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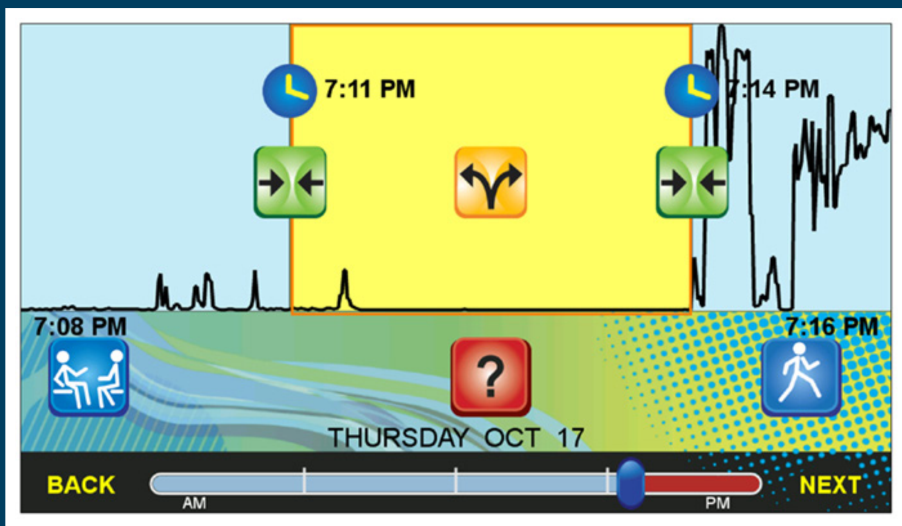

EMERGING TECHNOLOGIES TO PROMOTE AND EVALUATE PHYSICAL ACTIVITY

Topic Editors
Dan J. Graham, James Aaron Hipp, Simon Marshall and Jacqueline Kerr

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EMERGING TECHNOLOGIES TO PROMOTE AND EVALUATE PHYSICAL ACTIVITY

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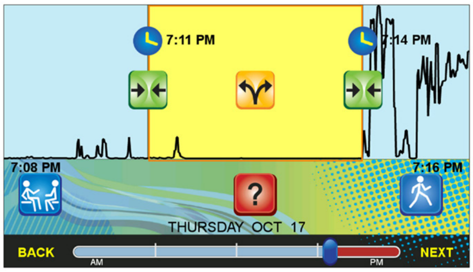

User interface for sensor-assisted end-of-day recall from Dunton and colleagues' (2014) smartphone app, Mobile Teen.

Increasingly, efforts to promote and measure physical activity are achieving greater precision, greater ease of use, and/or greater scope by incorporating emerging technologies. This is significant for physical activity promotion because more precise measurement will allow investigators to better understand where, when, and how physical activity is and is not occurring, thus enabling more effective targeting of particular behavior settings. Emerging technologies associated with the measurement and evaluation of physical activity are noteworthy because: (1) Their ease of use and transferability can greatly increase external validity of measures and findings; (2) Technologies can significantly increase the ability to analyze patterns; (3) They can improve the ongoing, systematic collection and analysis of public health surveillance due to real-time capabilities associated with many emerging technologies; (4) There is a need for research and papers about the cyberinfrastructure required to cope with big data (multiple streams, processing, aggregation, visualization, etc.); and (5) Increasingly blurred boundaries between measurement and intervention activity (e.g., the quantified-self /self-tracking movement) may necessitate a reevaluation of the conventional scientific model for designing and evaluating these sorts of studies.

There have been many recent, disparate advances related to this topic. Advances such as crowdsourcing allow for input from large, diverse audiences that can help to identify and improve infrastructure for activity (e.g., large group identification of environmental features that are conducive or inhibiting to physical activity on a national and even global scale). Technologies such as Global Positioning Systems (GPS) and accelerometry are now available in many mobile phones and can be used for identifying and promoting activity and also understanding naturalistically-occurring activity. SenseCam and other personal, visual devices and mobile apps provide person point of view context to physical activity lifestyle and timing. Further, multiple sensor systems are enabling better identification of types of activities (like stair climbing and jumping) that could not previously be identified readily using objective measures like pedometers or accelerometers in isolation. The ability of activity sensors to send data to remote servers allows for the incorporation of online technology (e.g., employing an online social-network as a source of inspiration or accountability to achieve physical activity goals), and websites such as Stickk.com enable individuals to make public contracts visible to other users and also incorporates financial incentives and disincentives in order to promote behaviors including physical activity. In addition, the increasing use of active-gaming (e.g., Wii, XBox Kinect) in homes, schools, and other venues further underscores the growing link between technology and physical activity. Improvements in mathematical models and computer algorithms also allow greater capacity for classifying and evaluating physical activity, improving consistency across research studies.

Emerging technologies in the promotion and evaluation of physical activity is a significant area of interest because of its ability to greatly increase the amount and quality of global recorded measurements of PA patterns and its potential to more effectively promote PA. Emerging technologies related to physical activity build on our own and others' interdisciplinary collaborations in employing technology to address public health challenges. This research area is innovative in that is uses emerging resources including social media, crowdsourcing, and online gaming to better understand patterns of physical activity.

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Emerging technologies to promote and evaluate physical activity: cutting-edge research and future directions

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Keywords: physical activity, emerging technology, global positioning systems, accelerometers, smartphone app, built environment, online, interventions

Physical activity (PA) promotion and measurement efforts are achieving greater precision, ease of use, and scope by incorporating emerging technologies. This is significant for PA promotion because more precise measurement allows investigators to better understand where, when, and how PA occurs, thus enabling more effective targeting of particular behavior settings. Emerging technologies associated with measuring and evaluating PA are noteworthy because they can: (1) greatly increase external validity of measures and findings through ease of use and transferability; (2) significantly increase the ability to analyze patterns; (3) improve the ongoing, systematic collection and analysis of public health surveillance due to real-time capabilities; and (4) address the need for research about the cyber infrastructure required to cope with big data (multiple streams, aggregation, visualization, etc.). This special issue brings together a collection of the latest innovations and research on the application of technology to promote and measure PA, ranging from new video games aimed at children to measurement programs targeted at obese adults.

The first eight articles present emerging methodologies used to increase measurement specificity with regard to PA, the built environment, and geolocation. Combining multiple methodologies, Hurvitz et al. (1) provide a comprehensive overview of many emerging technologies including global positioning systems (GPS), accelerometers, smart phone applications (apps), and life logging. This article visually and systematically outlines the use of these emerging technologies and provides an exemplar case study. Use of GPS and accelerometers to track where and when PA occurs, as well as PA type, is covered by the next four manuscripts. Schipperijn et al. (2) test the accuracy of GPS in urban environments where building height, presence of water, and user speed and activity can each induce important GPS tracking errors. Testing various buffers around GPS-tracked bicycle trips, Madsen and colleagues (3) find that an elliptical buffer accounting for a participant's home and clustered primary destinations is effective for data reduction and does not lose key built environment exposures. Ellis et al. (4) used machine learning to further investigate GPS and accelerometer measurement, error, and congruence across transportation user groups (pedestrians, cyclists, public transit, and personal vehicles). Finally, Klinker et al. (5) employed GPS and accelerometers to provide context to when and where children and adolescents are active outdoors.

Both Hirsch et al. (6) and Adlakha et al. (7) used public web feeds of GPS data to investigate where users of the MapMyRun app and website perform PA. Hirsch provides detailed background on the app and users, with a case study of activity in North Carolina. Adlakha examined the percentage of runs and walks mapped in St. Louis, MO, USA, parks and neighborhoods and how these varied by neighborhood socioeconomic status.

Kelly et al. (8) measured the built environment with Google StreetView© and reported the validity of using StreetView© in measuring the relationship between PA and built environment variations.

Several contributors to this special issue devised and tested technology-based interventions delivered in whole or in part through internet-enabled devices aimed at increasing PA, decreasing sedentary behavior, or both.

Dunton et al. (9) designed a smartphone app to monitor and enhance adolescent PA by supplementing users' activity self-reports with objective data gathered through motion sensors already existent in smartphones. The use of existing technology inside apparatus many already own provides an affordable way for researchers to gather objective, real-time data. Further, apps like Dunton's can help interpret PA data by combining them with user self-reports that shed light on contextual factors related to PA. Adams and colleagues (10) found that an intervention aiming to reduce sedentary behavior among obese women and incorporating both face-to-face and online components can reduce sedentary behavior and increase PA in this high-risk population. Lubans and colleagues (11) also developed a smartphone app aimed at promoting PA; this app additionally emphasized reduced screen-time and focused on low-income adolescent boys. These researchers identified key barriers to using PA-promotion smartphone apps that will likely be common across similar interventions and highlight lessons learned in incorporating various technologies into health promotion interventions. Maddison et al. (12) demonstrate that an intervention delivered through internet and phone can enhance PA among cardiac patients by increasing their self-efficacy. These studies underscore the benefits of combining technology (e.g., interventions delivered via computer or smartphone) and objective measurement (e.g., accelerometry, GPS) with subjective reports (e.g., psychological and social factors related to behaviors being assessed objectively).

An additional way to use smartphones for promoting PA is described by Barnett and colleagues (13). These authors discuss the growing field of active gaming among children, noting great potential to capitalize on moving active games outside of homes by using smartphones' integrated features such as GPS, wireless internet, and camera. Synthesizing across these papers, excellent opportunities for measuring and promoting PA exist in interventions using smartphones, perhaps in conjunction with other technologies (e.g., online social networks), to facilitate active gaming in the real world.

Using technology to disseminate PA interventions enables PA advice to be distributed in a variety of ways. Alley et al. (14) using eye-tracking technology, demonstrate that online PA advice delivered via personally tailored videos better attracts and holds individuals' attention than text-based messaging.

Finally, Graham and colleagues (15) designed a tool to promote PA among youth during classroom learning. *Jump In!* classroom response mats translate existing clicker technology used to collect real-time data from groups, such as students in classrooms, into a system whereby input is provided by jumping onto a mat, rather than finger pressing a handheld response box. In this case, as in all of the articles in this special issue, technology being used in a PA context already exists in another form or context, and it is the potential for this technology to be applied to PA promotion and measurement that is demonstrated and evaluated.

Undoubtedly, additional technologies currently used in other fields could be adopted for PA measurement and/or promotion. We look forward to creative uses of technology by PA researchers, building on the ways in which researchers such as those contributing to this special issue have incorporated emerging technologies into PA promotion and evaluation. Adopting useful technologies can increase the amount and quality of global recorded measurements of PA patterns and the potential to more effectively promote PA.

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Emerging technologies for assessing physical activity behaviors in space and time

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Precise measurement of physical activity is important for health research, providing a better understanding of activity location, type, duration, and intensity. This article describes a novel suite of tools to measure and analyze physical activity behaviors in spatial epidemiology research. We use individual-level, high-resolution, objective data collected in a space-time framework to investigate built and social environment influences on activity. First, we collect data with accelerometers, global positioning system units, and smartphone-based digital travel and photo diaries to overcome many limitations inherent in self-reported data. Behaviors are measured continuously over the full spectrum of environmental exposures in daily life, instead of focusing exclusively on the home neighborhood. Second, data streams are integrated using common timestamps into a single data structure, the "LifeLog." A graphic interface tool, "LifeLog View," enables simultaneous visualization of all LifeLog data streams. Finally, we use geographic information system SmartMap rasters to measure spatially continuous environmental variables to capture exposures at the same spatial and temporal scale as in the LifeLog. These technologies enable precise measurement of behaviors in their spatial and temporal settings but also generate very large datasets; we discuss current limitations and promising methods for processing and analyzing such large datasets. Finally, we provide applications of these methods in spatially oriented research, including a natural experiment to evaluate the effects of new transportation infrastructure on activity levels, and a study of neighborhood environmental effects on activity using twins as quasi-causal controls to overcome self-selection and reverse causation problems. In summary, the integrative characteristics of large datasets contained in LifeLogs and SmartMaps hold great promise for advancing spatial epidemiologic research to promote healthy behaviors.

Keywords: accelerometry, behavior, environment, geographic information systems, global positioning systems, physical activity

INTRODUCTION

The health benefits of regular physical activity are well established, including weight control, improved cardiorespiratory fitness, and reduced risk of developing chronic diseases such as type 2 diabetes, cardiovascular disease, and some forms of cancer (1–5). Despite these recognized benefits, most people in the U.S. do not engage in physical activity at levels consistent with recommendations for health benefits (6, 7). Precise measurement of physical activity behaviors, including type, amount, context, and place, is essential for increasing physical activity at the population level because it enables a better understanding of where, when, and how much activity is or is not occurring. Emerging technologies are increasingly being used to improve the precision and accuracy of objective physical activity measurement and to enable detailed examinations of where and when physical activity behaviors actually occur. While these technologies greatly advance the field of physical activity research, they also present entirely new methodological challenges. For example, the large amount of data produced when multiple participants wear accelerometers and global positioning system (GPS) devices over the course of several days generates new requirements for data structure and processing. A typical 7-day period of monitoring using a 1-min collection window yields over 1000 observations per person; in one recent study, ~88% of these data points were dropped because of computational incapability with such a large data size (8). Because many studies collect refined data at high temporal resolution, new tools that can deal with such large data sets are necessary. In addition, the multiple activity, location, and environment data streams need to be integrated into a comprehensive structure that permits combined analyses of behaviors in time and space. Although increasing numbers of studies are using these integrated technologies, there is little technical guidance for researchers who want to use these methods in their studies.

This paper introduces a novel suite of data collection instruments, data management tools, and analytic methods to measure and analyze activity behaviors that have broad applications in spatial epidemiology. We focus on individual-level, high-resolution, objective data on activity, location, and environment. First, we describe and assess a range of instruments used to capture physical activity and its location over the course of daily life. These instruments include accelerometers, GPS data loggers, and travel diaries. Second, we present a set of tools, which were created to manage the large data sets generated by accelerometry and GPS. The first data management tool is the "LifeLog," which combines accelerometry- and diary-based activity and GPS-derived location data streams into a single temporal data structure using a common timestamp for data linkage. The LifeLog is in turn complemented by the "LifeLog View," a graphic display interface tool that enables simultaneous visualization of activity and location data streams. These tools yield a common spatial–temporal data structure for activity and location that is also necessary to investigate high-resolution built and social–environmental influences on physical activity behaviors. Third, we seek to bypass the limitations of past research, which only considered the influence of the home environment or "neighborhood" on behavior; instead, we measure physical activity across the full spectrum of exposures encountered in daily life. To do so, we have developed a new approach to capture the attributes of the built and social environments at the many locations generated by GPS data. We introduce SmartMaps, a tool for environmental data management. SmartMaps are rasterized or grid-based surfaces, which provide spatially continuous values of environmental attributes. The fine-grained grid-based measures of environment calculated by the SmartMaps serve to capture exposures with the same spatial and temporal resolution as that obtained by accelerometry and GPS.

The emerging technologies embodied in the set of instruments and management tools presented here promise to precisely measure and analyze physical activity behaviors in various settings over the full spatial–temporal continuum. They have been used in a few studies to date, two of which are described in this article, including a natural experiment to evaluate the effects of new transportation infrastructure on physical activity levels and a neighborhood-effects study that features twins as quasi-causal controls to overcome self-selection and reverse causation problems. Finally, we discuss both the great potential and limitations of the tools and methods presented and suggest future studies that would further advance spatial epidemiologic research.

MATERIALS AND METHODS

ACTIVITY BEHAVIOR AND LOCATION DATA COLLECTION INSTRUMENTS

Our instruments include accelerometers, GPS devices, smartphones, as well as both paper and digital travel diaries.

Accelerometer

We use accelerometers to assess physical activity patterns over time, configuring them for various purposes. In one study, accelerometers were configured to record at minimum acceleration in one-axis (orthogonal to earth surface) while in other studies, the configuration included three-axis accelerometry, steps, incline, and ambient light levels. Measurement epochs for the accelerometer were set to match GPS recording intervals, ranging from 15 s to 1 min.

We use standard off-the-shelf accelerometers such as the ActiGraph GT1M and GT3X models for the objective measurement of physical activity. As one explicit example, accelerometry data were downloaded using ActiLife software (v3.4.0, ActiGraph LLC., Pensacola, FL, USA) and exported as comma-separated value (CSV) text files containing fields for timestamps and the various sensor data streams (i.e., axis counts), text files containing an informational header, including starting timestamp, epoch duration, and epoch accumulated values ("DAT" format), or native structured query language (SQL) format ("AGD" files). Text files were imported into a PostgreSQL (9) database, either directly from CSV files or using scripts within the statistical program R (10) that preprocessed the DAT or AGD data into tables containing one record per epoch. Accessing data using R to connect to the SQLite AGD files allowed an automated approach for processing multiple files, rather than requiring a technician to export individual CSV or DAT files using ActiLife software on a per-subject basis.

Our group currently uses the GT3X+ model and the latest version of ActiLife software (v6.8.1). One major innovation is that the latest model now collects and stores raw accelerations, so that epoch duration can be chosen after data collection at the time of data export. This allows accelerometry data to be matched to the data collection interval of any other recording device. We use accelerometry data as the base table to enforce the temporal sequence of the merged dataset containing input from multiple instruments. We adopt this approach because, once the accelerometer starts collecting data, it continues to record regularly until the unit runs out of power, reaches the configured "stop recording" date/time, or malfunctions, whereas other data collection devices may not record regularly or continuously. The unit does not permit any participant input (e.g., it has no on/off switch or other end-user configuration options) or rely on any other input after starting, which reduces participant burden and avoids potential user error. Accelerometry activity count data were processed to yield time-stamped intensity levels for physical activity using commonly accepted thresholds for differentiating activity levels (11) and to examine records for the number of complete wearing days (7).

Using accelerometer count thresholds for estimating physical activity intensity is problematic because these *a priori* defined thresholds do not necessarily take into account individual-level biometric differences, such as variation in body size or aerobic fitness level, and they do not allow for the estimation of physical activity type or context. Promising work is being conducted using a variety of novel methods, including quadratic discriminant analysis and hidden Markov models (HMM) to recognize common physical activities (12), as well as machine-learning algorithms that exploit artificial neural networks (13, 14). Our own work with these novel methods is described briefly in Section "Multi-Sensor Board" below. Indeed, the measures proposed herein may be used as validation strategies for such algorithms. The "packaging" of these algorithms within easily used software will help researchers who are measuring activity levels with accelerometry but who have little experience in software development.

Global positioning systems

Our ongoing studies use GPS data loggers to record geospatial locations so that we can assess the spatial and temporal characteristics of travel and "dwell" patterns (e.g., sojourn at a home or work location), including characteristics of specific travel modes. We explain how we conflate the GPS and accelerometry data below in Section "Data Integration, Management, and Visualization Tools."

We currently use off-the-shelf models such as the GlobalSat (New Taipei City, Taiwan) DG-100 that is equipped with the SiRF Star III/LP 20-channel chipset, and the Qstarz (Taipei, Taiwan) BT-1000XT that contains the MTK 51-channel chipset. Both models feature solid-state memory and rechargeable batteries that allow at least one full day of measurement per charge and up to several weeks of data storage, depending on recording interval and data type.

The DG-100 manual states its accuracy as 10 m, whereas the stated accuracy of the BG-1000XT is 3 m. The DG-100 can record a maximum of only 5 values per record, including position, timestamp, speed, and altitude, whereas the BG-1000XT can record up to 19 values, including the previous 4, as well as data quality variables such as dilution of precision, number of satellites used in the fix, satellite position, and signal-to-noise ratio.

We collect data in binary format and export them as CSV files, with one record per logging interval during which a fix was determined (at least four satellites in view and a horizontal dilution of precision less than eight). Consumer-level GPS units such as the DG-100 and BG-1000XT can be configured to log at regular intervals, such as 15 s, but they begin recording as soon as a fix is obtained (rather than at a time evenly divisible by 15 s) and store the next record after the configured interval has elapsed.

The GPS data are processed and stored in a PostgreSQL database enabled with PostGIS, the spatial data storage and analysis extension (15). Longitude and latitude coordinates are used to generate spatial point features for mapping and spatial analysis. Unlike the data structure obtained from accelerometry, GPS data frequently contain large intervals without data, caused by signal reception failure due to such factors as obstruction of line-of-sight with GPS satellites, powering down during recharging, or cold starts (delays between starting up and acquiring a satellite signal).

Multi-sensor board

Our team also uses a multi-modal sensor known as the multi-sensor board (MSB), which was developed by researchers at the University of Washington in collaboration with Seattle Intel Labs. This is a pager-sized device worn clipped to a belt (16). It offers a suite of features, including multiple sensing (three-axis accelerometry, barometric pressure, humidity, temperature, light, audio, and GPS), data storage, communication, and local computation capabilities. Rather than outfitting study participants with several different (separate) devices, the MSB records multiple sensor data streams simultaneously. Its functionality yields notable benefits; participants need to wear and recharge only one device, and each variable is recorded in a single binary file, rather than in several files that need management and conflation after download.

As an experimental device, the MSB has various drawbacks, such as limited data storage, limited battery life, and the need for expert staff to configure the devices and to download and transform the multiple data streams. Despite these limitations, it enabled us to develop sophisticated machine-learning algorithms to quantify physical activity types and estimate corresponding energy expenditures that were subsequently validated in laboratory and field experiments (17, 18).

The advantages in using single devices that have multiple sensors and capabilities – such as the MSB and mobile phones – make them an important area for further development and eventual deployment. Although we are currently using stand-alone accelerometers, GPS devices, and mobile phones in many of our research projects, we are benefiting from our previous validation work and using our machine-learning algorithms to obtain richer data on activity amount (i.e., specific activity types and associated energy expenditures) than can be provided by accelerometry and GPS alone.

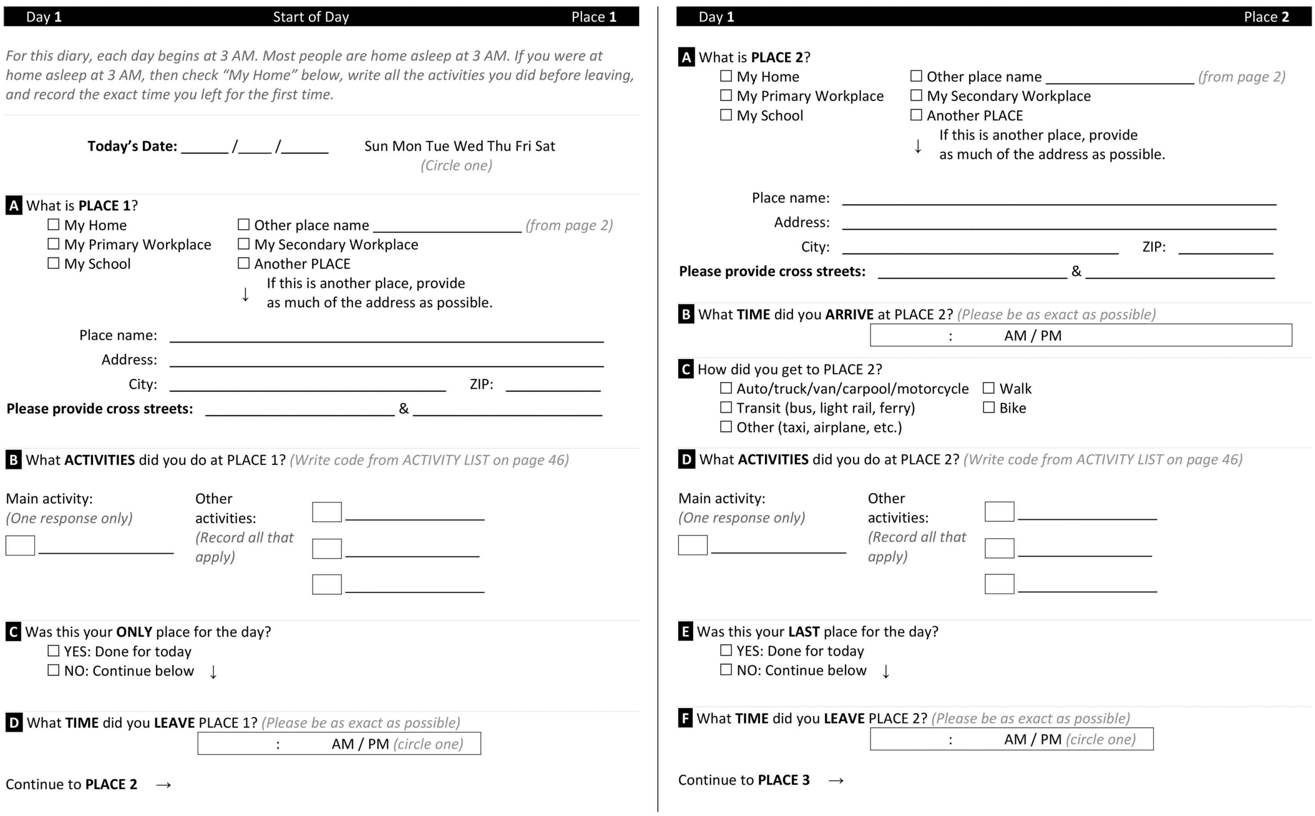
Travel diary instruments

Our research agenda is driven by objective data sources. However, we have found that an important set of behavioral data is not yet available solely through objective measurement. Data for behavioral variables or characteristics such as activity purpose, visited place names and addresses, and certain modes of travel between places cannot, in general, be collected without some user input. Other activities that are difficult to determine, such as walking or jogging on a treadmill or using a stationary bicycle or elliptical machine, would likely require substantial work to be identified solely from objective data.

Other behavioral variables are impractical or impossible to measure with existing instruments. For example, although some devices, such as the ActiGraph GT3X+, are water resistant, most current electronic devices, including GPS units, must be removed during bathing or swimming, preventing the recording of such activities. In addition, objectively sensing behaviors such as eating and food shopping would require the development of new instruments and data processing methods. Given the lack of such instruments, but also the need for obesity-related research to estimate where and when all exercise, travel, and food-related behaviors occur, we created several travel and food diary instruments. For each visited place, key variables include place name, address, arrival and departure time, arriving travel mode, and activity or purpose.

Paper version of travel diary. We originally created paper booklets with enough blank pages to account for 14 places per day, with extra pages for additional places and days. Participants logged place names, addresses, times of arrival and departure, activities at each place, and mode of travel from place to place. An example of a paper travel diary that we have used in our research is shown in **Figure 1**.

We wrote a custom Microsoft access database (MDB) application to facilitate transcription from the paper diary to a digital format. This database automatically links participants, recording days, and place records (see **Figure 2**). Each participant's data are stored in a hierarchy identified and linked by participant ID, day number, and record number. The application uses two separate MDB files, one containing the data and the other with the forms



Day **1** Start of Day Place **1**

For this diary, each day begins at 3 AM. Most people are home asleep at 3 AM. If you were at home asleep at 3 AM, then check "My Home" below, write all the activities you did before leaving, and record the exact time you left for the first time.

Today's Date: ______/____/______ Sun Mon Tue Wed Thu Fri Sat *(Circle one)*

A What is **PLACE 1**?
☐ My Home ☐ Other place name ________________ *(from page 2)*
☐ My Primary Workplace ☐ My Secondary Workplace
☐ My School ☐ Another PLACE
↓ If this is another place, provide as much of the address as possible.

Place name: ______________________
Address: ______________________
City: ______________ ZIP: ________
Please provide cross streets: __________ & __________

B What **ACTIVITIES** did you do at PLACE 1? *(Write code from ACTIVITY LIST on page 46)*

Main activity: *(One response only)*
Other activities: *(Record all that apply)*

C Was this your **ONLY** place for the day?
☐ YES: Done for today
☐ NO: Continue below ↓

D What **TIME** did you **LEAVE** PLACE 1? *(Please be as exact as possible)*
: AM / PM *(circle one)*

Continue to **PLACE 2** →

Day **1** Place **2**

A What is **PLACE 2**?
☐ My Home ☐ Other place name ________________ *(from page 2)*
☐ My Primary Workplace ☐ My Secondary Workplace
☐ My School ☐ Another PLACE
↓ If this is another place, provide as much of the address as possible.

Place name: ______________________
Address: ______________________
City: ______________ ZIP: ________
Please provide cross streets: __________ & __________

B What **TIME** did you **ARRIVE** at PLACE 2? *(Please be as exact as possible)*
: AM / PM

C How did you get to PLACE 2?
☐ Auto/truck/van/carpool/motorcycle ☐ Walk
☐ Transit (bus, light rail, ferry) ☐ Bike
☐ Other (taxi, airplane, etc.)

D What **ACTIVITIES** did you do at PLACE 2? *(Write code from ACTIVITY LIST on page 46)*

Main activity: *(One response only)*
Other activities: *(Record all that apply)*

E Was this your **LAST** place for the day?
☐ YES: Done for today
☐ NO: Continue below ↓

F What **TIME** did you **LEAVE** PLACE 2? *(Please be as exact as possible)*
: AM / PM *(circle one)*

Continue to **PLACE 3** →

FIGURE 1 | Paper travel diary for two places in a single travel day.

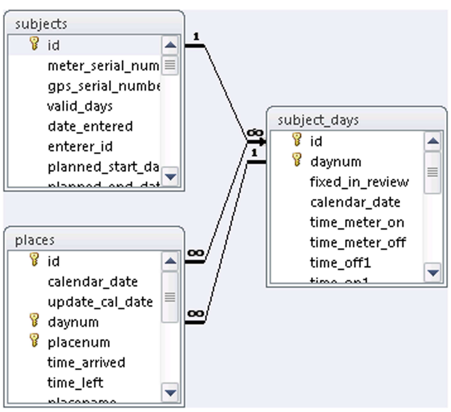


FIGURE 2 | Travel log database schema for data entry in Microsoft Access.

and visual basic for applications (VBA) code. The "code" database uses the Linked Data Manager in Access to display the data tables, which are actually stored in the separate "data" MDB file. This structure permits updates to the code database without the need for copying data tables.

The code database contains forms that allow easy navigation among records for participants, participant days, and places as illustrated in **Figure 3**. The data entry form for place data contains VBA code for simple error checking of intra-place records. For example, if a place record has the "time arrived" later than the "time left," a warning is generated similar to that shown in **Figure 4**. The code database also contains queries that display inter-place error checks (e.g., if the "time left" for place 1 is later than the "time arrived" at place 2), allowing data entry staff to review and correct inter-place sequencing errors.

Digital versions of travel diary. Although our paper diary was easy to create, edit, and administer, the tedious transcription process, which used the Access database, was vulnerable to errors. Quality control can expose errors (e.g., a.m. and p.m. substitutions, transposed numerals, missed records), but each potential error required manual review to determine whether it originated in the participant's initial recording or in the transcription process. Furthermore, because data entry and data processing were performed by different study staff, interpreting errors often required communication between research staff (at the same or across sites) and retrieving paper documents from archives.

To avoid the logistical problems associated with paper diaries, we wrote two separate travel diary applications for the Android smartphone platform. Data collected by smartphone do not require transcription, and error-checking can be built into the application, with immediate feedback asking the user to correct impossible entries (e.g., leaving a place before arriving at that

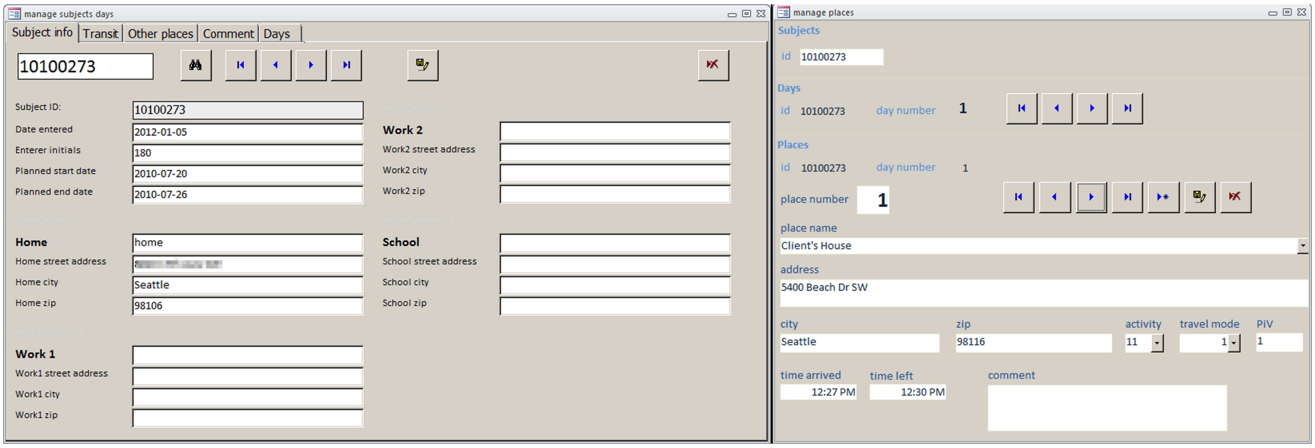


FIGURE 3 | Travel log database entry forms. Upper panel: common places; lower panel: a single place record.

