \geq 5$ (Fig. 2C). As shown in Fig 2D, morphological closing was then applied to the remaining pixels using a disk ($r = 9$) for the purpose of maximizing object shape information within the determined boundary.

Fig 2E shows the results of morphological reconstruction using the opened image as the marker and the original difference image frame as the mask. In order to derive a single connected component that delineates the object of interest, geodesic dilation was applied to the reconstructed image using the dilated reconstructed image as a marker, where the structuring element was a square ($w = 25$). Afterward holes were filled in the dilated image using 8-connected pixels (Fig 2F). Finally, the object was thinned for the purpose of reducing the size of any residual noise components in the image.

Image Description & Representation

The number of connected components in the thinned image were calculated and returned in an output image $z(x, y)$. Any components comprised of < 300 pixels were set to zero, and the resultant mask $z_1(x, y)$ was multiplied by the thinned image. Thus, any additional artifact in the image was removed, as shown in the final product of the algorithm (Fig 3).

In order to distill a single pixel that represents the position of the object, as needed for further motion analyses, the object centroid was evaluated using the thinned image. Fig 5A shows the object centroid superimposed on the original infrared image (with updated color mapping) and the depth image (scaled for visibility). As can be seen in the depth sensor image (Fig 4B), and as noted previously, there is a chance that the depth sensor pixel intensity at the centroid coordinates may be equal to zero given noise in the sensor.

To determine if an evaluable depth sensor intensity value was proximal to the centroid coordinates, an increasing window around the centroid was evaluated with a maximum windows size of 11 x 11 pixels (Fig 5). Any frame without a depth sensor intensity value was deemed unevaluable for triaxial acceleration calculations.

<u>Calibration</u>

A sensor calibration procedure was conducted in order to convert the distance between pixels into meters at various distances from the sensor. For this process, an object with known height (1.75m) was placed at various distances from the sensor. The pixel coordinates corresponding to the upper- and bottom-most edges of the object were manually collected within each frame of interest. The Euclidean distance between each respect pair of two points were calculated, and the depth sensor pixel intensity was conserved at each location where the object was located. The resultant Euclidean distance values were divided by the known height of the object giving m/pixel, and the Pearson's pairwise correlation between m/pixel ~ pixel intensity (depth) was evaluated. A line of best fit for the correlated data point yielded (2), which was used to determine m/pixel for a given depth pixel intensity value for the Fourier motion analyses.

$$\frac{m}{pixel} = 1.5 * 10^{-06} * (depth) + 6.4 * 10^{-04} \qquad (2)$$

Fourier Motion Analysis

Intensity values at each centroid location were used to conduct Fourier motion analyses. For each respective plane of movement (x, y, z), the singular intensity value at a given centroid location was extracted, and was used to develop a weighted projection (Gonzalez et al., 2008). For example, the intensity value given at centroid location (x, y) in the M x N image was projected onto a 1-D array of size 1 x N for, with pixel value at location y for all x-axis projection. The same was done for all y and z axis measurements.

The resultant triaxial weighted projections were each multiplied by (3), where a_1 is a positive integer equal to 30/max velocity expected in a given plane, x is each value in the projected vector, Δt is the relative time interval between frames, and j = $\sqrt{-1}$. The maximum velocities expected in the x and z planes was 4m/s and was 2.8m/s in the y plane. Following, the sum of all transformed elements in a given array was calculated.

$$\exp\,[j2\pi a_1 x \Delta t] \qquad (3)$$

Finally, the fast Fourier transform was computed for each of the aforementioned vectors of projected values, each of size $K = 30$, where K is the relative frame observed during a given second. A peak search over the 30 transformed data points collected at each second revealed the frequency-velocity relationship as the first peak within the signal. Velocity (V_1), in units of pixels, was then determined by dividing the corresponding frequency value located at the peak location by a_1. To derive the sign of the velocity component, the second derivative of the transformed projection was calculated for the real and imagined components of the values. Where the resultant signs for the real and imaged components were congruent, the velocity was positive, and was negative otherwise. To convert the velocity into m/s, V_1 was multiplied by the results of (2), where the depth value was the observed value in the given epoch. This process was iterated across observations and all planes.

Triaxial Accelerations

Velocity values obtained from Fourier motion analysis were transformed into acceleration (units *g*) using standard methods, and the Euclidean norm of the acceleration signals was used to calculate the vector magnitude. Finally, these observations were transformed from milli-g into standard activity counts by multiplying the vector magnitude values by 1000. Results from a comparison of the remote sensor derived triaxial accelerations from the lower- and higher-intensity experimental conditions showed that the *M*(SD) vector magnitudes were *4.7*(10.8) and *16.0*(15.3), respectively.

DISCUSSION

This study provides the requisite foundation for future work on the development of physical activity cut points for remote sensors, and specifically for Microsoft's Kinect for Windows (v1). Comparison of the results from the two experimental conditions showed that the derived vector magnitude values were higher in the condition that included jumping and running than in the condition that only included walking and standing. A delimitation of this study was that the algorithm only focused on analyzing data for one subject. Future studies that wish to track multiple objects simultaneously will need to employ a Kalman filter in order to predict centroid locations when objects may be obstructed by one another. Furthermore, future studies should focus on testing the validity of the derived acceleration signals against standard wearable monitors. Additionally, longer observational periods should be used in future work with along with a larger sample size.

CONCLUSIONS

The Microsoft Kinect can be used to capture and analyze physical activity data. Future research is needed to establish valid cut points, and to analyze multiple objects within a given image.

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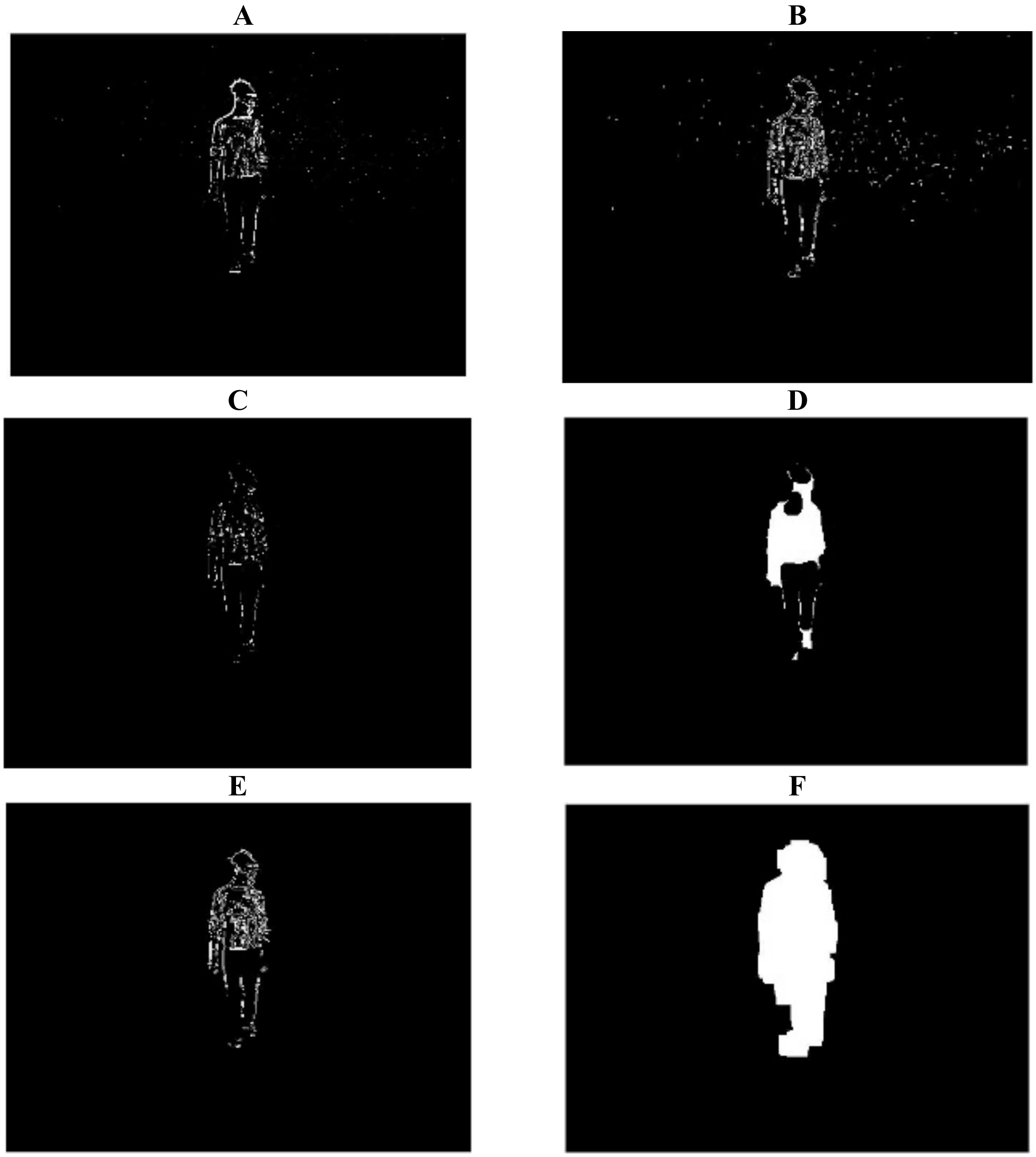
Fig 1. Frames of physical activity acquired with the Kinect infrared (A) and depth sensors (B & C)

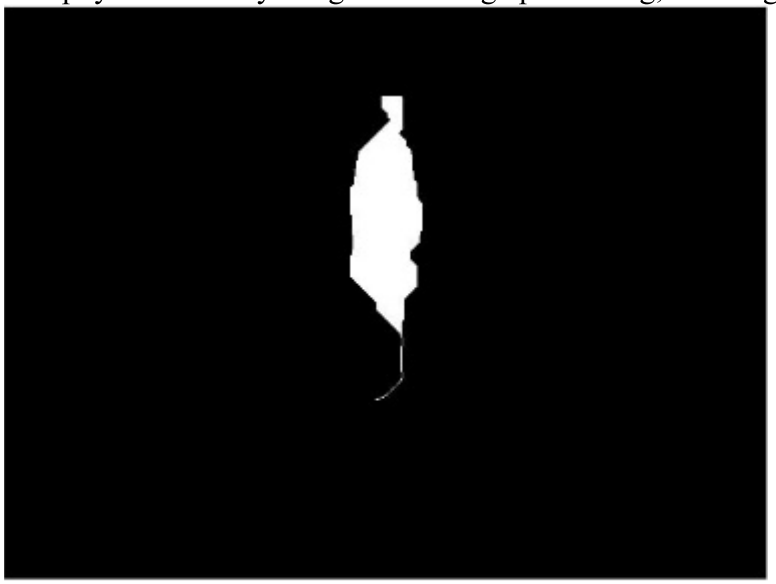
Note: Figure 1 shows results of the image acquisition algorithm (A & B), and also that the object of interest was unable to be quantized by the depth sensor when the subject was flush against the wall (C).

Fig 2. Iterative image processing of a physical activity frame acquired from the Kinect infrared sensor



Note: Figure 2 shows the iterative results of taking the difference image (A), Sobel edge detection (B), regional pixel majority (C), morphological closing (D), reconstruction (E), and geodesic dilation followed by the filling of any holes in the object (F).

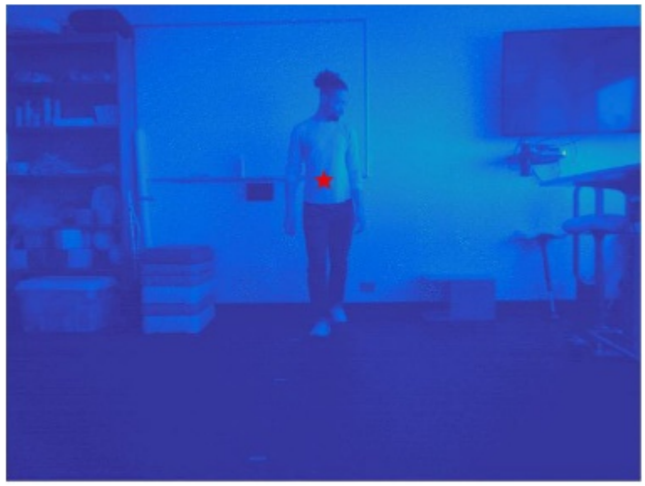
Fig 3. Final infrared physical activity image after image processing, thinning, and masking



Note: Figure 3 shows the results of the combination of image processing and image description (i.e., connected component) algorithms.