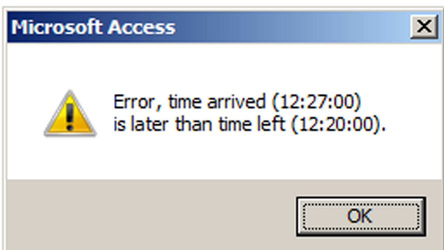


FIGURE 4 | System generated warning for illogical timestamps.

place). This approach minimizes or obviates the need for temporal error checking in post-processing.

My footprints. We initially used the *Footprints* application for HTC (New Taipei City, Taiwan) Android phones to record the time and location of specific activities (exercise, eating, and food shopping), to encourage participants to create diary records at the time specific activities occurred. This application works by enabling the user to take a digital photo that is automatically tagged with timestamp and location by the phone's locational sensor and then manually tagged with other user-entered variables. However, *Footprints* offered few options for configuration. For example, the values for the "activity" variable were pre-populated and not editable, so that it was impossible to record various activities of interest (e.g., food shopping) without resorting to the open-ended "comment" variable.

Instead, we wrote a separate application named *My Footprints* to be more directly useful in our research. A record in *My Footprints* is illustrated in **Figure 5**, which includes the digital photo filename, an automatically generated timestamp, spatial coordinates for the location where the photo was taken (although not shown in this image capture), and one of four different activities. Data collected with *My Footprints* can be directly transferred from a smartphone to the PostgreSQL database.

Smartphone-based travel diary. We also pilot-tested the *Memento* database application for Android phones as a place-based travel diary. This highly flexible and configurable app was able to store all our required fields. However, when data were exported, place records appeared in a seemingly random order, rather than in the order in which they were visited. This is problematic because place sequencing is a basic functional requirement for our research questions. Proper sequencing of places is not an issue for paper travel logs. Rows in the log are numbered sequentially, so we can assume that participants record places in the correct order, and that place numbers are transcribed accordingly.

Although we were unable to find an effective way to correct the sequencing problem in *Memento*, we created a second Android app simply called *Travel Diary*. This application allowed recording and reordering of days and places (shown in **Figures 6A,B**), place name, address, time arrived and left (**Figures 6C–E**), and travel mode and activity (**Figures 6F,G**).

Travel diary processing. Whether paper or digital, the travel diary uses place as the unit of measure. Instead of being stored as data, trips are created as the temporal interstices between places, and generated for each successive pair of place records. A set of R scripts converts the travel diary data into format-standardized CSV files. These files are uploaded to the PostgreSQL database for integration with the GPS and accelerometry data as described in Section "Data Integration, Management, and Visualization Tools" below.

BUILT ENVIRONMENT MEASURES USING SMARTMAPS

Using GPS to capture location information generates very large amounts of data. We needed a novel approach to effectively measure built environment characteristics at any or all GPS-derived locations recorded from participants. Previous approaches have used spatial buffers around participants' geocoded residential addresses to extract and summarize geographic information system (GIS) data within the local neighborhood, storing values as individual-level variables (19). However, this point-centric measurement approach requires a substantial amount of data processing for each location. It is also too computationally intensive

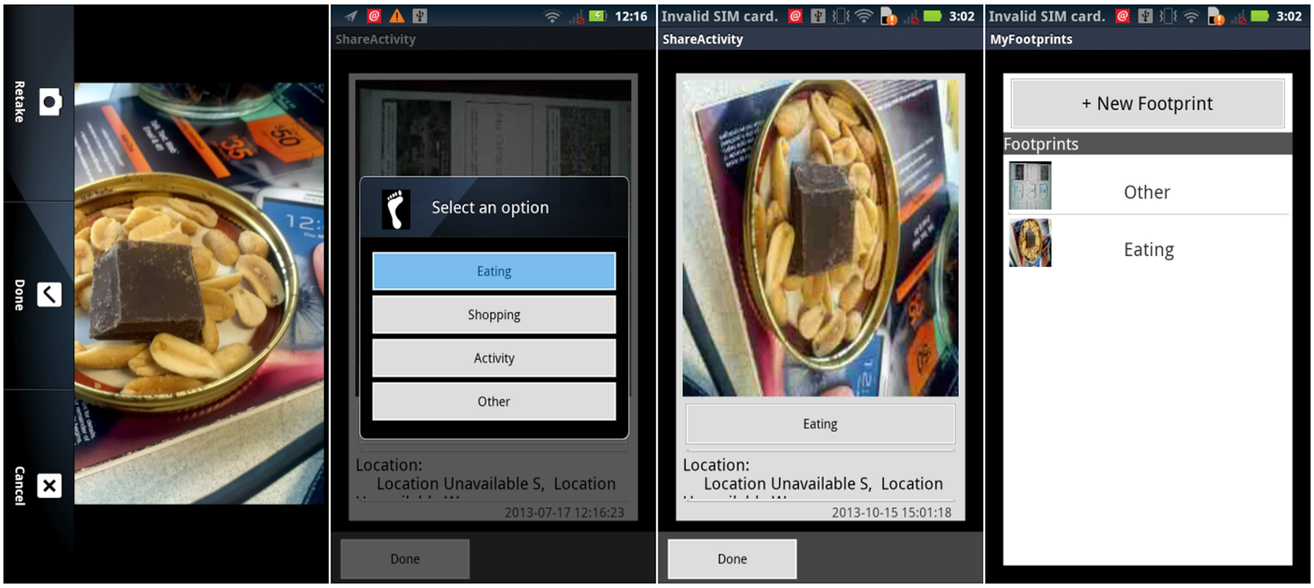


FIGURE 5 | Examples of *My Footprints* screen captures. Far left panel: capturing an image with the mobile phone camera; center-left panel: tagging the picture as "eating;" center-right panel: review of image and tag; far right panel: overview of recorded activities.

to be practical for large GPS datasets collected under participant free-roaming conditions.

To address these issues, rather than performing point-centric measures of the built environment at all GPS locations, we created SmartMaps for each built environment attribute of interest. SmartMaps are raster layers (20) – that is spatially continuous surfaces of grid cells – which enable efficient measurements at any number of locations within a study area. The point value at each SmartMap cell represents a summary of the local neighborhood value around that cell. SmartMaps provide the same built environment values as those generated by the traditional buffer method. However, instead of recording neighborhood summaries at specific, predefined point locations, SmartMaps do so for every cell, continuously across space, thereby enabling measures at any location in the study area.

SmartMaps are created by focal raster processing. The area of interest (in our case, King County, WA, USA) is represented as a grid of 30 m × 30 m cells, a resolution that has been shown to represent urban and suburban parcels with sufficient spatial fidelity (21). Each focal cell in the grid is processed independently by using the ArcGIS Spatial Analyst Extension. The software performs prescribed calculations for the neighborhood around the focal cell, places the resulting value on that cell, and then moves on to the next cell, repeating the process until values are calculated for all cells. In our current studies, we use a radius of 833 m to represent the focal "neighborhood," corresponding to the distance that can be walked in 10 min. For example, to calculate a SmartMap of the count of residential units within 833 m of a specified grid cell, parcels are first converted into a raster grid in which cell values represent the fraction of residential units within the cell (e.g., a 9000 m^2 parcel containing 20 residential units yields 10 cells with a value of 2 units per cell). The process then sums the values of all cells within each focal buffer to represent the number of residential units in that focal cell's neighborhood. SmartMap cell values can then be extracted for GPS points by using the ArcGIS Surface Spot analytical method.

For our studies, we have generated SmartMaps that characterize elements of the built environment. These SmartMaps cover domains that past research has associated with physical activity and obesity. For example, neighborhood composition could be represented by counts or densities of employes and residential units (22, 23). Utilitarian or recreational destinations could be captured as counts or densities of supermarkets, fast food outlets, traditional restaurants, coffee shops, fitness facilities (24, 25), or by count of parks, etc. (8, 26). Transportation infrastructure is measured as density of intersections, streets, urban trails, etc. (23, 27, 28). Traffic conditions are represented by estimated traffic volumes (23) and bus ridership as a measure of transportation system load (29).

Each one of our SmartMaps of the 5975 km^2 area of King County contains more than 6.8 million 900 m^2 (30 m × 30 m) cells, with each cell providing values for the various built environment variables in the associated neighborhood. A SmartMap of the count of residential units within 833 m of each cell is shown in **Figure 7**.

Using SmartMaps to obtain environmental measures for point locations is considerably more efficient than performing a series of point-centric buffer analyses. For the 3.8 million GPS locations that we collected in one study, less than 1 h per SmartMap was required to extract built environment data in the form of summaries of each 833 m neighborhood (30). Although creating SmartMaps for an area requires substantial effort, the resulting rasters can readily be used in any subsequent study to analyze point measures of the environment within a specified area. SmartMaps are essential for the growing number of studies that

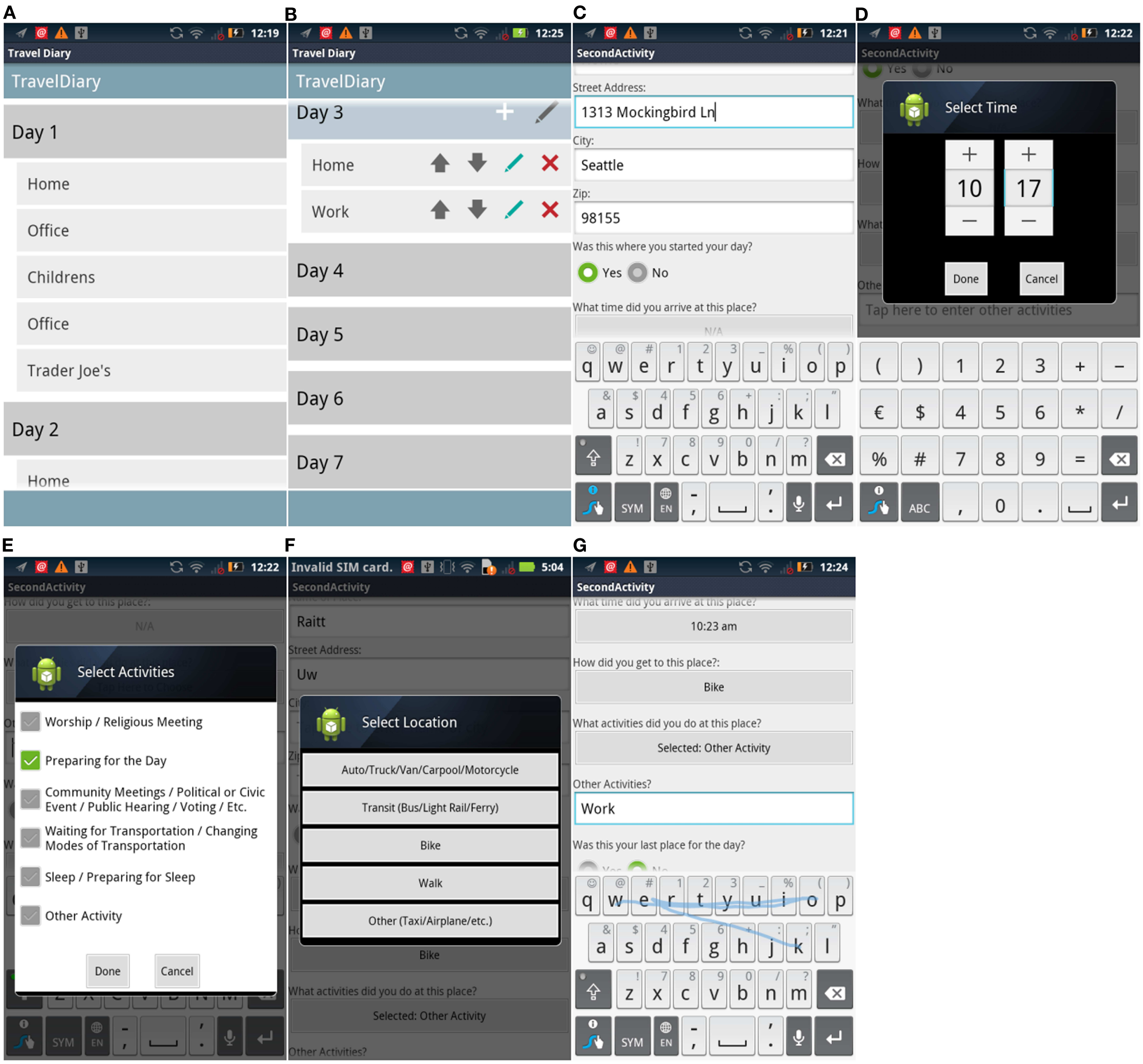


FIGURE 6 | Travel Diary screen captures. From left to right, top to bottom: **(A)** layout of place records; **(B)** editing mode for places within a day; **(C)** address place data entry; **(D)** assigning timestamps; **(E)** selecting activity for a place; **(F)** selecting predefined location; **(G)** entering open-ended activity.

use geolocation technologies to track individual movements. Ideally, urban areas would develop sets of SmartMaps for use by multiple agencies or research entities that examine the effects of built environment on behavior. Similar efforts have already been made in fields such as meteorology and noise mitigation (31). Furthermore, SmartMaps can be archived from data sources measured at different points in time for use in longitudinal studies.

DATA INTEGRATION, MANAGEMENT, AND VISUALIZATION TOOLS

We created tools to manage and integrate the massive data streams collected by devices in order to examine relationships between exposures and behaviors. These include LifeLogs and rasterized SmartMaps.

LifeLogs

Common timestamps are the "glue" that enables our three basic datasets (accelerometry, GPS, and travel diary) to come together. Each record from each data source is stored with an explicit timestamp, and tabular joins are enforced by common timestamps or time ranges across tables known as LifeLogs. A graphical work flow to create LifeLogs is shown in **Figure 8**; the basic SQL code for creating a LifeLog is provided in Example 1 in Supplementary Material.

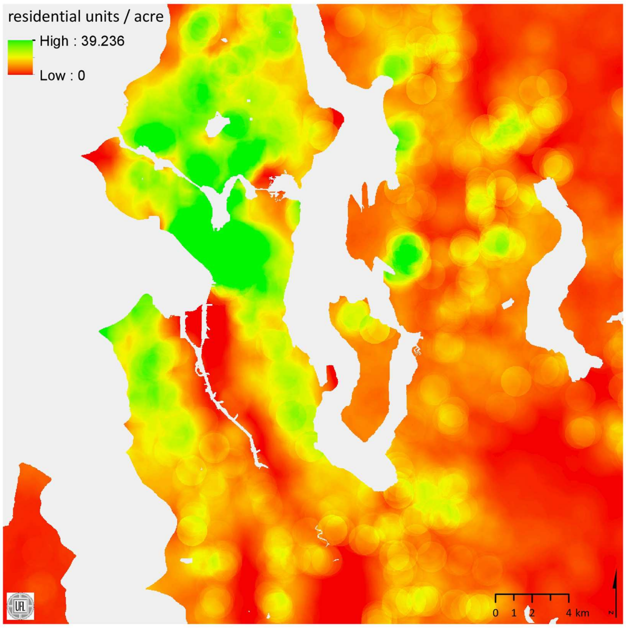


FIGURE 7 | A SmartMap of residential unit density. Values are count of residential units per acre within 833 m of each raster cell.

Although creating LifeLogs from individual constituent tables is simple in PostgreSQL, some issues need to be addressed to ensure that tabular relationships are sound (e.g., all devices must have their "clocks" aligned).

Time zones. Each moment in time can be represented as a timestamp. Timestamps can be rounded to the nearest second with no loss of information to provide the level of precision needed in this type of spatial epidemiologic research. A commonly accepted standard is the number of seconds elapsed since January 1, 1970, 00:00 UTC (Coordinated Universal Time, or Greenwich time zone); this is often called "Unix time." Several factors can introduce errors in timestamps. Although one of the benefits of UTC is that each moment can be represented unambiguously, errors result if time zones are not explicitly specified and handled. The R script shown in Example 2 in Supplementary Material illustrates how a timestamp can be handled to account for specific time zones. PostgreSQL has similar functionality.

When datasets containing timestamps are passed from one software package to another, careful attention is required to avoid errors resulting from conversions that assume that timestamps are stored in local time.

Daylight saving time. Across the U.S. and in many regions worldwide, daylight saving time is used to increase the number of daylight hours after the work day in summer. When clocks are set to change ("spring ahead" or "fall back"), they either lose or gain an hour. Unless completely specified timestamps are used with software that properly handles daylight saving time, errors are possible in measuring intervals that span the moment when daylight saving time begins or ends. The software packages used for LifeLog data processing and storage, R and PostgreSQL, correctly account for daylight savings time transitions as shown in Example 3 in Supplementary Material, but other software may not.

Analytic boundary for days. Midnight marks the transition between calendar days, but many people are active past midnight. In order to assign periods of activity to a behaviorally based unit, we decided to use 03:00 a.m. as the transition between analytic days. Any activity occurring between 23:59 and 02:59 was assigned to the previous calendar day. The simulated example in Example 4 in Supplementary Material shows the day transition after 02:50.

Timestamp rounding. Accelerometry timestamps are typically collected at regular intervals, such as 10, 15, 30, or 60 s. The GPS units are also configured to record at set intervals, but the actual time of acquisition is often more sporadic, depending on when the GPS unit can obtain a satellite fix. Therefore, to relate accelerometry records with GPS records, the records that are the closest in time in each dataset should be matched. One approach to matching is to loop through the accelerometry records and find the GPS record with the closest timestamp; however, this method is inefficient from a processing perspective. A better approach is first to determine the interval of the accelerometry recording and then to round the GPS timestamps to the same interval. Because several different GPS timestamps might round to the same value (e.g., 00:01 and 00:02 both round to 00:00), the GPS table is truncated to include records with unique rounded timestamps. Truncation should give precedence to the GPS timestamp closest to the rounded timestamp and delete other candidate matches (e.g., matching 00:00 with candidates 00:01 and 00:02 would retain 00:01 and delete 00:02). For ties (e.g., 00:01 and 00:59), PostgreSQL will select the first matching record in internal tabular order.

The SQL code for generating rounded timestamps shown in Example 5 in Supplementary Material allows the use of any interval. An example of the rounding function is also shown in Example 6 in Supplementary Material, which is based on a single participant's data with a subset of results shown in **Table 1**. The raw GPS dataset for this study participant consisted of 29,382 records, but after rounding and selecting unique timestamp-rounded records, the resulting table contained 17,073 records. For a table of this size, the processing time was <1 s on a RedHat Linux machine with a 64-bit Intel Xeon E31270 3.40 GHz processor and 16 GB of RAM.

LifeLog View

LifeLog Views provide multiple illustrations of complex data derived from the LifeLog. Data for a walking bout are illustrated in **Figure 9**. The left panel shows accelerometry, GPS, and place and trip information within the same temporal X-axis graph, created using R. The map portion of the LifeLog View (right panel) shows all GPS locations for a given study participant, with bout-specific GPS locations in red, and was created using University of Minnesota MapServer software[1]. A green line identifies

[1] http://mapserver.org/

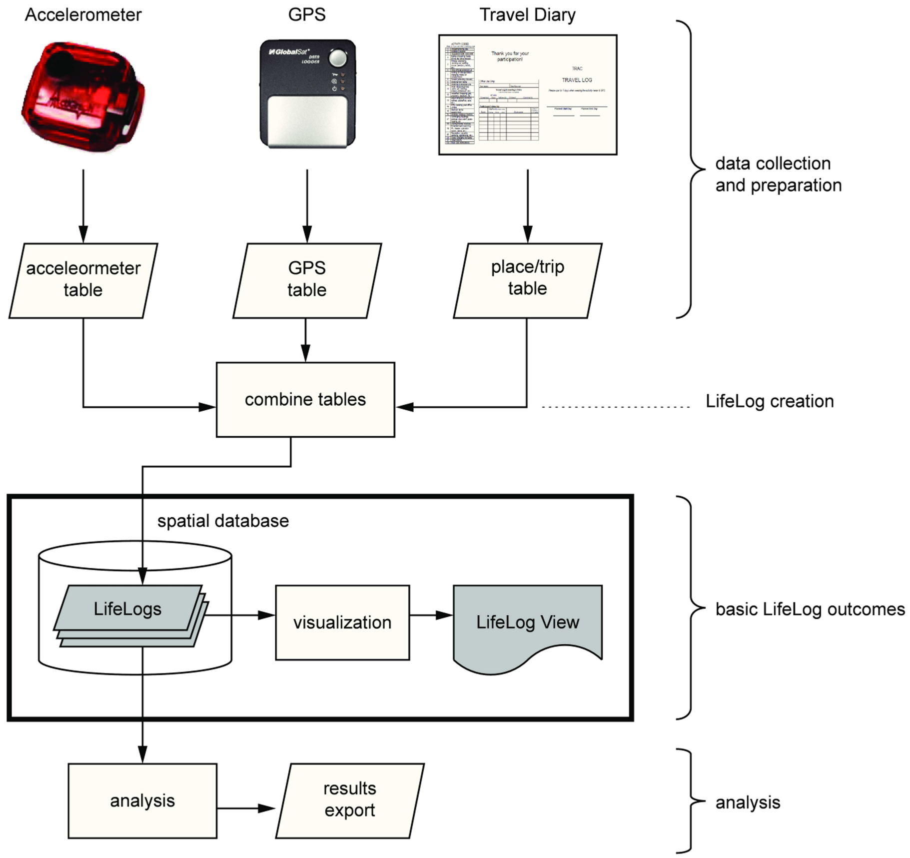


FIGURE 8 | Illustration of LifeLog work flow.

the minimum bounding circle drawn around 95% of the most tightly clustered points in the bout. Participant ID, sequential bout number, and activity type are printed as the main title of the image (top left). Each component image (graph and map) was created using automated scripts, and the images were automatically mosaicked using Imagemagick[2]. Each data element in LifeLog View is useful for developing empirically based tolerances for activity classification. A second LifeLog View shows one combined accelerometry/GPS/diary graph per day (right panel) and GPS locations (left panel) collected over 1 week (**Figure 10**). LifeLog Views were instrumental in developing and validating the algorithms used to classify bouts of walking (32).

Analytical tools

Data compiled as LifeLogs can be used for many purposes. Because LifeLogs contain original data from all sources (accelerometry, GPS, and travel diary), they can be used for analyzing, graphing, and mapping of activities and locations, either as separate or combined components, as a spatially and temporally explicit database. Possible analyses are briefly discussed using the identification of physical activity and walking bouts as examples. Also presented is a new tool to graph and map all data in the LifeLog.

[2]http://www.imagemagick.org

Physical activity bouts from accelerometry. Accelerometry data can be processed by using established methods to stratify records by levels of physical activity. We have considered periods of at least 20 min of zero accelerometry counts as non-wearing, while days with at least 8 h of wearing time are considered valid (33, 34). Within valid days, wearing and non-wearing intervals are differentiated following the approach described by Matthews and colleagues (35); intervals of at least 60 min of zero counts, with no more than two consecutive minutes of 1–50 counts per epoch (using a 30-s epoch), are coded as non-wearing. Sustained bouts of physical activity are defined as having accelerometry epochs above a threshold of 1000 counts per minute for at least 5 min, with allowance for 2 min of interstitial epochs below the threshold. A threshold of 1000 counts per minute is lower than the thresholds commonly used to represent moderate-to-vigorous physical activity (11) to identify walking bouts.

Classification of walking type from physical activity bouts. Processing accelerometry data alone allows us to identify bouts of physical activity and their relative intensity, but it provides no additional information on bout characteristics. Integrating GPS and travel diary data adds substantial power to contextualize physical activity bouts. GPS can characterize both the instantaneous speed and spatial clustering of individual locations within

Table 1 | Illustration of original and rounded timestamps from one dataset.

Rec.	Time_gps_utc	Time_gps_utc_std	Diff. time
1	2009-01-16 02:22:52	2009-01-16 02:23:00	−8
2	2009-01-16 02:23:22	2009-01-16 02:23:30	−8
3	2009-01-16 02:23:52	2009-01-16 02:24:00	−8
4	2009-01-16 02:24:22	2009-01-16 02:24:30	−8
5	2009-01-16 02:24:52	2009-01-16 02:25:00	−8
6	2009-01-16 02:25:22	2009-01-16 02:25:30	−8
7	2009-01-16 02:25:52	2009-01-16 02:26:00	−8
8	2009-01-16 02:26:22	2009-01-16 02:26:30	−8
9	2009-01-16 02:26:52	2009-01-16 02:27:00	−8
10	2009-01-16 02:27:22	2009-01-16 02:27:30	−8
11	2009-01-16 02:27:52	2009-01-16 02:28:00	−8
12	2009-01-16 02:28:35	2009-01-16 02:28:30	5
13	2009-01-16 08:44:33	2009-01-16 08:44:30	3
14	2009-01-16 08:45:06	2009-01-16 08:45:00	6
15	2009-01-16 08:45:39	2009-01-16 08:45:30	9
16	2009-01-16 08:46:12	2009-01-16 08:46:00	12
17	2009-01-16 08:46:45	2009-01-16 08:47:00	−15
18	2009-01-16 08:47:18	2009-01-16 08:47:30	−12
19	2009-01-16 08:47:51	2009-01-16 08:48:00	−9
20	2009-01-16 08:48:24	2009-01-16 08:48:30	−6

Columns represent sequential record number, global positioning systems (GPS) measurement time in UTC (Coordinated Universal Time), GPS measurement time rounded to a standard 30 s interval, and the difference between raw and standardized timestamps.

bouts. For example, place names, activity types, and transportation modes recorded in the travel diary can be used in conjunction with accelerometry and GPS data for fine-grained classification of walking types (32).

APPLICATIONS TO RESEARCH

In this section, we describe two ongoing studies in which we apply our suite of tools to spatially oriented research questions. One study involves a natural experiment to evaluate the effects of new transportation system on physical activity levels. The other study evaluates neighborhood effects on physical activity, using identical twins as quasi-causal controls to overcome the self-selection and reverse causation problems that plague the literature on this topic.

TRAVEL ASSESSMENT AND COMMUNITY

The travel assessment and community (TRAC) study focuses on public transit use. Public transit users tend to engage in higher levels of physical activity than non-users. However, we want to know if users' physical activity is directly attributable to transit use and/or changes in transit access. To address these questions, we need data that can tell us when study participants use transit and what kind of behavior they exhibit before and after transit trips. We hypothesize that they will walk to and from the points where they access public transit. Therefore, we need to determine whether physical activity that happens in the temporal vicinity of transit trips is consistent with walking or with some other form of activity, such as working out at a gym. Based on the methods described here, and reported by us recently (32), we have successfully used the LifeLog to identify the time, place, and type of physical activity performed for participants in the TRAC study, and to make estimates of the amount of physical activity directly attributable to transit use as described by us in a paper currently in press (36).

In the first longitudinal measurement phase in the TRAC study, we recruited 748 participants who had recorded data for any of the three instruments. Compliance with measures completion was relatively high; 715 participants had at least some data from each of the three instruments. Of the 701 participants with accelerometer and GPS data on valid days, there was a mean of 12.3 accelerometer wearing hours per day (SD, 1.6 h) and 11.3 GPS hours (SD, 7.3 h). The average accelerometer wear hours was slightly lower than reported in several other studies (between 12.5 and 14.2 h per day) (7, 8, 37); however, GPS wear times were not usually reported. Some participants who did not satisfactorily complete data collection were asked to re-wear the devices and fill out travel diaries for additional days; accelerometer data were collected from 730 participants, with 49 participants (6.7%) providing re-wear accelerometry data.

TWIN STUDY OF ENVIRONMENT, LIFESTYLE BEHAVIORS, AND HEALTH

Since 2008, all residential addresses for adult twins who are members of the University of Washington Twin Registry (UWTR) have been stored in a central database to enable temporal and spatial matching with survey data. The Registry is now poised to take advantage of the array of data assembled over the past several years in analyses of associations among genetic, environmental, behavioral, and health variables. Such analyses depend on linking all our available data types (survey, biological, and environmental). Because twin participants in the Registry are surveyed every 2 years, we are also able to follow them longitudinally to investigate temporal associations between changes in built and social environments and changes in activity behaviors.

Each individual twin's home address is geocoded in ArcGIS by using ESRI (Redlands, CA, USA) StreetMap Premium with a minimum match score of 100%. Addresses that fail the automatic geocoding process (~40%) are matched manually. The following are examples of the environmental exposures we use in our research: neighborhood walkability (22, 27, 38–44), level of urban sprawl (45), amount of vegetation or "green space" (46, 47), material and social deprivation (48), residential property values (49, 50), and crime rates (51). These indices rely on multiple data sources, including the U.S. Census, parcel-level and tax-lot level data, county-level assessor data, and InfoUSA, a commercially available resource that provides information on food sources as well as fitness, service, and retail facilities. Point-in-polygon analysis attaches values from our environmental indices to each twin by using the twin's geocoded residential address. Although much of our environmentally based work focused on the residential neighborhood, newer studies such as the one described in the paragraph below also include data on the work and school

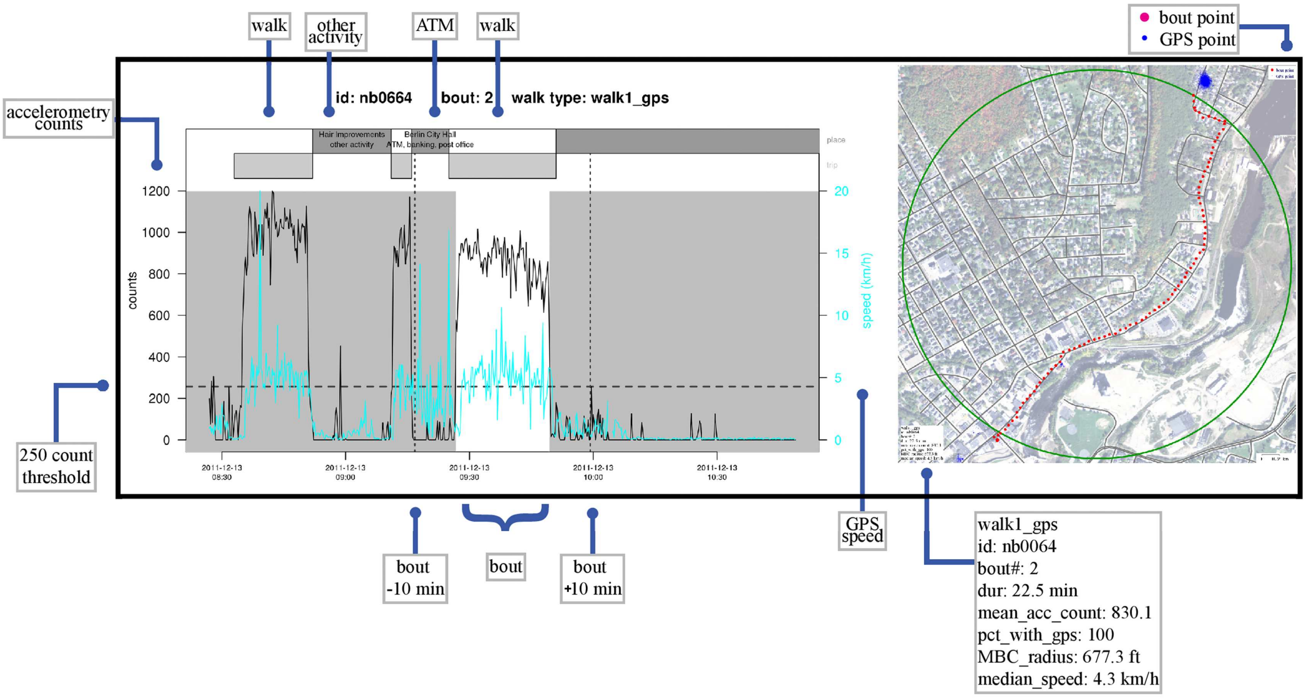


FIGURE 9 | An illustration of LifeLog View for a single bout of activity for one subject. Left panel: time-indexed combined accelerometry counts (black lines), global positioning system (GPS) speed (cyan lines), and place and trip data from a travel diary (gray boxes with text labels). A physical activity bout is centered in the graph within a white background. The dashed horizontal line indicates the accelerometry threshold used to define a bout of walking. The dashed vertical lines are at 10 min on either side of the bout. Right panel: map of bout location. Larger red dots are individual GPS locations for the bout, with all GPS locations shown as small blue dots. The green circle indicates the boundary for the 95% most tightly clustered points in the bout.

environment, as well as "distal" environments that participants might frequent on a regular basis (e.g., a favorite coffee shop, a gym, etc.). Thanks to the novel applications on which we focus in this article, we can now exploit the full activity space over time.

In this research, we will investigate the effects of the built environment on lifestyle behaviors and health in a community-based sample of 200 adult monozygotic twin pairs (400 individuals) from the UWTR who were reared together but now live apart. This unique sample will permit us to examine environmental influences on lifestyle behaviors and health, free of the genetic and shared environmental (familial) effects that might otherwise introduce selection biases into the choice of living environments. We describe each twin's residential environment in terms of the indices previously noted. Participants are outfitted with an accelerometer, a GPS data logger, and an Android smartphone for continuous tracking in time and space over 2 weeks. The data from these three tools are joined in a LifeLog indexed by common timestamps across devices. An example of data collected for one twin pair is shown in **Figure 11**; LifeLog data will assist us in investigating multiple issues. For example, we will determine the association between the home-built environment and levels of both walking and total physical activity in twins who live apart. We will also compare location-based physical activity and eating episodes in real-time to assess whether proximity to features of the home-built environment are associated with use by measuring how many physical activity and eating episodes occur in the home-built environment versus in-distal built environments, including work, transit, and recreation-related settings. Our study design is notable in several ways: it overcomes the measurement bias inherent in self-report data, addresses the problem of defining "neighborhood," and engages in novel spatial–temporal measures of behaviors that correspond to ecological exposures.

To date, we have completed data collection on 70 twin pairs. Compliance with wearing the devices has been exceptional; of 106 individual twins whose data has been processed thus far, average wearing days for the accelerometer and GPS is 13.8 (out of 14 days of measurement). The average wearing days for the mobile phone with entries for *MyFootprints* and *Travel Diary* are 6.6 and 7 days, respectively (out of 7 days of measurement for each program). Of course, when we enter the data analysis phase our group will need to determine the actual number of valid wear days based on the number of valid hours for each day for each device. Nonetheless, this preliminary "peak" at the data on wear time is promising.

LIMITATIONS

Our methods and analyses are based on objective measures of location and physical activity; however, the devices and basic data

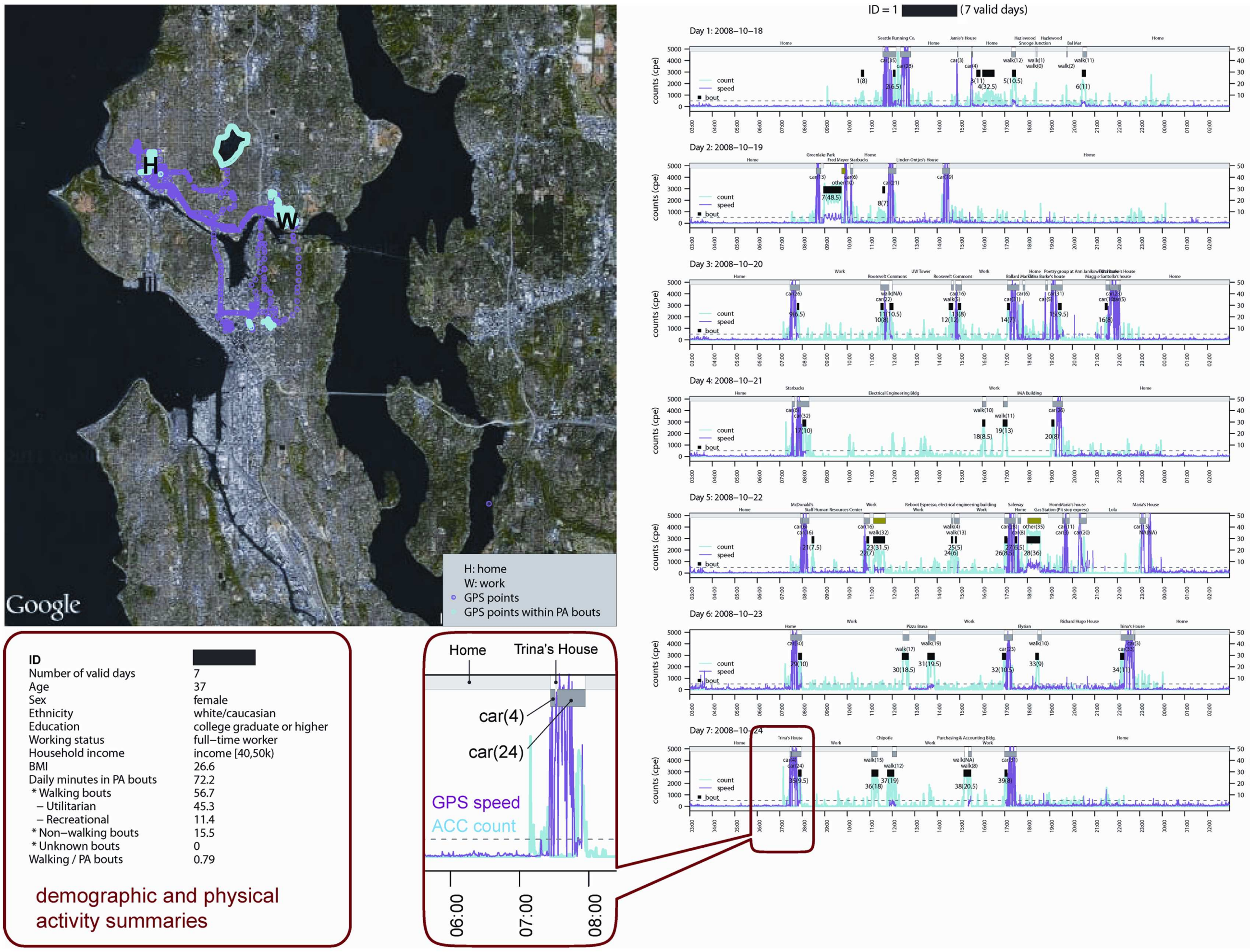


FIGURE 10 | Example LifeLog data collected over 1 week for a single subject. Graphs (right) indicate accelerometry counts in cyan, GPS speed in magenta, places and trips (gray boxes), and physical activity bouts (black rectangles) for each day. The map (left) shows all GPS points in magenta and those that occurred within a physical activity bout in cyan, as well as home and work locations ("H" and "W" markers). A summary of demographic characteristics and overall subject-level activity, as well as a close-up of graph data, are shown in the callouts.

processing methods for these are not perfect. GPS data of sufficient duration and quality are challenging given such inherent problems as urban canyons, cold starts, and limited battery life. When GPS data are not present, it is not possible to determine whether data loss was due to power being turned off or loss of signal. Likewise, when a GPS is powered on and recording, but not worn (e.g., recording when charging overnight), data will be logged even though these will not reflect actual movement patterns. Newer generation locational technologies using combined GPS and WiFi triangulation combined with other sensors for detecting movement through space are likely to provide better locational data in the near future.

Capturing behavior through time is problematic; we still rely on participants to record their travel and activity behavior. Although the use of smartphones as diary recording devices provides benefits such as obviating the need for data transcription and automatic time-stamping of recorded activities, there is still a relatively high participant burden to enter travel and activity information, regardless of the instrument used. Several investigators are exploring the use of portable cameras to capture periodic images for use in activity classification (52–54); however, such methods rely on manual annotation of images, which is a tedious and lengthy process. At this time, it is unknown when a reliable method for automatically classifying behaviorally defined activity types will be developed.

CONCLUSION

In summary, there is a growing interest in obtaining more precision and more information about the amount, type, and context of physical activity and other health behaviors. Newer devices (e.g., portable GPS) and their combined use offer opportunities to improve precision and collect this additional information. However, standard methods and procedures are needed to best capture and integrate the large volume of data obtained from these devices.

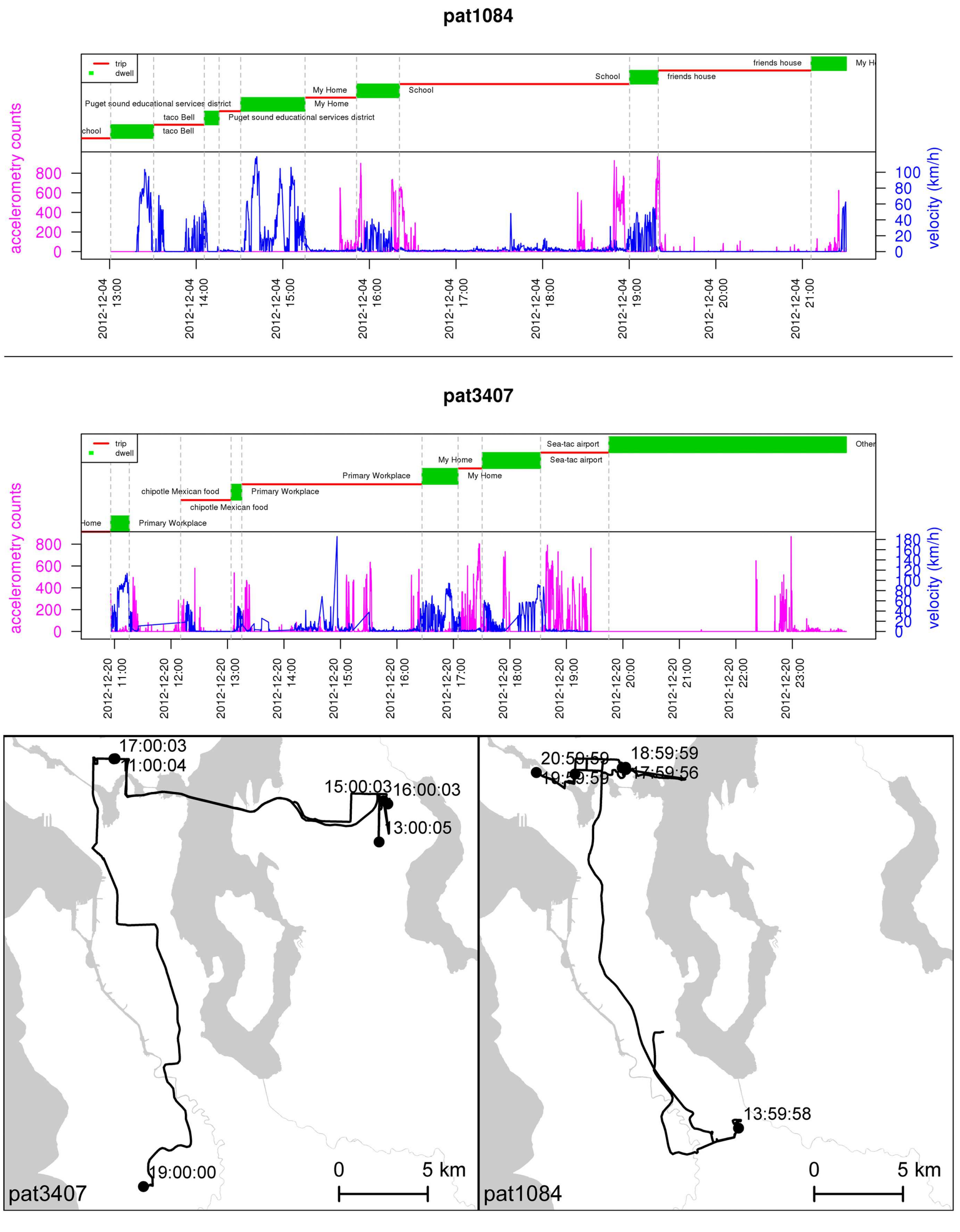


FIGURE 11 | One-day LifeLogs collected from a twin pair. The upper panel shows self-reported data on place (red) and trip (green) from the travel diary along with objective accelerometry counts (magenta) and GPS velocity (blue). The lower panel maps travel patterns for the same individuals over the same days, with markers shown at hourly intervals.

The integrative characteristics of the large datasets contained in LifeLogs and SmartMaps hold great promise for advancing spatial epidemiologic research, especially work whose goal is to facilitate behaviors that promote health.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at http://www.frontiersin.org/Journal/10.3389/fpubh.2014.00002/abstract

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Dynamic accuracy of GPS receivers for use in health research: a novel method to assess GPS accuracy in real-world settings

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The emergence of portable global positioning system (GPS) receivers over the last 10 years has provided researchers with a means to objectively assess spatial position in free-living conditions. However, the use of GPS in free-living conditions is not without challenges and the aim of this study was to test the dynamic accuracy of a portable GPS device under real-world environmental conditions, for four modes of transport, and using three data collection intervals. We selected four routes on different bearings, passing through a variation of environmental conditions in the City of Copenhagen, Denmark, to test the dynamic accuracy of the Qstarz BT-Q1000XT GPS device. Each route consisted of a walk, bicycle, and vehicle lane in each direction. The actual width of each walking, cycling, and vehicle lane was digitized as accurately as possible using ultra-high-resolution aerial photographs as background. For each trip, we calculated the percentage that actually fell within the lane polygon, and within the 2.5, 5, and 10 m buffers respectively, as well as the mean and median error in meters. Our results showed that 49.6% of all ≈68,000 GPS points fell within 2.5 m of the expected location, 78.7% fell within 10 m and the median error was 2.9 m. The median error during walking trips was 3.9, 2.0 m for bicycle trips, 1.5 m for bus, and 0.5 m for car. The different area types showed considerable variation in the median error: 0.7 m in open areas, 2.6 m in half-open areas, and 5.2 m in urban canyons. The dynamic spatial accuracy of the tested device is not perfect, but we feel that it is within acceptable limits for larger population studies. Longer recording periods, for a larger population are likely to reduce the potentially negative effects of measurement inaccuracy. Furthermore, special care should be taken when the environment in which the study takes place could compromise the GPS signal.

Keywords: global positioning system, travel mode, environmental conditions, Qstarz BT-Q1000XT, epoch, validation study, dynamic accuracy

INTRODUCTION

The importance of understanding the environmental context in which health-related behaviors take place is becoming increasingly accepted in behavioral health research [see Ref. (1) for a comprehensive overview of the reviews in this field]. The emergence of portable global positioning system (GPS) receivers over the last 10 years has provided researchers with a means to objectively assess spatial position in free-living conditions. Coupled with other instruments, such as motion sensors (accelerometers), travel diaries, and geographic information systems (GIS), the positional data obtained from GPS can enable the environmental context of health-related behaviors to be elucidated (2). Each year, new GPS receivers are released that improve on previous generations of devices, becoming smaller, cheaper, more reliable, and with extended battery duration. As a consequence, the collection of supplementary contextual information in behavioral health research has become more feasible than ever. GPS has for example been used to investigate the effects of food environments on eating patterns (3), various physical activity related behaviors [see Ref. (4) for a review], independent mobility in youth (5, 6), and the health effects of exposure to pollutants (7, 8). Given the advantages of the objective assessment of environmental exposure, it is likely that the use of GPS in health research will continue to increase.

However, the use of GPS in free-living conditions is not without challenges: a recent review revealed that many studies had significant problems with data loss due to signal drop-outs, loss of battery power, and poor participant compliance (4). Issues with inconsistent GPS signals, such as total signal loss or poor accuracy typically occur due to signal reflection off buildings, or shading by buildings or tree-cover. Signal strength can also be influenced by the availability of GPS satellites in the sky during different times of the day, season, and at different latitudes (lower altitude, northern hemisphere locations typically have the best satellite coverage). The signal strength at a given time and location is expressed as the dilution of precision (DOP), given these limitations, the purpose of this study is to establish the measurement accuracy of GPS receivers under a variety of environmental conditions prior to implementation as a research tool.

Previous research has demonstrated the varying levels of positional accuracy between different GPS receivers and environmental conditions when stationary (9). Conducting a high quality assessment of the static positional accuracy of GPS units is relatively straightforward: GPS units are placed on an official geodetic point for which the exact location is known, with the difference between the recorded position and the actual position of the geodetic point providing an estimate of positional accuracy [see, e.g., Ref. (9)]. Evaluating the positional accuracy of GPS units under dynamic conditions (i.e., free-living) is more challenging as precise data on the "true" route is often not readily available. In many GIS roads are digitized as center-lines with the road-width specified as a category in the attribute-table; i.e., data on the exact width of vehicle lanes, bicycle lanes, and sidewalks are often not available in the GIS. Different methods have been used by various researchers to test the dynamic accuracy of many different GPS devices. Rodriguez et al. (10) used the average location recorded from multiple units of the same device (Garmin Foretrex 201) to assess accuracy under a variety of free-living scenarios. They found that the average distance between each unit and the average of five other identical units was 10.7 ± 11.9 m in open space scenarios and 20.1 ± 21.8 m in clustered development scenarios (10). However, the method used by Rodriguez and colleagues was essentially a test of consistency across identical devices, rather than systematically testing dynamic accuracy under different environmental conditions. The dynamic accuracy of five GPS devices (GlobalSat DG-100 and BT-335, Wintec WBT-201, Visiontac VGPS-900, Qstarz BT-Q1000X) was tested by Wu et al. (11) by digitizing six different routes on a high resolution (1 m) aerial photograph and calculating the percentage of points within 10 and 20 m of the route. Results showed considerable variations by route, mode of travel, and GPS device, with values ranging from 20 to 50% of points falling within 10 m of the route. Each route was traveled twice, and there were considerable differences in accuracy between the two runs (11). The median error varied between GPS devices from 3.5 m for the GlobalSat DG-100 to 5.5 m for the Visiontac VGPS-900; the Qstarz BT-Q1000X had a median error of 4.6 m (11). The study by Wu and colleagues focused on testing the difference between devices and did not systematically test different environments, for different modes of transport. Wieters and colleagues (12) tested the dynamic accuracy of four GPS devices (Garmin Forerunner 205, Garmin Foretrex 201, GlobalSat DG-100, Wintec Easy Showily). Four test persons walked one-time along one pre-defined route and the percentage of recorded data points that fell within five feet of the prescribed course was calculated; more detail on how this was done was not reported in the paper. For the four different GPS devices, the percentage of points that were correctly located on the sidewalk ranged from 57.2 to 76.0% (12). Beekhuizen and colleagues (13) tested dynamic accuracy of two vehicle tracking GPS devices (TracKing Key Pro and the Adapt AD-850), as well as a hiking GPS (Garmin Oregon 550). Their test included assessment of the dynamic accuracy in various modes of transport during commuting. The "true routes" of 12 test persons were mapped as a line on top of a high resolution aerial photograph and the median positional errors compared to these routes were calculated. Each route was traveled twice and the median error was 3.7 m for walking, 2.9 m for biking, 4.8 m for train, 4.9 m for bus, and 3.3 m for car trips (13). There were no significant differences between the three tested devices. In a second phase, spatial accuracy was tested during a walking trip under six different environmental conditions and repeated 10 times. There were considerable differences and the overall median error ranged from 2.2 m for a relatively open residential area to a median error of 7.1 m for a commercial high-rise area (13).

The results from these four studies are difficult to compare directly to each other as they used different methods and devices. Furthermore, none of these studies reported studying the potential interaction of various modes of transport within different environmental conditions. Since participants in free-living studies are likely to spend a significant amount of time in dynamic movement, and transportation mode is an important correlate of health, it is vital to know the dynamic accuracy during different modes of transport under a variety of environmental conditions. Further, if researchers wish to study use of existing facilities such as bicycling lanes, or environmental changes such as new sidewalks and pedestrian crossings, it is important to understand whether tracking behavior at this level of accuracy is possible under different environmental conditions.

Finally, the potential effects of changing the data collection interval on positional accuracy are poorly understood. It could be that collecting data more often (i.e., with a shorter epoch) improves the overall positional accuracy by being able to track a route more precisely, e.g., in situations with many changes of direction the number of "cut corners" might be reduced. Frequent pinging to the satellite, however, in high interference environments could result in more missing or misplaced data. Further, the advantage of collecting more points might be outweighed by reduction in the total data collection period due to the available device memory filling-up more quickly without improving spatial accuracy.

The aim of this study was to test the dynamic accuracy of a portable GPS device under real-world environmental conditions, for four modes of transport, using three data collection intervals.

MATERIALS AND METHODS

INSTRUMENTS

We selected four routes in the City of Copenhagen, Denmark, to test the dynamic accuracy of the Qstarz BT-Q1000XT GPS device. This model was selected not only for its common usage in previous and current research, but also for its relatively high accuracy under various environmental conditions, good signal acquisition time, data storage, and battery life (9). Two research assistants followed a predetermined protocol of walking, cycling, driving, and bussing on all routes, in both directions, while wearing three GPS devices, each set to record data at a different data collection interval (epoch).

TEST ROUTES

The four test routes were on different bearings, passing through a variation of environmental conditions. We selected the routes on different bearings as we hypothesized that the effect of buildings

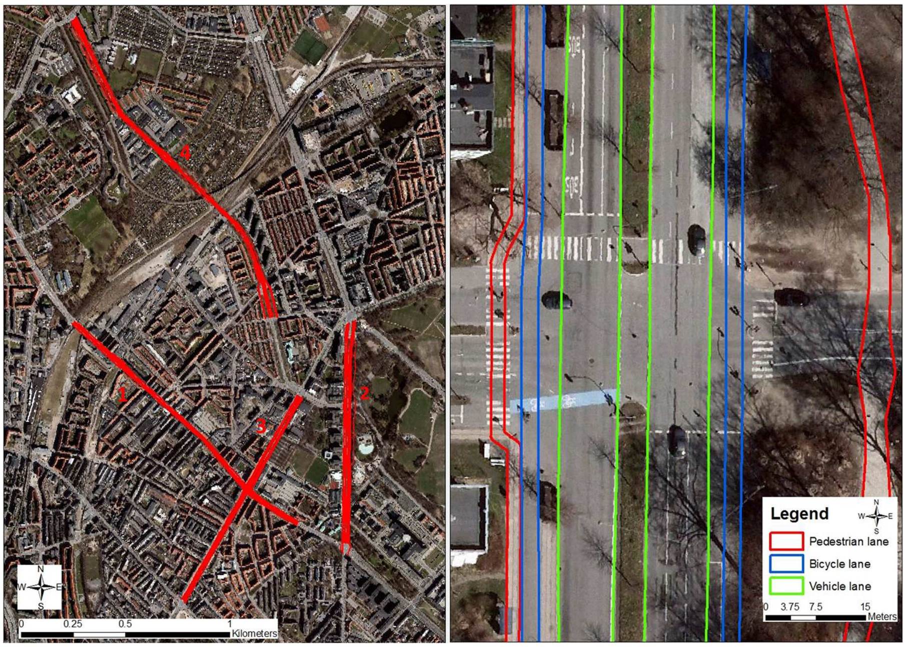

FIGURE 1 | Location of the four study routes (left) and example of the detailed digitization of vehicle, bicycle, and pedestrian lanes (right).

shading for GPS signal reception would vary according to bearing. In Denmark, the position of satellites in the sky is predominantly southwards, which, in theory, should favor satellite reception on more north–south directed routes, whereas east–west directed routes, especially the south-side of route, are more likely to be shaded from good satellite reception by adjacent buildings. We furthermore made sure that each route consisted of separate pavements, bicycle lanes and vehicle lanes in both directions, and that public busses were running along each route. Each route consisted of a walk, bicycle, and vehicle lane in each direction, in total six different lanes per route (see **Figure 1**, left). All 24 lanes were manually digitized as polygons in ArcGIS 10.1 using ultra-high-resolution (10 cm pixels) aerial photographs as background. The actual width of each walking, cycling, and vehicle lane was digitized as accurately as possible. Euclidean (as the crow flies) buffers of 2.5, 5, and 10 m were created for each lane (see **Figure 1**, right). To classify the environment along the routes, all buildings along the route were buffered with 25 m, and the environment was classified as open if there were no buildings within 25 m of the route, half-open if there were buildings within 25 m on one side of the route, and an urban canyon if there were buildings closer than 25 m on both sides. Finally, along one of the routes, there was a smaller area where the environment was classified as tree-covered since there were trees next to the lanes and the tree canopy was fully covering the bicycle and pedestrian lanes. Route 1 was 1.4 km long relatively narrow road with five to six story buildings directly adjacent to the route for the most part, and on a bearing varying between 332° and 334°. Route 2 was 1.1 km long relatively wide road with a large park on one side of the road, with part of road under tree-cover, and scattered six to seven story buildings close to the road on the other side. Route 2 ran almost exactly north–south with a bearing of 1°. Route 3 was 1.2 km long, with some sections with five to six story buildings directly adjacent, whereas other sections only had buildings on one side. The bearing for route 3 was 22°. Route 4 was 1.8 km long on a bearing varying between 324° and 338°. For the most part, route 4 did not have buildings directly adjacent to the road; they were typically placed 10–25 m from the road.

DATA COLLECTION

Two research assistants followed a predetermined protocol of walking, cycling, driving, and bussing on all routes, in both directions, recording data on 300 trips. The date and exact start and end times of each trip were recorded by the research assistants, using a digital watch that was synchronized to the GPS satellite time. To be able to determine if GPS data recording intervals influenced the positional accuracy, data were collected simultaneously at three different epochs, 5, 15, and 30 s respectively. The three GPS devices were worn on one elastic belt around the waist, covered by clothing. Using the open source bt747 GPS software (www.bt747.org), the GPS units were set to collect longitude and latitude, elevation, speed, the number of satellites used and in view, the satellite number of the used satellites, and the DOP values, for the horizontal (HDOP), vertical (VDOP), and positional, i.e., 3-dimensional (PDOP) DOP. DOP values express the expected uncertainty associated with the alignment of available satellites at a certain time and location; a DOP value <1 is considered ideal, one to two is excellent, whereas a DOP value of more than 10 indicates unfavorable satellite geometry.

DATA PROCESSING

After each trip the data were downloaded using the open source bt747 GPS software and not processed further before analyses (i.e., potential outliers or otherwise clearly faulty data was not removed). Based on the date–time log for start and end times of each trip, all GPS points belonging to each trip were identified. Using the spatial join function in ArcGIS, we identified the GPS points for each trip that fell within the corresponding lane polygon, or within the 2.5, 5, and 10 m buffers of that lane polygon. For each trip, we calculated the percentage that actually fell within the lane polygon, and within the 2.5, 5, and 10 m buffers respectively, as well as the mean and median error in meters. We differentiated results for each of the four trip modes, for each of the three data collection epochs, and for each of the four environmental types.

RESULTS

OVERALL DYNAMIC SPATIAL ACCURACY

The results in **Table 1** show that the overall median distance error from the lane traveled in was 2.9 m (IQR 0.4–8.4 m), and that 78.9% of the GPS points fell within 10 m of the actual lane and 46.9% within 2.5 m. The median error of the GPS receiver during walking trips was 3.9, 2.0 m for bicycle trips, 1.5 m for bus, and 0.5 m for car. The 10-m dynamic accuracy was 73.5% (walk), 86.8% (bicycle), 84.9% (bus), and 89.3% (car), respectively. Across modes of transport and type of area, the median error for the three data collection epochs was the same, and also the IQR's and percent of points within 2.5 and 10 m from the lane was similar. The four different types of areas along the route showed considerable variation in the median error: 0.7 m in open areas, 2.6 m in half-open areas, and 5.2 m in urban canyons. Points on the small tree-covered section had a median error of 1.0 m. There were also clear differences between the four routes, with a 0.7-m median error for route 2, 3.5 and 3.7 m for routes 3 and 4, respectively, and 4.5 m for route 1.

VARIATION BY AREA TYPE AND TRIP MODE

As can be seen in **Table 2**, the GPS performed poorest for walking trips in urban canyons (with lots of five to six story directly adjacent buildings) with a median error of 6.7 m. Walking lanes were typical directly adjacent to buildings, and as low as 61.9% of all GPS points were within 10 m of the walking lanes. GPS data collected during car trips within urban canyons had a surprisingly high 10 m accuracy, 88.4%, only slightly less than the 89.5% in open areas. The median error for car trips in urban canyons was 1.5 m.

VARIATION BY AREA TYPE, TRIP MODE AND DATA COLLECTION EPOCH

Looking at the results in **Table 3** for the dynamic spatial accuracy of the GPS devices in different data collection epoch, divided by area types and by trip modes, it seems that the differences are small. In urban canyons however, the shortest epoch seems to perform slightly better for all trip modes; the median error is 0.2–0.4 m lower at a 5-s data collection epoch than it is at a 15-s epoch. The 15-s epoch does not consistently perform better than the 30-s epoch, but slight improvements can be seen in some conditions, e.g., for walking and bicycling in urban canyons the median error is lower at 15 s compared to a 30-s epoch.

VARIATION BY MODE AND ROUTE

The data presented in **Table 4** shows differences between the half-open sections of the four routes, for walking, bicycling, and bus trips. Clear differences between the routes can be seen, even though the points included in **Table 4** were all within half-open environments. Across the three trip modes, the GPS's performed best along route 2, with a north–south bearing (median error 0.0–0.9 m). For walking the GPS performed poorest on route 4, with a northwest–southeast bearing (median error 5.4 m) while it

Table 1 | Dynamic spatial accuracy in percent of points and mean and median errors in meters, overall as well as divided by trip mode, epoch, area type, and route.

		n	% Of points			Distance from lane in meters				
			Within lane	<2.5 m Outside of lane	<10 m Outside of lane	Mean	SD	Median	IQR	
Trip mode	Walking	40,154	13.2	40.0	73.5	8.2	11.8	3.9	1.0	10.7
	Bicycle	13,777	22.3	55.1	86.8	5.0	8.7	2.0	0.2	5.5
	Bus	11,656	37.1	57.3	84.9	5.7	12.0	1.5	0.0	6.2
	Car	2338	45.6	64.4	89.3	4.1	9.5	0.5	0.0	4.4
Epoch	5 s	45,008	20.3	47.0	79.3	6.8	10.7	2.9	0.4	8.1
	15 s	15,394	20.5	46.7	77.5	7.4	11.7	2.9	0.3	8.9
	30 s	7523	19.8	46.6	77.5	7.7	13.6	2.9	0.4	8.8
Area type	Open	5827	36.3	71.9	88.8	4.3	9.6	0.7	0.0	2.9
	Half-open	36,834	20.8	49.1	82.2	5.9	9.3	2.6	0.3	7.0
	Urban canyon	20,171	14.3	33.3	69.6	9.3	12.4	5.2	1.3	12.2
	Tree-covered	2656	24.3	74.2	97.9	1.9	3.0	1.0	0.0	2.6
Route	1	19,751	15.5	36.6	71.7	9.0	13.1	4.5	1.0	11.5
	2	13,801	34.7	76.0	92.8	3.6	10.3	0.7	0.0	2.4
	3	14,958	18.0	42.7	76.0	7.6	11.1	3.5	0.6	9.6
	4	19,415	16.5	39.9	78.0	6.9	9.4	3.7	0.9	8.8
Overall		67,925	20.3	46.9	78.7	7.0	11.3	2.9	0.4	8.4

Table 2 | Dynamic spatial accuracy in percent of points and mean and median errors in meters, for four modes of transport within three area types.

Area type	Trip mode	*n*	% Of points			Distance from lane in meters				
			Within lane	<2.5 m Outside of lane	<10 m Outside of lane	Mean	SD	Median	IQR	
Open	Walking	2592	26.6	43.6	85.9	5.1	10.2	1.0	0.0	3.3
	Bicycle	1559	37.8	35.9	91.4	3.4	7.7	0.6	0.0	2.7
	Bus	1399	50.3	23.0	91.2	3.8	10.0	0.0	0.0	2.8
	Car	277	48.0	22.4	89.5	4.3	9.8	0.1	0.0	3.0
Half-open	Walking	22,910	13.4	27.6	77.0	7.2	10.1	3.6	0.9	9.2
	Bicycle	7620	24.7	36.5	91.3	3.9	7.3	1.6	0.0	4.1
	Bus	5410	40.4	22.0	89.7	4.0	8.0	1.0	0.0	4.8
	Car	894	58.7	15.8	92.2	2.5	5.4	0.0	0.0	2.7
Urban canyon	Walking	11,124	8.0	18.3	61.9	11.5	14.0	6.7	2.3	15.7
	Bicycle	3969	13.1	22.1	76.1	7.7	10.7	4.4	1.4	9.6
	Bus	3959	27.0	17.5	79.1	6.1	8.2	3.4	0.0	8.7
	Car	1119	35.7	21.1	88.4	4.2	7.0	1.5	0.0	5.3

did poorest for cycling on route 1, also on a northwest–southeast bearing (median error 4.5 m), and for bus trips on route 3, types on a northeast–southwest bearing (median error 2.4 m).