Fig 4. Object centroid superimposed onto infrared (A) and depth (B) frames of physical activity

A



B

Note: Fig 4 shows infrared image with color remapping (A), depth sensor with color axis scaling (B), and the object centroid as a red star

Fig 5. Iterative depth sensor intensity value algorithm, with increasing window size

```
Sub depth_window( )
    window_size = 0
    while depth_intensity = 0
        do window_size = window_size + 1
            if window_size ≤ 10     then
                center window at centroid (x, y)
                remove pixels with intensity = 0 in window
                calculate median of remaining pixels
                depth_intensity = median pixel value
            else
                depth_intensity = Inf
            end
        end
    end
End Sub
```

Note: Figure 5 outlines an algorithm that searched for the nearest pixel intensity to a given centroid

Appendix D

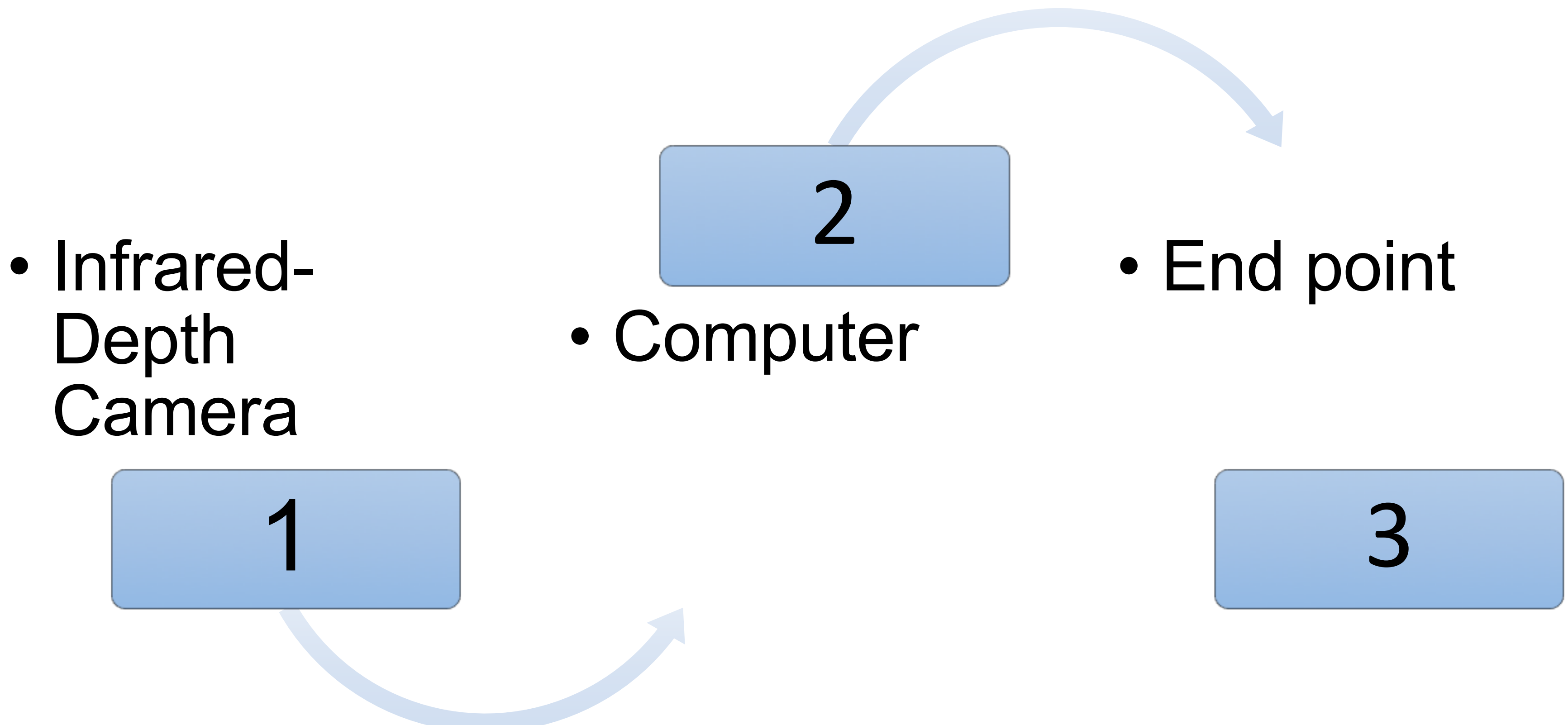
KinetiWave: A platform for health-related biometrics

Acquiring, processing, and analyzing infrared-depth camera data for physical activity measurement

A computer vision algorithm by:

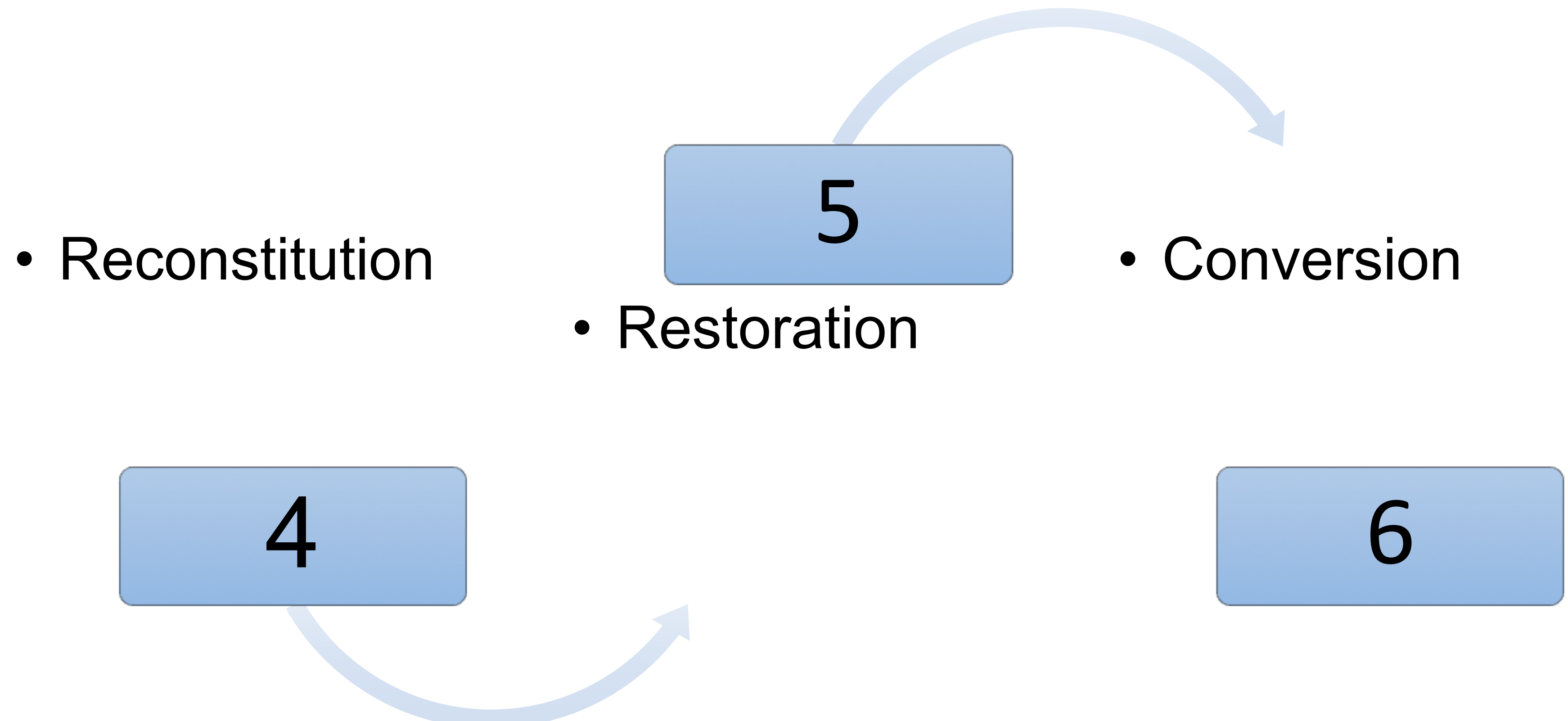
Aston K. McCullough, MPhil, MS, MA, CFP

Signal Acquisition



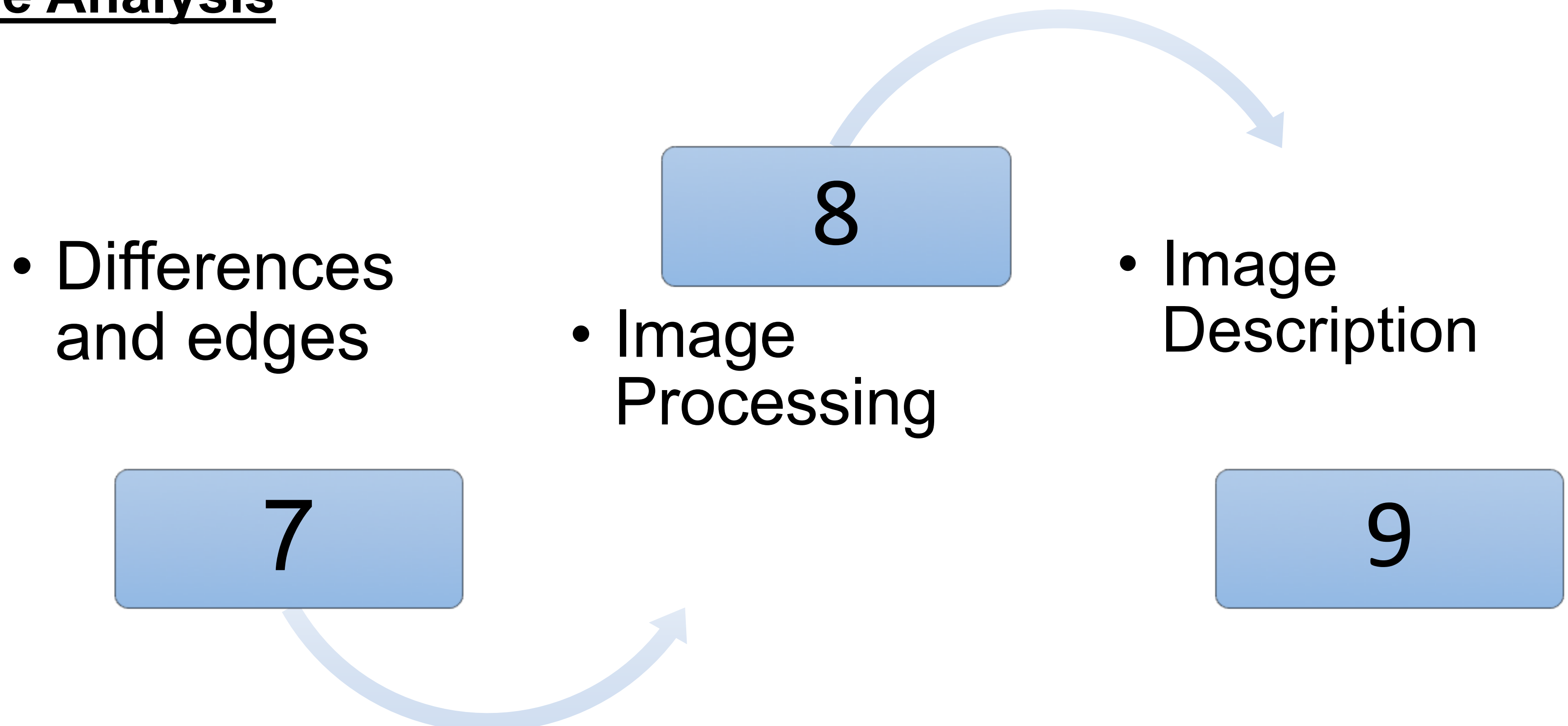
1: Images (resolution: 480 x 640 pixels) of the environment are collected in 3 dimensions via infrared-depth sensors at 30Hz as a video
2: Infrared and depth sensor data are passed to a computer, as two separate channels, and each as 16-bit unsigned integers. Each frame is labeled with a timestamp using the local CPU time. Data (acquisition start time, frame-by-frame timestamps, depth images, infrared images) are respectively converted into a *.bin format
3: Data are passed as separate *.bin files to a user-defined end point where they are stored

Image Restoration



4: Image data are taken from the end point (as in 3), and converted from *.bin files into 16-bit unsigned integers, with a resolution 480 x 640 pixels
5: Images are restored and cleaned in both the spatial and frequency domains. Spatial domain techniques include adaptive histogram equalization followed by a log transform. Frequency domain techniques were applied after implementing a Fast Fourier Transform and included, removal of periodic noise through masking, value exponentiation, and image sharpening. Following, the Inverse Fast Fourier Transform is applied
6: Restored images are converted into *.avi files for viewing as videos for coding, direct observation, or other purposes

Image Analysis

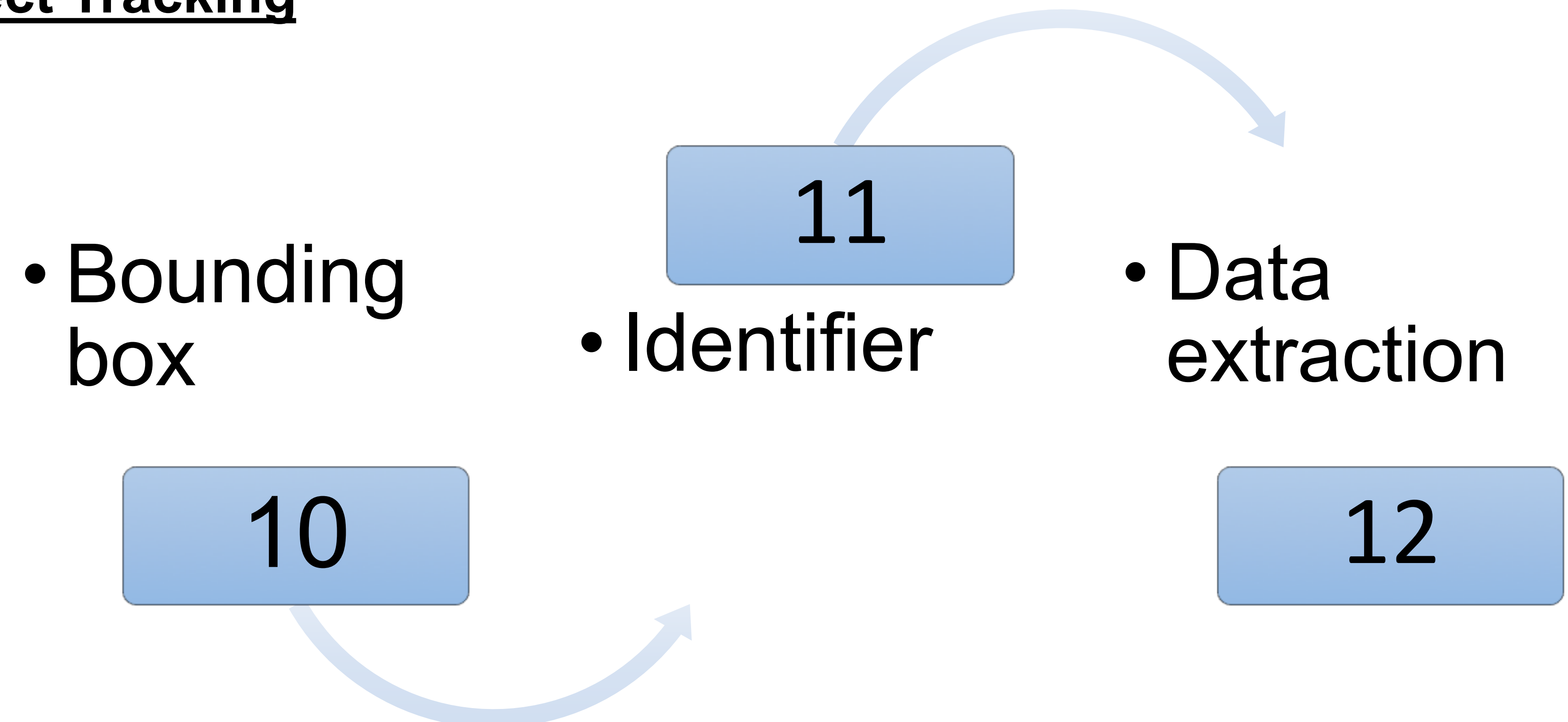


7: Infrared and depth sensor images are taken 30 frames at a time, the difference image between consecutive frames is distilled, the edge information from the difference image is assessed

8: In order to separate objects of interest from noise, difference images from both the infrared and depth sensors images are iteratively and simultaneously treated using a series of image processing steps (i.e., pixel majority estimation, geodesic dilation, geodesic erosion, morphological restriction by dilation, opening, closing, hole filling and thinning)

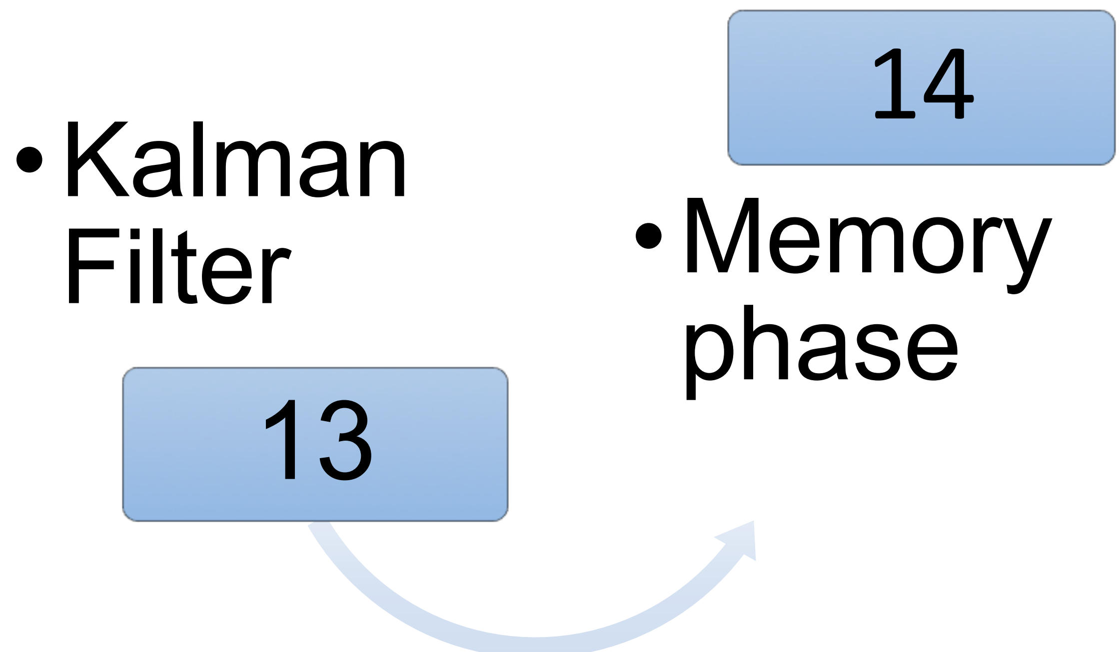
9: The number of blobs, the location of their respective centroids, and their sizes are assessed. Blobs over or under a given threshold, in terms of their size, are removed as noise, and others are conserved as objects of interest

Object Tracking



10: The height and width of each extracted object of interest (i.e., blobs) within a given frame are determined, and a bounding box is centered around each blob at its centroid framing the object of interest
11: A numeric identifier is assigned to each bounding box and the time at which the blob was registered is stored
12: The intensity value of the pixel located at each respective centroid is stored for every blob for both the infrared and depth images for each frame

Object Tracking



13: The centroid data and pixel information are passed to a standard Kalman filter for signal smoothing

14: (a) The location of the Kalman filtered centroid is compared to the location of all other historical centroids. If the centroid coordinates fall within a single existing bounding box that has been stored within the memory, the new centroid information is stored under that identifier, and the location of the bounding box is re-centered and resized at the location of the new centroid. (b) The size of the new bounding box is determined by the standard deviation of the historical errors between the location of the observed and Kalman filtered centroids, which is calculated using the Euclidean Distance between the two locations. In both the vertical and horizontal dimensions, if the height/width of the box is > 2 standard deviations than the error, the box shrinks to the median size of the last $\leq$3 box in each respective dimension. Otherwise, the max size of the last several boxes is chosen to resize the box in each dimension

Object Tracking

- Translation and Expansion

15

15: If the newly observed centroids fall within no exiting bounding box, the process is reiterated, after 1) translating the location of the newly observed centroid by 2 times the standard deviation of respective errors (as in 14b) for each bounding box, and 2) the size of each bounding box is temporarily increased to 2 times the standard deviation of the historical errors associated with the bounding box. If a single match is found, the algorithm resizes the bounding box as in 14b. If the centroid falls within multiple boxes, the algorithm moves to a tie breaker phase

Object Tracking

- Tie breaker

16

16: If multiple potential candidate bounding boxes are discovered in 15, a tie breaker protocol is initiated for each respective candidate bounding box. First, the Kalman filtered value of the new centroid is determined under the assumption that it belongs to the candidate bounding box. Thus, the *a posteriori* values from the candidate box are used to determine smoothed location of the new. Then a cost function is applied, in which 1) the log-likelihood of the new centroid belonging to the candidate box is calculated, and then 2) log-likelihood is weighted by the inverse of the proportion of pixels that overlap between the new centroid's bounding box and the candidate bounding box. The bounding box with the lowest cost is assigned the new centroid. If no candidate bounding box was found in 15, however, then a new bounding box is added to the memory as in 11-12

Object Tracking

- Vanishing boxes

17

17: For any historical bounding box where a new centroid has not been added for a given period of time, the bounding box is removed as a candidate for all future observations. The criteria for determining if a bounding box should no longer be an active candidate are 1) there was only a single observation for that box within the last 1s, 2) there were no observations in the last 2s for bounding boxes with <10 stored observations, 3) there were no observations in the last 3s for bounding boxes with a $\geq$ 10 stored observations

Motion Analysis

- Fourier motion analysis

18

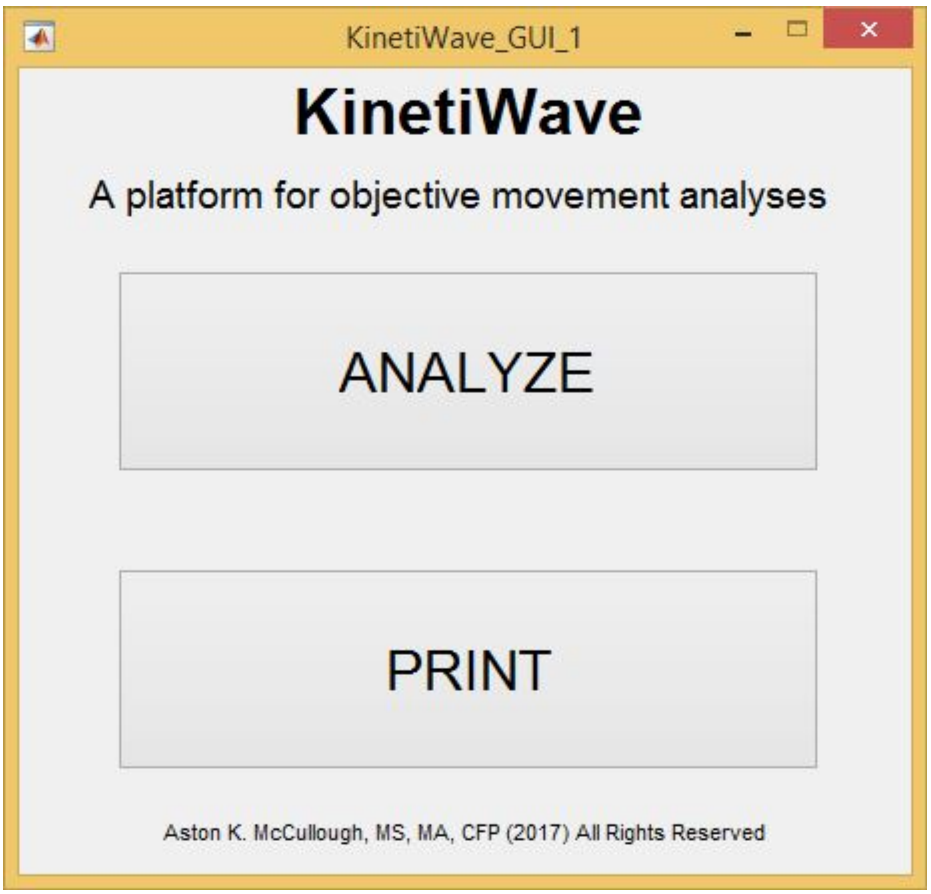
18: After the end of a video signal is reached, the iteratively stored centroids for each bounding box are processed using a Fourier Motion Analysis technique. Taking 30 frames at a time, the centroid locations and intensity values are multiplied by a constant factor (see Appendix C), and the Fast Fourier Transform of the transformed centroids values are assessed using a periodogram. A peak finding algorithm is applied to the data in the periodogram, and the real and imaginary parts of the value at the given peak are determined. This process is reiterated for data collected in each dimension (x, y, z). The resultant signal is a m x 3 array of centroid velocities. The velocities are given positive or negative values using the imaginary and real parts of the signal, and the updated velocity values are transformed into accelerations.