The HDOP values (data not shown) for 76.4% of the data points were under 1, which is considered ideal, and 95.2% had a value lower than 2, which is considered excellent. The highest HDOP value (6.2) was recorded during one walking trip along route 2, but the median error or percentage of points within the lane during this trip were similar to those of other walking trips along route 2 (data not shown).

DISCUSSION

The aim of this study was to test the dynamic accuracy of a high performing GPS device that many researchers in public health are employing (Qstarz Q1000XT portable GPS receiver) under different real-world environmental conditions, for four modes of transport, using three data collection epochs. Our results showed that almost half (49.6%) of all ≈68,000 recorded GPS points fell within 2.5 m of the expected location, and 78.7% fell within 10 m. The median error was 2.9 m. There were differences by trip mode, area type, and route, while the three data collection epochs had the same median error (2.9 m for all epochs). The median error of the GPS receiver during walking trips was 3.9, 2.0 m for bicycle trips, 1.5 m for bus, and 0.5 m for car. The four different types of areas showed considerable variation in the median error: 0.7 m in open areas, 2.6 m in half-open areas, and 5.2 m in urban canyons. There were also clear differences between the four routes, with a 0.7-m median error for route 2, 3.5, and 3.7 m for routes 3 and 4, respectively, and 4.5 m for route 1. In practice our results indicate that care should be taken when a high spatial accuracy is required. For example, in study that tries to determine the use of a new playground element, a median error of 5 m under dense urban conditions could mean that a large percentage of points that fall "on" the playground element might in reality be "on" the adjacent element, or vice versa, which could easily lead to wrong conclusions.

Comparing our results to those of Beekhuizen et al. (13), the median error of walking was comparable (3.9 m in our study versus 3.7 m in theirs), while the median errors for cycling, car, and bus trips were smaller in the present study (cycling 2.9 versus 2.0 m; bus 4.9 versus 1.5 m; and car 3.3 versus 0.5 m). Roughly 85% of all errors in the Dutch study were <10 m (13), which is slightly better than the 78.7% in our study. This could be due to the fact that the data was gathered during commuting trips that were located outside dense urban areas (where interference is a problem) to a much larger extent than the present study.

Beekhuizen et al. (13) reported median errors for walking trips in a high-rise commercial area (median error 7.1 m), which is similar to our median error recorded during walking trips in urban canyons (6.7 m). Our finding that there is an interaction between environment and mode of transport was, as far as we know, not reported by other researchers. The accuracy of GPS data collected during car trips within urban canyons was surprisingly high, with a 10-m accuracy of 88.4%, and only slightly less than in open areas (89.5%). The median error for car trips in urban canyons was only 1.5 m; however, this could partly be due to the fact that sidewalks and bicycle paths were typically less wide than the vehicle lanes and considerably closer to buildings. In some parts of the route, the vehicle lane could be as wide as 12 m, which likely increased the chance of the GPS point falling within the lane polygon. This does not diminish the fact that for car and bus trips in real-world settings, the Qstarz GPS device has a surprisingly good spatial accuracy, also in difficult environmental conditions. Nonetheless, our finding also implies that care has to be taken when studying walking and/or cycling behavior in dense urban environments. As walking and cycling lanes are typically located closer to buildings and much narrower than vehicle lanes, the spatial accuracy can be compromised. Furthermore, we also found differences between routes on different bearings, within similar environmental conditions. These differences are likely explained by a different degree of shading by buildings depending on their positions in relation to the observed route. In practice, this means that the dynamic error

Table 3 | Dynamic spatial accuracy in percent of points and mean and median errors in meters, for three different data collection epochs, within four modes of transport, within three area types.

Area type	Trip mode	Epoch (s)	*n*	% Of points			Distance from lane in meters				
				Within lane	<2.5 m Outside of lane	<10 m Outside of lane	Mean	SD	Median	IQR	
Open	Walking	5	1673	26.5	44.6	87.3	4.6	9.2	1.0	0.0	3.1
		15	624	28.2	40.4	84.0	5.7	11.0	1.0	0.0	3.4
		30	295	23.7	44.4	81.7	6.5	13.3	1.1	0.0	4.2
	Bicycle	5	1013	38.7	36.4	91.7	3.1	7.0	0.6	0.0	2.5
		15	364	36.3	36.3	90.1	3.9	8.7	0.6	0.0	2.8
		30	182	35.7	31.9	92.3	4.0	9.2	0.9	0.0	3.0
	Bus	5	910	51.9	21.5	90.4	3.8	10.0	0.0	0.0	2.7
		15	326	50.0	25.5	93.3	3.8	11.1	0.0	0.0	2.4
		30	163	41.7	26.4	91.4	3.5	7.9	0.7	0.0	3.4
	Car	5	171	50.9	21.6	92.4	3.1	7.4	0.0	0.0	2.7
		15	68	52.9	22.1	91.2	3.5	8.4	0.0	0.0	2.5
		30	38	26.3	26.3	73.7	11.1	17.1	1.9	0.0	10.9
Half-open	Walking	5	15,271	13.2	27.0	77.6	7.0	9.6	3.7	1.0	9.0
		15	5130	14.1	28.7	75.2	7.8	11.0	3.4	0.8	9.9
		30	2509	13.2	28.9	76.5	7.4	10.7	3.5	0.8	9.4
	Bicycle	5	5069	25.7	37.8	92.5	3.6	7.0	1.5	0.0	3.8
		15	1675	22.9	33.6	87.3	4.8	8.3	2.0	0.1	5.4
		30	876	22.1	35.3	91.3	3.9	6.7	1.9	0.2	4.5
	Bus	5	3531	40.5	22.3	89.9	3.9	7.9	0.9	0.0	4.7
		15	1246	40.1	21.2	89.4	4.3	8.6	1.0	0.0	5.1
		30	633	40.4	21.6	89.1	4.0	7.4	1.0	0.0	5.1
	Car	5	578	62.5	13.8	94.3	2.2	5.2	0.0	0.0	2.1
		15	219	54.3	21.0	90.4	2.5	4.7	0.0	0.0	2.5
		30	97	46.4	15.5	83.5	4.4	7.2	0.4	0.0	5.6
Urban canyon	Walking	5	7430	8.0	18.6	62.1	11.5	13.9	6.6	2.3	15.7
		15	2533	8.3	17.6	62.9	11.1	12.8	6.8	2.3	15.2
		30	1161	7.3	18.3	58.5	12.7	16.7	7.2	2.4	16.5
	Bicycle	5	2663	13.2	22.9	76.4	7.3	9.7	4.3	1.3	9.6
		15	875	12.9	19.3	76.5	8.0	11.1	4.7	1.6	9.5
		30	431	13.0	22.5	73.8	9.2	15.3	4.8	1.4	10.6
	Bus	5	2626	27.2	17.3	80.6	5.8	7.7	3.3	0.0	8.1
		15	908	27.0	16.9	76.8	6.7	9.6	3.7	0.0	9.6
		30	425	26.1	19.5	75.3	6.4	8.4	3.6	0.0	9.9
	Car	5	735	36.1	21.6	89.0	4.0	6.5	1.3	0.0	4.8
		15	255	38.0	20.4	87.8	3.9	6.1	1.6	0.0	6.0
		30	129	28.7	19.4	86.0	5.9	10.6	2.7	0.0	5.9

will differ depending on the angle toward the available satellites, which will differ during the day.

STRENGTHS AND WEAKNESSES

This study is, to our knowledge, the largest and most rigid test of dynamic GPS accuracy conducted to date. Earlier studies (10–13) have also assessed the dynamic accuracy, but with different methods and smaller samples, and without looking specifically at different modes of transport in varying environmental conditions, or at different data collection epochs. Digitizing all traffic lanes individually on top of high resolution aerial photographs led to highly detailed route maps that were used as the "true" route.

This study demonstrated that it might be important to test routes with narrower vehicle lanes, although such streets may not have separate bicycle lanes or public buses along the same route. In addition, all data were collected in late fall, winter, and early spring, and most trees had little or no leaves, which could have improved the average satellite reception on two of the four routes. A study comparing the impact of tree-cover across the seasons would be an important next step.

Furthermore, there is a range of other factors not included in this study that could influence the positional accuracy. GPS receivers require a direct line of sight with at least four satellites to determine a spatial position by means of triangulation.

Table 4 | Dynamic spatial accuracy in percent of points and mean and median errors in meters, for four different routes, within three modes of transport, within half-open areas.

Half-open	Route	*n*	% Of points			Distance from lane in meters				
Trip mode			**Within lane**	**<2.5 m Outside of lane**	**<10 m Outside of lane**	**Mean**	**SD**	**Median**	**IQR**	
Walking	1	3776	11.5	24.2	69.4	10.0	15.0	4.7	1.3	13.0
	2	4179	29.0	48.4	95.5	2.1	4.5	0.9	0.0	2.3
	3	3447	15.5	33.7	82.5	6.0	9.2	2.6	0.5	6.7
	4	11,508	7.7	19.3	71.1	8.5	9.1	5.4	2.3	11.4
Bicycle	1	1339	11.2	23.2	76.8	7.5	9.4	4.5	1.4	9.3
	2	1291	35.2	47.8	95.3	2.8	8.2	0.6	0.0	1.9
	3	1099	22.7	32.2	83.3	5.8	9.7	2.0	0.2	6.0
	4	3891	26.3	38.7	97.1	2.5	4.1	1.4	0.0	3.5
Bus	1	1094	35.9	20.5	83.1	5.2	9.3	1.8	0.0	6.5
	2	865	58.6	19.5	98.5	1.5	2.6	0.0	0.0	1.7
	3	1211	29.8	20.8	77.5	7.5	12.4	2.4	0.0	9.0
	4	2240	41.3	24.2	96.2	2.5	3.8	0.8	0.0	4.0

In obstructed conditions, such as indoors or underneath a tree canopy, or in the "shade" of a tall buildings, signal inconsistencies arising from limited satellite visibility, and/or reflection of signal off nearby buildings or objects (multipath effect) can result in significant positional error (7, 9, 10, 14). In particular the presence of water reservoirs, metal, or other reflecting surfaces tends to result in so-called multipath effect; i.e., the GPS does not only receive signals directly from the satellites, but also signals reflected from such surfaces.

Other potential sources of GPS inaccuracy include timing errors, orbital errors, and atmospheric disturbances (9). The Qstarz Q1000XT is equipped with differential GPS (DGPS) capability – a system that broadcasts corrections from ground-based reference stations to surrounding GPS receivers in real time – which can reduce this type of errors.

RECOMMENDATIONS FOR USING GPS IN PUBLIC HEALTH STUDIES

Based on our findings, the positional accuracy of the Qstarz Q1000XT GPS receiver in dynamic and varied conditions is acceptable for use in larger population studies, especially with relatively long data collection periods (7 days or more). For studies where participants live in, or travel through, dense urban areas we would recommend conducting a dynamic accuracy test similar to the one presented here to determine if the accuracy achieved is acceptable in relation to the research question. Based on our findings, we would also recommend that researchers interested in recording behavior in specific dense urban locations (e.g., recording the use of new pedestrian or bicycle facilities, or other challenging environments such as schoolyards) to field test GPS accuracy in those specific locations, during different times of the day to determine if the error is acceptable for their study. In future, it will be useful to also test the dynamic accuracy of other GPS units to be used for public health studies.

CONCLUSION

Our results showed that almost half (49.6%) of all ≈68,000 GPS points recorded with the Qstarz Q1000XT GPS units fell within 2.5 m of the expected location, 78.7% fell within 10 m and the median error was 2.9 m. The median error of the GPS receiver during walking trips was 3.9, 2.0 m for bicycle trips, 1.5 m for bus and 0.5 m for car. The four different types of areas showed considerable variation in the median error: 0.7 m in open areas, 2.6 m in half-open areas and 5.2 m in urban canyons.

The dynamic spatial accuracy of this device is not perfect, but we feel that it within acceptable limits for larger population studies. However, it is important for researchers to consider when deciding on sample sizes and recording periods. Longer recording periods for a larger population are likely to reduce the potentially negative effects of measurement inaccuracy. Furthermore, special care should be taken when the environment in which the study takes place could compromise the GPS signal (i.e., very dense urban locations).

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Developing suitable buffers to capture transport cycling behavior

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The association between neighborhood built environment and cycling has received considerable attention in health literature over the last two decades, but different neighborhood definitions have been used and it is unclear which one is most appropriate. Administrative or fixed residential spatial units (e.g., home-buffer-based neighborhoods) are not necessarily representative for environmental exposure. An increased understanding of appropriate neighborhoods is needed. GPS cycling tracks from 78 participants for 7 days form the basis for the development and testing of different neighborhood buffers for transport cycling. The percentage of GPS points per square meter was used as indicator of the effectiveness of a series of different buffer types, including home-based network buffers, shortest route to city center buffers, and city center-directed ellipse-shaped buffers. The results show that GPS tracks can help us understand where people go and stay during the day, which can help us link built environment with cycling. Analysis showed that the further people live from the city center, the more elongated are their GPS tracks, and the better an ellipse-shaped directional buffer captured transport cycling behavior. In conclusion, we argue that in order to be able to link built environment factors with different forms of physical activity, we must study the most likely area people use. In this particular study, to capture transport cycling, with its relatively large radius of action, city center-directed ellipse-shaped buffers yielded better results than traditional home-based network buffer types. The ellipse-shaped buffer types could therefore be considered an alternative to more traditional buffers or administrative units in future studies of transport cycling behavior.

Keywords: cycling, transport, GPS, built environment, physical activity, MAUP, buffers

INTRODUCTION

Built environment characteristics can influence health; both directly and indirectly, linked to health-related behavior and activities in general (1–4). Notwithstanding, ongoing discussions on defining the relevant geographic extent when studying built environment characteristics have not yet resulted in a commonly accepted "best practice" for defining neighborhoods. Different ecological and multilevel analyses often use varying notions of neighborhood which has shown to be problematic (5, 6). The modifiable areal unit problem (MAUP) is often discussed as it is related to the geographic scale and unit of aggregation. Correlation and association might change unpredictably as the scale and unit of aggregation changes (7). This is challenging as "any study about neighborhoods is a spatial investigation" (8) and "effective neighborhoods, such that they exist as contiguous geographic areas, are not likely to be neat circles" (7). Furthermore, Kwan has argued that the uncertain geographic context problem (UGCoP) is as fundamental as MAUP as the spatial and temporal uncertainty of where, when, and how long individuals experience environmental influences is great (9). This might explain inconsistencies in research findings as the commonly used methods may not correctly represent the spatial area in which the behavior in question occurs (5, 10, 11). Administrative units, which are often used as "neighborhoods," simplify and fragment space which leads to potential misestimating of associations between the built environment and behavior (5, 12). Nevertheless, in real life it might be necessary to simplify assumptions to make a "draft of reality" that allows us to conceptualize neighborhoods in a useful way (7). Simplification and the fact that information is often easily available for administrative units might explain the numerous studies using them. Recommendations on using person-centered neighborhoods to better reflect a more reasonable exposure area have been published, and these neighborhoods are typically described as centers (e.g., home address) with boundaries created on the basis of a threshold distance. This threshold distance varies from study to study, but should ideally be related to the outcomes of interest, contextual factors, and study area (5).

Built environment correlates of walking have been reported (13–15), but literature concerning the relationship between the built environment and transport cycling is still limited. As many major cities and countries have discovered the potential of bicycles to replace cars on shorter trips in everyday transport, it is relevant to study the correlates of transport cycling (16). In Denmark, cycling holds an important place in everyday life with a cycle mode share of 16% of all trips (17, 18). More knowledge on how the built environment is associated with transport cycling is still wanted to be able to further increase the cycle mode share. Studies have shown that several factors are important for cycling, e.g., distance, network layout/street connectivity, residential density, land use mix, bicycle infrastructure, continuity of cycle lanes, traffic-controlling systems (19). The geographic area in which factors should be measured is not clear though. A geospatial analysis should use appropriate buffers, instead of fixed administrative areas (census tracts, zones), circular buffers, or even whole cities, yet there is limited empirical data to support an informed choice of study area (1, 5, 7, 20). It seems necessary to study cyclist's behavior and construct more appropriate buffers in relation to size and shape to better capture the environment cyclists' transport behavior occurs in (6, 20). The interaction with the built environment often results in asymmetric and directional behavior which varies accordingly to destinations of interest (sports, work, education, recreational areas, retail, etc.). Many cyclists can easily cover 5 km, in approximately 20 min (21), but they will most likely do so in a certain area and, for many transport purposes, probably in the direction a cluster of daily destinations. When studying active transport and human movement in general, people only access a fraction of the buffer areas commonly used for analysis (11, 22). The spatial uncertainty challenges might be lessened if the spatial unit is defined on the basis of behavior and contextual environment (9, 23).

Numerous papers have addressed the challenge of creating suitable buffers for different types of behaviors and discuss the use of, e.g., activity spaces, home ranges, kernel density estimations, daily life centers (hotspots), road network buffers, relative time travel zones, or similar methods (1, 10, 24–26). Rainham et al. emphasized the need for better knowledge of the dynamics of human movement and discuss the issues of spatial bounding, for example by using advanced data collection methods such as GPS technology. The aim should be to collect and analyze space–time–activity data where locations and movement of individuals can be followed and visualized as continuous tracks (1). Cycling behavior can be studied by GPS and provide empirical data to construct buffers which better capture cycling activity and allow for detection of destinations.

As Spielman and Yoo put it: "If you are going to spend time and money painting a picture of the relationship between the environment and health invest in the frame – unless the frame is well-designed, the painting is not going to be very good" (7).

Perchoux et al. outline components of mobility in relation to activities which are "daily life centers" (home, work, etc.), "clusters of minor activities locations" (restaurants, banks, daily shopping, etc.), "circulation corridors" (the familiar routes between usual places), and "transport interfaces" (underground stations or car parks) (5). In the present study, we used home as starting point, the city center as activity location cluster, and the shortest route network from home to city center as corridor.

The purpose of the present study is to develop a method using GPS technology and geographical information systems to analyze behavioral patterns and construct buffers that can be used for analyses of the relation between built environment and transport cycling. The percentage of GPS points per square kilometer is used as indicator for buffer effectiveness, attempting to reduce the non-frequented area of the buffer and address both MAUP and UGCoP (9). We hypothesize that the method is viable and that in the case of transport cycling, the further people live from a cluster of daily destinations, i.e., a city center, the more elongated and city center-directed their buffer should be in order to effectively capture transport cycling behavior.

MATERIALS AND METHODS

PARTICIPANTS, CITY LAYOUT, AND DESIGN

The participants were recruited among the regular cyclists ($N = 331$) who participated in the Danish part of the IPEN study ($N = 642$)[1] conducted in Aarhus. Aarhus is the second largest city in Denmark (323.893 inhabitants and approximately 470 km^2) and has a cycle mode share of approximately 17% of all trips (27). Aarhus is a typical Danish fjord city with a waterfront and relatively large differences in altitude from the inner city to the city outskirts. The city layout is traditional and consists of ring roads and main roads leading from the suburbs toward the inner city with smaller crossroads. There is a well-connected cycle path network throughout the city and in general good cycle facilities compared to many other European and American cities. Furthermore, Aarhus is an educational hub and approximately 50,000 students live and study in Aarhus. This leads to a relatively high cycling mode share (17%) as Danish students traditionally cycle more than other population groups (17). **Table 1** shows the characteristics of the participants.

The 331 participants who stated in the IPEN questionnaire that they were regular cyclists were invited to participate in the GPS study. Ninety-three joined the study, and 78 met the inclusion criteria of having at least one valid GPS-measured cycle trip during the study period.

GPS TRACKING

Participants were asked to wear the GPS (QStarz BT-Q1000X Travel Recorder; 15 s sampling interval) for 7 days (Wednesday to Wednesday) to be able to detect differences in travel behavior between weekdays and weekends. The QStarz BT-Q1000X Travel Recorder has shown to be an accurate GPS receiver with long battery life well-suited for free-living studies (28, 29). The cyclists were instructed to wear the GPS for transport cycle trips only, as other modes of transport were not of interest in the present study. Cycling for transport includes cycling to, e.g., work, education, shopping, sport facilities, etc. and does not include recreational trips. Non-transport trips were excluded based on the trip description in the diaries. One potential challenge with the use of GPS is the classification of transport modes after data collection (30–32) and by instructing the participants to limit the use to transport cycling only we hoped to overcome this. Daily SMS text messages were sent in the morning to remind participants to bring the GPS device and in the evening to remind them to charge the device if necessary. GPS device configuration and data download were performed using the open source BT747 GPS data logger software[2].

[1] www.ipenproject.org
[2] www.bt747.org

Table 1 | Participants' characteristics.

Participants' characteristics	Female	Male	Total
Participants, no. (%)	51 (65.4)	27 (34.6)	78
Age (years, mean ± SD)	34.7 ± 14.0	43 ± 12.1	37.5 ± 13.9
<30 years (%)	25 (49.0)	4 (14.8)	29 (37.2)
30–40 years (%)	11 (21.6)	8 (29.6)	19 (24.4)
40–50 years (%)	3 (5.9)	5 (18.5)	8 (10.3)
50–60 years (%)	7 (13.7)	7 (25.9)	14 (17.9)
Over 60 years (%)	5 (9.8)	3 (11.1)	8 (10.3)
Education and employment status, no. (%)			
Municipal primary and lower secondary school	1 (1.9)	1 (3.7)	2 (2.6)
Vocational	3 (5.9)	7 (25.9)	10 (12.8)
Upper secondary/high school	15 (27.4)	0 (0.0)	15 (19.2)
Higher education	32 (62.8)	19 (70.4)	51 (65.4)
Working	24 (47.1)	20 (74.1)	44 (56.4)
Studying	22 (43.14)	4 (14.8)	26 (33.3)
Welfare, pension	5 (9.8)	3 (11.1)	8 (10.3)

GPS DATA PROCESSING

GPS trackers yield massive data quantities and in order to make the best of the data, we decided to process and clean the data using the personal activity location measurement system (PALMS) which is developed and maintained by the University of California, San Diego. PALMS uses extreme differences in speed and altitude to filter out "bad" GPS point, and produces data sets that, among other, include trips separated by trip mode (30). The results from PALMS were imported into geographical information system software (ArcGIS 10.1) for further analysis.

Even though we only intended to collect GPS data for cycling trips, there were a large number of static GPS points in our dataset. Random manual inspection of the data revealed that this was primarily due to participants forgetting to turn the GPS device off at home or at their destination. In order to create cyclist buffers, more than three million GPS points were reduced to approximately 70,000 by excluding all stationary points and only using the points that PALMS had classified as being part of a trip. The GPS track points make it possible to outline the true geographic extent of transport cycling for each participant during the study period.

CREATION OF BUFFERS

From the GPS trip points, we calculated standard deviational (SD) ellipse buffers which are widely recognized as a good summary of the spatial patterns derived from all data collected with the GPS device (1, 26). We used both 1 and 2 SD ellipse buffers to be able to analyze the difference in area and effectiveness. The 1 SD ellipses theoretically include 68% of all the GPS points, whereas the 2 SD ellipses contain 95% of the GPS points. Furthermore, 1- and 2-km network buffers were constructed around every participant's residential address.

On the basis of the hypothesis that much cycling for transport would be directed toward a cluster of destinations, the location with the highest concentration of daily destinations was calculated for Aarhus, which is a city with a strong center orientation. Based on their relevance as regularly reoccurring destinations, the following building categories were counted as daily destinations: retail, supermarkets, sport-clubs, schools and educational institutions, and cultural facilities such as libraries and theaters. The centroid of the location with the highest density was used as city center point.

Based on the location of the highest concentration of daily destinations (the city center), we developed different types of directional buffers. Shortest route buffers (500, 750, and 1000 m wide respectively) from home to the city center were created as well as ellipse-shaped buffers based on the Euclidian distance (as the crow flies) and bearing (direction) from home to the city center. We created three ellipse-shaped buffers with a fixed width of 500, 750, and 1000 m, respectively, and a length based on the distance from home to city center, to which an additional 500 m were added (250 m in each end of the ellipses). Finally, we created one buffer with a variable width based on the distance to the city center; respondents living closer than 2 km from the city center were assigned a buffer with a 1-km width, whereas respondents living more than 5 km from the city center were assigned a buffer with a 500-m width. The buffer width for respondents living between 2 and 5 km from the city center gradually decreased from 1 km to 500 m. The aim was to decrease buffer size but still capture as many GPS points as possible in order to create buffers that most effectively capture transport cycling behavior without including large areas where people never cycle.

STATISTICS AND CALCULATIONS

Descriptive statistics (age, education, gender, number of cycling trips, cycled kilometers, and average trip length) were calculated for all participants, and all GPS cycle tracks were plotted on a map. Per person, we calculated the shortest network distance between home and all GPS points. Based on this, we calculated the distance within which a certain percentage of GPS points were located (1, 5, 10, 25, 50, 75, 90, and 100%). Pearson's correlation coefficients between distance from home address to city center and ellipse circumference, ellipse area, and ellipse length–width ratio were also calculated.

For each buffer type, we calculated the buffer area in square kilometers, the number of GPS points, and the percentage of GPS points per square kilometer. To be able to test which buffer performs best in capturing transport cycling behavior, we analyzed the "effectiveness" of different buffer types by comparing the relative density of GPS points. We hypothesized that buffers with a higher relative density of GPS points were more effective at capturing cycling behavior. Regression analyses were conducted to test buffer shape and effectiveness where buffer types without significant differences in effectiveness between respondents were considered more appropriate. Not finding a difference between participants indicates that the buffers are equally good at capturing respondents' GPS points, regardless of how far from the city center they live.

All statistical analysis were performed in STATA version 11 (STATA Corp., Fort Walton, TX, USA) and an alpha level of 0.05. Data conversions between ArcGIS and STATA, and vice versa, were carried out using Stat/Transfer, Circle Systems.

RESULTS

Table 1 shows the characteristics of the participants regarding age, gender, educational level, and employment status. **Table 2** shows the transport cycling in detail for the 7 days, with almost 25 cycling trips per person on average, and an average trip length of just under 500 m.

Visual inspection of the GPS tracks and analysis of GPS point distances showed patterns in transport cycling behavior that confirmed the initial hypothesis. Fifty percentage of GPS points were located within 1440.9 m for people living within 2 km of the city center. For people living more than 2 km from the city center, the distance to capture 50% of all GPS points was 2548.2 m. The maps and distance analysis indicate that people living further away from the city center have a transport pattern between home and city center whereas people living closer to the city center had points spread more equally in various directions.

This supports that the transport pattern differs according to where people live in the city, not only regarding their closest neighborhood, but also related to the distance from the city center, which should be taken into account when constructing transport cycling buffers. The buffer types with different distance thresholds are depicted in **Figure 1**.

The results from the analyses are shown in **Table 3**. For every buffer, the area, number of GPS points, percentage of GPS points, density (GPS points per square kilometer), and relative density (percentage GPS points per square kilometer) were calculated.

In theory, 1 and 2 SD ellipses capture 68 and 95% of all GPS points. But **Table 3** shows that the results for the 1 and 2 SD buffers were 64.5 and 97.8%, respectively. These discrepancies are due to the elliptic form making it impossible to include the exact percentage of GPS points. As a benchmark value, the 1 SD buffer captures 43% of GPS points per square kilometer, but as SD buffers can only be constructed when GPS data is available, they are not suitable for studies without GPS data. The most effective constructed buffer type is the directional ellipse 500 as it captures 29.3% of GPS points per square kilometer. The ellipse-shaped buffers capture a relative high percentage of GPS points while covering a smaller area with direction toward the city center.

The association between distance from home address to city center and percentage of GPS points captured by the network buffers showed negative correlation coefficients of −0.23 ($p < 0.05$) for the 1-km network buffer and −0.46 ($p < 0.05$) for the 2-km network buffer. The correlation coefficients between distance from home address to city center and ellipse circumference, ellipse area, and ellipse length–width ratio were also calculated. The coefficients were 0.40 ($p < 0.05$), 0.23 ($p < 0.05$), and 0.33 ($p < 0.05$), respectively. The coefficient between distance from home address to city center and total GPS points was −0.0015 ($p = 0.98$) (data not shown). The above mentioned coefficients indicate that people living further away from the city center had larger and more stretched ellipses but no difference in total number of GPS points collected during cycling trips.

Table 2 | Transport cycling for 7 days.

	Female	Male	Total
Cycling trips	22.6 ± 10.9	28.2 ± 25.4	24.5 ± 17.4
Cycling kilometers	9.8 ± 11.9	15.2 ± 21.0	11.7 ± 15.8
Average trip length (m)	484.1 ± 924.0	494.5 ± 418.3	487.7 ± 783.3

Table 4 presents the results from the regression analyses between the percentage of GPS points inside the 11 buffer types and distance from home to center. The results are supported by additional regression analyses between length–width ratio and distance from home address to city center. The coefficient for 1 and 2 SD was 0.39 ($p < 0.005$), for 1- and 2-km network buffers −0.01 ($p < 0.05$) and −0.03 ($p < 0.001$), respectively (data not shown). The further away people live from the city center, the lower the percentage of GPS points 1- and 2-km network buffers capture, even though the coefficients are small they are significant. As opposed to this, none of the elliptical buffers had significant coefficients (p-values between 0.096 and 0.784) indicating a more constant capacity to capture GPS points regardless of the distance from home to city center. The 500, 750, and 1000 m shortest route buffers had coefficients of 0.02 ($p < 0.005$), 0.02 ($p = 0.05$), and 0.01 ($p = 0.1$), respectively.

DISCUSSION

This study aimed to combine a mixture of hypothesized reasoning and exploratory analysis to develop methods to determine buffering-radius size and buffer shape, as recommended by Chaix et al. (24). The methods can be used in studies of active transport behavior or other types of behavior where researchers are interested in knowing where study participants primarily go and stay in order to get a more precise comprehension of the concept "neighborhood." In line with Boruff et al. (10), we distinguished and tested a variety of buffers that can be used when studying the relationship between the built environment and active transport. People living within the city center have easy access to a variety of destinations which means that a circular or network buffer will capture most of their activity while this is not the case for people living further away from a city center. Based on a comparison of the effectiveness of 11 different buffer types, we argue for different neighborhood buffer types, shapes, and sizes to mimic the behavior in question. Using ellipse-shaped buffers directed from the residential address to a city center (i.e., a high concentration of daily destinations) is, to our knowledge, a novel way of delineating an active travel neighborhood.

We assume that people in general transport themselves toward meaningful destinations in a rather direct way and therefore have confidence that the methodology holds for cities with one or more areas with a high concentration of daily destinations. However, it is unlikely that the methodology holds for city layouts without clear concentrations of daily destinations. Similar analyses of cycling in other types of cities might help overcome this challenge, and other types of buffers could be constructed to reflect cycling behavior.