Motion Analysis

- Triaxial Accelerations

19

19: The triaxial acceleration signals are transformed into an m x 1 array of vector magnitude values by taking the Euclidean Norm of the m x 3 vector of accelerations given by 18.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KinetiWave
A platform for objective movement analyses
ANALYZE
PRINT
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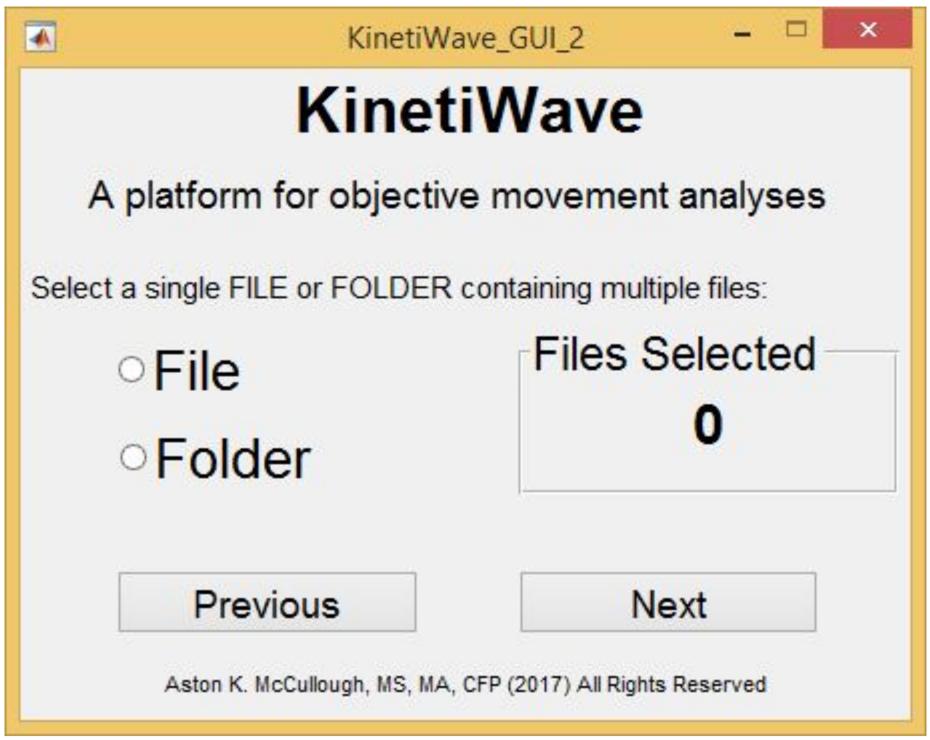
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KinetiWave
A platform for objective movement analyses
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File
Folder
Files Selected
0
Previous
Next
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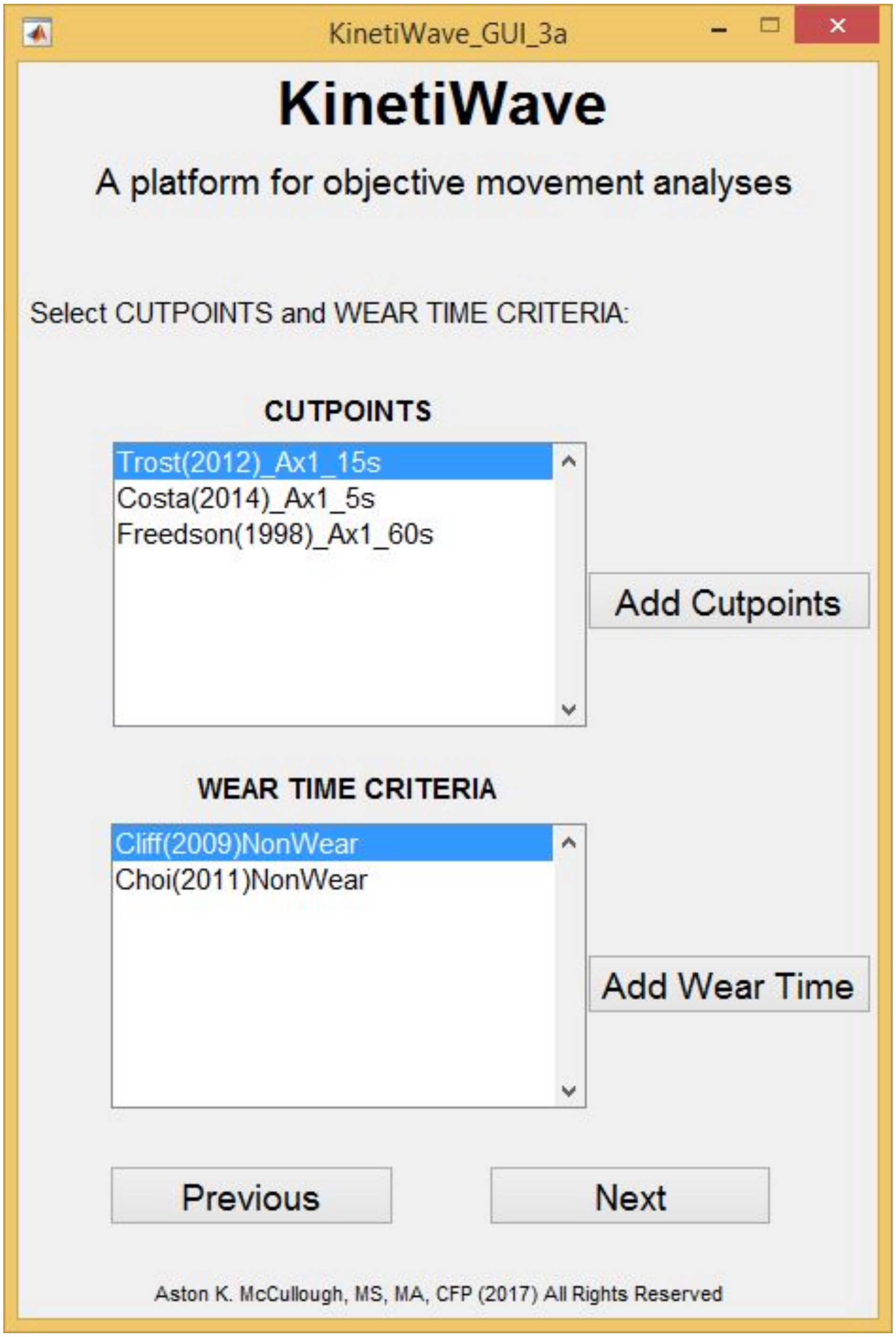
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KinetiWave
A platform for objective movement analyses
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Costa(2014)_Ax1_5s
Freedson(1998)_Ax1_60s
Add Cutpoints
WEAR TIME CRITERIA
Cliff(2009)NonWear
Choi(2011)NonWear
Add Wear Time
Previous
Next
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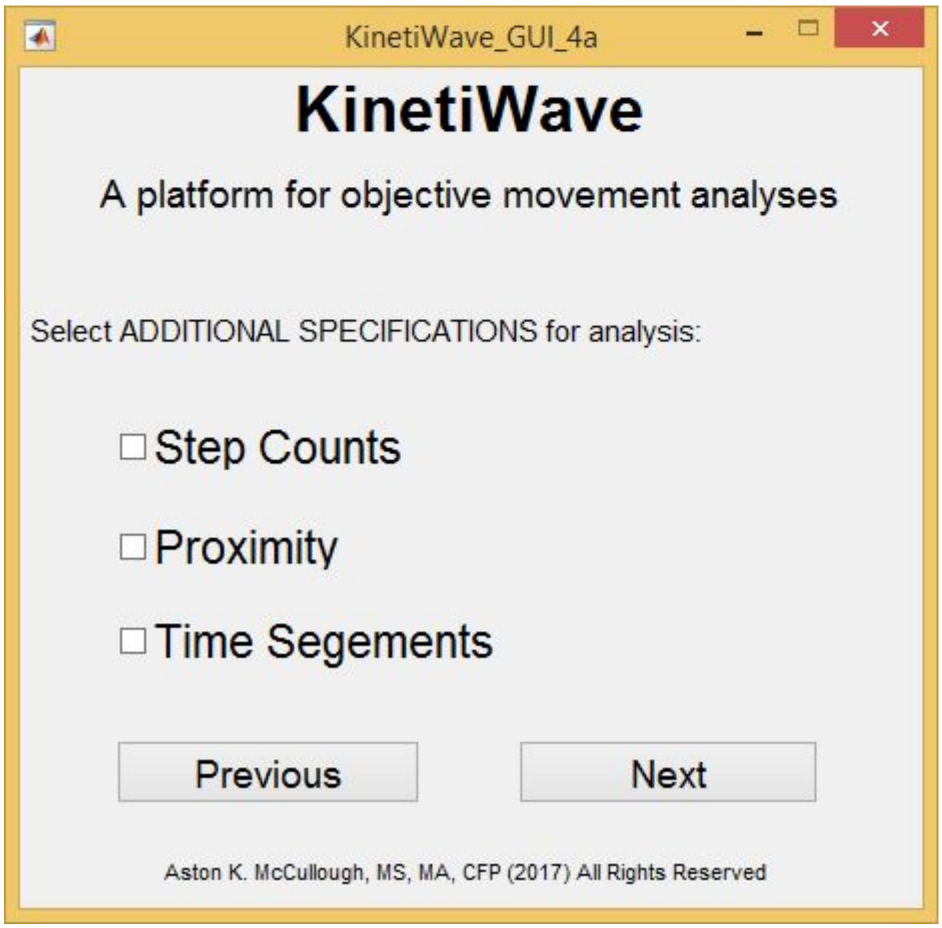
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A platform for objective movement analyses
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Step Counts
Proximity
Time Segements
Previous
Next
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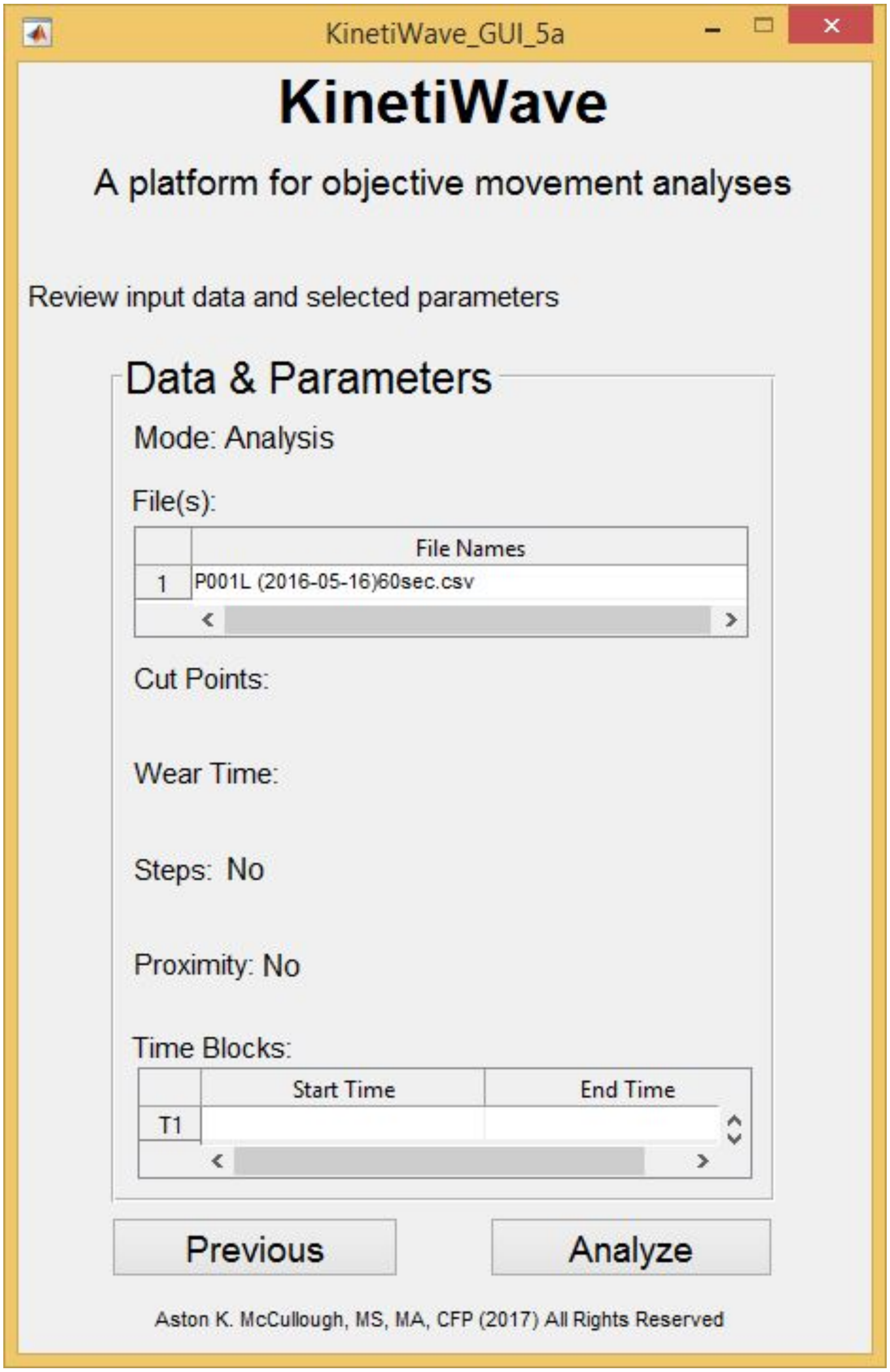
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KinetiWave
A platform for objective movement analyses
Review input data and selected parameters
Data & Parameters
Mode: Analysis
File(s):
File Names
1
P001L (2016-05-16)60sec.csv
Cut Points:
Wear Time:
Steps: No
Proximity: No
Time Blocks:
Start Time
End Time
T1
Previous
Analyze
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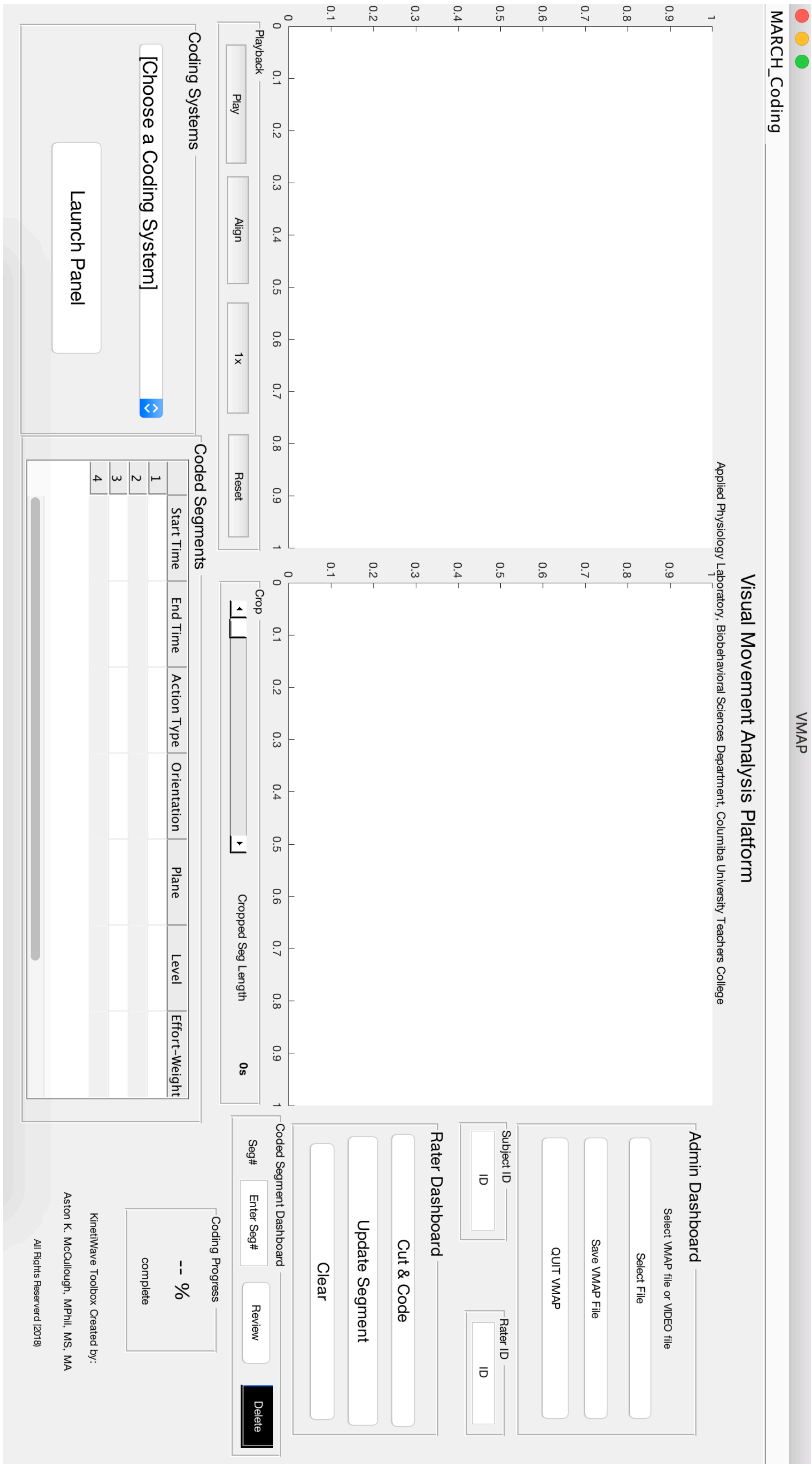

MARCH_Coding
VMAP
Visual Movement Analysis Platform
Applied Physiology Laboratory, Biobehavioral Sciences Department, Columbia University Teachers College
Playback
Play
Align
1x
Reset
Crop
Cropped Seg Length
0s
Coding Systems
[Choose a Coding System]
Launch Panel
Coded Segments
Start Time
End Time
Action Type
Orientation
Plane
Level
Effort-Weight
Admin Dashboard
Select VMAP file or VIDEO file
Select File
Save VMAP File
QUIT VMAP
Subject ID
ID
Rater ID
ID
Rater Dashboard
Cut & Code
Update Segment
Clear
Coded Segment Dashboard
Seg#
Enter Seg#
Review
Delete
Coding Progress
-- %
complete
KinetiWave Toolbox Created by:
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Appendix E

Glossary

Note: All definitions are provided with respect to movement/physical activity

Energy Expenditure—calories burned as a result of basal physiological processes and physical activity

Indirect Calorimetry—a method of measuring energy expenditure through the analyses of gas exchange via inhalation and exhalation.

Laban Movement Analysis—a codified method of qualitative movement analysis that deconstructs movements in terms of space, time, energy, and relationships

METs—(Metabolic Equivalent) a measure of energy expenditure. For reference, 1 MET is associated with 1 min of sedentary behavior (e.g. sitting). Moderate intensity physical activity (e.g., walking briskly at 4mph) is associated with 3-6 METs. Vigorous intensity activity (e.g., jogging/running at 6mph) is associated with 6 METs.