There is an absence of studies that provide measures of "true" exposure to environmental factors even though the discussion on buffer types has been around for years and several studies conclude that a standard network buffer around the home might not adequately reflect the activity space examined in the studies (5, 11). Villanueva et al. (11) show how children only access up to a quarter of the calculated traditional "neighborhood" (defined with

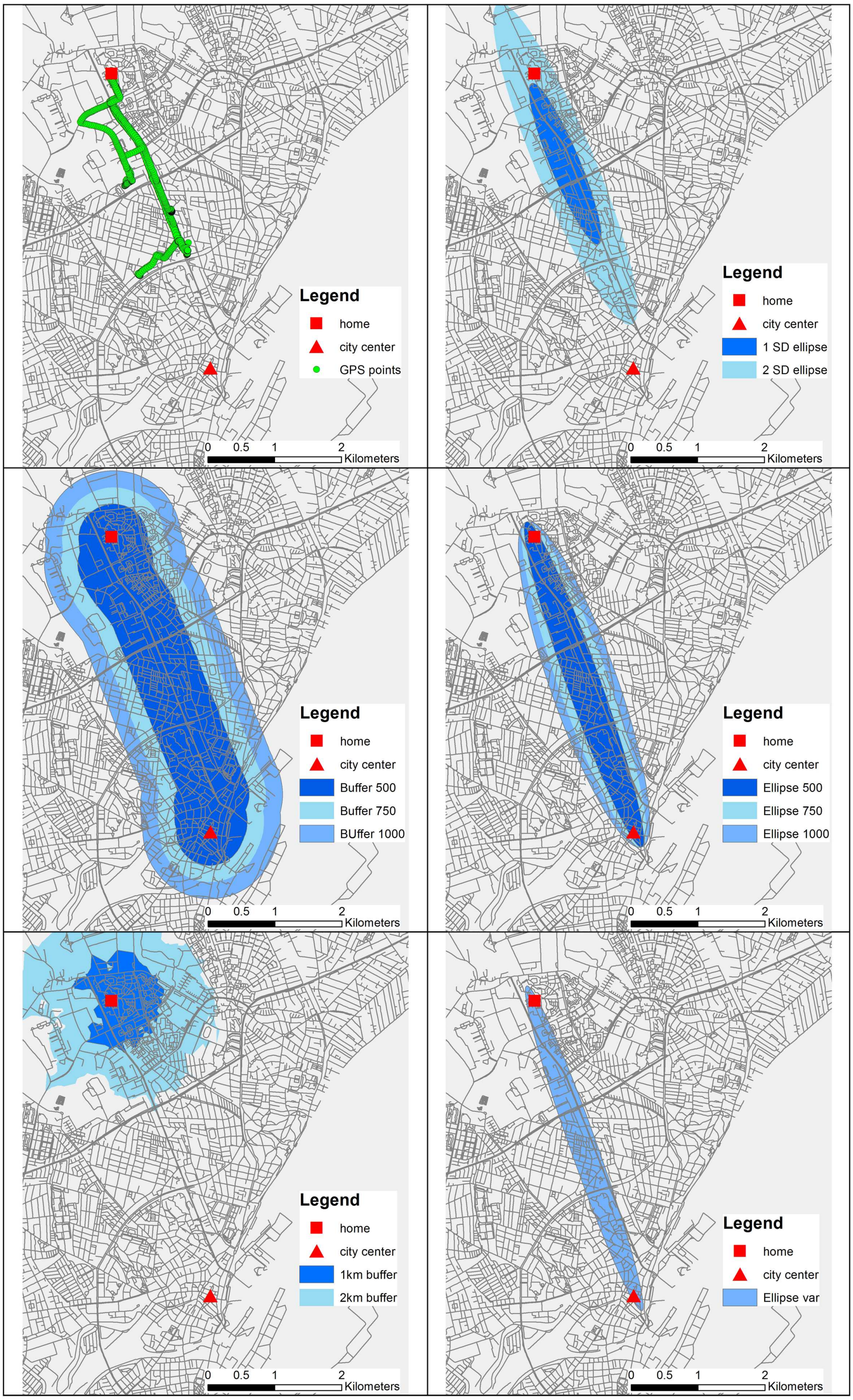

FIGURE 1 | The six buffer types and sub-buffers for one participant. The figure displays how some buffers are developed on the basis of the GPS track and directed toward the city center, while the more traditional buffers are created solely on home address and information derived via the geographical information system.

Table 3 | Buffer area, GPS points, percentage GPS points, density (GPS points per square kilometer), and relative density (percentage GPS points per square kilometer).

Buffer characteristics (mean ± SD)	Area in km^2	GPS points	% GPS points	Density, GPS points/km^2	Relative density, % GPS points/km^2
1 SD ellipse	6.84 (0.9)	594.2 (503.2)	64.5 (7.6)	225.7 (232.4)	43.0 (70.7)
2 SD ellipse	27.3 (3.5)	874.3 (631.3)	97.9 (2.3)	84.6 (84.9)	16.3 (26.4)
1-km network buffer	1.57 (0.2)	269.6 (277.1)	33.4 (20.3)	171.5 (167.1)	21.4 (13.2)
2-km network buffer	6.75 (0.8)	443.9 (321.4)	56.4 (25.6)	65.8 (46.4)	8.3 (3.5)
Shortest route buffer (500 m)	4.55 (3.5)	410.9 (362.6)	50.4 (27.2)	124.9 (137.6)	15.6 (11.1)
Shortest route buffer (750 m)	7.4 (5.2)	482.6 (380.7)	59.4 (27.5)	86.7 (82.9)	10.9 (7.2)
Shortest route buffer (1000 m)	10.6 (6.9)	533.0 (394.3)	65.1 (26.8)	64.1 (56.4)	7.9 (4.7)
Ellipse (500 m)	1.57 (1.3)	232.2 (290.9)	28.6 (21.8)	237.1 (377.4)	29.3 (28.9)
Ellipse (750 m)	2.36 (1.9)	288.8 (326.4)	35.0 (23.7)	190.0 (263.7)	23.3 (20.4)
Ellipse (1000 m)	3.14 (2.5)	328.1 (338.2)	40.0 (24.9)	159.2 (202.7)	19.6 (16.4)
Variable buffer	1.62 (0.8)	250.1 (295.2)	30.1 (21.9)	186.4 (234.8)	23.03 (18.4)

Table 4 | Results for the regression analysis between the percentage of GPS points inside the 11 buffer types and distance from home to center.

Buffer type	Coefficient	*p*-Value
1 SD ellipse	−0.007	0.002
2 SD ellipse	0.001	0.052
1-km network buffer	−0.01	0.048
2-km network buffer	−0.03	0.001
Shortest route buffer (500 m)	0.02	0.008
Shortest route buffer (750 m)	0.02	0.050
Shortest route buffer (1000 m)	0.01	0.108
Ellipse (500 m)	−0.002	0.783
Ellipse (750 m)	0.002	0.784
Ellipse (1000 m)	0.006	0.452
Variable buffer	−0.01	0.096

an 800- or 1600-m network buffer) and thus not travel completely within or use all of their neighborhood area. Clustered destinations and specific directions could be reasons for this and future studies should explore the directional movement and spatial orientation of visited (or probable) destinations to explore the built environment characteristics people are exposed to (11).

The question is whether we want "neighborhood" buffers to capture most of the expected environmental "exposure" as well as include large areas that people never visit. Or do we measure the "possible exposure" less accurate by not including large areas of non-exposure? Using GPS-derived activity space is often not possible in large population studies (1) but the use of GPS-derived buffer construction might act as a precursor to future studies. A reason not to construct GPS route buffers in the present study is the desire to be able to construct buffers that can be used for large population studies without having access to GPS data. Chaix et al. (6) describe how the strength of environment–behavior associations might decrease in GPS mobility studies compared to classical residential studies, indicating that the use of GPS to construct residential buffers suited for that particular behavior might prove useful.

One reason to keep the more traditional buffers is that they include and center around the residential address which focuses on the area close to home. Tobler's first law of geography: "everything is related to everything else, but near things are more related than distant things" is very much linked to the argument that "overcoming space requires expenditure of energy and resources, something that nature and humans try to minimize" (33). That said, a trade-off between area size and captured behavior is present and while smaller areas cannot capture all behavior, analyses within large areas includes built environments people never visit. One potential problem with buffer types that capture more of the daily cycling transport is that the significance of the closest neighborhood is diluted. By using city center-directed ellipse-shaped buffers, the residential address is kept as one of two important focus points, the other being a cluster of daily destinations. In doing so, the importance of the nearest neighborhood is acknowledged, yet the presumed area visited is kept relatively small. One could argue that work place is an important destination as well and that identifying an ellipse-shaped buffer based on the home–work route would also be useful, as well as a home–work–city center triangulation. This is speculative but nonetheless important to consider in future studies.

Findings of this study are not conclusive, but it seems that people living outside the city center generally cycle toward the city center (a cluster of destinations), with individual variations. Probably other factors such as age, education, gender, and income also affect the buffer (5). This suggests that future studies could benefit from using GPS to visualize movement patterns and construct more accurate representation of neighborhoods across population groups (children, elderly, pedestrians, cyclists, etc.). The use of GPS technology provides accurate representations of human–environment interactions in relation to, e.g., active transport and makes it possible to develop appropriate buffers (10).

The present results enable us to carry out analyses in a larger population using the city center-directed ellipse-shaped buffers studying the relationship between the built environment and transport-related physical activity (cycling and walking). The hypothesis for future studies is that the new buffers will better encapsulate transport cycling behavior and that the environmental characteristics in such buffers will show better correlation with behavior than the previously used buffers.

STRENGTHS AND WEAKNESSES

As the participants were recruited via the Danish IPEN study, several covariates had been collected via questionnaire, but for the present study only background data was analyzed and reported. The IPEN participants who participated in the study were regular cyclists which could have diminished the representativeness of the sample. However, a more random selection of participants could have resulted in large part of the participants not engaging in cycling for transport. The participants are however representative as cyclists, and as we wanted to study transport cycling behavior, this was crucial.

Even though GPS measures of transport behavior have proven beneficial in describing the actual movement, the use of GPS is still developing and is associated with challenges in both data collection and processing. Using GPS makes it possible to know the exact spatial footprint and measures of actual contact with the environment, but more often only potential contact is available. In this study, as in other studies using GPS, we had to overcome the typical problems with slow connectivity, satellite inference caused by physical structures or normal atmospheric conditions, and compliance in general (30). Furthermore, data processing and cleaning proved to be challenging but we managed to overcome some of the traditional problems like determining mode of transportation and an abundance of static points. By instructing the participants to wear the GPS when cycling and excluding all the data points which were not part of a trip as detected by PALMS, we were able to diminish the above mentioned. That said, we cannot rule out the possibility of errors and likewise acknowledge that the elliptical buffers might not adequately mimic individual transport behavior when transferred to other studies.

CONCLUSION

In conclusion, GPS technology and geographical information systems are appropriate tools to study active transport behavior and subsequently display and analyze different buffer types, shapes, and sizes that best fit the behavior in question.

We found that transport patterns were affected by the distance from residential address to a cluster of destinations and that an elliptical-shaped buffer was more effective than traditional buffers such as network buffers or shortest route buffers in order to capture transport cycling in a Danish context. This has implications in studies of the relationship between the built environment and transport cycling. Acknowledging that constructing GPS-based individual buffers is not possible in most larger studies, we suggest using an elliptical buffer based on the distance and direction from home to a cluster of daily destinations (in Denmark often the city center) resulting in more circular buffers proximal to destinations and more elongated buffers for people living further from the cluster of destinations. The same approach might be advantageous in correlation with walking or other transport modes, as it seems plausible that most people move in direction of meaningful destinations. Meaningful destinations can vary from urban green spaces to shops, schools, or sport facilities so the buffer direction should reflect the study question and scope of the study.

AUTHOR CONTRIBUTIONS

Thomas Madsen and Jasper Schipperijn designed research, the conception of the study, and carried out the GPS and GIS work as well as data analysis. Thomas Madsen drafted the initial manuscript and revised it according to input from co-authors. Lars Breum Christiansen provided respondents and data from the Danish IPEN study, gave advice and input on the data analysis, and critically reviewed the manuscript. Thomas Sick Nielsen gave advice and input on the data analysis and critically reviewed the manuscript. Jens Troelsen conceived the original idea and critically reviewed the manuscript. All authors have responsibility for the final content and approve the final manuscript.

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Identifying active travel behaviors in challenging environments using GPS, accelerometers, and machine learning algorithms

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Background: Active travel is an important area in physical activity research, but objective measurement of active travel is still difficult. Automated methods to measure travel behaviors will improve research in this area. In this paper, we present a supervised machine learning method for transportation mode prediction from global positioning system (GPS) and accelerometer data.

Methods: We collected a dataset of about 150 h of GPS and accelerometer data from two research assistants following a protocol of prescribed trips consisting of five activities: bicycling, riding in a vehicle, walking, sitting, and standing. We extracted 49 features from 1-min windows of this data. We compared the performance of several machine learning algorithms and chose a random forest algorithm to classify the transportation mode. We used a moving average output filter to smooth the output predictions over time.

Results: The random forest algorithm achieved 89.8% cross-validated accuracy on this dataset. Adding the moving average filter to smooth output predictions increased the cross-validated accuracy to 91.9%.

Conclusion: Machine learning methods are a viable approach for automating measurement of active travel, particularly for measuring travel activities that traditional accelerometer data processing methods misclassify, such as bicycling and vehicle travel.

Keywords: physical activity, random forest

INTRODUCTION

Individual travel behavior has been important in transportation research and traffic planning for decades (1). More recently, active travel has also become a focus for public health (2). Studies of adults and children have shown that individuals who walk or bike for transportation, or use public transportation, accumulate more physical activity and are more likely to meet public health recommendations (3, 4). In some countries active travel has been related to obesity (5). These relationships, however, have been poorly studied because they are reliant on self-report data, which provide crude metrics (e.g., number of days vs. total minutes of active travel). The premise of active living research is that built environment can support more routine physical activity behaviors, and that if active travel is an equal choice compared to car travel, more people are likely to take advantage. Improvement in measurement of active travel will enable intervention studies trying to promote routine daily behaviors such as active travel.

Traditionally, travel behavior has been measured by travel and time use diaries or self-report surveys (6). Not only are these burdensome to participants, but also recall of events is often inaccurate and potentially biased (7–9). The emergence of lightweight, low cost, and accurate global positioning system (GPS) devices has enabled researchers to objectively track the location of individuals. However, while it is relatively straightforward to view and understand GPS data using Geographic Information System (GIS) packages, it would be extremely time consuming to do large-scale data analysis by manually interpreting each GPS track. In light of this, researchers began looking into automated ways of segmenting trips and identifying transportation mode from GPS data. Early studies of GPS data in transportation research focused on vehicle travel, simplifying the development of algorithms somewhat. More recently, multiple transportation modes have been studied, including active transportation.

There have been a variety of approaches to predicting transportation mode automatically from GPS data. These include heuristic rule-based algorithms, (10–13), fuzzy logic (14, 15), neural networks (16, 17), Bayesian models (18, 19), and decision trees (20, 21). These approaches rarely include non-travel activities (e.g., sitting or standing), and many incorporate map matching or GIS components, which are particularly useful in order to ascertain when a user is traveling on a public transit route. Physical activity researchers, however, may not have access to GIS data. In contrast, they are likely to include accelerometer data when assessing active travel (3, 4). Previous studies have shown that specific behaviors such as housework can be derived from accelerometer signals (22). These studies rarely include vehicle travel as an activity mode, are often performed in highly controlled lab settings, and mostly do not include GPS data that can inform trip mode.

Only a few studies have employed GPS and accelerometer data. Reddy et al. (23) use decision trees and Markov models to determine transportation mode on mobile phones, using both GPS and accelerometer data. They report 93% accuracy in predicting five activities (still, walking, running, bicycling, and vehicle). Troped et al. (24) also combine accelerometer and GPS data, but from standalone devices, using linear discriminant analysis to predict five activities (walking, running, bicycling, inline skating, and driving a car). They report 90% accuracy in predicting activities, but with a relatively small dataset of 712 min of data.

Many of these algorithms in the literature to date are only tested in ideal conditions or controlled environments, which may overestimate their accuracy. Conditions like instantaneous mode changes, cold start journeys, and trips in urban canyons can all interfere with signal detection and challenge the effectiveness of algorithms. Our novel contribution to the research includes a validation protocol that tested travel modes in multiple real world conditions, and collected a comprehensive dataset consisting of about 150 h of annotated data. We employed both GPS and accelerometer data, and used machine learning algorithms to identify transportation mode, using multiple features of both devices to inform the prediction model. We used a random forest algorithm, an efficient algorithm that to our knowledge has not previously been used to predict transportation modes from accelerometer and GPS data, although Lustrek and Kaluza (25) use a random forest algorithm for activity recognition from 12 small infrared motion tags placed on a user's body and Casale et al. (26) use random forests for physical activity recognition from accelerometer data.

Table 1 | Prescribed trip parameters for data collection.

Condition	Description	Number of trips
First level environment variation		511 (total)
Urban canyon	Downtown areas with high rise buildings that interfere with GPS signal	259
Open space	Areas without high rise buildings where GPS signal connectivity is high	252
Second level transition and location variation		
Continuous	A continuous connection between transportation modes, e.g., stop car and passenger started walking immediately. Most naturally occurring trip transitions are continuous	142
Pause	A 2-min pause between transportation modes. Pauses enable trip ends to be detected more easily	192
Indoor/outdoor transition	Stationary periods indoors and outdoors were tested, as well as transitions between indoors and outdoors including transitions every 30 s from indoor to outdoor environments. The Qstarz device allows collection of satellite ratios, which can help to detect indoor vs. outdoor locations.	22
Building types		
Full/partial signal buildings	Single story buildings with large windows, wooden roofs, and open courtyards	12
Blocked signal	Multistory buildings, underground garages	12

MATERIAL AND METHODS

DATA COLLECTION PROCEDURES

Two trained research assistants in San Diego followed a data collection protocol. They collected data under varying conditions (i.e., open space vs. urban, indoor vs. outdoor), for a variety of transportation modes (walking, driving, etc.). The researchers wore an Actigraph GT3X+ accelerometer on the hip and 12 devices attached to 2 wooden boards (9″ × 12″) carried in a backpack. Board-mounted devices were attached with Velcro to ensure device antennae were all aligned in the same way. The board contained 12 devices, each with different settings: 2 different GPS models, at 3 different epochs with either warm or cold start conditions (i.e., device on and signal obtained or device switched on immediately before travel and no signal established). The GPS device we used in this analysis was a Qstarz BT1000X set to collect data at 15 s epochs using warm starts. The accelerometer device collected data at 30 Hz on three axes. The researchers followed a set protocol of trips, pauses, and locations. There were at least 4 example trips per condition resulting in over 500 trips. The researchers kept a log of each trip, location, and condition settings and noted start times for each event. A research manager reviewed files on a daily basis and reallocated trips that were not successfully completed or noted. (The full study protocol is available from the authors). All the data are considered at the trip level, the individual characteristics of the two data collectors were not included.

Table 1 outlines the different conditions under which GPS and accelerometer data were collected following the protocol. **Table 2** reports the total minutes of data collected in each transportations mode, and includes periods of time between the prescribed trips during data collection.

CLASSIFICATION PIPELINE

Each step in the data classification pipeline is detailed in the following sections. Raw data were first preprocessed to remove common GPS errors. The data were then split into 1-min windows and feature vectors were extracted from each window. Each window was then classified using a machine learning algorithm. **Figure 1** shows an overview of the classification pipeline, which starts from raw sensor data and produces classifications for each minute of data.

DATA PREPROCESSING

Data smoothing typically occurs before data are employed in a machine learning environment. GPS data were first processed by the Personal Activity Location Measurement System (PALMS) (27). PALMS filters spurious data points and smoothes out common GPS interference patterns. PALMS uses a set of simple filters to remove invalid coordinates and reduce data volume. The filters include removal of points with excess speed; large changes in elevation or very small changes in distance between consecutive points; and scatter caused by interference from buildings. For periods of signal loss PALMS imputes the previous valid coordinates (28).

TRIP SEGMENTATION

Many previous approaches to travel mode classification do a first step of segmenting the GPS stream into cohesive trips consisting of a single travel mode (10, 12, 14). This segmentation is usually done based on simple rules that make some assumptions about the way people travel – for example, people always walk in between trips of different modes, or are always stationary for a certain length of time in between trips. However, these assumptions may not hold in the real world – in fact the data in this study were collected in order to explicitly violate these assumptions. Therefore, instead of segmenting the data into trips, in our method we individually classified each minute of data with a travel mode. These predictions are then smoothed with a simple moving average filter that encourages consecutive minutes of data to be classified with the same mode. Trips can then be easily defined by grouping consecutive minutes classified with the same travel mode. This approach prevents the use of heuristics that enforce a specific ordering of transportation modes.

Table 2 | Minutes of data collected for each transportation mode.

	Minutes of data	Percent of total (%)
Bike	857.5	10
Bus	632.3	7
Car	2063.0	23
Sit	849.5	9
Stand	1631.3	18
Walk	2490.3	28
Unclassified	464.0	5
Total	8987.8	100

FEATURE EXTRACTION

Most machine learning algorithms require inputs to be example data points consisting of real numeric data. These inputs are called feature (or attribute) vectors. Our input data consist of streams of accelerometer and GPS data. The feature extraction step is the process of transforming these data streams into feature vectors that capture relevant and predictive information. We used a sliding window to break the data stream into 1-min windows of accelerometer and GPS data, each with a corresponding transportation mode label. If the window spanned multiple different transportation modes, or an unlabeled segment of data, we left it unlabeled. Consecutive windows overlap by 30 s. We summarized each 1-min window by computing a feature vector consisting of descriptive statistics of the data in that window (e.g., average speed, correlation between accelerometer axes, etc.). We normalized the features to have mean zero and standard deviation one, to account for the scale difference between features (i.e., acceleration measurement is between ±6 G, while GPS speed is commonly above 40 mph). We computed a 49-dimensional feature vector for each minute of data, consisting of 43 acceleration features and 6 GPS features. Using a 1-min window resulted in 17,916 example minutes in our dataset, 14,307 of which had valid labels.

Acceleration features

An 1-min window of acceleration measurements contains $T = 60\text{s} \times 30\,\text{Hz} \times 3\ \text{axes} = 5400$ samples of acceleration

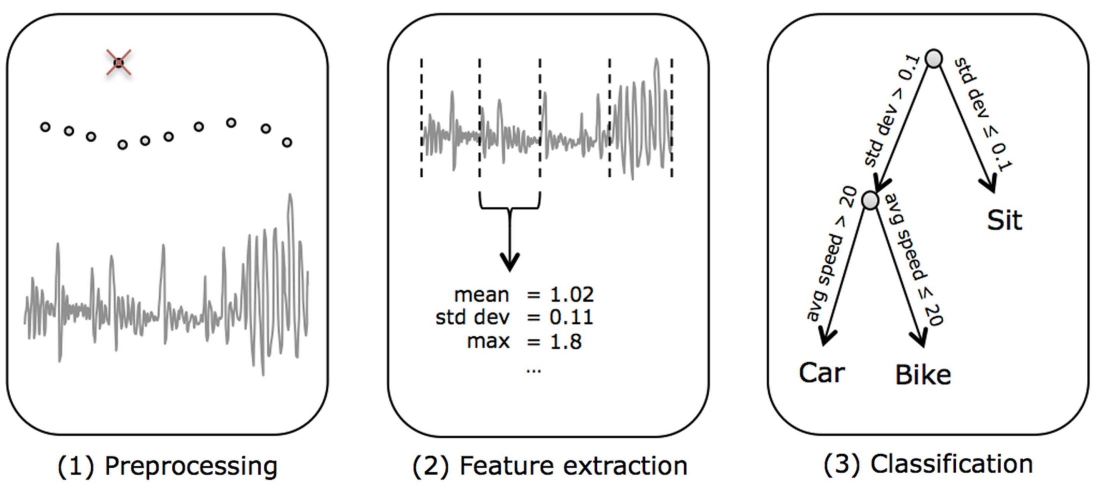

FIGURE 1 | The classification pipeline. (1) We started from raw sensor data, which was split into 1-min windows. (2) Features were extracted from each window of data. (3) Then the features from each window were classified into transportation modes.

measurements along the x, y, and z axes, which we represent as a matrix,

$$A = \begin{bmatrix} a_{1,x} & a_{2,x} & \cdots & a_{T,x} \\ a_{1,y} & a_{2,y} & \cdots & a_{T,y} \\ a_{1,z} & a_{2,z} & \cdots & a_{T,z} \end{bmatrix}.$$

The data from this window are condensed to 43 acceleration features. Most features are computed from the vector magnitude of the 3-axis acceleration,

$$a_t = \sqrt{a_{t,x}^2 + a_{t,y}^2 + a_{t,z}^2},$$

although some features (for example, correlations between axes) are computed differently. We compute the following features:

- *Basic descriptive statistics* computed from the vector magnitudes $a_{1:T}$: mean, standard deviation, 25th and 75th percentiles, minimum, and maximum. These are features commonly used in previous work predicting physical activity from accelerometers (21, 23, 24).
- *Skewness and Kurtosis*, descriptive statistics derived from the third and forth moments of the data distribution, that measure the asymmetry and peakedness, respectively, of the distribution of accelerometer magnitudes in a minute.
- *Autocorrelation* of the vector magnitude with 1-s lag (17).
- *Correlations* between each pair of axes of the accelerometer (i.e., x–y correlation, x–z correlation, and y–z correlation).
- *Entropy*, a measurement of the randomness of the distribution of accelerometer magnitudes.
- *Angular features*, to provide information about the orientation of the accelerometer in space. The roll, pitch, and yaw are measurements used in aeronautics to describe the rotation of an aircraft, and are calculated by:

$$\text{average roll} = \frac{1}{T}\sum_{t-1}^{T} \tan^{-1}\left(a_{t,y}, a_{t,z}\right)$$

$$\text{average pitch} = \frac{1}{T}\sum_{t-1}^{T} \tan^{-1}\left(a_{t,x}, a_{t,z}\right)$$

$$\text{average yaw} = \frac{1}{T}\sum_{t-1}^{T} \tan^{-1}\left(a_{t,y}, a_{t,x}\right)$$

Figure 2 shows these angles on the coordinate axes.

- *Principal direction of motion*, obtained via Eigen-decomposition of the acceleration covariance matrix, AA^T. In particular, we determined the principal direction of motion by taking the eigenvector v of AA^T with corresponding maximal eigenvalue – this corresponds to the direction with maximum variation.
- *Autoregressive coefficients*: we model the acceleration vector magnitude by an autoregressive model of order $p = 5$,

$$a_t = c_0 + \sum\nolimits_{i=1}^{p} c_i x_{t-i} + \varepsilon_t,$$

where $c_0, \ldots, c_p$ are the model coefficients, and ε_t is white noise.

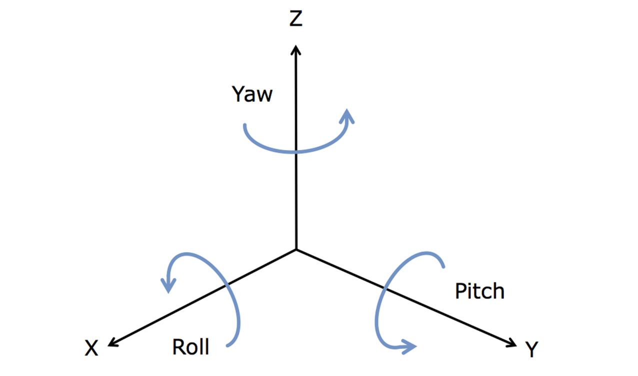

FIGURE 2 | Average roll, pitch, and yaw angles.

- *Fast Fourier Transform (FFT) coefficients*: the FFT decomposes the signal, e.g., the time series of acceleration measurements, into components of different frequencies, transforming a time domain signal a_t to a frequency domain signal A_f. From the FFT, we computed the power spectrum $|A_f|^2$ for frequencies $f = 1$–15 Hz.
- *Total power* in the signal from 0 to 15 Hz.
- *Dominant frequency*, the frequency corresponding to maximal power in the power spectrum, and corresponding power.

GPS features

We obtained six features from the GPS device: average speed, average number of satellites used and in view, average signal-to-noise ratio (SNR) of satellites used and in view, and net distance traveled in the minute. These 6 features were appended to the 43 acceleration features to obtain the 49-dimensional feature vector that describes each minute of data.

MACHINE LEARNING METHODS

Our goal in this work is to use supervised machine learning methods to predict transportation mode from streams of accelerometer and GPS data. The term "supervised" refers to the fact that we make use of a training data set containing examples of accelerometer and GPS data with known corresponding labels (i.e., transportation mode). A supervised learning algorithm analyzes the training data and produces an inferred function, or classifier, which maps a data point (represented by its feature vector), to a label. This is in contrast to "unsupervised" learning algorithms, which use data without labels to identify some sort of underlying structure in the data (i.e., clustering methods). A labeled training dataset is made up of pairs of feature vectors and labels. There are a wide variety of classifier functions and learning algorithms that could be used, and we tested several of the more popular choices.

Classification

We tested several well-known machine learning algorithms to classify transportation mode: k-nearest neighbor (kNN), support vector machines (SVM), naive Bayes, decision trees, and random forests. Many software packages exist that implement these algorithms and allow them to be used as a "black box" to perform classification of data. Of these algorithms, the random forest algorithm, which is an ensemble method based on decision trees, produced the highest accuracy, and thus the remainder of the analysis in this paper will focus on the random forest algorithm. A decision tree is a type of classifier that consists of leaves representing class labels and branches representing conjunctions of features that lead to those class labels. For a test data point, the class label is found by traversing the tree according to the conjunctions in the branches of the tree, and when a leaf is reached the label in that leaf is assigned to the data point. The training phase of the algorithm consists of building the decision tree, i.e., learning the branches that lead to a tree that correctly classifies as many examples in the training data set as possible. A random forest combines the outputs of multiple randomized decision trees. Shotton et al. (29) use random forests to do human pose recognition for the Xbox Kinect. To learn each decision tree, we chose a random subset of 10,000 training examples (at 1-min epoch) and a random subset of 25 features. We learned 100 of these randomized decision trees. To classify a given test example, we traversed each tree until we arrived at a leaf node. Each leaf node has a probability score for each transportation mode, according to the ratio of training examples of each transportation mode that land in that node. We summed these probability scores in the final leaf node over the 100 trees, and chose the transportation mode with highest probability for our test example. We choose the parameters for our classification algorithms (i.e., number of trees to use) using a held-out day of data that was not included in the final cross-validation results. For the decision trees, we set the minimum number of examples in a leaf to be 10. For the *k*NN algorithm *k* was chosen to be 3 and for SVM the regularization parameter was chosen to be 10.

MOVING AVERAGE OUTPUT FILTER

We filter the output predictions from the random forest classifier with a simple moving average filter. This filter looks at the predictions made in the 2 min previous to and 2 min following the minute in question, and outputs the mode that is predicted the highest number of times. If there is a tie, it outputs either the prediction from the current minute (if this is one of the tied predictions), or the prediction from the earlier of the tied minutes. This prevents rapid switching between different modes and encourages successive predictions to belong to the same travel mode.

RESULTS

We tested the performance of each machine learning algorithm by performing leave-one-day-out cross-validation. This corresponds to a realistic setting in which the algorithm would be used – the data from within a trip are never used as training data to classify another piece of data from that same trip. Using standard *k*-fold cross validation that allows data from the same trip in the test and training set produces artificially high accuracy scores.

In addition to overall accuracy, we evaluated the performance of each classifier using precision, recall, and *F*-score. Precision measures the proportion of predicted examples of an activity type that are correct. Precision (P) is calculated as $P = \mathrm{TP}/(\mathrm{TP} + \mathrm{FP})$, where TP is the number of true positives, and FP is the number of false positives. Recall measures the proportion of true examples of an activity type that are correctly identified (also called sensitivity). Recall (R) is calculated as $R = \mathrm{TP}/(\mathrm{TP} + \mathrm{FN})$, where TP is the number of true positives, and FN is the number of false negatives. *F*-score is a measure of accuracy, and is computed as the harmonic mean of precision and recall, $F\text{-score} = 2PR/(P + R)$. These metrics provide detailed information about how the algorithm performs on each class. The *F*-scores obtained from each algorithm are shown in **Table 3**. The random forest algorithm showed the highest performance, with an overall accuracy of 89.8%.

Using the moving average output filter to smooth predictions significantly improved results, leading to an average precision of 0.900, average recall of 0.882, and overall accuracy of 91.9%. **Table 4** reports the precision, and recall scores before and after output filtering. **Figure 3** shows an example day of data, before and after smoothing, compared to the ground truth annotations for the day. **Table 5** shows the confusion matrix for the

Table 3 | Performance results for various classifiers (without output filtering).

	F-score							Overall accuracy (%)
	Bike	Bus	Car	Sit	Stand	Walk	Average	
*k*NN	0.924	0.585	0.855	0.682	0.829	0.955	0.805	86.2
Naïve Bayes	0.872	0.220	0.824	0.503	0.484	0.920	0.637	74.2
SVM	0.962	0.609	0.884	0.724	0.833	0.954	0.828	87.7
Decision tree	0.922	0.537	0.846	0.674	0.792	0.936	0.785	83.6
Random forest	0.971	0.601	0.888	0.778	0.855	0.962	0.843	89.8

Table 4 | Precision (*P*) and recall (*R*) results for the random forest classifier with and without output filtering.