Multiplanar—transverse, sagittal, and coronal planes of motion

Physical Activity—any bodily movement caused by musculoskeletal contractions that results in an increase in energy expenditure

Short-burst physical activity—relatively brief, usually ≤15s, episodes of physical activity that naturally occur in children

Appendix F

Study Instruments

Patient Health Questionnaire-2: Screening Instrument for Depression

OVER THE PAST TWO WEEKS, HOW OFTEN HAVE YOU BEEN BOTHERED BY ANY OF THE FOLLOWING PROBLEMS?	***NOT AT ALL***	***SEVERAL DAYS***	***MORE THAN ONE-HALF THE DAYS***	***NEARLY EVERY DAY***
Little interest or pleasure in doing things	0	1	2	3
Feeling down, depressed, or hopeless	0	1	2	3

Play Session Data Sheet

TEMPORAL CALIBRATION:

ActiLife CPU Time: ____H ____ M ____S

Kinect CPU Time: ____H ____ M ____S

BioCapture CPU Time: ____ ActiLife ____ Kinect

Devices synchronized using Atomic Time: _____ Yes ____ No

External time piece used (?): If yes, time __ H __ M __ S

NOTES:

ANTHROPOMETRICS:

HEIGHT: WEIGHT:

PLAY ACTIVITIES:

_____ Crawling

_____ Jumping (in place)

_____ Jumping (traveling)

_____ Walking

_____ Running (in place)

_____ Running (traveling)

_____ Climbing

_____ Rolling

_____ Sedentary

For younger children:

_____ Stroller

_____ Carried by parent

Notes:

Subject ID: ________ Date: ______________

Early Childhood Active Play Study

Pediatric Bruce Protocol Data Sheet

ACCOMODATION PERIOD:

- Start at 0% grade and 0.5mph
- Increase speed incrementally (0.5mph) until 3.5mph
- Then, increase grade incrementally (1%) until 6%
- Cool down

Max speed	**Max incline**	**Steady gait (check one)**	
		YES	
		NO	

NOTES:

PEDIATRIC BRUCE:

Stage	**Speed/Incline**	**Time in Stage**	**HR**	**Steady gait (check one)**	
Warm-up	<1.7mph / 0%	2mins		YES	
				NO	
1	1.7mph / 10%	3mins		YES	
				NO	
2	2.5mph / 12%	3mins		YES	
				NO	
3	3.4mph / 14%	3mins		YES	
				NO	
4	4.2mph / 16%	3mins		YES	
				NO	
5	5.0mph / 18%	3mins		YES	
				NO	
6	5.5mph /20%	3mins		YES	
				NO	
Cool Down	-	2mins		YES	
				NO	
TERMINATE TEST: HR >200bpm **OR** any sign of unsteady gait					

NOTES:

Subject ID: _________ Date: _______________

Baseline Data Collection

Record ID ______________________

Outside your house (but associated with it) is there ample space for your child to play or move around freely? (backyard, front yard, garden, etc)
☐ Yes
☐ No
(If you answered YES please proceed with the next question, if you answered NO please go to SECTION B)

SECTION A- In the outdoor space is (are) there:

More than one type of ground texture? (grass, dirt, concrete, wood, sand, etc)
☐ Yes
☐ No

One or more sloped surfaces? (varied degrees and types of inclines or gradual slopes and slopes)
☐ Yes
☐ No

Any apparatus (man made or natural) that your child can grasp and hang from?
☐ Yes
☐ No

Any stairs? (at least two (2) or more steps)
☐ Yes
☐ No

Any apparatus or platform that permits your child to climb on/off and step or jump from. (It must be about eight-inches or more)
☐ Yes
☐ No

A play area (playground) designed for your young children ?
☐ Yes
☐ No

SECTION B- Inside your house is (are) there:

Enough space for your child to play or move around freely?
☐ Yes
☐ No

More than one type of ground texture? (carpet, wood, tile, linoleum, etc).
☐ Yes
☐ No

Material for your child to fall safely on? (carpet with padding, one-inch mat,, etc)
☐ Yes
☐ No

Any furniture or apparatus that your children can grasp and hang from safely?
☐ Yes
☐ No

Any stairs? (at least two (2) or more steps)
☐ Yes
☐ No

Any furniture or apparatus that permits your child to climb on/off and step or fall from? (Examples are sofas, small tables, chair, etc).
☐ Yes
☐ No

Any furniture or apparatus with a platform eight-inches (8") tall or more, the child can use to jump from?
☐ Yes
☐ No

A playroom? (room used only for kids to play)
☐ Yes
☐ No

A special place for toys that is accessible to the child so that she/he may choose when and with what to play? (toy bins, drawers, or shelves)

☐ Yes
☐ No

A special place for toys that is accessible to the child so that she/he may choose when and with what to play? (toy bins, drawers, or shelves)

☐ Yes
☐ No

SECTION C- During the day (but only referring to the time spent in your house):

My child plays with other children as a usual and ordinary every day event.

☐ Yes
☐ No

I (or my husband/wife) usually have a daily special time for playing with my child.

☐ Yes
☐ No

Other adults, rather than parents, regularly play with my child.

☐ Yes
☐ No

When playing, my child is always allowed to choose the toys or physical activities by herself / himself.

☐ Yes
☐ No

My child usually wears clothes that allow freedom to move and explore.

☐ Yes
☐ No

My child is often barefoot in the house.

☐ Yes
☐ No

I (or my husband/wife) usually try to encourage my child to reach and grasp objects.

☐ Yes
☐ No

I (or my husband/wife) usually try to engage my child in movements, games or actions in order to teach her/him parts of the body.

☐ Yes
☐ No

I (or my husband/wife) regularly try to teach my child movement or action words as "stop", "run", "walk", "crawl", etc.

☐ Yes
☐ No

SECTION D- On a typical day, how would you describe the amount of awake time your child spends in each of the situations below? (Read carefully each question and mark the box respective to your answer)

Carried in adult arms, attached to caregiver's body or in some carrying device.

☐ No time
☐ Very little time
☐ Some time
☐ A long time

In a seating device (high chair, stroller, car seat, sofa, or any other type of seating devices)

☐ No time
☐ Very little time
☐ Some time
☐ A long time

In a Playpen or some other similar equipment.

☐ No time
☐ Very little time
☐ Some time
☐ A long time

On the bed or crib (while awake).

☐ No time
☐ Very little time
☐ Some time
☐ A long time

Restrained to a specific space in the floor	☐ No time ☐ Very little time ☐ Some time ☐ A long time
Free to move in any space of the house	☐ No time ☐ Very little time ☐ Some time ☐ A long time
How do you consider the living space inside your house?	☐ Very Small ☐ Small ☐ Reasonable/Moderate ☐ Ample/Big

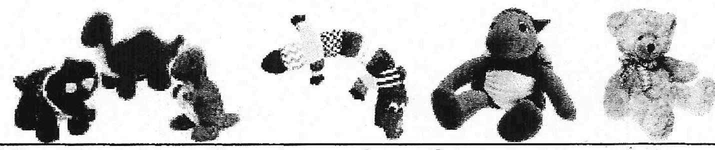
Play materials in the home

On each toy group listed below please check the box for the number of toys you have in your house.
Please read carefully each group general descriptions for deciding if you have this type of toy in your house.

Figures are only examples to help you better understand the description. You do not need to have the exact toy represented to count it in the group. ***Similar toys should be counted***

40 Stuffed toys

Examples are:

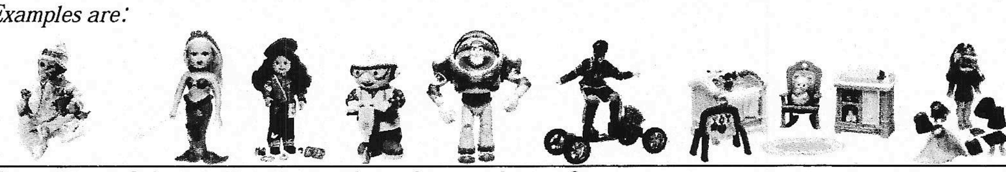


How many of these toys do you have in your house?

None ☐ *One* ☐ *Two* ☐ *Three* ☐ *Four* ☐ *Five* ☐ *More than 5* ☐

41 Dolls and other play figures and respective equipment.

Examples are:

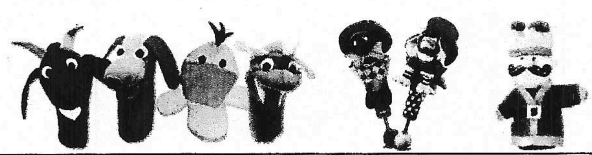


How many of these toys do you have in your house?

None ☐ *One* ☐ *Two* ☐ *Three* ☐ *Four* ☐ *Five* ☐ *More than 5* ☐

42 All kind of puppets (small hand puppets)

Examples are:



How many of these toys do you have in your house?

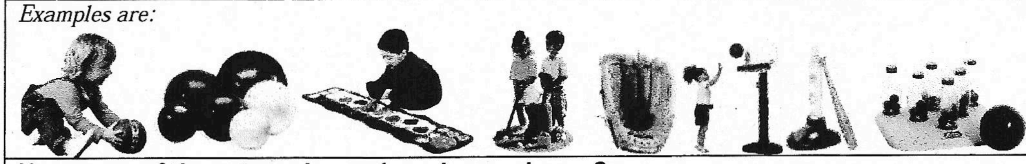
None ☐ *One* ☐ *Two* ☐ *Three* ☐ *Four* ☐ *Five* ☐ *More than 5* ☐

44 Vehicles, animals or other toys to be pushed and rolled
Examples are: 
How many of these toys do you have in your house?
None ☐ *One* ☐ *Two* ☐ *Three* ☐ *Four* ☐ *Five* ☐ *More than 5* ☐

60. Musical materials, All rhythm instruments (bells, rattles, cymbals, drums, triangle, rhythm stick, xylophones), Horns and whistles
Examples are: 
How many of these toys do you have in your house?
None ☐ *One* ☐ *Two* ☐ *Three* ☐ *Four* ☐ *Five* ☐ *More than 5* ☐

61. Play materials used for gross movements with the arm and legs (throwing, catching, kicking, rebounding, striking, etc). Balls of different sizes and colors, Bats, Baseball Gloves, Throwing Targets, etc.

Examples are:



How many of these toys do you have in your house?

None ☐ *One* ☐ *Two* ☐ *Three* ☐ *Four* ☐ *Five* ☐ *More than 5* ☐

62. Play materials used with upright locomotion. Examples are Pull or push toys, Little horses to ride on, Scooters, etc

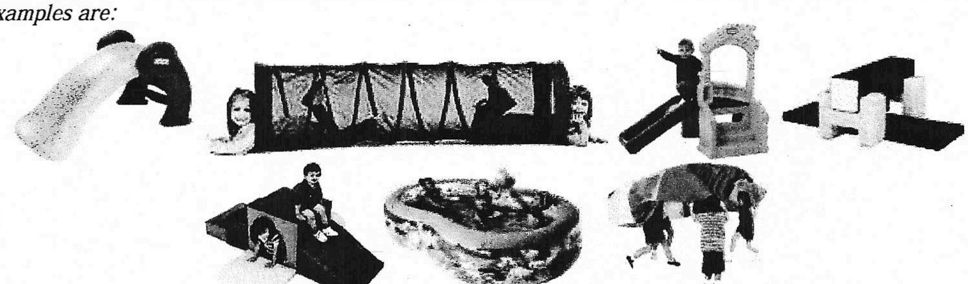
Examples are:

How many of these toys do you have in your house?

None ☐ *One* ☐ *Two* ☐ *Three* ☐ *Four* ☐ *Five* ☐ *More than 5* ☐

63. Play materials used for gross movement exploration (sliding, creeping, climbing, rolling, etc). Examples are Slides, Stairs, Tunnels, Climbing apparatus, Exercise mattresses, Pools, Parachutes, etc.

Examples are:



How many of these toys do you have in your house?

None ☐ *One* ☐ *Two* ☐ *Three* ☐ *Four* ☐ *Five* ☐ *More than 5* ☐

64. Auto propelled play materials used for riding on, all types of ride-on toys (propelled by bouncing or pushing) and tricycles.

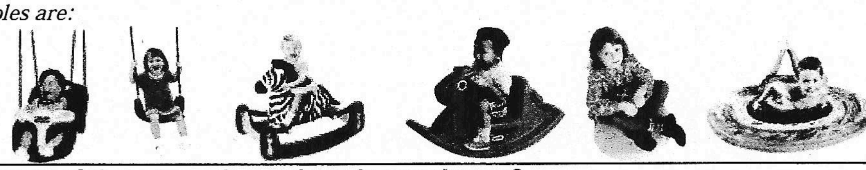
Examples are:

How many of these toys do you have in your house?

None ☐ *One* ☐ *Two* ☐ *Three* ☐ *Four* ☐ *Five* ☐ *More than 5* ☐

65 Swings, rocking and twisting toys.

Examples are:

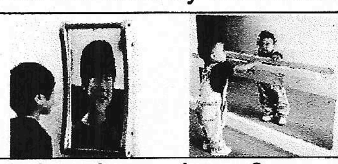


How many of these toys do you have in your house?

None ☐ *One* ☐ *Two* ☐ *Three* ☐ *Four* ☐ *Five* ☐ *More than 5* ☐

66. Mirror (full-length) that can be used by the children in their motor activities.

Examples are:

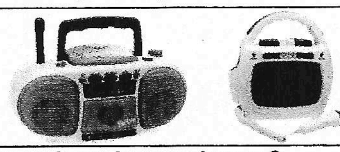


How many of these toys do you have in your house?

None ☐ *One* ☐ *Two* ☐ *Three* ☐ *Four* ☐ *Five* ☐ *More than 5* ☐

67. Audio equipment (CD or tape Players and children's music CD's or Tapes)

Examples are:



How many of these toys do you have in your house?

None ☐ *One* ☐ *Two* ☐ *Three* ☐ *Four* ☐ *Five* ☐ *More than 5* ☐

TBAQ: Physical Activity

Record ID ______________________

Study ID ______________________

As you read each description of your child's behavior below, please indicate how often your child did this during the last month by checking one of the numbers on the scale. These numbers indicate how often you observed the behavior described during the last month.

The "Not Applicable" (NA) option is used when you did not see your child in the situation described during the last month. For example, if the situation mentions your child going to the doctor and there was no time during the last month when your child went to the doctor, check the (NA) option. "Not applicable" (NA) is different from "Never" (1). "Never" (1) is used when you saw your child in the situation but s/he never engaged in the behavior mentioned during the last month.

1. When playing inside the house or apartment (for example, because of bad weather), how often did your child run through the house?

◯ (1) Never
◯ (2) Very Rarely
◯ (3) Less than half the time
◯ (4) About half the time
◯ (5) More than half the time
◯ (6) Almost always
◯ (7) Always
◯ (NA) Not applicable

2. When playing on a movable toy, such as a tricycle, how often did your child attempt to go as fast as s/he could?

◯ (1) Never
◯ (2) Very Rarely
◯ (3) Less than half the time
◯ (4) About half the time
◯ (5) More than half the time
◯ (6) Almost always
◯ (7) Always
◯ (NA) Not applicable

3. How often during the past month did your child play games which involved running around, banging, or dumping out toys?

◯ (1) Never
◯ (2) Very Rarely
◯ (3) Less than half the time
◯ (4) About half the time
◯ (5) More than half the time
◯ (6) Almost always
◯ (7) Always
◯ (NA) Not applicable

4. When being dressed or undressed, how often did your child lie or sit quietly long enough for you to get her/him ready?

◯ (1) Never
◯ (2) Very Rarely
◯ (3) Less than half the time
◯ (4) About half the time
◯ (5) More than half the time
◯ (6) Almost always
◯ (7) Always
◯ (NA) Not applicable

5. When your child needed to sit still, as in a waiting room or restaurant, how often did s/he play quietly?

◯ (1) Never
◯ (2) Very Rarely
◯ (3) Less than half the time
◯ (4) About half the time
◯ (5) More than half the time
◯ (6) Almost always
◯ (7) Always
◯ (NA) Not applicable

6. When your child needed to sit still, as in a waiting room or restaurant, how often did s/he try to climb all over the chairs?

- ◯ (1) Never
- ◯ (2) Very Rarely
- ◯ (3) Less than half the time
- ◯ (4) About half the time
- ◯ (5) More than half the time
- ◯ (6) Almost always
- ◯ (7) Always
- ◯ (NA) Not applicable

7. When in the bathtub, how often did your child splash or kick?

- ◯ (1) Never
- ◯ (2) Very Rarely
- ◯ (3) Less than half the time
- ◯ (4) About half the time
- ◯ (5) More than half the time
- ◯ (6) Almost always
- ◯ (7) Always
- ◯ (NA) Not applicable

8. When being dressed or undressed, how often did your child squirm or try to get away?

- ◯ (1) Never
- ◯ (2) Very Rarely
- ◯ (3) Less than half the time
- ◯ (4) About half the time
- ◯ (5) More than half the time
- ◯ (6) Almost always
- ◯ (7) Always
- ◯ (NA) Not applicable

9. When placed in a car seat or stroller, how often did your child squirm?

- ◯ (1) Never
- ◯ (2) Very Rarely
- ◯ (3) Less than half the time
- ◯ (4) About half the time
- ◯ (5) More than half the time
- ◯ (6) Almost always
- ◯ (7) Always
- ◯ (NA) Not applicable

10. When placed in a car seat or stroller, how often did your child sit still?

- ◯ (1) Never
- ◯ (2) Very Rarely
- ◯ (3) Less than half the time
- ◯ (4) About half the time
- ◯ (5) More than half the time
- ◯ (6) Almost always
- ◯ (7) Always
- ◯ (NA) Not applicable

*The next questions are going to ask you about some of the things you may have around your house and how much you use them. Please think about items both **inside** and **outside** your house. Read each item and select the best answer for you. We are interested in what you do, what you have, and how you feel. Take your time and answer as accurately as possible.*

1. How many **working** televisions are in your house?

PPA1 1 ○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ more ______

if "0" skip to 7

2. Does your child have a TV in their bedroom? PPA1 2 ○ yes ○ no

3. Do you have a TV in your bedroom? PPA1 3 ○ yes ○ no

4. Do you have a TV in your kitchen? PPA1 4 ○ yes ○ no

5. On an average day, how many minutes do **you** spend watching TV, movies, or videos? PPA1 5 [ ][ ][ ] *minutes*

6. How often is the TV in your house on when people are at home?

PPA1 6 ○ very rarely ○ rarely ○ sometimes ○ often ○ very often ○ always

7. How many video game systems (X-box, Gameboy, Playstation, Nintendo DS, Wii) are in your house? *[This does not include computers.]*

PPA1 7 ○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ other

if "0" skip to 10

8. Does **your child** have a video game system **in their bedroom**? PPA1 8 ○ yes ○ no

9. On an average day, how many minutes do **you or another adult in your house** spend playing video games? PPA1 9 [ ][ ][ ] *minutes*

10. How many computers (laptop or desktop) are in your house?

PPA1 10 ○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ other

11. Does your family have a dog? *PPA1 11* ○ yes ○ no ➔ ***if "no" skip to 13***

12. How often does **your child** play with your dog **outside**?

PPA1 12 ○ never ○ very rarely ○ rarely ○ sometimes ○ often ○ very often

13. Please fill in the bubble that best represents how often you use each item while at home: **very rarely**, **rarely**, **sometimes**, **often** or **very often**. If you do not have an item at home, please mark **"do not have."**

		very rarely	*rarely*	*sometimes*	*often*	*very often*	*do not have*
a. stationary exercise equipment (bike, treadmill, elliptical)	*PPA1 13a*	○	○	○	○	○	○
b. weight lifting/resistance training equipment (free weights, Nautilus, Total Gym)	*PPA1 13b*	○	○	○	○	○	○
c. workout DVDs/videos	*PPA1 13c*	○	○	○	○	○	○
d. shoes for running/walking	*PPA1 13d*	○	○	○	○	○	○
e. exercise/yoga mat	*PPA1 13e*	○	○	○	○	○	○
f. adult bicycle	*PPA1 13f*	○	○	○	○	○	○
g. bicycle trailer (for hauling kids or groceries)	*PPA1 13g*	○	○	○	○	○	○
h. jogging stroller	*PPA1 13h*	○	○	○	○	○	○
i. canoe/kayak	*PPA1 13i*	○	○	○	○	○	○
j. skiis (water or snow)	*PPA1 13j*	○	○	○	○	○	○

14. Please fill in the bubble that best represents how often **your child** uses each item while **at home**: **very rarely**, **rarely**, **sometimes**, **often** or **very often**. If you do not have an item at home, please mark **"do not have."** For example, if you do not have tumbling mats at your house, but you do have a snow sled that is used once or twice a year, you should mark "do not have" for the mats and "very rarely" for the sled.

		very rarely	*rarely*	*sometimes*	*often*	*very often*	*do not have*
a. basketball hoop	*PPA1 14a*	○	○	○	○	○	○
b. climbing structure	*PPA1 14b*	○	○	○	○	○	○
c. balancing surface *(balance beams, boards)*	*PPA1 14c*	○	○	○	○	○	○
d. playhouse	*PPA1 14d*	○	○	○	○	○	○
e. sandbox	*PPA1 14e*	○	○	○	○	○	○
f. slide	*PPA1 14f*	○	○	○	○	○	○
g. swing *(swing, rope)*	*PPA1 14g*	○	○	○	○	○	○
h. pool *(permanently installed in-ground or above)*	*PPA1 14h*	○	○	○	○	○	○
i. trampoline	*PPA1 14i*	○	○	○	○	○	○
j. balls *(soccer, baseball, kick, foam, basket, etc)*	*PPA1 14j*	○	○	○	○	○	○
k. baseball equipment *(bat, mitt, tee)*	*PPA1 14k*	○	○	○	○	○	○
l. hockey sticks	*PPA1 14l*	○	○	○	○	○	○
m. racquets *(tennis, badminton)*	*PPA1 14m*	○	○	○	○	○	○
n. soccer/hockey goal	*PPA1 14n*	○	○	○	○	○	○
o. yard games *(croquet, horse shoes)*	*PPA1 14o*	○	○	○	○	○	○

		very rarely	rarely	sometimes	often	very often	do not have
p. bicycle/tricycle/balance bike	PPA1 14p	○	○	○	○	○	○
q. skates *(roller/inline/ice)*	PPA1 14q	○	○	○	○	○	○
r. push/pull toys *(wagon, wheelbarrow, dump truck, etc.)*	PPA1 14r	○	○	○	○	○	○
s. jumping play equipment *(jump ropes, hula hoops, mini trampolines)*	PPA1 14s	○	○	○	○	○	○
t. twirling play equipment *(ribbons, scarves, batons)*	PPA1 14t	○	○	○	○	○	○
u. tumbling mats	PPA1 14u	○	○	○	○	○	○
v. buckets or shovels	PPA1 14v	○	○	○	○	○	○
w. Frisbee or activity disc	PPA1 14w	○	○	○	○	○	○
x. sand/water table	PPA1 14x	○	○	○	○	○	○
y. snow sled	PPA1 14y	○	○	○	○	○	○

*The next set of items is about the rules around your house. We are interested in what **you** do and how **you** feel. Please read each item and select the **best answer** for you. Take your time and answer as accurately as possible. Your responses are important to us.*

1. Fill in the bubble that describes how often your child is allowed to do each of the following activities while playing **inside** your house. *For example, we don't have a swing or rope in the house and we don't want the kids swinging on anything else, so they are not allowed to swing on anything while playing.*

a. hopping, skipping or galloping	PPA2 1a	O anytime	O sometimes	O never
b. running around	PPA2 1b	O anytime	O sometimes	O never
c. chasing	PPA2 1c	O anytime	O sometimes	O never
d. rough housing or wrestling	PPA2 1d	O anytime	O sometimes	O never
e. jumping from a height	PPA2 1e	O anytime	O sometimes	O never
f. flipping (somersault) or tumbling	PPA2 1f	O anytime	O sometimes	O never
g. climbing	PPA2 1g	O anytime	O sometimes	O never
h. swinging or hanging	PPA2 1h	O anytime	O sometimes	O never
i. balancing	PPA2 1i	O anytime	O sometimes	O never
j. piling up pillows and juming on them	PPA2 1j	O anytime	O sometimes	O never
k. throwing, kicking or bouncing a ball	PPA2 1k	O anytime	O sometimes	O never

		strongly disagree	***disagree***	***not sure***	***agree***	***strongly agree***
2. When my child is **inside** the house his/her play should be calm and quiet.	PPA2 2	O	O	O	O	O
3. When **inside** the house, my child can use toys and equipment for physically active play. *(for example, gross motor activities like running, jumping, hopping or tumbling)*	PPA2 3	O	O	O	O	O

4. How **often** do you ask your child to calm down his/her **indoor** play?

PPA2 4 O never O very rarely O rarely O sometimes O often O very often

Please fill in the bubble that best describes how often you do each of the following things related to your child's ***outdoor*** *play:* ***never, very rarely, rarely, sometimes, often****, or* ***very often****.*

How often do you . . .		***never***	***very rarely***	***rarely***	***sometimes***	***often***	***very often***
5. ask your child **not** to run when (s)he is playing **outside**?	*PPA2 5*	○	○	○	○	○	○
6. ask your child to try and stay clean when playing **outside**?	*PPA2 6*	○	○	○	○	○	○
7. let your child play **outside** on hot days?	*PPA2 7*	○	○	○	○	○	○
8. let your child play **outside** on cold days?	*PPA2 8*	○	○	○	○	○	○
9. ask your child to calm down his/her **outdoor** play?	*PPA2 9*	○	○	○	○	○	○
10. ask your child not to get his/her clothes dirty while (s)he is playing **outside**?	*PPA2 10*	○	○	○	○	○	○
11. ask your child not to play in puddles when (s)he is playing **outside**?	*PPA2 11*	○	○	○	○	○	○

12. Do you limit the amount of time your child watches TV, videos, or movies **during the week** (Monday - Friday)?

PPA2 12 ○ yes ○ no ➔ *If no, skip to #14*

13. About how much time is (s)he allowed to watch **each weekday**? *(Please report total minutes.)*

PPA2 13 [ ][ ][ ] *total minutes*

14. Do you limit the amount of time your child watches TV, videos, or movies **on the weekend** (Saturday - Sunday)?

PPA2 14 ○ yes ○ no ➔ *If no, skip to #16*

15. About how much time is (s)he allowed to watch each **weekend day**? *(Please report total minutes.)*

PPA2 15 [ ][ ][ ] *total minutes*

16. Do you limit the amount of time your child plays video games **during the week** (Monday - Friday)?

PPA2 16 ○ yes ○ no ➔ *If no, skip to #18*

17. About how much time is (s)he allowed to play video games **each weekday**? *(Please report total minutes.)*

PPA2 17 [ ][ ][ ] *total minutes*

18. Do you limit the amount of time your child plays video games **on the weekend** (Saturday - Sunday)?

PPA2 18 ○ yes ○ no ➔ *If no, skip to #20*

19. About how much time is (s)he allowed to play video games **weekend day**? *(Please report total minutes.)*

PPA2 19 [ ][ ][ ] *total minutes*

Please fill in the bubble that best describes how often you do each of the following things: ***never, very rarely, rarely, sometimes, often**, or **very often**.*

How often do you . . .		***never***	***very rarely***	***rarely***	***sometimes***	***often***	***very often***
20. offer TV, video, or movie time to your child as a reward for good behavior?	PPA2 20	○	○	○	○	○	○
21. take away TV, video, or movie time as a punishment for bad behavior?	PPA2 21	○	○	○	○	○	○
22. offer sports or physical activities to your child as a reward for good behavior?	PPA2 22	○	○	○	○	○	○
23. use sports or phywical activities to get your child to do something? *(for example: "You can't go outside to play until you eat your peas.")*	PPA2 23	○	○	○	○	○	○

*Pleaseread each of the following statements and then fill in the bubble that best describes how much you agree or disagree with that statement: **strongly disagree, disagree, neither agree not disagree, agree,** or **strongly agree**.*

I tightly monitor the *time* ***my child. . .***		strongly disagree	disagree	not sure	agree	strongly agree
24. watches TV or videos during the **week** (Monday - Friday).	PPA2 24	O	O	O	O	O
25. watches TV or videos on the **weekend** (Saturday - Sunday).	PPA2 25	O	O	O	O	O
26. plays videos games during the **week** (Monday - Friday).	PPA2 26	O	O	O	O	O
27. plays video games on the **weekend** (Satday - Sunday).	PPA2 27	O	O	O	O	O