		Bike	Bus	Car	Sit	Stand	Walk	Average	Overall accuracy (%)
No output filter	*P*	0.982	0.795	0.880	0.779	0.844	0.968	0.874	89.8
	R	0.979	0.545	0.934	0.832	0.880	0.945	0.853	
Output filter	*P*	0.985	0.860	0.910	0.807	0.878	0.962	0.900	91.9
	R	0.976	0.701	0.952	0.821	0.871	0.970	0.882	

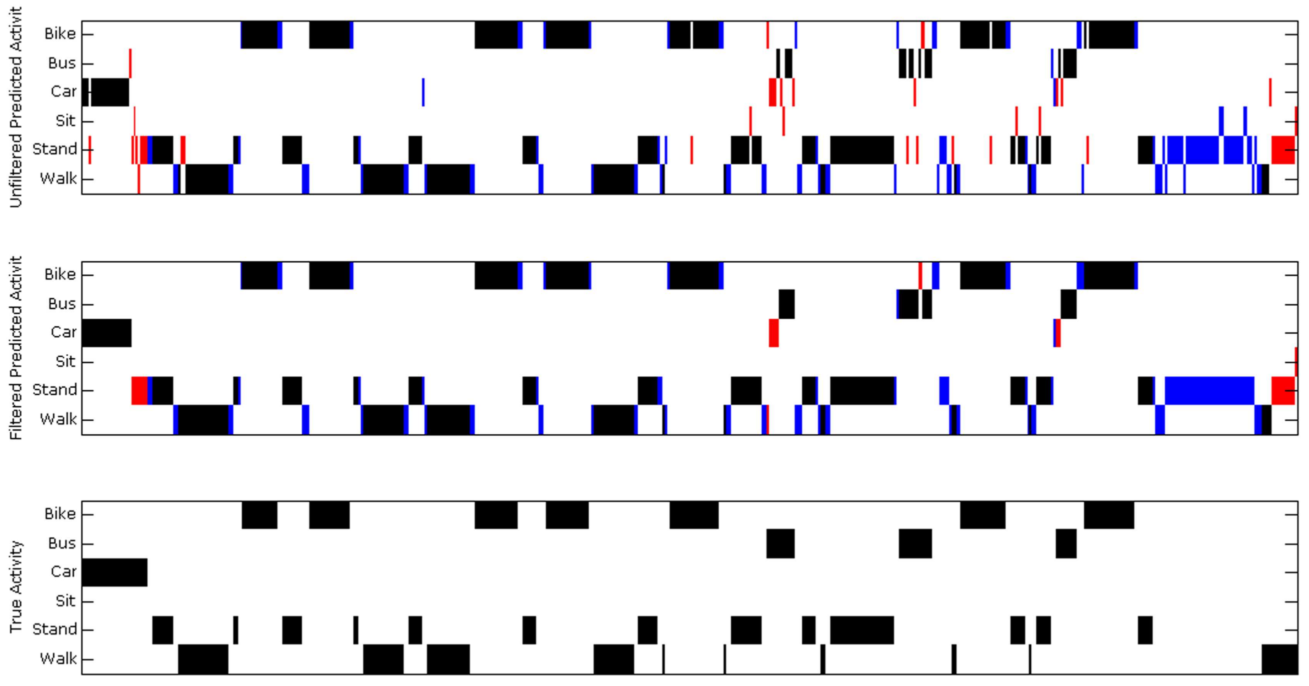

FIGURE 3 | Example output for 1 day of data. We plot the activity mode vs. time for 1 day of data. In the top plot, we show the activity mode predicted by the random forest algorithm. In the middle plot, we show the smoothed predictions output by the moving average filter. In the bottom plot, we show the ground truth annotations for this day. Minutes in black were correctly classified, minutes in red were misclassified, and minutes in blue had no ground truth annotation with which to compare.

Table 5 | Confusion matrix for the random forest classifier with output filtering.

	Bike	Bus	Car	Sit	Stand	Walk
Bike	1526	18	4	0	8	3
Bus	2	611	409	54	34	11
Car	2	127	3563	42	69	13
Sit	0	1	44	1232	186	17
Stand	5	8	8	228	2546	97
Walk	19	4	22	26	174	4228

Rows represent number of examples of true activities; columns represent number of examples of predicted activities. Entries along the diagonal indicate correct predictions.

smoothed random forest classifier, which reports the number of test examples classified in each transportation mode. The diagonal emboldened numbers represent the correct predictions by mode.

IMPORTANCE OF FEATURES

In order to gain insight into the usefulness of each feature, we computed an importance score. This score was computed by summing the changes in the training error each time a feature was used to create a new branch in a decision tree, and averaged over each tree in the random forest. We then normalize the scores to sum 1 over all the features. **Table 6** shows the top 15 features according to this importance score.

Table 6 | Top 15 most informative features.

	Score
Standard deviation	0.251
Average speed	0.147
Net distance covered	0.085
Power at dominant frequency	0.082
Autocorrelation	0.061
Average yaw	0.044
Average roll	0.039
Minimum	0.034
FFT 4 Hz	0.029
FFT 3 Hz	0.022
Correlation between x and y axes	0.018
Maximum	0.018
25th Percentile	0.013
Total power	0.013
Average SNR used	0.013

We computed an importance score for each feature and ranked the features according to this score

DISCUSSION

This study employed GPS and accelerometer data to identify transportation mode for trips collected in varying environmental conditions. Machine learning methods were employed to extract features of the data stream and build an algorithm to predict transportation mode. The algorithm was shown to have over 90% accuracy on leave-one-day-out cross-validation.

Few previous studies have employed GPS and accelerometer data [for example, Reddy et al. (23)] and machine learning techniques to predict transportation mode. Our study demonstrated similar accuracy rates as Reddy et al., but deployed the devices over a larger number of trips, which varied by environmental features, thereby providing a more challenging test of the algorithms. Another difference was the Reddy study employed smart phones whereas we used research-grade accelerometers and GPS devices mounted at specific locations. Although smartphones are becoming ubiquitous technologies for continuous sensing of geolocation and acceleration data, they are limited because of competing power demands of the phone or other functions (e.g., there must be sufficient power for the phone to make calls, text, read email, surf the web, etc., with limited interruption to other sensor inputs). It is also unclear if the integrity of smartphone sensor data relies on the phone being in a fixed position (i.e., the person keeping the phone in the same position all day). Although recent studies have attempted to circumvent these issues, solutions appear largely experimental or prototypical (30, 31). Importantly, there have been few studies in the transportation literature that have included accelerometer data to improve prediction of transportation mode. Previous studies have employed machine learning techniques on GPS data alone, but the diversity of the training data was unknown.

The analysis of the importance of each feature demonstrated that the accelerometer data contribute additional predictive power above the GPS data. The feature with highest importance was the standard deviation of the acceleration, which captures information about the signal variability. Stationary sitting and standing should consistently produce low speeds and accelerations, while bus and car have a much wider range of possible values. The feature with the second highest importance score was the speed from the GPS, which differentiates fairly well between activities with very different average speeds, such as vehicle vs. walking and sitting or standing. Although vehicle speeds are often higher than active transportation modes, in downtown corridors vehicle speeds can be slow including periods where the vehicle has stopped altogether, such as at a traffic light. These movements may mimic that of walking or biking. The net distance covered feature is computed from the GPS data, by simply computing the distance between the first and last latitude and longitude points in a data window. It is helpful in determining whether substantial forward progress was made during the minute, which is helpful, for example, in differentiating walking from standing. Another important feature was the power at the maximum frequency – this measures whether the acceleration signal has a strong dominant frequency, which is exhibited in signals that are highly periodic, such as walking or bicycling. Walking in particular has a very consistent dominant frequency between 3 and 4 Hz, which accounts for the high importance of the 3–4 Hz feature. Another interesting feature is the average roll, which provides information about the angle with which the device is positioned. Since the device is firmly affixed to the participant's hip can provide information about whether the subject is bent at the hip, i.e., sitting vs. standing.

This study demonstrated that under varied environmental conditions known to affect GPS signal, transportation modes could be detected with high accuracy. Although the accelerometer and GPS data were collected from separate devices, most mobile phones now collect GPS and accelerometer data. Additional studies could investigate algorithms applied to such mobile phone data. While mobile phone implementation of this study would lose some standardization of device placement (i.e., subjects could hold the phone wherever they like), which may make the angular features in particular less helpful, these features may instead provide some information about device placement, which can be correlated with transportation mode. Studies in free-living populations should also be conducted to confirm the generalizability of these algorithms. New sensors such as the SenseCam that provides accompanying image data may make this possible (32).

Limitations of this study include the small sample of subjects ($n = 2$; although each subject provided over 200 trips). When participants are performing prescribed trips, there should be less variation between participants than in a free-living scenario. In particular, the GPS data of two participants performing the same prescribed trip should look very similar. For this reason we chose to focus on collecting data from a wide variety of environments rather than a wide variety of participants. Validating methods on a controlled dataset is a first step before applying them to larger free-living dataset, which is the subject of future work. Additional limitations are that the data were only collected in one county (although the environments purposefully varied), and application of the algorithms to only one GPS model. Additionally, we only tested our algorithms on windows of data that fell completely within a bout of certain transportation mode – i.e., we did not include windows containing transitions between activities. This was done because evaluating the performance of our algorithm on these windows that have no single ground truth label is not straightforward. Future work should determine a metric for assessing the performance of the algorithm on these split class windows. One of the main sources of error in our classification was confusion between bus and car transportation modes, which is to be expected since the two modes are so similar. Including information from GIS systems, such as the proximity of public transportation routes, has the potential of greatly improving the distinction between these two modes, and we plan on addressing this in future work. Additionally, future work will test the effect of warm vs. cold start GPS data.

AUTHOR CONTRIBUTIONS

Katherine Ellis developed and implemented the algorithm, analyzed results, and wrote the manuscripts. Suneeta Godbole coordinated data collection and data management and critically revised the manuscript. Simon Marshall and Jacqueline Kerr developed the study design, coordinated data collection, and critically revised the manuscript. Gert Lanckriet and John Staudenmayer advised on algorithms and critically revised the manuscript.

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Context-specific outdoor time and physical activity among school-children across gender and age: using accelerometers and GPS to advance methods

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Introduction: Being outdoors has a positive influence on health among children. Evidence in this area is limited and many studies have used self-reported measures. Objective context-specific assessment of physical activity patterns and correlates, such as outdoor time, may progress this field.

Aims: To employ novel objective measures to assess age and gender differences in context-specific outdoor weekday behavior patterns among school-children [outdoor time and outdoor moderate to vigorous physical activity (MVPA)] and to investigate associations between context-specific outdoor time and MVPA.

Methods: A total of 170 children had at least one weekday of 9 h combined accelerometer and global positioning system data and were included in the analyses. The data were processed using the personal activity and location measurement system (PALMS) and a purpose-built PostgreSQL database resulting in context-specific measures for outdoor time, outdoor MVPA, and overall daily MVPA. In addition, 4 domains (leisure, school, transport, and home) and 11 subdomains (e.g., urban green space and sports facilities) were created and assessed. Multilevel analyses provided results on age and gender differences and the association between outdoor time and MVPA.

Results: Girls compared to boys had fewer outdoor minutes ($p < 0.05$), spent a smaller proportion of their overall daily time outdoors ($p < 0.05$), had fewer outdoor MVPA minutes during the day ($p < 0.001$) and in 11 contexts. Children compared to adolescents had more outdoor minutes ($p < 0.05$). During school and within recess, children compared to adolescents had more outdoor MVPA ($p < 0.001$) and outdoor time ($p < 0.001$). A 1-h increase in outdoor time was associated with 9.9 more minutes of MVPA ($p < 0.001$).

Conclusion: A new methodology to assess the context-specific outdoor time and physical activity patterns has been developed and can be expanded to other populations. Different context-specific patterns were found for gender and age, suggesting different strategies may be needed to promote physical activity.

Keywords: children, physical activity, accelerometer, GPS, spatial behavior, context-specific, outdoor behavior

INTRODUCTION

Being outdoors, as opposite to being indoors, may have a positive influence on a range of health parameters among children and adolescents (1). Being outdoors has also been identified as a correlate for more active play (2), enhanced physical activity levels (3–5), lower prevalence of overweight (6), and independent mobility (2). Being outdoors may help children and adolescents to reach 60 daily minutes of moderate to vigorous physical activity (MVPA); a minimum level recommended for children under the age of 18 by the World Health Organization and many national health authorities (7). Sustained low levels of physical activity are seen in many countries (8, 9), and often a decline in physical activity in the transition from childhood to adulthood is reported (10, 11).

Effective interventions or policies are needed to promote physical activity, and ecological models underpinning the importance of an active living lifestyle and built environmental influences, have received widespread recognition (12). The built environment consists of neighborhoods, roads, buildings, food sources, and recreational facilities: the places in which people live, work, are educated, eat, and play (13). If outdoor time is shown to be important for physical activity, policies to provide safe outdoor environments may be warranted. Evidence in this area is still limited and mixed as many studies on the association between the built environment and physical activity have used cross-sectional study designs and relied on self-reported data or daily averages from objective data. The association between the built environment and physical activity seems to be highly context-specific (4, 5), and inconsistencies in correlate studies may be partly explained by some studies measuring overall physical activity and not context-specific physical activity (e.g., physical activity during active transport, activity in urban green space or at playgrounds). An even better precision and perhaps correlation may be obtained if *physical activity patterns* are assessed (14–17) meaning that daily physical activity is assessed in different context throughout the day. Context-specific knowledge of physical activity patterns and correlates, such as outdoor time, may be a way to progress this field. Due to methodological challenges, this association has rarely been investigated using objective measures.

A valuable tool for improving the assessment of physical activity and outdoor behavior is the global positioning system (GPS). The GPS is a satellite-based global navigation system that provides a precise location at any point on the surface of Earth based on the position of satellites in the sky. The development of lightweight, affordable, and portable GPS receivers that can log individuals' locations continuously during consecutive days means that they can be used to objectively assess context-specific behavior. With the rapid development of the market for GPSs the battery life, memory capacity, and precision are improving (18). When combined with a device measuring physical activity, such as an accelerometer, it becomes possible to accurately assess patterns of context-specific physical activity (15–17, 19–24). The GPS receivers also collect information on the number of satellites used by and in view of the GPS receiver that can be used to provide estimates for outdoor times, and if assessed, outdoor physical activity (19, 20, 25, 26). A feasibility study by Tandon and colleagues among preschoolers concluded that it was feasible and valid to use a Qstarz GPS to distinguish indoor and outdoor time when using the personal activity and location measurement system (PALMS) (27) to process the data (26). Furthermore, information on speed and distance traveled can be used to assess mode of transport (28, 29). At the moment, new evidence about context-specific physical activity behaviors is being generated on the basis of combined accelerometer and GPS data and this paper is part of a developing research area.

The aim of this paper is to employ objective measures to assess the context-specific outdoor weekday pattern among schoolchildren and determine which contexts contribute to most outdoor time. Furthermore, the aim is to assess the contexts where weekday outdoor MVPA occurs and investigate how much of total daily MVPA is outdoors. As gender is a strong correlate for physical activity, and age a probable correlate (3), age and gender differences were assessed for these two aims. Finally, the aim was to investigate the association between context-specific outdoor time and MVPA.

MATERIALS AND METHODS

PARTICIPANTS AND PROCEDURES

Children in grade 5–8 (11–16 years old) were recruited from four schools, participating in the When Cities Move Children (WCMC) study. The WCMC study is a natural experiment conducted in a deprived neighborhood in Copenhagen, the capital of Denmark, evaluating how major improvements to the built environment influences physical activity and movement patterns. There are 9300 people living in the district; children comprise 20% of the population, and almost 70% of the children are immigrants or descendants of immigrants (30). Only baseline data collected in 2010–2011 were employed for the current analyses conducted in summer 2013. We chose to sample participants in a time period where it was hypothesized that the average day length, temperature, and rain were comparable in a Danish context. Data from three schools were collected in spring while data from the fourth school were collected in fall, corresponding to 85% of the data collected in spring and 15% in fall. There were no differences between participants from these two seasons by gender, age, BMI, MVPA or combined accelerometer, and GPS wear time.

Eligible children ($N = 623$) and their parents received personalized information about the nature and procedures of the study in Danish and if needed in one of four other languages (Arabic, Somali, Turkey, and Urdu) to match the ethnic background of the parents. The parents and children were notified that participation was voluntary and that they could withdraw at any stage. A passive informed consent procedure was used, where students were included unless the parents withdrew consent as this procedure has been found to be ethically appropriate in low-risk research in adolescents (31). The Danish Ethical Regional Committee reviewed the study protocol and concluded that formal ethics approval was not required. The study is registered and approved by the Danish Data Protection Agency (reference number: 2009-41-3943). Consent was obtained from 523 children and there were no overall differences between responders and non-responders by gender, ethnicity, BMI, or parental work status. However, the non-response was unequally distributed by age and school with the drop-out being greater among adolescents (children 11.7%, adolescents 21.4%, $p = 0.001$) and in two schools ($p < 0.001$).

The inclusion criteria were at least one valid weekday of 9 h combined accelerometer and GPS wear time, excluding day 1 data, weekend data, participants not staying in their primary home during data collection (for participants with divorced parents), and participants who did not have any outdoor data. Data from day 1 were removed as the equipment was fitted at different times during the day, leaving the participants with unequal opportunities to obtain enough hours to become a valid day. Furthermore, the analyses conducted required a full day behavior pattern. Weekend data were removed as weekday data provided the greatest variability in domains and subdomains and because weekends and weekdays are not directly comparable in terms of domains/subdomains, i.e., children do not attend school on weekends. Data from children with divorced parents who stayed in their secondary home during data collection were removed as only the primary parent's address was known to be located within the assessed neighborhood. Due to a software problem with the initializing system used to set-up the GPS devices, almost all GPS on two schools did not record the satellite signal to noise ratio (SNR), which meant that the time spent outdoors could not be assessed. The majority of participants from these two schools were excluded, leaving 204 participants with combined accelerometer and GPS data and outdoor time measures. Eight participants were excluded as they only had weekend data or data from day 1, 6 participants were excluded as they only were in their secondary home during data collection, and 20 were excluded as they did not have one valid day of 9 h of combined weekday data. This led to a total sample for this study of 170 participants out of the 523 consenters (32.5%). There were no differences in background characteristics, such as gender, BMI, parental employment status, and immigrant status, between those who provided complete measures ($n = 170$) and those who were excluded ($n = 353$). However, the drop-out was unequally distributed by school ($p < 0.001$) and age ($p < 0.001$). **Figure 1** displays a flow diagram of the reduction of the population.

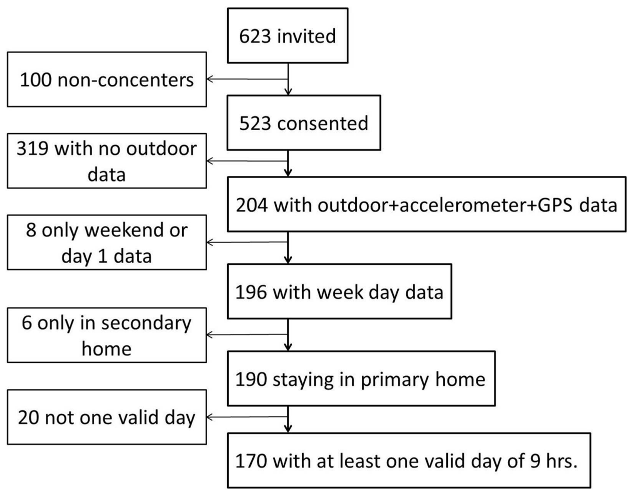

FIGURE 1 | Reduction of the study population.

PHYSICAL ACTIVITY – ACCELEROMETER MEASURES

Objective physical activity levels were assessed using the tri-axial Actigraph GT3X accelerometer during seven consecutive days. On day 8, the participants handed in the equipment. Only the vertical axis was used for this study. The accelerometer has the ability to yield measures of volume, frequency, intensity, and duration of children's physical activity (32). Several reviews have concluded that accelerometers provide an accurate, reliable, and practical objective measure of physical activity in children and adolescents (33, 34). The data were recorded at 2 s epochs. All students were instructed to wear the monitor on their hip during waking hours and to take it off only for showering, bathing, or any water sports. They were asked to record in a diary the times they took the monitor off and the reason for doing so. Data from the returned monitors were downloaded using the ActiLife 4.4.1 software and screened for file size to detect potential equipment or download problems.

CONTEXTS – GPS MEASURES

QStarz BT-Q1000X GPS units were used to record movement. The QStarz unit has shown relatively high accuracy across a range of sites (e.g., canopy and open sky) and good inter-unit reliability compared to other units (18, 29, 35). The GPS units were set-up using BT747 open source software (bt747.org). Units were configured to log data every 15 s, a compromise between optimal frequency (i.e., 2 s as the accelerometer) and data storage capacity of the units over a 7-day period. The units were set to stop logging when the memory was full and to record: date, time, longitude and latitude (used to calculate location), elevation, speed (used to calculate transport mode), and the number of satellites in view and used (used to calculate the Signal-to-Noise-Ratio (SNR)). SNR's can be used to estimate if the GPS is outdoors. After set-up, the fully charged GPS were turned off. On day 1 of data collection the research team turned the GPS units on, and taped the on/off button to prevent it from sliding to off. The children were instructed to leave the tape on, and *not* turn the unit off during data collection. They were instructed to wear the GPS on the same belt as the accelerometer but on the opposite hip, and only to take it off as instructed with the accelerometer. After data collection, the data were downloaded using bt747 software and screened for file size to detect the potential equipment or download problems.

Participants who lost or had malfunctioning devices during data collection, and informed the research team, had their device exchanged, and their data were later merged into one data-file. A total of 14 participants lost one or both devices, or returned malfunctioning devices when data collection was complete.

CORRELATES

Children's immigrant status was obtained from Statistics Denmark using a unique personal identification number assigned to all people in Denmark (36) and children were categorized as Danish versus immigrant (not born in Denmark) or descendent (born in Denmark but parents not born in Denmark). Parental employment status was obtained from Danish registers on personal labor market affiliation (37) and categorized as parents working versus one or both unemployed. Age was dichotomized into grade 5–6 (age 11–13) versus grade 7–8 (13–16), to best approximate children and adolescents. Information on self-reported height and weight was obtained from a questionnaire (E-survey) completed during data collection. BMI was calculated using Cole's age and gender specific cut off points (38) and included as a continuous variable.

STEPS TAKING TO INCREASE VALIDITY

Questionnaire data were used to assess if children living with divorced parents were residing in their primary home (i.e., the local neighborhood) during the data collection period. Participants completed a daily diary during data collection to assess non-wear and changes to the ordinary school schedule. Students were asked to note school (non-)attendance times, and if it had been a regular school day (if not, why not?). The schools furthermore provided detailed class timetables for the data collection period including information on start and end of school days, recess and physical education (PE). These measures were used to adjust and improve the quality of the combined GPS and accelerometer data during data processing.

DATA PROCESSING

The PALMS is a web-based application capable of combining activity data (e.g., accelerometers) with location data (GPS). PALMS aggregated and processed the accelerometer data to provide values for MVPA using 15 s cut points (39, 40). Evenson cut points (39) were used in this study with 574 counts per 15 s as threshold for MVPA. Continuous periods of 60 min of zero values were classified as non-wear time and removed (33, 41). PALMS processed the GPS data by identifying invalid data points using extreme speed or extreme changes in distance and elevation, and replaced invalid points by imputing data from the last known valid point, for up to 10 min. Using algorithms that utilize SNR PALMS categorized epochs as occurring indoors or outdoors. For this study, PALMS marked the locations as outdoor when the total SNR of all satellites in view exceeded a threshold of 250 (26, 29). Furthermore, PALMS identified and categorized trips (defined as a continuous period of movement of at least 3 min, allowing for stationary periods of maximum 5 min) into three modes: walking, bicycling, and vehicle (29). Processed GPS data were then matched to the accelerometer data in 15 s epochs, forming a PALMS dataset. The PALMS dataset consisted of 15 s accelerometer epochs with the following information appended: location (GPS coordinates: latitude and longitude), activity intensity (MVPA), outdoor (yes, no), and trip mode (walk, bicycle, and vehicle). In case no GPS signal was available the accelerometer epochs were retained to calculate the daily physical activity variables. The PALMS dataset is very rich in information and no available data management systems were able to handle the data load, or the specific requirements developed to obtain high quality, precise context-specific measures. Therefore, a purpose-built PostgreSQL database was developed. The PostgreSQL database was set-up to combine PALMS datasets with data from participant dairies, class timetables, and location data from a Geographical Information System (GIS, ArcGIS 10.1) to compute variables for days and context-specific settings. The context-specific settings included were the active living domains: leisure, school (scheduled school hours) (42), transport, and home (43) and a range of subdomains within these domains reflecting places where children and adolescents can be involved in MVPA. The subdomains constituting leisure were: school grounds (outside scheduled school hours) (44), clubs (after school programs), sports facilities (45), playgrounds (46, 47), urban green space (19, 20), shopping centers, and "other places." The Municipality of Copenhagen provided the addresses of public schools, clubs, sports facilities, and playgrounds, enabling a manual digitizing of school grounds, clubs, sports facilities, and playgrounds in GIS. All urban green spaces were available from the Danish Geodata Agency. Major indoor shopping centers were identified online, and manually digitalized in GIS. Epochs not categorized as school, home, transport, or other leisure subdomains were categorized as other places. Epochs were assigned to school, recess, or PE according to the school schedule, adjusting for individual variations based on the individual student diary, and total recess and PE were then assessed within the school domain. All epochs classified by PALMS as trips, and not part of any other domain, constituted the transport domain, and PALMS trips were dichotomized into active (walking and biking) and passive (vehicle) transport. All students' primary addresses were geocoded and each home was digitalized manually in GIS to constitute the home domain. A house was in GIS defined as the parcel, while an apartment was defined as the building and adjacent outdoor area. No subdomains were defined within the home domain. A 10-m Euclidian buffer was applied to all GIS derived domains and subdomains to account for signal and location errors. The database applied a hierarchical process to ensure an epoch could only be assigned to one context. All epochs belonging to the school domain were categorized first, followed by epochs belonging to first the home and then the leisure domain. Epochs belonging to a trip were then assigned to the transport domain, while the left over epochs finally were assigned to the leisure subdomain "other places". The data were aggregated on an individual level by day, domain, and subdomain in the database before being imported into a statistical software package for further analyses.

OUTCOME MEASURES

For weekdays, 4 domains, and 11 subdomains, five daily context-specific outcome measures were calculated and used in this study: minutes of outdoor time, the proportion of time spent outdoors, minutes of outdoor MVPA, the proportion of MVPA spent outdoor, and MVPA. Proportion of time spent outdoors was calculated as minutes of outdoor time out of (wear) time during the average weekday or context-specific setting and hence expresses the proportion of time accumulated in a context that was outdoors. The proportion of MVPA spent outdoors was calculated as minutes of outdoor MVPA in a weekday, domain or subdomain out of total minutes of MVPA accumulated in the day, domain or subdomain and hence expresses the percentage of how much of all MVPA accumulated during the day, domain, and subdomain that is occurring outdoors. These measures were included to account for potential differences in movement patterns among groups, e.g., boys and girls may spend equal amount of time in a context but one part may spend double the amount of outdoor time.

DATA ANALYSES

All analyses were performed using STATA SE12. Descriptive statistics were used to assess age, gender, and BMI by means of frequency distribution (%), and mean and standard deviation. Median and inter quartile ranges (IQR) were used to describe minutes of daily MVPA and wear time as these variables were not normally distributed. Univariable analyses were performed to evaluate the association between the two age groups and between boys and girls using a chi-square, t-test, or Wilcoxon rank-sum test. As the majority of outcome measures were not normally distributed, median and IQR were used to describe four of the outcome measures: outdoor times, the proportion of time spent outdoors, outdoor MVPA and the proportion of MVPA spent outdoors in total, domains and subdomains by gender, age, and totals. Multilevel analyses were used to provide results on age and gender differences. All models included students within school, further adjusting for BMI, number of valid weekdays (1–4) and daily wear time (models based on total days) or time in overall domain being investigated, e.g., the subdomain playground was adjusted for time in the leisure domain. Each model accounted for the nested nature of children within schools (48) by including school as a fixed effect. Models with a non-normal distribution of the residuals (49 out of 64 models) had their outcome transformed to fulfill the model assumptions, 22 by square root, 17 by log, 8 by x^2, and 2 by x^3 transformation. For the 17 log transformed models, zeros were replaced with a small number (0.03125 corresponding to half the value of the lowest non-zero number across the models) before transformation. The transformed model p-value and the untransformed model coefficient for age and gender differences are shown for ease of interpretation. Age and gender interactions were found in 15 out of 64 models (significance level $p = 0.05$). The interaction p-value and the significant gender and age subgroup differences are presented separately. Multilevel analyses were used to provide unadjusted and adjusted results on the association between MVPA and outdoor time during the total day, domains, and subdomains. All the adjusted models accounted for the nested nature of children within schools by including school as a fixed effect, further adjusting for age, gender, BMI, number of valid weekdays (1–4) and registered time in day (models based on total days), or time in overall domain being investigated. All models were tested for interactions between outdoor time, age, and/or gender (significance level $p = 0.05$) to investigate if the association was persistent across age and gender groups. An interaction was present in 7 out of 16 contexts; however, the pattern of the association (i.e., the size of the p-value) was the same across all subgroups with four exceptions. For ease of interpretation, the results from the untransformed models showing totals rather than subgroups are shown, while the text specifies the four subgroup exceptions.

RESULTS

PARTICIPANTS

Table 1 shows characteristic for the study participants ($n = 170$). On average, the participants had a daily median of 12.9 h (IQR, 11.7–13.6) of combined accelerometer and GPS data and a mean of 2.7 valid days (SD 1.1) out of 4 possible. Boys compared to girls had more minutes of daily MVPA (82.8 versus 61.2 min, $p < 0.001$). As expected, BMI was greater among adolescents compared to children ($p < 0.05$).

TIME OUTDOOR PATTERN

Table 2 shows the daily median minutes of outdoor time (minutes, IQR) in total, domains, and subdomains by gender and age, and age and gender differences assessed in multilevel analyses. Across all groups, the majority of outdoor time was accumulated during the school hours, followed by leisure time, transport, and home. However, the pattern was less clear among adolescents.

While boys were outdoors 226.7 min per day, girls were outdoors 194.5 min per day ($p < 0.05$) (**Table 2**). This difference was predominantly due to a difference during leisure, where boys were outdoors 71.9 min and girls were outdoors only 45.0 min ($p < 0.001$). Within leisure, boys spent more time outdoors when in sports facilities and other places (all $p < 0.05$). Boys also spent more time outdoors when in transport ($p < 0.05$). There was no gender difference in the time spent outdoors during school or home.

Children were outdoors a median of 226.5 min per day and adolescents 172.6 min per day ($p < 0.05$) (**Table 2**). This difference originated predominantly from a difference during school hours, were children compared to adolescents had almost the double amount of outdoor time (96.5 versus 44.5 min, $p < 0.001$). Children also spent more time outdoors when at school grounds outside school hours (15.3 versus 4.1 min, $p < 0.05$) but spent fewer minutes outdoors than adolescence during transport (24.8 versus 30.2 min, $p < 0.05$).

Table 3 shows the daily median proportion of time spent outdoors (%, IQR) in total, domains, and subdomains by gender and age, and age and gender differences assessed in multilevel analyses. Boys spent a greater proportion of their time during a day being outdoors: boys were outdoors 29.0% of the day while girls were outdoors 22.2% of the day ($p < 0.05$). The proportion of time spent outdoors when in a particular domain or subdomain varied; with home being the place where the lowest proportion of time was spent outdoors (girls 8.5%, boys 7.9%) and playgrounds had the highest proportion (girls 87.5%, boys 99.8%). Besides spending a larger proportion of time outdoors in leisure, sports facilities, other places, and in transport, boys compared to girls also spent a greater proportion of their time outdoors in school grounds, during recess, and PE. No gender difference was detected in the proportion of time spent outdoors when in active transport, despite boys spending significant more minutes outdoors in active transport.

A trend of an overall age difference in the proportion of time spent outdoors during the total day was detected with children being outdoors 27.3% of the day and adolescents 20.6% of the day ($p = 0.05$) (**Table 3**). Children compared to adolescents accumulated a larger proportion of their MVPA at school grounds ($p < 0.05$), during school hours ($p < 0.001$), and during recess ($p < 0.001$).

An analysis of age and gender interactions further revealed that adolescent girls had less daily outdoor time and spent a lower proportion of time outdoor on school grounds and at other places

Table 1 | Study participants ($n = 170$).

	Girls	Boys	Children	Adolescents	Total
Population (%)	87 (51.2)	83 (48.8)	129 (75.9)	41 (24.1)	170 (100)
Mean age (SD)	12.9 (1.2)	12.8 (1.0)	**12.4 (0.7)*****	**14.2 (0.8)*****	12.8 (1.1)
Mean BMI (SD)[a]	18.1 (2.8)	18.6 (3.2)	**18.1 (3.1)***	**19.4 (2.8)***	18.4 (3.0)
Mean valid days (SD)	2.7 (1.1)	2.6 (1.1)	2.7 (1.1)	2.4 (0.9)	2.7 (1.1)
Median daily minutes MVPA (IQR)	**61.2 (46.7–75.8)*****	**82.8 (58.4–99.1)*****	69.5 (53.5–91.9)	58.3 (46.8–85.6)	68.4 (52.0–91.8)
Median daily hours combined data (IQR)	13.0 (11.9–13.6)	12.7 (11.5–13.6)	12.9 (11.9–13.6)	13.0 (10.9–13.7)	12.9 (11.7–13.6)

**Significant difference p < 0.05.*

****Significant difference p < 0.001.*

[a] *n = 156.*

BMI, body mass index; IQR, inter quartile range; MVPA, moderate to vigorous physical activity; SD, standard deviation.