28. How many **days per week** does your family have the television on during **breakfast**?

PPA2 28 O 0 O 1 O 2 O 3 O 4 O 5 O 6 O 7

29. How many **days per week** does your family have the television on during the **evening meal**?

PPA2 29 O 0 O 1 O 2 O 3 O 4 O 5 O 6 O 7

How often . . .		never	very rarely	rarely	sometimes	often	very often
30. does your child get extra TV, video, or movie time as a reward?	PPA2 30	O	O	O	O	O	O
31. does your child get extra outside time as a reward?	PPA2 31	O	O	O	O	O	O
32. do you use TV time to control your child's behavior? *(example: "If you don't stop that you will not be ble to watch TV today.")*	PPA2 32	O	O	O	O	O	O
33. do you use sports or physical activities to control your child's behavior? *(example: "If you don't stop that you will not be ble to go to karate tonight.")*	PPA2 33	O	O	O	O	O	O
34. do you take outside time away from your child for bad behavior?	PPA2 34	O	O	O	O	O	O

We are interested in what you do and how you feel. Please read each item and select the ***best answer*** *for you. Take your time and answer as accurately as possible. Your responses are important to us.*

For the following items, please read each statement and fill in the bubble which best describes how much you agree or disagree with that statement: ***strongly disagree, disagree, neither agree nor disagree, agree*** *or* ***strongly agree****.*

		strongly disagree	disagree	neither agree nor disagree	agree	strongly agree
1. **My child** needs my help getting out the toys or equipment (s)he likes to play with outside.	PPA3 1	○	○	○	○	○
2. **My child** enjoys being physically active.	PPA3 2	○	○	○	○	○
3. I have control over how much TV my child watches.	PPA3 3	○	○	○	○	○
4. **Other adults** in my child's life make it hard to get my child to be physically active.	PPA3 4	○	○	○	○	○
5. My child would rather play inside than outside.	PPA3 5	○	○	○	○	○
6. My family is physically active.	PPA3 6	○	○	○	○	○
7. I enjoy watching TV/movies with my child.	PPA3 7	○	○	○	○	○

Each week, how often (on average) do you participate in ***moderate*** *or* ***vigorous*** *physical activities or sports? Moderate or vigorous physical activities get you breathing harder and your heart beating faster. Examples include: walking brisky, hiking, jogging or running, dancing, yard work, swimming, aerobics and basketball.*

8. How often do you participate in moderate or vigorous physical activities or sports each week? ***PPA3 8*** ☐☐ *times per week* *if 0, skip to #10*

9. About how many minutes each time? ***PPA3 9*** ☐☐ *minutes per session*

10. How much do **you** enjoy physical activities or sports?

PPA3 10 ○ don't enjoy ○ sort of enjoy ○ really enjoy ○ thoroughly enjoy

11. How much do **you** enjoy watching TV or movies during your free time?

PPA3 11 ○ don't enjoy ○ sort of enjoy ○ really enjoy ○ thoroughly enjoy

12. How often does your family use physical activities or sports as a form of family recreation? (for example, going on bike rides together, hiking, ice skating)

PPA3 12 ○ rarely ○ once in a while ○ relatively often ○ frequently

13. How often do you go to your child's sporting events, lessons, or other organized physical activities with them? (for example, watch your child perform in a dance recital, swim meets, or practice)

PPA3 13 ○ rarely ○ sometimes ○ usually ○ almost always

14. How valuable is it to **you** that **your child** be physically active?

PPA3 14 ○ not valuable ○ of little value ○ moderately valuable ○ valuable ○ very valuable

15. During the **past year** has an adult in your family **paid fees** so your child could take lessons, classes or play sports involving moderate or vigorous physical activity? (for example, dance, soccer, karate, basketball, swimming, gymnastics, horseback riding)

PPA3 15 ○ yes ○ no ➔ *If no, skip to #17*

16. For how many activities have you or other adults paid fees? *PPA3 16* ☐☐

17. How much do you use **your own behavior** to encourage your child to be physically active?

PPA3 17 ○ I don't use my own behavior to encourage my child to be active.

○ I rarely use my own behavior to encourage my child to be active.

○ I often use my own behavior to encourage my child to be active.

○ I constantly use my own behavior to encourage my child to be active.

18. How important is it to you to be actively involved in your child's sporting events?

PPA3 18
- ○ It is not particularly important to me to be involved.
- ○ It is sort of important to me to be involved.
- ○ It is important to me to be involved.
- ○ It is extremely important to me to be involved.

19. How active are you in enrolling your child in sports?

PPA3 19
- ○ I rarely enroll my child in sports.
- ○ I enroll my child once in a while.
- ○ I frequently enroll my child in sports.
- ○ I go out of my way to enroll my child in sports.

20. During the **last month**, how many times have **you** taken your child to play at a park? PPA3 20 ☐☐ *time(s) to park in last month*

For the following items, please read each statement and fill in the bubble which best describes how much you agree or disagree with that statement: ***strongly disagree, disagree, neither agree nor disagree, agree*** *or* ***strongly agree****.*

		strongly disagree	***disagree***	***neither agree nor disagree***	***agree***	***strongly agree***
21. My child does not like being physically active.	PPA3 21	○	○	○	○	○
22. I am in charge of how much TV my child watches during his/her free time at home.	PPA3 22	○	○	○	○	○
23. **When inside**, my child can easily get toys that are used for physically active play.	PPA3 23	○	○	○	○	○
24. **When outside**, my child can get to toys or equipment **without** help from an adult.	PPA3 24	○	○	○	○	○

		strongly disagree	disagree	neither agree nor disagree	agree	strongly agree
25. My child would rather watch TV than play a sport or active game.	PPA3 25	○	○	○	○	○
26. I can get my child to be physically active at home.	PPA3 26	○	○	○	○	○
27. **Other adults** in my child's life make it hard to enforce household rules about TV viewing.	PPA3 27	○	○	○	○	○
28. I like being physically active with my child.	PPA3 28	○	○	○	○	○

*The next questions are about some of the things that you and your child do during a typical week. We are interested in what **you** do and how **you** feel. Please read each item and select the **best answer** for you. Take your time and answer as accurately as possible. Your responses are important to us.*

During the past 7 days, about how many hours did **your child** spend **watching TV, videos, or movies**? *Please report separately for weekdays and weekend days. Estimate to the nearest .5 hour.*

1. Total hours for last 5 weekdays (Mon-Fri): PPA4 1 __ __ . __ *hours*
2. Total hours for last 2 weekend day (Sat-Sun): PPA4 2 __ __ . __ *hours*

*On the scale provided, fill in the bubble that best describes how often **you** do each of the following during a typical week: **never, very rarely, rarely, sometimes, often**, or **very often**.*

During a typical week, how often . . .	*never*	*very rarely*	*rarely*	*sometimes*	*often*	*very often*
3. do you tell your child how sedentary habits can be unhealthy? PPA4 3	○	○	○	○	○	○
4. do you watch TV or videos with your child? PPA4 4	○	○	○	○	○	○
5. do you send your child outside to play so you can get things done around the house? PPA4 5	○	○	○	○	○	○
6. do you take your child to the park to play? PPA4 6	○	○	○	○	○	○

During the past 7 days, about how many hours did **your child** spend **playing outside**? *Please report separately for weekdays and weekend days. Estimate to the nearest .5 hour.*

7. Total hours for last 5 weekdays (Mon-Fri): PPA4 7 __ __ . __ *hours*
8. Total hours for last 2 weekend days (Sat-Sun): PPA4 8 __ __ . __ *hours*
9. During the past 7 days, about how many **hours** did **your child** spend doing an organized sport, class or lessons that included vigorous physical activity? *Estimate to the nearest .5 hour.* PPA4 9 __ __ . __ *hours*

Please fill in the bubble that best represents how often each of the following things happen during a typical week: ***never, very rarely, rarely, sometimes, often****, or* ***very often****.*

During a typical week, how often . . .	*never*	*very rarely*	*rarely*	*sometimes*	*often*	*very often*
10. do you tell your child that physical activity is good for health? PPA4 10	○	○	○	○	○	○
11. does your behavior encourage your child to be sedentary? PPA4 11	○	○	○	○	○	○
12. do you praise your child for participating in sports or physical activities? PPA4 12	○	○	○	○	○	○
13. do you turn on the TV, a video, or movie for your child when the weather is bad? *(for example, raining, too hot, too cold)* PPA4 13	○	○	○	○	○	○
14. do you say things to encourage your child to do physical activities or play sports? PPA4 14	○	○	○	○	○	○

15. How do you rate **your child's** level of physical activity, compared to others the same age and sex?

PPA4 15
- ○ much less than others
- ○ somewhat less than others
- ○ about the same as others
- ○ somewhat more than others
- ○ much more than others

Please fill in the bubble that best represents how often each of the following things happen during a typical week: ***never, very rarely, rarely, sometimes, often****, or* ***very often****.*

During a typical week, how often . . .	*never*	*very rarely*	*rarely*	*sometimes*	*often*	*very often*
16. does your child **hear you say** that you were too tired to be active? PPA4 16	○	○	○	○	○	○
17. does your child **see** you watching TV or movies? PPA4 17	○	○	○	○	○	○

During a typical week, how often . . .		***never***	***very rarely***	***rarely***	***sometimes***	***often***	***very often***
18. do **you** play sports, active games, or do other physical activities with your child?	PPA4 18	○	○	○	○	○	○
19. do you try to get your child to play outside when the weather is nice?	PPA4 19	○	○	○	○	○	○
20. do you transport your child to a place where (s)he can be physically active or play sports?	PPA4 20	○	○	○	○	○	○

21. What does your child usually do when (s)he has a choice about how to spend free time?

PPA4 21
- ○ almost always chooses activities like TV, reading, listening to mucic, or computers
- ○ usually chooses activities like TV, reading, listening to mucic, or computers
- ○ just as likely to choose TV and reading as active games or sports
- ○ usually chooses activities like bicycling, dancing, outdoor games, or active sports
- ○ almost always chooses activities like bicycling, dancing, outdoor games, or active sports

Please fill in the bubble that best represents how often each of the following things happen during a typical week: ***never, very rarely, rarely, sometimes, often****, or* ***very often****.*

During a typical week, how often . . .		***never***	***very rarely***	***rarely***	***sometimes***	***often***	***very often***
22. does your child **hear you** talk about participating in a sport or being physically active?	PPA4 22	○	○	○	○	○	○
23. does your child see you doing, or going to do, something that is physically active? *(for example, walking , biking, playing sports)*	PPA4 23	○	○	○	○	○	○
24. do you turn on the TV, a video, or movie for your child so you can get things done around the house?	PPA4 24	○	○	○	○	○	○
25. do you try to get your child be to physically active instead of watching TV?	PPA4 25	○	○	○	○	○	○
26. do you say things to encourage your child to spend less time being sedentary?	PPA4 26	○	○	○	○	○	○

Pt ID ☐ - ☐☐☐

Please fill in the bubble that best represents how important each of the following this is to you:
unimportant, of little importance, moderately important, important, *or* ***very important***.

How important is it for your child . . .		***unimportant***	***of little importance***	***moderately important***	***important***	***very important***
27. to participate in sports?	PPA4 27	○	○	○	○	○
28. to be physically active when (s)he grows up?	PPA4 28	○	○	○	○	○

Child's Name:

Child's DOB:

Child's Gender: ☐ Male

☐ Female

Parent's name: Parent's DOB:

Ethnicity:

Father's education: ☐ Less than High School

☐ High School or GED

☐ Associate degree, vocational school or some college

☐ B.S or Advances Degree

Mother's education: ☐ Less than High School

☐ High School or GED

☐ Associate degree, vocational school or some college

☐ B.S or Advances Degree

Living arrangements: ☐ Family lives in own apartment

☐ Family shares apartment with others

☐ Living in a shelter

Family components: ☐ Single parent

☐ Both parents

Number in family: Number in household:

Annual Income: ☐ less than/equal to $12,950

☐ between $12,951 and $49,400

☐ between $49,401 and $127,550

☐ more than $127,550

Appendix G

Institutional Review Board Documents

Columbia University Consent Form

Protocol Information

Attached to Protocol: IRB-AAAK9304
Principal Investigator: Carmen Rodriguez (cr14)
IRB Protocol Title: SKIP! Small Kids in Physical Activity

General Information

Consent Number: CF-AABB8450
Participation Duration:
Anticipated Number of Subjects: 200
Research Purpose: Research Purpose
The purpose of this study is to assess whether the SKIP! program makes participating families more active than non-participating families, and whether their physical activity can be effectively measured using accelerometers.

Contacts

Contact	Title	Contact Information
Carmen Rodriguez	Principal Investigator	Phone: 212-660-6200 Email: cr14@cumc.columbia.edu

Information on Research

Information on Research

The purpose of this form is to give you information to help you decide if you want to take part in a research study. One of the investigators (the researchers for this project) will discuss the study with you. If at any time you have questions about the study, please ask a member of the study team. Take all the time you need to decide whether you want to take part in this research study. This consent form is written to address a research subject. If, however, you will be providing permission as the parent or legal guardian of a minor, the words 'you' and 'your' should be read as 'your child'.

Why is this study being done?
We are doing this research study to find out whether the SKIP! program is effective in making families more physically

active in their daily lives. SKIP! is a program designed to encourage physical activity in toddlers and support active play time between parents and children. We are also doing this study to find out whether it makes sense to use a small device called "accelerometer" to measure the amount of physical activity a toddler experiences. Accelerometers are small, unobtrusive devices that can be worn on a belt around a person’s waist or arm. They have been used to measure physical activity in preschool-aged children, older children, and adults, but we do not know whether accelerometers will be effective for toddlers.

You are being asked to participate in this study because you have a child between 24 and 36 months of age and because he/she attends the Columbia University Early Head Start program. About 200 parent/child pairs are expected to be enrolled in this study, and we expect this study will be completed by the end of the school year.

What is involved in this study?
If you decide to participate in this study, we will collect height and weight measurements for you and your child and ask you to complete a brief demographic questionnaire. You will then join the following 6 parts of the study.

In part 1, we will ask both you and your child to wear an accelerometer for 7 days in a row (5 weekdays, 2 weekend days) at the beginning of the semester. We will provide your family with the accelerometers and will provide you with training on what they are and how they are used. During the semester, you and your child will also be asked to wear the accelerometer during your normal group sessions on eight separate days throughout the semester. Finally, at the end of the semester, you will be asked to take the accelerometer home for 7 days (5 weekdays, 2 weekend days) in a row.