Table 2 | Daily outdoor time in total/domain/subdomain by age and gender ($n = 91–170$) and adjusted age and gender differences ($n = 81–156$).

	Unadjusted median minutes (IQR)						Adjusted differences, minutes				
	Girls	Boys	Children	Adolescent	Total	*n*	Gender Reference: girls		Age Reference: children		*n*
							Coefficient	*p*-Value	Coefficient	*p*-Value	
Total	194.5 (129.1–259.3)	226.7 (184.8–291.3)	226.5 (175.0–284.5)	172.6 (111.7–225.3)	215.1 (157.7–278.5)	170	**34.9**	**0.001**	**−29.3**	**0.037**	156
Leisure	45.0 (21.2–73.0)	71.9 (33.3–110.5)	62.9 (32.0–107.5)	33.4 (23.1–73.0)	56.6 (29.0–96.8)	170	**21.3**	**0.000**	1.6	0.91	156
School grounds	9.3 (3.9–26.8)	15.3 (6.3–28.9)	15.3 (6.8–33.0)	4.1 (2.7–9.3)	11.7 (4.6–28.5)	170	3.9	0.12	**−8.7**	**0.004**	156
Clubs	0.0 (0.0–0.5)	0.0 (0.0–0.6)	0.0 (0.0–0.5)	0.0 (0.0–0.6)	0.0 (0.0–0.6)	170	−4.5	0.41	−4.0	0.49	156
Sports facilities	0.0 (0.0–0.6)	0.1 (0.0–12.8)	0.0 (0.0–1.0)	0.1 (0.0–29.3)	0.0 (0.0–2.9)	170	**8.1**	**0.002**	**9.7**	**0.001**	156
Playgrounds	0.0 (0.0–0.4)	0.3 (0.0–0.9)	0.0 (0.0–0.8)	0.2 (0.0–0.4)	0.0 (0.0–0.7)	170	0.1	0.10	−0.4	0.46	156
Urban green space	4.7 (2.0–9.8)	6.6 (2.0–11.8)	5.0 (2.0–10.8)	5.8 (2.8–9.3)	5.2 (2.0–10.3)	170	0.8	0.23	1.5	0.60	156
Shopping center	0.0 (0.0–0.1)	0.0 (0.0–0.0)	0.0 (0.0–0.0)	0.0 (0.0–0.8)	0.0 (0.0–0.1)	170	−0.1	0.43	**0.3**	**0.000**	156
Other places	10.5 (4.7–23.5)	23.3 (8.9–36.3)	16.1 (7.2–33.8)	11.5 (3.8–25.1)	14.8 (7.0–32.3)	170	**12.8**	**0.000**	3.2	0.44	156
School	80.6 (45.6–114.4)	91.5 (62.8–131.5)	96.5 (65.2–138.3)	44.5 (28.1–84.4)	87.0 (53.5–126.8)	168	0.4	0.90	**−36.4**	**0.000**	154
Recess	27.7 (18.4–34.7)	29.8 (21.3–40.3)	30.5 (23.2–39.0)	17.3 (12.9–28.8)	28.7 (19.4–36.4)	164	2.5	0.15	**−11.8**	**0.000**	151
PE	21.9 (6.0–65.5)	49.3 (16.5–85.3)	52.8 (8.4–86.3)	19.5 (13.3–44.3)	34.5 (11.0–83.8)	91	9.7	0.08	−11.2	0.92	81
Transport	23.7 (14.0–36.3)	29.0 (18.4–43.5)	24.8 (14.8–36.3)	30.2 (21.0–49.3)	25.9 (15.5–38.3)	170	**4.1**	**0.004**	**1.6**	**0.049**	156
Active	15.9 (8.6–25.4)	20.9 (11.5–31.1)	18.8 (9.8–26.3)	21.0 (10.5–31.3)	19.0 (10.5–28.5)	170	**3.1**	**0.019**	−1.5	0.83	156
Passive	4.2 (0.0–15.5)	3.0 (0.0–14.3)	2.1 (0.0–11.4)	10.0 (0.0–19.5)	3.8 (0.0–14.3)	170	0.4	0.48	2.1	0.13	156
Home	17.8 (4.8–51.4)	14.3 (4.8–51.5)	16.6 (4.4–49.7)	14.3 (5.3–55.4)	16.6 (4.8–51.4)	170	−4.5	0.99	6.3	0.80	156

Bold: significance level at $p < 0.05$.

Differences in age (or gender) were estimated using multilevel analyses adjusted for differences in gender (or age), BMI, number of valid days, and time in domain. School included as fixed effect to account for clustering of students within school.

IQR, inter quartile range; MVPA, moderate to vigorous physical activity; PE, physical education.

Table 3 | Daily proportion of time in total/domain/subdomain that is spent outdoor by age and gender ($n = 53–170$) and adjusted age and gender differences ($n = 48–156$).

	Unadjusted median % (IQR)						Adjusted differences, %				
	Girls	Boys	Children	Adolescent	Total	*n*	Gender Reference: girls		Age Reference: children		*n*
							Coefficient	*p*-Value	Coefficient	*p*-Value	
Total	22.2 (16.0–30.7)	29.0 (22.7–36.8)	27.3 (20.5–35.3)	20.6 (13.9–27.2)	25.7 (19.2–34.5)	170	**4.3**	**0.001**	−3.2	0.05	156
Leisure	18.7 (9.9–30.7)	26.0 (16.3–41.9)	23.3 (14.2–33)	21.1 (10.2–33.7)	22.6 (12.5–33.2)	170	**7.7**	**0.001**	1.0	0.92	156
School grounds	41.7 (27.8–58.5)	63.0 (48.0–73.2)	55.7 (36.2–70.5)	32.2 (22.6–56.1)	51.7 (30.9–68.3)	167	**8.7**	**0.004**	**−8.0**	**0.043**	154
Clubs	37.1 (1.6–72.8)	53.9 (14.5–100.0)	47.4 (2.9–97.5)	33.3 (11.1–72.2)	46.0 (4.0–95.1)	91	14.9	0.09	−3.7	0.60	84
Sports facilities	54.3 (1.4–96.4)	92.7 (7.5–100.0)	66.7 (0.0–100.0)	93.2 (50.0–100.0)	76.3 (6.3–100.0)	109	**15.4**	**0.017**	22.2	0.10	102
Playgrounds	87.5 (38.1–100.0)	99.8 (50.0–100.0)	94.0 (36.4–100.0)	95.7 (72.7–100.0)	94.0 (44.9–100.0)	88	13.9	0.15	9.8	0.37	82
Urban green space	66.6 (38.5–78.9)	71.3 (41.2–92.2)	67.4 (33.3–88.8)	77.1 (57.6–86.6)	68.5 (38.9–88.2)	167	8.9	0.05	5.5	0.35	154
Shopping center	41.6 (11.5–60.0)	15.5 (1.7–74.2)	24.0 (0.8–55.2)	50.0 (14.3–75.0)	33.3 (3.7–60.3)	53	−0.5	0.96	10.4	0.40	48
Other places	7.2 (3.2–15.9)	11.5 (5.6–22.5)	9.8 (4.8–16.7)	8.2 (3.3–21.0)	9.3 (4.2–17.2)	170	**6.8**	**0.000**	3.7	0.23	156
School	25.0 (13.6–36.8)	30.7 (17.3–45.9)	31.1 (19.4–46.4)	13.8 (9.2–29.5)	28.3 (15.4–43.7)	168	0.0	0.84	**−12.7**	**0.000**	154
Recess	43.6 (28.8–62.6)	55.9 (41.6–73.2)	57.4 (41.7–72.2)	26.0 (20.2–42.7)	49.8 (33.8–66.7)	164	**5.1**	**0.030**	**−23.6**	**0.000**	151
PE[5]	32.8 (6.0–73)	59.9 (21.6–95.0)	71.3 (9.8–96.1)	21.8 (14.0–52.5)	52.0 (12.0–93.3)	91	**14.2**	**0.030**	−8.9	0.84	81
Transport	73.8 (58.6–85.8)	76.5 (65.6–89.4)	76.5 (62.5–87.3)	74.5 (62.9–86.9)	75.0 (62.6–87.3)	170	**7.9**	**0.003**	3.0	0.39	156
Active	81.1 (68.5–92.9)	83.7 (69.2–91.3)	81.1 (67.0–92.6)	83.0 (74.4–92.6)	81.2 (68.9–92.6)	168	2.9	0.34	4.9	0.24	154
Passive	52.1 (38.7–65.5)	60.4 (47.6–79.4)	53.4 (38.7–69.5)	59.4 (48.3–77.5)	55.3 (40.9–72.5)	111	**10.4**	**0.011**	4.9	0.34	101
Home	8.5 (2.9–22.6)	7.9 (3.3–26.1)	8.9 (3.2–23.1)	7.8 (2.8–22.6)	8.5 (3.1–22.9)	169	2.9	0.987	−1.4	0.937	155

Bold: significance level at $p < 0.05$.

Differences in age (or gender) were estimated using multilevel analyses adjusted for differences in gender (or age), BMI, number of valid days, and time in domain. School included as fixed effect to account for clustering of students within school.

IQR, inter quartile range; MVPA, moderate to vigorous physical activity; PE, physical education.

than child girls and boys (**Table 6**). Girl children also spent a smaller proportion of time in other places than boys. Adolescent boys spent more leisure time outdoor and spent a larger proportion of time outdoor than girls and child boys. Child boys spent more leisure time outdoor and spent a larger proportion of outdoor time than adolescent girls. Adolescent boys spent more time outdoors in urban green space than adolescent girls.

OUTDOOR MVPA PATTERN

Table 4 shows the daily median minutes of outdoor MVPA time (outdoor MVPA minutes, IQR) in total, domains, and subdomains by gender and age and age and gender differences assessed in multilevel analyses. Girls accumulated a daily median of 42.3 min of outdoor MVPA, while boys accumulated a daily median of 61.8 min of outdoor MVPA ($p < 0.001$). In 10 out of the 15 investigated contexts, boys compared to girls accumulated more minutes of outdoor MVPA, with no gender differences present in clubs, playgrounds, urban green space, shopping centers, and passive transport ($p > 0.05$).

Among children and adolescents, no overall difference was found in how many minutes of outdoor MVPA were accumulated during the whole day ($p > 0.1$) (**Table 4**). Children compared to adolescents had more outdoor MVPA during school hours and recess ($p < 0.001$) while adolescent compared to children had more outdoor MVPA at sport facilities, shopping centers, and passive transport ($p < 0.05$).

In the analyses investigating the proportion of MVPA occurring outdoors during the day and in different contexts (**Table 5**), a significant gender difference was detected overall and in 6 out of the 15 investigated contexts. Boys accumulating a larger proportion of their MVPA outdoors when in leisure overall, in school grounds, sports facilities, playgrounds, school, and PE. During the total day, 73.8% of boys MVPA was spent outdoors with girls spending 65.3% of their MVPA outdoors ($p < 0.001$). No overall difference was found between children and adolescents in the proportion of daily MVPA that was spent outdoors, but children spent a larger proportion of their MVPA outdoors during school hours and recess ($p < 0.001$).

When in transport, clubs, sport facilities, playgrounds, urban green space, and in recess a high proportion of MVPA took place outdoors for both boys and girls, and children and adolescents (84.8–100%). Boys and children also accumulated a large proportion of their MVPA outdoors when in PE (boys 85.3%, children 91.9%) (**Table 5**).

Adolescent boys accumulated more outdoor MVPA minutes in urban green space and home than child boys and girls (**Table 6**). Adolescent boys also spent a larger proportion of their MVPA outdoors during leisure, in school grounds, and other places. Adolescent boys spent a larger proportion of their MVPA outdoors when at home compared to adolescent girls. Child boys had more minutes of outdoor MVPA compared to adolescent boys and girls. Child girls spent a lower proportion of their MVPA outdoors while at sports facilities compared to adolescent girls and boys.

TIME OUTDOOR AND MVPA

In multilevel analyses, time spent outdoors (hours) was a significant predictor of MVPA (minutes) both in unadjusted models and in models adjusted for potential confounders (gender, age, BMI, number of valid days, time in day, or overall domain) (**Table 7**). Models were run for days, domains, and subdomains to investigate if the association varied by context, but a consistent relationship was found throughout the day (all $p < 0.001$) with only four exceptions detected in supplementary analyses investigating interactions between outdoor time, gender, and age (data not shown). No association was found between outdoor time and MVPA for child boys when at shopping centers ($p > 0.1$) and in transport ($p > 0.1$). Also a weaker association was found for adolescent girls when in transport ($p = 0.05$) or at home ($p = 0.06$). During the course of the whole day, a 1-h increase in outdoor time was associated with 9.9 more minutes of MVPA. An association was also found for contexts in leisure time where a 1-h increase in outdoor time was associated with an increase of 23.5 more minutes of MVPA in school grounds, 20.2 more minutes of MVPA in urban green space, and 18.6 more minutes of MVPA when at sports facilities. One more hour of outdoor time during active transport was associated with 28.5 more minutes of MVPA (all $p < 0.000$).

DISCUSSION

This study investigated the volume and pattern of context-specific weekday outdoor time, outdoor MVPA, and the association between context-specific daily MVPA and outdoor time using combined accelerometer and GPS data for 170 children aged 11–16 years old. Four domains, 11 subdomains, and daily medians were assessed as context-specific measures and age and gender differences were investigated. A different pattern was found for boys and girls, as well as for children and adolescents. Girls compared to boys had fewer outdoors minutes and spent a lower proportion of their daily time outdoors overall and in the majority of investigated contexts. Girls compared to boys had fewer outdoor MVPA minutes during the day and in 11 contexts. A less consistent difference was found for the proportion of MVPA spent outdoors; gender differences were only detected in five contexts. During the total weekday, children compared to adolescents had more outdoor minutes ($p < 0.05$) while no difference in daily outdoor MVPA behavior was found. However, across all investigated outcomes a difference in behavior in the school context was detected, with children engaging in more outdoor MVPA and spending more time outdoors during school hours and within recess. Finally, it was found that outdoor time was a correlate for MVPA across the total day, all domains and subdomains.

Overall, 21.8–29.3% of time was spent outdoors, corresponding to approximately 3 h a day. Compared to other studies, even though the studies are not directly comparable as the methods used differ, it appears that the Danish children studied were spending more time outdoors than children included in studies from the UK (19, 25), Australia (2, 6), and Switzerland (49). This discrepancy could be due to outdoor time being measured differently; the Australian and Swiss studies relied on self-report data and the UK studies used a GPS device that assessed outdoor time differently from the present study. Another difference might be time of year when the data were collected as seasonality and weather conditions previously have been related to objectively assessed physical activity in children (50) and this association is likely to also apply to outdoor times.

Table 4 | Daily outdoor MVPA in total/domain/subdomain by age and gender ($n = 91–170$) and adjusted age and gender differences ($n = 81–156$).

	Unadjusted median minutes (IQR)						Adjusted differences, minutes				
	Girls	**Boys**	**Children**	**Adolescent**	**Total**	***n***	**Gender Reference: girls**		**Age Reference: children**		***n***
							Coefficient	***p*-Value**	**Coefficient**	***p*-Value**	
Total	42.3 (25.3–52.3)	61.8 (41.0–76.0)	50.1 (36.5–65.5)	38.4 (23.8–66.3)	48.1 (34.3–65.7)	170	**24.3**	**0.000**	1.0	0.57	156
Leisure time	7 (4.1–14.5)	14.8 (5.8–26.8)	12.1 (5.0–21.6)	7.8 (4.3–19.6)	11.1 (4.7–21.3)	170	**8.8**	**0.000**	3.7	0.07	156
School grounds	1.8 (0.9–5.0)	3.5 (1.5–9.0)	3.4 (1.5–7.1)	1.4 (0.8–2.2)	2.5 (1.2–6.2)	170	**3.6**	**0.002**	−0.8	0.06	156
Clubs	0.0 (0.0–0.3)	0.0 (0.0–0.2)	0.0 (0.0–0.3)	0.0 (0.0–0.1)	0.0 (0.0–0.2)	170	−0.4	0.22	−0.4	0.61	156
Sports facilities	0.0 (0.0–0.1)	0.0 (0.0–4.5)	0.0 (0.0–0.4)	0.0 (0.0–5.1)	0.0 (0.0–0.7)	170	**2.1**	**0.000**	**2.4**	**0.004**	156
Playgrounds	0.0 (0.0–0.3)	0.0 (0.0–0.4)	0.0 (0.0–0.4)	0.0 (0.0–0.3)	0.0 (0.0–0.3)	170	0.2	0.06	0.0	0.52	156
Urban green space	1.5 (0.8–3.8)	1.8 (0.8–4.9)	1.5 (0.6–3.6)	2.3 (1.1–4.4)	1.8 (0.8–3.8)	170	0.9	0.14	1.2	0.06	156
Shopping center	0.0 (0.0–0.0)	0.0 (0.0–0.0)	0.0 (0.0–0.0)	0.0 (0.0–0.1)	0.0 (0.0–0.0)	170	0.0	0.19	**0.0**	**0.006**	156
Other places	0.8 (0.3–2.1)	1.3 (0.5–3.9)	1.0 (0.5–2.5)	1.3 (0.3–2.6)	1.0 (0.4–2.5)	170	**2.5**	**0.001**	1.2	0.09	156
School	13.4 (8.7–19.9)	21.5 (12.1–30.4)	18.9 (12.3–28.2)	7.7 (4.0–17.8)	16.7 (10.2–27.4)	168	**7.1**	**0.000**	**−10.1**	**0.000**	154
Recess	4.6 (2.7–7.3)	6.6 (4.3–11.1)	6.3 (4.2–9.3)	2.9 (1.4–6.7)	5.5 (3.5–8.9)	164	**2.8**	**0.000**	**−3.4**	**0.000**	151
PE	8.9 (1.3–17.5)	21.5 (5.0–34)	13.9 (1.3–32.1)	8.3 (4.3–20.4)	11.3 (1.8–25.0)	91	**9.5**	**0.001**	−1.6	0.68	81
Transport	10.1 (3.6–16.7)	11.9 (5.8–19.6)	10.3 (4.8–15.8)	15.9 (5.2–20.1)	10.9 (4.8–17.5)	170	**2.3**	**0.039**	3.0	0.09	156
Active	6.8 (3.0–13)	9.3 (5.3–15.1)	8.1 (3.4–13.3)	9.1 (4.3–16.4)	8.3 (3.5–14.6)	170	**2.3**	**0.020**	1.2	0.42	156
Passive	0.3 (0.0–3.7)	0.6 (0.0–4.7)	0.3 (0.0–3.2)	2.3 (0.0–7.3)	0.4 (0.0–4.2)	170	0.0	0.87	**1.7**	**0.002**	156
Home	1.8 (0.6–5.3)	2.5 (0.4–9.3)	1.8 (0.5–6.4)	3.3 (1.0–9.6)	2.3 (0.5–6.8)	170	**5.0**	**0.035**	−0.4	0.32	156

Bold: significance level at $p < 0.05$.

Differences in age (or gender) were estimated using multilevel analyses adjusted for differences in gender (or age), BMI, number of valid days, and time in domain. School included as fixed effect to account for clustering of students within school.

IQR, inter quartile range; MVPA, moderate to vigorous physical activity; PE, physical education.

Table 5 | Proportion of daily MVPA that is spent outdoor in total/domain/subdomain by age and gender ($n = 34–170$) and adjusted age and gender differences ($n = 32–156$).

	Unadjusted median % (IQR)						Adjusted differences, %				
	Girls	Boys	Children	Adolescent	Total	*n*	Gender Reference: girls		Age Reference: children		*n*
							Coefficient	*p*-Value	Coefficient	*p*-Value	
Total	65.3 (55.9–71.4)	73.8 (68.6–78.4)	70.0 (63.5–76.5)	67.4 (52.1–74.7)	69.9 (62.5–76.1)	170	**7.7**	**0.000**	−5.5	0.06	156
Leisure time	55.6 (41.7–67.0)	63.3 (48.7–76.1)	61.2 (45.1–70.6)	62.5 (46.3–72.2)	61.3 (45.1–71.6)	170	**10.0**	**0.000**	3.3	0.47	156
School grounds	59.8 (46.7–75.0)	72.6 (60.3–84.6)	68.0 (56.3–79.7)	64.3 (46.7–82.1)	66.9 (50.8–80.5)	167	**10.1**	**0.001**	0.5	0.91	154
Clubs	100.0 (75.6–100.0)	84.8 (33.3–100.0)	95.8 (55.9–100.0)	100.0 (50.0–100.0)	100.0 (50.0–100.0)	65	−14.3	0.11	−24.6	0.11	61
Sports facilities	97.5 (45.0–100.0)	100.0 (99.4–100.0)	100.0 (50.0–100.0)	100.0 (99.4–100.0)	100.0 (87.5–100.0)	70	**24.0**	**0.000**	17.5	0.10	68
Playgrounds	100.0 (70.0–100.0)	100.0 (97.4–100.0)	100.0 (84.5–100.0)	100.0 (87.5–100.0)	100.0 (87.5–100.0)	73	**9.0**	**0.048**	−12.0	0.17	67
Urban green space	96.3 (82.9–100.0)	98.7 (81.3–100.0)	97.0 (78.7–100.0)	97.5 (85.7–100.0)	97.3 (81.3–100.0)	158	0.5	0.56	2.1	0.62	148
Shopping center	61.0 (27.4–100.0)	45.0 (22.2–100.0)	62.5 (37.9–100.0)	33.3 (22.2–100.0)	54.8 (22.2–100.0)	34	1.6	0.90	11.9	0.41	32
Other places	24.9 (9.2–36.3)	26.8 (11.6–45.1)	25.6 (10.4–40.4)	26.7 (5.3–36.7)	26.2 (10.2–40.0)	169	5.6	0.07	1.7	0.52	155
School	62.0 (51.6–70.4)	72.2 (63.3–78.4)	67.3 (58.3–77.9)	49.7 (31.2–69.4)	66.0 (53.7–76.6)	168	**5.8**	**0.014**	**−17.4**	**0.000**	154
Recess	67.4 (57.0–79.3)	78.3 (61.9–83.4)	76.4 (63.0–82.7)	57.6 (36.1–76.4)	73.8 (59.2–81.5)	164	4.2	0.09	**−22.7**	**0.000**	151
PE	52.2 (6.0–91.9)	85.3 (36.7–98.9)	91.9 (15.7–98.7)	59.6 (29.4–85.3)	81.4 (20.0–98.1)	89	**13.7**	**0.033**	5.7	0.11	79
Transport	89.5 (83.3–96.5)	91.4 (84.0–96.0)	89.4 (82.4–96.3)	91.7 (88.1–96.1)	90.1 (83.4–96.1)	168	2.3	0.25	1.5	0.56	155
Active	91.6 (83.9–97.9)	92.7 (84.6–97.1)	91.7 (83.1–97.4)	93.4 (87.6–97.5)	92.0 (84.0–97.4)	167	1.6	0.46	2.8	0.32	154
Passive	91.0 (77.4–100.0)	91.1 (78.8–98.4)	89.5 (77.3–100.0)	94.0 (83.3–98.7)	91.0 (77.4–100.0)	104	0.8	0.58	2.5	0.72	94
Home	38.1 (16.7–61.6)	36.9 (23.1–64.0)	36.4 (16.3–61.0)	52.8 (24.0–66.7)	37.1 (20.3–63.2)	169	3.4	0.39	1.8	0.72	155

Bold: significance level at $p < 0.05$.

Differences in age (or gender) were estimated using multilevel analyses adjusted for differences in gender (or age), BMI, number of valid days, and time in domain. School included as fixed effect to account for clustering of students within school.

IQR, inter quartile range; MVPA, moderate to vigorous physical activity; PE, physical education.

Table 6 | Gender and age interactions by outdoor time, proportion of time spent outdoor, outdoor MVPA and proportion of MVPA spent outdoors in total, domains, and subdomains.

	Outdoor time		% Time spent outdoors		Outdoor MVPA		% Of MVPA spent outdoors	
	***p*-Value[a]**	**Significant interaction group differences**	***p*-Value[a]**	**Significant interaction group differences**	***p*-Value[a]**	**Significant interaction group differences**	***p*-Value[a]**	**Significant interaction group differences**
Total outdoor time	0.003	GA < GC, BA, BC	0.002	GA < GC, BA, BC				
Leisure	0.003	BA > GA, GC, BC > GA	0.004	BA > GA, GC, BC > GA			0.017	BA > BC, GA, GC
School grounds			0.037	GA < GC, BA, BC			0.003	BA > GC, GA, BC > GA
Clubs								
Sports facilities							0.012	GC < GA, BA, BC
Playgrounds								
Urban green space	0.045	BA > GA			0.017	BA > GC, GA, BC		
Shopping center								
Other places			0.040	GA < BA, BC, GC < BC, BA			0.036	BA > BC, GC, GA
School								
Recess								
PE					0.008	BC > BA, GA, GC		
Transport								
Active								
Passive								
Home					0.021	BA > BC, GA, GC	0.044	BA > GA

[a] *Interaction p-value in multilevel analyses adjusted for BMI, number of valid days, and time in domain. School included as fixed effect to account for clustering of children within school.*

GC, girl child (n = 60); GA, girl adolescent (n = 27); BC, boy child (n = 69); BA, boy adolescent (n = 14).

IQR, inter quartile range; MVPA, moderate to vigorous physical activity; PE, physical education.

Table 7 | Association between time outdoors (hours) and MVPA (minutes) in total weekdays, domains, and subdomains.

	Model 1			Model 2		
	Coef.	***p***	**95% CI**	**Coef.**	***p***	**95% CI**
Total day	10.9	<0.001	8.0–13.8	9.8	<0.001	6.9–12.8
Leisure time	14.8	<0.001	12.3–17.4	13.5	<0.001	10.7–16.4
School grounds	21.7	<0.001	19.5–23.9	23.5	<0.001	21.1–25.9
Clubs	10.7	<0.001	9.0–12.4	11.2	<0.001	9.4–13.0
Sports facilities	18.0	<0.001	16.4–19.6	18.6	<0.001	16.8–20.3
Playgrounds	16.3	<0.001	15.5–17.1	16.4	<0.001	15.6–17.3
Urban green space	20.2	<0.001	18.5–21.8	20.2	<0.001	18.4–21.9
Shopping center	15.9	<0.001	12.5–19.3	17.3	<0.001	13.7–20.9
Other places	7.3	<0.001	4.9–9.7	5.5	<0.001	2.9–8.1
School	9.0	<0.001	6.5–11.4	8.3	<0.001	5.8–10.8
Recess	11.6	<0.001	7.8–15.4	8.5	<0.001	4.3–12.6
PE	13.1	<0.001	8.2–18.0	10.9	<0.001	5.9–15.9
Transport	21.2	<0.001	17.7–24.6	15.0	0.002	5.6–24.4
Active	29.3	<0.001	25.4–33.2	28.5	<0.001	23.5–33.6
Passive	10.6	<0.001	8.6–12.6	6.5	<0.001	3.6–9.3
Home	10.1	<0.001	8.3–11.9	9.1	<0.001	7.1–11.2

Model 1: unadjusted multilevel analyses.

Model 2: multilevel analyses adjusted for age, gender, BMI, valid days, time in day/domain, and clustering of students within schools.

Coef., mean increase in minutes of MVPA associated with a 1-h increase in outdoor time.

IQR, inter quartile range; MVPA, moderate to vigorous physical activity; PE, physical education.

In agreement with other studies, boys spent more time outdoors than girls (6, 25) and children spent more time outdoors compared to adolescents (49). The majority of outdoor time was for all groups occurring during school hours followed by leisure time. This study is one of the first to estimate the proportion of outdoor time occurring in domains during the day and further studies are needed to confirm this finding.

Between 62.3 and 71.0% of all total daily MVPA was accumulated outdoors. In the PEACH study, it was found that 26.4–35% of MVPA took place outdoors on weekdays outside the school hours (19). Even though not directly comparable, it seems like the present study population experienced a greater proportion of MVPA outdoors. Similar to the PEACH study, outdoor time in the present study was found to be a significant predictor of daily MVPA in all investigated contexts, and a 1-h increase in outdoor time was associated with almost 10 more minutes of MVPA per day. This study shows a stronger relationship between outdoor time and MVPA than a previous study using self-reported measures from parents (6). Here it was found that for every additional hour spent outdoors per week, MVPA increased by 27 min per week (almost 4 min per day) among 10–12 year old children. The stronger association found in this study may be due to self-reported measures from children or parents being imprecise, and the inclusion of GPS data may provide a more reliable estimate of actual outdoor time, and the accelerometer a more reliable estimate of physical activity. The overall level of daily MVPA among the participants in our study was also high, reaching a daily median of 67.3 min of MVPA. As this study is based on a cross-sectional sample it is not possible to conclude the causal direction of outdoor time and MVPA. Longitudinal studies are needed to establish a causal relationship between outdoor time and MVPA, but promoting outdoor time among the investigated group may have a range of health benefits beyond the association with physical activity. Modifiable characteristics in the neighborhood such as sidewalks, parallel or grouped parking places, traffic safety, and roundabouts have been associated with outdoor play (51), and parental concern about traffic safety has been associated with less time playing outdoors (49, 51). When planning urban renewal programs or new neighborhoods, factors that may be associated with increased or decreased outdoor time are important to consider.

No studies to date have investigated what is needed to obtain reliable estimates of children's context-specific physical activity patterns based on the combination of accelerometers and GPS, and measurement decisions are relaying on recommendations for accelerometer studies. Future methodological studies are needed to investigate if and how the use of combined accelerometers and GPS should differ in the design from a study based solely on accelerometers. Experiences from this study indicate some specific areas that need careful consideration before embarking on research studies using combined accelerometer and GPS measurements. A larger drop-out was seen in this study compared to a similar project using only accelerometers conducted simultaneous (52). Both during data collection (fewer persons consented, more opted out or lost equipment during data collection, device-failure, e.g., software resulting in missing information on SNR), but also in the data analyses were it was evident that less rigid demands had to be applied to wear time and number of valid days to retain a reasonable study population. It may be reasonable to hypothesize that the inclusion of the GPS placed a greater burden on the participants, leading to less compliance with the study protocol.

Therefore, it is recommended that studies using accelerometer and GPS should consider: (a) to oversample or (b) to ask participants to wear the equipment for a longer period of time. Solution: (a) implies either a longer data collection period or a greater pool of equipment while solution (b) again increases the participant burden. A method seen and recommended in accelerometer studies to increase the number of valid participants is to quickly download and screen data to see if a participant complied with the protocol. If not, they are asked to re-wear the accelerometer (53). Similar procedures for the GPS may also be feasible; however, it is time-consuming.

Using a combination of accelerometers and GPS to develop context-specific measures has a large potential to lead to new knowledge on physical activity, inform the development of new interventions, and perhaps later lead to new policies or recommendations for specific subgroups. Still, it is not an easy fix. The data collection is more complex, the recruitment of participants harder, and the data processing and complexity of the data is overwhelming. Practical issues of data storage capacity and run times of 2–3 weeks to generate variables in the purpose-built database for subsamples of 100 participants were a reality in this study, making the analyses time-consuming and labor-intensive. The development of PALMS is one major step toward a resource that can help researchers to start process their data. Integrating the methodology behind this study into PALMS has the potential to increase the number of studies investigating context-specific behaviors, as well as lead to greater conformity across studies, making comparisons possible, and hence perhaps increase knowledge on generalizable context-specific behaviors more quickly.

STRENGTHS AND LIMITATIONS

The use of PALMS to detect outdoor time is relatively novel and the algorithm used by PALMS has been validated in one study (26), however further validation may be needed. We found a large proportion of the participant's time during school hours was spent outdoors. This may be a true finding but it may also be due to a problem with detecting outdoor time accurately at the schools included in this study. In many school buildings in Denmark, classrooms are situated along the outer walls with large windows. This combination may lead to a good satellite reception inside some classrooms, which could give some misclassification of indoor points being classified as outdoors. By definition, the proportion of time spent outdoors in contexts like playgrounds, urban green space, and active transport should have approximated 100% while we found averages ranging from 66.6 to 99.8%. Manual inspection of the data confirmed that some epochs taking place outdoors were misclassified as indoors due to the SNR under heavy tree canopies or close to tall buildings presenting as low as 65. PALMS requires the SNR to be above 250 before classifying an epoch as outdoors. The PALMS classifications employ an SNR threshold, and reducing it would affect accuracy overall. Tree canopies are known to affect SNR so it is difficult to envisage a solution based on the GPS data alone. Post processing matched green space with the GPS data may help but cannot be automated. The prevalence of this problem is not known, but the impact of this misclassification will be an underestimation of the association between outdoor time and MVPA.