In the second part of the study, we will time how long it takes your child to move from lying down on the floor to a standing position at the beginning and end of the semester.

The third part of the study is allowing trained research assistants to visit your home and observe your child’s physical activity. The researcher will setup a convenient time to visit the home. There will be 2 visits, and each visit will last 30 minutes. While at your home the researchers will fill out a form about your child’s movement behaviors. Then, we will compare the information provided by the accelerometer with the information gathered by the research assistants in order to determine if the accelerometer measurements of physical activity are correct.

The fourth part of the study is allowing a CUEHS teacher to complete a short questionnaire with you during your regular home visits. The questionnaire will help to identify the number and kinds of opportunities your child has available to develop his or her various movement skills while at home.

The fifth part of this study will ask you to fill out a short weekly questionnaire regarding your child's participation in physical activity or health and wellness activities over the last seven days throughout the semester.

For the last part of this study, we will ask you to participate in a focus group where we will ask you, along with a small group of other parents who are participating in the study for your opinions on the physical activity intervention in which you and your child are participating. We will use this information to evaluate and improve the intervention.

Risks

Risks
What are the risks of this study?

General Risks
There may be risks or discomforts if you take part in this study. For example, you and/or your child may become bored, frustrated or annoyed. We will make every effort to prevent and minimize these discomforts. In addition, you may be uncomfortable having a research assistant visit your home. Research assistants will receive training in proper conduct during home visits to ensure that they are respectful of your home and your needs. While there is no evidence that accelerometers can cause any harm to you or your child, there is a chance that you or your child may not want to wear the accelerometer. To help with children who do not want to wear the accelerometer, we will provide you with training on how to help your child to be more comfortable with the devices. However, you and your child can stop using the accelerometers at any time if you or the child becomes too uncomfortable to continue with the study.

Benefits

Benefits
Are there benefits to participating in this study?
You and your child will not receive personal (direct) benefit from taking part in this research study. However, the information collected from this research may help researchers to measure physical activity in toddlers in the future, and may help researchers better understand toddlers' physical activity experiences.

Alternative Procedures

Alternative Procedures
What other options are there?
You may choose not to take part in this research study. Your child's Head Start services will not be impacted in any way.

Confidentiality

Confidentiality
What about confidentiality?

Any information collected during this study that can identify you by name will be kept confidential. All of the information collected by research assistants and through the use of accelerometers will be coded with a numerical system which will be entered into a password secured computer database. This number will be the only identifier to appear on any data collection tools. Hard copies of completed consent forms will be secured in separate, locked filing cabinets at Head Start accessible by the PI. We will do everything we can to keep your data secure, however, complete confidentiality cannot be promised. Despite all of our efforts, unanticipated problems, such as a stolen computer, may occur, although it is highly unlikely. The research file that links your name to the code number will be kept in a locked file cabinet and only the investigator and study staff will have access to the file.

Access to your health information is required to be part of this study. If you choose to take part in this study, you are giving us the authorization (i.e. your permission) to use the protected health information and information collected during the research that can identify you. The project does not involve collecting health information that may be considered sensitive.

The following individuals and/or agencies will be able to look at and copy your records:

-The investigator, study staff and other professionals who may be evaluating the study
-Authorities from Columbia University and New York Presbyterian Hospital, including the Institutional Review Board (IRB),
-The Office of Human Research protections (OHRP).

Loss of Confidentiality
A risk of taking part in this study is the possibility of a loss of confidentiality. Loss of confidentiality includes having your personal information shared with someone who is not on the study team and was not supposed to see or know about your information. The study team plans to protect your confidentiality. Their plans for keeping your information private are described in the 'confidentiality' section of this consent form.

Your authorization to use and share your health information does not have an expiration (ending) date.

You may change your mind and revoke (take back) this consent and authorization at any time and for any reason. To revoke this consent and authorization, you must contact Carmen Rodriguez, Ph.D.,212-660-6200.

However, if you revoke your consent and authorization, you will not be allowed to continue taking part in the Research. Also, even if you revoke this consent and authorization, the Researchers and the Sponsor (if applicable) may continue to use and disclose the information they have already collected.

Compensation

Compensation.

You will receive $10 for attending Play Day and consenting to participate in this research study. Your child will receive a toy after wearing the accelerometer for 7 consecutive days.

Additional Costs

Additional Costs
There are no costs to you for taking part in this study.

Voluntary Participation

Voluntary Participation
Participation in this study is voluntary. Refusal to participate will involve no penalty or loss of benefits to which you are otherwise entitled. You may discontinue participation at any time without penalty or loss of benefits to which you are otherwise entitled.

Additional Information

Permission for Future Contact
The researchers may want to contact you in the future via text message in order to offer reminders and suggestions for at-home play.All future contact will be directly related to the SKIP! program.

Please initial below to show whether or not you give permission for future contact.

______ (initial) I give permission to be contacted in the future for reminders and suggestions related to the SKIP! program.

If you give permission for future contact, please fill out the information below:

Name:________________________________

Child's Name: _______________________

Child's Birth Date: _______________________

Cell Phone Number: _______________________

Whom do I call if I have any questions or problems?
If you have any questions or concerns about the study, you may contact Carmen Rodriguez, Ph.D., 212-660-6200.

If you have any questions about your rights as a subject, you may contact:
Institutional Review Board
Columbia University Medical Center
154 Haven Avenue, 1st floor New York, NY 10032
Telephone: 212-305-5883

An Institutional Review Board is a committee organized to protect the rights and welfare of human subjects involved in research. More information about taking part in a research study can be found on the Columbia University IRB website at: http://cumc.columbia.edu/irb.

Statement of Consent
I have read the consent form and talked about this research study, including the purpose, procedures, risks, benefits and alternatives with the researcher. Any questions I had were answered to my satisfaction. I am aware that by signing below, I am agreeing to take part in this research study and that I can stop being in the study at any time. I am not waiving (giving up) any of my legal right by signing this consent form. I will be given a copy of this consent form to keep for my records.

Signatures

Participant Signature Lines

Study Participant
Print Name ______________________________ Signature ____
Date ___________________________________

Child (PRINT NAME)
Print Name ______________________________

Research Signature Lines

Person Obtaining Consent
Print Name ______________________________ Signature ____
Date ___________________________________

Teachers College, Columbia University
525 West 120th Street
New York NY 10027
212 678 3000
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Principal Investigator: Aston K. McCullough, M.A.

Study: Validation of the ActiGraph accelerometer RSSI-based Location Based Services

INFORMED CONSENT

DESCRIPTION OF THE RESEARCH:

Research Purpose
The purpose of this study is to learn more about how the radio signals sent between wireless devices can be converted into distances.

Information on Research
The purpose of this form is to give you information to help you decide if you want to take part in a research study. One of the investigators (the researchers for this project) will discuss the study with you. If at any time you have questions about the study, please ask a member of the study team. Take all the time you need to decide whether you want to take part in this research study.

Why is this study being done?

We are doing this research study to learn more about how the radio signals that are sent between wireless devices can be recalculated into measures of distance (i.e., meters). To do this, we will ask you to wear a small, unobtrusive device called an accelerometer that is worn on a belt around a person's waist. The wireless signals sent between devices are Bluetooth-based, and are similar or identical to the ones commonly used to communicate between devices you might use daily such as a smart phone or laptop.

You are being asked to participate in this study because you have already completed a brief health questionnaire during an initial screening, and you are a healthy adult (i.e., aged 18+). About 52 participants are expected to enroll in this study, and we expect this study will be completed by July 2016.

What is involved in this study?

If you decide to participate in this study, it will have 2 parts, involving 2 visits to our laboratory or a community space. The first visit is today and you have already agreed to attend this 20 minute introductory session where you have learned about the study and have been given an opportunity to ask any questions. If you agree to participate in the study, you will be invited to remain here to be fitted with the small accelerometer device and to participate in the first session. We will also ask you to repeat the brief health questionnaire once more to ensure that your health status has not changed since the time of the initial screening, and then will measure the distance of the hip-worn accelerometer to the floor in order to record its exact placement.

Following, you and three other participants will be asked to complete simple tasks such as standing at specific markers on the floor for 60 seconds at a time, and walking short distances at two different speeds in time with a metronome. You will be asked to complete the simple standing and walking tasks several times for a total of 60 minutes. At the end of the session, we will set up another visit to our laboratory or a large community space within 8-10 days.

During your next and final visit to the laboratory (or large community space) (visit 2), you will be asked to wear the accelerometer while you complete a series of simple tasks outdoors during the 90 minute session that will be held on the Columbia University campus or an outdoor community space. The outdoor session will be very similar to the first session with the primary difference being the distance you will be asked to travel and the addition of a jogging/running task. Once outdoors, you will again be asked to stand at specific spatial markers for 60 seconds at a time, and also to walk for short distances at two speeds in time with a metronome. Finally, we will ask you to jog/run at two different speeds also in time with a metronome. You will be asked to complete the simple standing, walking, jogging/running tasks several times.

In order for us to code where you are in space as you travel in each session, both sessions (indoors and outdoors) will be videotaped. All or part of you, including facial features, may be videotaped; however since your moving profile is the intended primary image that we wish to record, we will be placing the cameras such that your faceless profile should appear more prominently than other distinguishing features. The video coding process will require all externally distinguishing features to be obscured, such that your likeness will appear as a shadow on a white background during the analysis process. The portable video cameras will be placed in locations such that the entire Teachers College Applied Physiology Laboratory (or indoor community space)/outdoor space on Columbia University's campus (or outdoor community space) and all of the study participants can be seen. You must be comfortable being videotaped in order to participate in this particular study.

During videotaping, there is no one operating the camera and thus, the videos will not zoom in on a particular participant. Additionally, while the participants will not be individually audiotaped, all or part of their conversations may also be recorded from the internal microphones on the Samsung portable video cameras. The conversations will not be analyzed as part of the study, and in reviewing the videotapes there will be no audio.

Videotape files will be stored on an encrypted, password protected hard-drive kept in a locked office. The files will be stored on the encrypted hard-drive until all data analysis has been completed and all manuscripts have been published. The original videotape files will be immediately deleted from the video camera.

RISKS AND BENEFITS:

Risks
What are the risks of this study?

General Risks
There may be some risks or discomforts if you take part in this study, although these are minimal. For example, you may become bored, frustrated or annoyed when engaging in the measurement sessions. There is also a remote possibility that you could fall or be hurt while engaging in the sessions. We will make every effort to prevent and minimize these discomforts by allowing appropriate time for rest and by supervising the sessions carefully. There is the chance that you may find the accelerometer belt to be somewhat uncomfortable. There is no evidence that accelerometers can cause any harm to you, but there is a chance that you may not want to wear the accelerometer. You can stop using the accelerometers at any time if you wish.

Benefits
Are there benefits to participating in this study?
You will not receive personal (direct) benefit from taking part in this research study. However, the information collected from this research may help researchers to better measure social and environmental factors that may impact physical activity behaviors.

Alternative Procedures
What other options are there?
You may choose not to take part in this research study at any time without any penalty.

PAYMENTS:

You will not receive any payment for taking part in this study. You will receive a 4-ride Metro card at the end of the second session.

DATA STORAGE TO PROTECT CONFIDENTIALITY:

All information collected during this study will be kept confidential. All of the information collected by research assistants and through the use of accelerometers will be encrypted with a code and not by your name. We will keep a record of your name and code in a separate file that will not be connected to your data. This file will be stored in password secured computer database.

The following individuals and/or agencies will be able to look at and copy your records:

-The investigator, research study staff
-Authorities from Columbia University, including the Institutional Review Board (IRB),
-The Office of Human Research protections (OHRP)

TIME INVOLVEMENT:

You will be asked to come to Teachers College on two separate days, and to participate in the study for approximately 170 minutes. Participation in this study is voluntary; you can decide whether or not to participate. Refusal to participate will involve no penalty or loss of benefits to which you are otherwise entitled. You may discontinue participation at any time without penalty or loss of benefits to which you are otherwise entitled.

HOW WILL RESULTS BE USED:

The results of the study will be presented as the analyses of aggregated data and will be used for publication in research journals, conference presentations, and for educational purposes.

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www.tc.edu

PARTICIPANT'S RIGHTS

Principal Investigator: Aston K. McCullough, M.A.

Study: Validation of the ActiGraph accelerometer RSSI-based Location Based Services

- I have read and discussed the Research Description with the researcher. I have had the opportunity to ask questions about the purposes and procedures regarding this study.
- My participation in research is voluntary. I may refuse to participate or withdraw from participation at any time without jeopardy to future medical care, employment, student status or other entitlements.
- The researcher may withdraw me from the research at his/her professional discretion.
- If, during the course of the study, significant new information that has been developed becomes available which may relate to my willingness to continue to participate, the investigator will provide this information to me.
- Any information derived from the research project that personally identifies me will not be voluntarily released or disclosed without my separate consent, except as specifically required by law.
- If at any time I have any questions regarding the research or my participation, I can contact the investigator or Dr. Carol Ewing Garber, who will answer my questions. The investigator's phone number is (212) 678-3355. Dr. Carol Ewing Garber’s phone number is 212-678-3891.
- If at any time I have comments, or concerns regarding the conduct of the research or questions about my rights as a research subject, I should contact the Teachers College, Columbia University Institutional Review Board /IRB. The phone number for the IRB is (212) 678-4105. Or, I can write to the IRB at Teachers College, Columbia University, 525 W. 120th Street, New York, NY, 10027, Box 151.
- I should receive a copy of the Research Description and this Participant's Rights document.

- The written, video and/or audio taped materials will be viewed only by the principal investigator and members of the research team. If video and/or audio taping is part of this research,

  I ( ) consent to be audio/video taped.

  I ( ) do NOT consent to being video/audio taped.

- Written, video and/or audio taped materials

  ( ) may be viewed in an educational setting outside the research

  ( ) may NOT be viewed in an educational setting outside the research.

- My signature means that I agree to participate in this study.

Participant's signature: ________________________________ Date:____/____/____

Name: ________________________________

Investigator's Verification of Explanation

I certify that I have carefully explained the purpose and nature of this research to __________________________________ (participant's name) in age-appropriate language. He/She has had the opportunity to discuss it with me in detail. I have answered all his/her questions and he/she provided the affirmative agreement (i.e. assent) to participate in this research.

Investigator's Signature: ____

Date: ______________________