Almost all participants on two out of four schools had to be excluded as their GPS did not record the information needed to estimate outdoor time. This loss of data was due to malfunctioning Qstarz software not encountered during a pilot study. When detected, the open source software bt747 (bt747.org) was used instead, which eradicated the problem. When using novel technologies and devices, errors will inevitably happen, introducing possible systematic errors. The error happening in this study limited the number of participants that could be included, however it is not likely that this introduced a systematic error as the excluded participants did not differ from the included participants on important background characteristics.

This study focused on urban Danish children and as other studies have found differences in the urban/suburban/rural physical activity patterns (15, 54) the results may not be generalizable to more rural children. Also the children were selected based on their school attendance in four schools situated close to each other as they were part of a larger natural experiment evaluating changes to one specific local neighborhood. As such, further studies are needed to confirm the generalizability of the results. Data were only collected during early fall and late spring, where daylight and overall weather conditions were quite similar, and therefore it is also not known if the results are valid during the winter months (16).

This study is one of the first studies to describe the daily context-specific outdoor time and outdoor MVPA patterns among school-children using objective measures during weekdays. Future studies should also consider examining the weekend pattern as different patterns of physical activity have been described between week and weekend days (17). Also future studies should investigate if the association found between outdoor time and MVPA is consistent across subgroups. Age and gender interactions were present in some domains or subdomains but we chose not to stratify the data by subgroups due to sample size limitations. The sample size also cautions interpretation of the interactions presented in this paper and these results may not be generalizable to other populations. Future studies should further investigate age and gender interactions present in context-specific behavior and also investigate if other subgroups, e.g., overweight/obese, high/low socio-economic position, have a distinct context-specific pattern. However, researchers must consider the increased complexity this adds in presenting the data.

CONCLUSION

Different context-specific behaviors were found for gender and age, suggesting different strategies may be needed to promote physical activity among these groups. Studies using a combination of accelerometer and GPS devices are increasing in numbers as the need for context-specific physical activity patterns to inform effective health promotion is being acknowledged. Using novel technologies involves novel data processing methods and analytic strategies, and to promote a strong evidence base it is important that uniform methods are used, making it possible to compare results across studies and perhaps in the future to pool data to investigate country differences. This study proposed a domain based methodology expanded with a number of subdomains to assess the context-specific outdoor time and physical activity patterns among school-children and this methodology can easily be transferred to other populations.

AUTHOR CONTRIBUTIONS

Charlotte Demant Klinker conceived and coordinated the study, was responsible for its design, acquisition of data, data cleaning, statistical analyses, and drafted the manuscript. Jasper Schipperijn handled and processed the data, contributed to the acquisition of data, and data cleaning. Jens Troelsen conceived the study, and participated in its design. Jacqueline Kerr contributed with significant input to the outline of the manuscript and Annette Kjær Ersbøll came with statistical input. All authors revised the manuscript critically, and read and approved the final manuscript.

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Using MapMyFitness to place physical activity into neighborhood context

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It is difficult to obtain detailed information on the context of physical activity at large geographic scales, such as the entire United States, as well as over long periods of time, such as over years. MapMyFitness is a suite of interactive tools for individuals to track their workouts online or using global positioning system in their phones or other wireless trackers. This method article discusses the use of physical activity data tracked using MapMyFitness to examine patterns over space and time. An overview of MapMyFitness, including data tracked, user information, and geographic scope, is explored. We illustrate the utility of MapMyFitness data using tracked physical activity by users in Winston-Salem, NC, USA between 2006 and 2013. Types of physical activities tracked are described, as well as the percent of activities occurring in parks. Strengths of MapMyFitness data include objective data collection, low participant burden, extensive geographic scale, and longitudinal series. Limitations include generalizability, behavioral change as the result of technology use, and potential ethical considerations. MapMyFitness is a powerful tool to investigate patterns of physical activity across large geographic and temporal scales.

Keywords: physical activity, GPS, quantified self, big data, recreation, parks, MapMyFitness, MapMyRun

INTRODUCTION

Physical activity plays a role in the etiology of numerous chronic diseases, including cancer and cardiovascular disease (1, 2). Tracking where, when, and by whom physical activities occur could clarify the ways that public health can encourage more activity and lower chronic disease risk. However, to date, lack of fine-grain geographic data have limited research into national spatial patterns of physical activity. Fitness apps, seven of which reached at least 16 million downloads apiece as of August 2013, could act as tools to supply this type of data to health research (3).

Increasingly, individuals in the United States are turning to technology in order to monitor and manage their health. As of 2013, cell phone ownership among adults exceeds 90% (4, 5), and according to different estimates, over 60% use smartphones (5–7). Mobile phones have entered into numerous research contexts, particularly because of the rich dynamic spatial information they can provide (8). Self-tracking by individuals, particularly of health and fitness information, has become increasingly common. Nineteen percent of all mobile internet users have downloaded a fitness or health app and 9–11% have integrated that app into their daily lives (9). By monitoring their routes and workouts through an app, consumers passively contribute their logs to a non-specific, multi-regional data pool (10, 11). The use of these health apps, many of which include a built-in global positioning system (GPS), enables the analysis of individual and group fitness trends across broad large spatial scales (12–14).

In the past, studies exploring spatial patterns in physical activity using personal sensors have often been designed from a researcher-driven perspective (15, 16). Investigators assigned participants a personal sensor and asked them to self-report behaviors over time (15, 17, 18). Due to the effort required to collect data, the specialized nature of the datasets, and the limited geographic areas in which it was feasible to conduct the research, these studies have resulted in limited generalizability (19).

MapMyFitness is a suite of interactive tools for individuals to track their workouts online or using GPS in their phones or other wireless trackers. Our intent is to present an illustration of how data tracked using MapMyFitness can be applied to the investigation of physical activity patterns over space and time. In doing so, we will emphasize the potential benefits associated with the use of this technology as a powerful tool in scientific research. Finally, we describe the conceivable limitations and ethical concerns involved in using these data to deepen our understanding of the interplay between context and physical activity (20–22).

MAPMYFITNESS DESCRIPTION

MapMyFitness[1] provides interactive tools for individuals to track their workouts. MapMyFitness was started in July 2005, as "MapMyRun.com." In December 2006, MapMyFitness was created. By April 2007, the MapMyRide, MapMyFitness, MapMyWalk, and MapMyHike websites were all made available to the public and by September 2008, MapMyRide and MapMyRun were among the first 200 iPhone® apps in the App Store. As of October 2013, MapMyFitness had a community of over 20 million registered users.

MapMyFitness is an open platform that integrates with more than 400 fitness tracking devices, sensors, and wearable trackers. Users can track workouts and plot the route of walks, runs, and bicycle rides, among other activities. Route data are collected using GPS within the mobile app, by manual mapping through their website, and through linked devices, such as Garmin GPS monitors. Approximately 97% of all routes are tracked via GPS and the mobile app, rather than recorded manually by users online. Users can save the route and share it with the MapMyFitness community or with other social media outlets. A route can then be re-used by that user, or another user, for additional workouts. The MapMyFitness basic features are free or users can upgrade to an "MVP" membership to unlock additional benefits such as advanced heart rate analytics, mobile coaching, training plans, route recommendations, and live tracking to social media. While 74% of the routes tracked by October 2013 were within the United States, users recorded routes throughout the world (23). To date, there are over 197900000 workouts logged, covering over 1005900000 miles and more than 163700000 h.

TECHNICAL DETAILS

Some data [e.g., age group, sex, and body mass index (BMI)] are input and updated by users, while other data (e.g., route path and speed) are recorded and calculated by the MapMyFitness suite. Data from MapMyFitness are stored across three domains: workouts, routes, and users (**Figure 1**). Workouts represent a specific instance of physical activity. Each workout includes a route identification number, if applicable, and a user identification number. Workouts that are tracked in a gym for strength training or on a treadmill do not have a route. Workouts include information on start dates and times, duration, distance, type, estimated calories, and speed. Estimated calories are calculated from corrected Metabolic Equivalent (METS), which first estimate a resting metabolic rate based on age, gender, height, and weight (24). Then, the type of activity, speed, and duration are factored in to a multiplier of the resting metabolic rate, giving an estimate of calories burned for each activity.

As of October 2013, public data could be downloaded from MapMyFitness using an API (Application Programing Interface) to directly search and download workouts, routes, or users. Alternately, we contacted MapMyFitness directly to acquire a larger dataset for specific locations and years. Data are provided in Comma Separated Value (CSV) format with one row per workout. Routes are available in two formats: a CSV of route information and a Keyhole Markup Language (KML) of the geographic path taken during the route. The route CSV includes a user identification number and route type. Geographic data are represented by a route KML file with the route identification number as the name. The KML stores latitude, longitude, and altitude of each point along a route. For researchers who aim to combine the route geographic information with ArcGIS software (ESRI, Redlands, CA, USA), individual KML files can be imported into ArcGIS. Alternatively, in this paper, we opted to convert points from KML files to DBF using Python (Python Software Foundation. Python Language Reference, version 2.7 available at www.python.org). User information is provided in a CSV format that includes one row for each user with an identification number, sex, age group, and BMI.

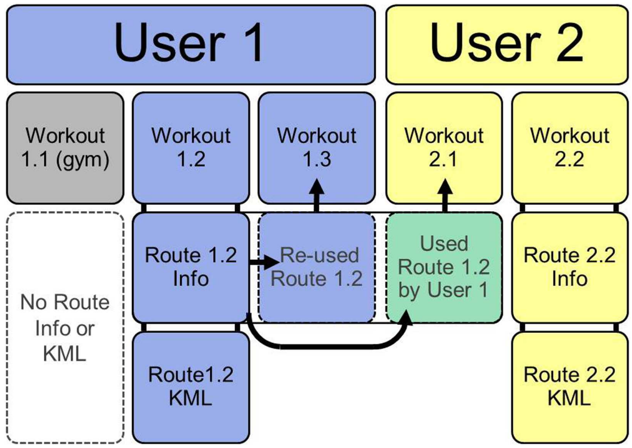

FIGURE 1 | Structure of MapMyFitness data. If users log workouts that do not have geographic information (e.g., in a gym) no route information or route KML is created (workout 1.1). Most workouts are logged by tracking a route. This creates a route information file and a route KML of the geographic path (workout 1.2 and 2.2). Once a route is saved, it can be re-used by the same user for a new workout (workout 1.3) or by another user for a new workout (2.1).

APPLICATION TO PHYSICAL ACTIVITY RESEARCH (IMPLEMENTATION)

MapMyFitness has numerous applications to investigate physical activity within large-scale geographic and temporal contexts. The widespread adoption of GPS fitness tracking provides a picture of broad geographic physical activity patterns, across the United States and internationally. It therefore allows for substantially larger samples of physical activity behavior and location than have been previously available across time and space. International analyses would allow researchers to understand broad societal influences on physical activity while also identifying common small-scale cues for increasing physical activity.

The fine resolution GPS data provided by MapMyFitness users also allows researchers to link geocoded physical activity information to other geographic features for specific dates and times. These linkages enable researchers to understand where individuals obtain physical activity, as well as to identify specific features that might serve as barriers or enablers for physical activity. This facilitates research exploring not only large-scale physical activity

[1] http://about.mapmyfitness.com/

patterns by region, but also the influence of small-scale factors such as neighborhood socioeconomic status, built environment features, or parks and green space.

Physical activity patterns can also be examined by different individual-level factors, such as age, sex, and BMI. MapMyFitness can be used to disaggregate the way that individual-level characteristics shape the environment's influence on physical activity. As illustrated in **Figure 2**, patterns of physical activity can be examined geographically by sex to identify locations in which each sex is more likely to exercise. Similar analyses could investigate the locations that different age or BMI groups are most likely to traverse. MapMyFitness data could potentially be used as a unique way to augment surveillance data, such as the National Health and Nutrition Examination Survey (NHANES) and other repeated cross-sectional studies, to explore longitudinal fine-grained location data within a national context.

The ability to observe physical activity across large temporal and spatial scales also lends itself to evaluations of policy and environmental interventions to improve physical activity. Researchers could examine patterns of physical activity before and after policy changes at the local, state, national, or even international level. At a local level, field work could identify design changes in the environment and then evaluate their effects based on subsequent changes that occurred in MapMyFitness routes. At a state level, researchers could compare municipalities with and without complete streets or housing policies, as well as trends pre- and post-policy adoption. At a national level, researchers could compare physical activity trends between different regions to estimate the effectiveness of active living programs, such as Center for Disease Control and Prevention's Community Transformation Grants (25). MapMyFitness data also have the potential to be used in Health Impact Assessments (HIAs) to establish baseline levels of physical activity and to determine which populations will be impacted by changes to policies or the environment. For example, if a HIA was conducted on improvements to an urban park, MapMyFitness data could be used to demonstrate baseline levels of physical activity taking place in the park. Researchers and policy makers could also capitalize on MapMyFitness data during the monitoring and evaluation phase of the HIA to estimate shifts in physical activity taking place in the park after the improvements.

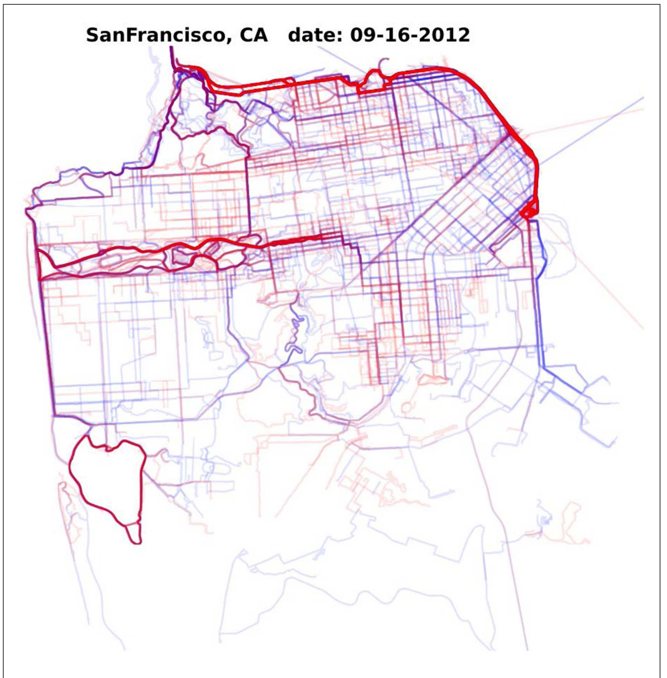

FIGURE 2 | Density of MapMyFitness routes in San Francisco, CA, USA on September 16, 2012 by sex. Blue represents routes by male MapMyFitness users, red represents routes by female MapMyFitness users. Thicker lines indicate more routes.

EXAMPLE

BACKGROUND

Park access has been shown to be an important correlate of physical activity, and the creation of new parks is a suggested intervention to increase physical activity levels in the United States (26, 27). Recent research has begun to use GPS to assess where physical activity occurs (11, 28) and describe patterns of physical activity in parks among participants who are asked to wear both accelerometer and GPS devices (29). Using data from a self-tracker, such as MapMyFitness, allows for an investigation of the links between parks and physical activity over long time periods and with a larger sample.

OBJECTIVES

This example documents MapMyFitness users and characteristics of their physical activity in Winston-Salem, NC, USA from 2006 through 2013. This example then uses MapMyFitness to examine what percent of tracked physical activity occurred in parks and compares characteristics of users and physical activity by park use.

METHODS

County boundaries were used to delineate the Winston-Salem study area, which included Davidson, Davie, Guilford, Forsyth, Randolph, Rockingham, Stokes, Surry, and Yadkin County, NC, USA (1837 miles^2) (**Figure 3**). Parks were defined as public places set aside for physical activity and enjoyment. Cemeteries, mobile home parks, historic sites, professional stadiums, country clubs, zoos, private parks, private facilities (such as stand-alone baseball or tennis facilities), and stand-alone recreation centers were not included in this definition. Park data were collected as part of the Multi Ethnic Study of Atherosclerosis (MESA). Neighborhood study using two methods. First, we contacted municipal and county GIS, planning, and parks and recreation offices to acquire electronic copies of park files from 2009 to 2012. The parks data were assembled into shape files, which included the name and two-dimensional outline of each park, drawn as a polygon. In a few instances, we drew the park boundary using Google maps when no other outline of the park was available. If only part of the polygon for a confirmed park was in the study area, it was retained. Parks with multiple polygons but the same name were manually merged and assigned as one park. Second, we assembled commercial park shape files from the 2010 ESRI file. The metadata (a summary statement or document containing information on the data set) indicated that parks and forests were identified at the national, state, and local level, including county and regional parks, and referenced Tele Atlas MultiNet North America. All parks were verified similarly to the municipal/county sources, mainly through online searching or phone inquiries and removed if it did not meet our park definition. More details are provided elsewhere and this method of combining commercial and municipal/county data sources provides the most complete and accurate geographic data on parks (30).

Workouts ($n = 85765$), routes ($n = 74298$ in a route information CSV, $n = 93384$ route KML files), and user information ($n = 4312$) for Winston-Salem, NC, USA were obtained from MapMyFitness, Inc. Data included workout information (user, route, workout date, workout type, duration, distance, estimated calories, and speed), route KML files, route information (user, route name, route type, route distance, and city/state), and user information (sex, age group, BMI category, and joining date). Types of activities included in the workout information were run, walk, hike, bicycle ride, swimming, sports/activities, and gym/health club. BMI categories were designated by MapMyFitness as underweight (<18.5), normal weight (18.5–24.9), overweight (25.0–29.9), and obese (≥30.0) (31). Discrepancies between the number of records in each data type arose since data were pulled from the main MapMyFitness database by geographic location (route KML) or by city name (route, user, and workout information). For example, a route KML may have been pulled from the MapMyFitness database because it fell within the geographic boundaries of Winston-Salem; however, if the user did not write "Winston-Salem" as the location of the workout when tracking the route, the route may not appear in the route CSV. Workouts were included in this analysis if they had corresponding user and route information, and if they were entirely contained within the collected study area ($n = 46248$). This restriction resulted in a sample of routes that were geographically within the study area, were coded as being in Winston-Salem for the route and the workout, and were logged by users who indicated they lived in Winston-Salem. Workouts were excluded if speed was ≤0 or >20 mph for walks, runs, hikes, swims, or sports ($n = 1418$) or >50 mph for bicycle rides ($n = 191$) and if distance recorded was more than 1 mile different between the route and workout file ($n = 386$). We further restricted to only adult users ≥18 years of age, excluding 381 workouts and 375 routes performed by 67 youth or adolescent users <18 years of age, leaving a final sample size of 43872 unique workouts on 42003 unique routes by 3094 unique users.

We calculated means and frequencies among workouts', routes', and users' characteristics overall and by time period. We divided the data into an early time period (2006–2009), representing early MapMyFitness adopters, and later time period (2010–2013), coinciding with when the majority of MapMyFitness users joined. Route KML files were mapped in ArcGIS. Each route line was divided into its component points and intersected with park data. This process indicated whether each point was located inside or outside of a park. **Figure 3** illustrates a sample of route points within the study area, colored by whether the point is in a park. We calculated percent of points inside a park and compared characteristics of routes that did not enter any parks (0% in parks), were in parks >0% but <50% of the route, were in parks for 50% or more of the route but less than the entire time, and were entirely within parks (100% in parks). Chi-square tests, Analysis of Variance (ANOVA), or Kruskal–Wallis non-parametric tests were used to test for differences across categories as appropriate. All statistical analyses were done in SAS 9.2 (Cary, NC, USA).

RESULTS

MapMyFitness workouts included in this analysis ranged in time from April 28, 2007 to September 24, 2013. Time-trends in the Winston-Salem MapMyFitness data showed that the number of MapMyFitness workouts increased exponentially starting in 2010 (**Figure 4**). User joining date ranged from June 15, 2006 to September 23, 2013. A majority of users joined after 2010, with only 7.2% of users joining between June 2006 and December 2009 and 92.8% joining between January 2010 and September 2013.

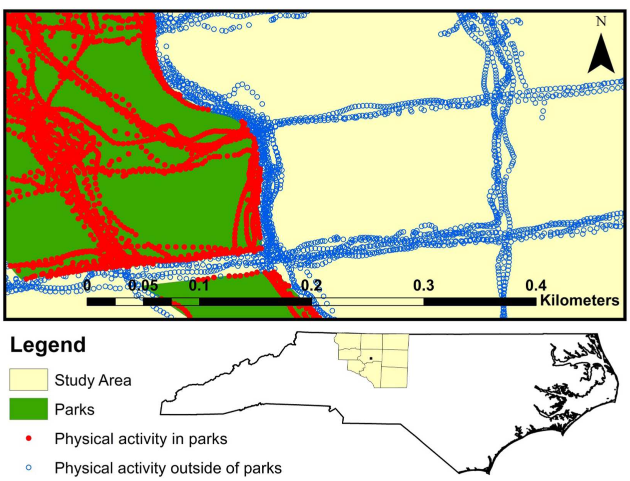

FIGURE 3 | Winston-Salem study area included in analysis (Davie, Davidson, Forsyth, Guilford, Rockingham, Stokes, Surry, Yadkin, and Randolph counties). A sample of MapMyFitness points within the Winston-Salem study area, colored by whether they are in a park.

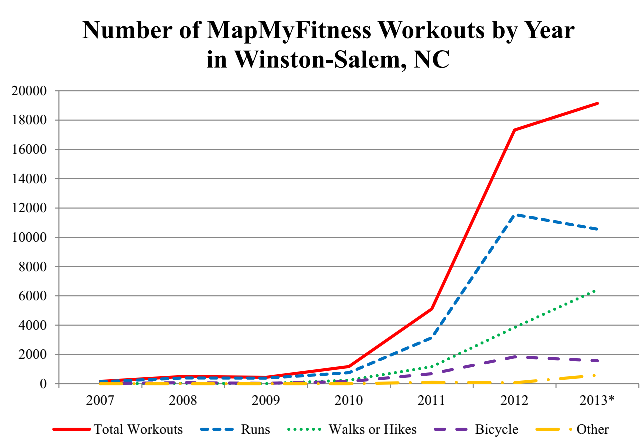

FIGURE 4 | Time-trends in MapMyFitness workout data for Winston-Salem, NC, USA by workout type. *Data for 2013 only represents January 1, 2013 through September 24, 2013.

Of the 43872 unique workouts, 61.4% were runs, 26.7% were walks or hikes, 10.0% were bicycle rides, and 1.8% were other (**Table 1**). On average, workouts lasted for 46.3 minutes [Standard Deviation (SD) 120.7]. Workouts that were runs, walks, or hikes traveled a mean of 3.3 miles (SD 2.3) at an average speed of 5.1 mph (SD 1.7). Bicycle workouts traveled a mean of 13.9 miles (SD 10.6) at an average speed of 11.8 mph (SD 3.8). Other workouts traveled a mean of 3.7 miles (SD 4.4) at an average speed of 5.3 mph (SD 2.9). Overall, workouts burned a mean of 394.0 estimated calories (SD 536.8). Workouts logged in the earlier time period (between 2007 and 2009) were more likely to be runs or bicycle rides, be longer in terms of both distance and time, and be faster.

Routes were used between 1 and 47 times and on average each route was utilized by only one workout. Of the 42003 unique routes, 71.3% did not enter a park at all and 2.9% were entirely within a park. On average, 11.1% (SD 27.1%) of each route was within a park. Routes by workouts from the earlier time period (2007–2009) were more likely to not enter a park at all, less likely

Table 1 | Characteristics of MapMyFitness workouts, routes, and users within Winston-Salem, NC, USA overall and by time period (June 2006–September 2013).

	Overall	**Early (2006–2009)[a]**	**Late (2010–2013)[a]**
	Mean (SD) or percent (*n*)	**Mean (SD) or percent (*n*)**	**Mean (SD) or percent (*n*)**
Workouts (*n*)	43872	1133	42739
Workout type			
Run	61.4% (26946)	82.4% (934)	60.9% (26012)
Walk or hike	26.7% (11743)	4.9% (55)	27.3%(11688)
Bicycle	10.0% (4408)	12.7% (144)	10.0% (4264)
Other[b]	1.8% (775)	-------[b]	1.8% (775)
Distance (mi)			
Run, walk, or hike mean	3.3 (2.3)	5.3 (3.9)	3.3 (2.2)
Bicycle mean	13.9 (10.6)	22.2 (14.6)	13.6 (10.4)
Other mean	3.7 (4.4)	-------[b]	3.7 (4.4)
Speed (mph)			
Run, walk, or hike mean	5.1 (1.7)	6.4 (1.6)	5.1 (1.7)
Bicycle mean	11.8 (3.8)	15.0 (2.2)	11.7 (3.8)
Other mean	5.3 (2.9)	-------[b]	5.3 (2.9)
Time taken (min)	46.3 (120.7)	69.4 (222.6)	45.7 (127.3)
Estimated calories burned (kcal)	394.0 (536.8)	605.1 (687.5)	388.3 (531.0)
Routes (*n*)	42003	794	41209
Park information			
Not touching any park	71.3% (29943)	78.0% (619)	71.2% (29324)
Entirely in a park	2.9% (1228)	0.3% (2)	3.0% (1226)
Percent of route in a park	11.1 (27.1)	2.9 (11.4)	11.2 (27.3)
Users (*n*)	3094	224	2870
Female[c]	57.1% (1755)	43.9% (94)	58.1% (1661)
Age group[c]			
18–24	21.6% (657)	6.0% (12)	22.7% (645)
25–34	37.1% (1130)	37.0% (74)	37.1% (1056)
35–44	21.9% (668)	30.5% (61)	21.3% (607)
45–54	12.7% (386)	18.5% (37)	12.3% (349)
55 and over	6.7% (204)	8.0% (16)	6.6% (188)
Body mass index (BMI)[c]			
Underweight	2.1% (61)	2.6% (5)	2.1% (56)
Normal weight	49.8% (1423)	59.3% (115)	49.1% (1308)
Overweight	29.6% (845)	28.9% (56)	29.6% (789)
Obese	18.6% (531)	9.3% (18)	19.3% (513)

[a] *Year range represents year workout was performed (for workouts and routes) or year account was created (for users). Routes were counted in whichever time period had more than 50% of the workouts using that route.*

[b] *Other includes swimming, sports/activities, and gym/health club. There were no workouts logged in the early time period that fall into other.*

[c] *Sex missing information on 21 users, age missing information on 49 users, and body mass index missing information on 234 users.*

to be entirely in a park, and had a lower percent within a park than routes by workouts occurring later (2010–2013).

Users had a mean of 14 workouts (median 5, range 1–410). Of the 3094 unique adult users, only 21, 49, and 234 were missing information on sex, age group, and BMI, respectively. A majority of users were female (57.1%), although among earlier users (joined between 2006 and 2009), men were the majority (female 43.9%). A majority of users were between the ages of 18 and 44. Just under half of the users were normal weight (49.8%), with 29.6% overweight, and 18.6% obese. Newer users had a wider age range and wider BMI range; a lower percentage of earlier users were overweight or obese and the age distribution among earlier users was slightly older.

Type of workout, distance, time taken, speed, estimated calories burned, and characteristics of the user who performed the workout (sex, age group, and BMI) varied by amount of workout route in a park (**Table 2**). Compared to workouts outside or partially in parks, a higher percentage of workouts entirely within parks were runs (68.8%), while a higher percent of workouts with more than half of points in parks were bicycle rides (33.5%). Overall, workouts that were partially in parks were longer, took more time, were faster in speed, and burned more estimated calories than workouts

Table 2 | Characteristics of Winston-Salem, NC,USA MapMyFitness workouts by percent of workout in parks (June 2006–September 2013).

	Not in park[c]	**Less than half in park**[c]	**More than half in park**[a]	**Entirely in park**[c]	***p*-Value**[b]
	Mean (SD) or percent (*n*) *n* = 31549	**Mean (SD) or percent (*n*) *n* = 8127**	**Mean (SD) or percent (*n*) *n* = 2957**	**Mean (SD) or percent (*n*) *n* = 1239**	
Workout type					<0.0001
Run	62.0% (19563)	63.4% (5153)	46.6% (1378)	68.8% (852)	
Walk or hike	28.6% (9011)	22.7% (1841)	18.8% (555)	27.1% (336)	
Bicycle	7.3% (2314)	13.0% (1060)	33.5% (991)	3.5% (43)	
Other[c]	2.1% (661)	0.9% (73)	1.1% (33)	0.7% (8)	
Distance (mi)					
Run, walk, or hike mean	3.1 (2.0)	3.9 (2.8)	4.2 (3.0)	3.0 (1.8)	<0.0001
Bicycle mean	12.5 (9.4)	18.3 (14.8)	12.9 (6.0)	4.8 (4.3)	<0.0001
Other mean	3.3 (3.3)	5.6 (8.4)	7.6 (6.4)	2.0 (1.6)	<0.0001
Speed (mph)					
Run, walk, or hike mean	5.1 (1.7)	5.2 (1.6)	5.2 (1.7)	5.0 (1.7)	<0.0001
Bicycle mean	12.1 (4.0)	12.3 (3.6)	10.9 (3.4)	7.5 (2.7)	<0.0001
Other mean	5.1 (2.7)	6.8 (3.4)	7.1 (4.7)	4.1 (1.7)	<0.0001
Time taken (min)	43.2 (134.0)	53.1 (63.6)	62.0 (171.9)	45.7 (221.4)	<0.0001
Estimated calories burned (kcal)	353.1 (450.2)	487.8 (618.6)	589.9 (957.4)	340.6 (348.8)	<0.0001
Characteristic of user performing workout					
Female[d]	59.5% (18702)	56.2% (4554)	49.6% (1459)	64.7% (798)	<0.0001
Age group[d]					<0.0001
18–24	14.6% (4573)	9.6% (774)	11.8% (346)	9.0% (110)	
25–34	33.9% (10594)	44.4% (3583)	29.4% (862)	30.0% (369)	
35–44	25.4% (7938)	23.7% (1914)	25.5% (748)	32.6% (401)	
45–54	15.3% (4775)	13.3% (1074)	22.7% (666)	21.9% (269)	
55 and over	10.9% (3403)	9.0% (730)	10.5% (309)	6.5% (80)	
Body mass index[d]					<0.0001
Underweight	1.8% (553)	2.8% (219)	1.9% (54)	0.9% (11)	
Normal weight	53.9% (16390)	52.2% (4086)	44.7% (1272)	50.7% (599)	
Overweight	30.9% (9397)	32.1% (2508)	32.8% (934)	27.3% (322)	
Obese	13.4% (4090)	12.9% (1012)	20.6% (586)	21.1% (249)	

[a] *"Not in park" represents routes where no point along the route is within park boundaries. "Less than half in park" represents routes that are between >0% in parks, but <50%. "More than half in park" represents routes that are at least 50% in parks but not 100%. "Entirely in park" represents a route where 100% of points are within park boundaries.*

[b] *p-Value from Chi-square and ANOVA or Kruskal–Wallis non-parametric tests for categorical and continuous variables, respectively comparing across amount of workout in park.*

[c] *Other includes swimming, sports/activities, and gym/health club.*

[d] *Sex missing information on 141 workouts, age missing information on 354 workouts, and body mass index missing information on 1590 workouts.*

that did not enter any park or workouts that were entirely in a park. A higher percentage of workouts entirely in parks were performed by females (64.7%). The age distribution was slightly younger for workouts that were 50% or more or entirely within parks. Additionally, a higher percent of workouts that were 50% or more or entirely within parks were done by obese individuals.

EXAMPLE SUMMARY

This example illustrates how MapMyFitness can be used to describe characteristics of physical activity episodes and for identifying parks' influence on types of physical activity. Use of MapMyFitness grew exponentially starting in 2010. Users from the earlier time period had a narrower age and BMI range and higher average physical activity levels. Over a quarter of routes entered a park at least once during their workout (28.7%) and workout type, distance, duration, speed, and estimated calories differed across the proportion of the workout that took place in a park. Additionally, users who conducted workouts in parks were more likely to be female, were younger, and had a higher BMI than users who did not work out in parks.

This example has several limitations. By restricting to workouts in which we had corresponding routes and users, we are only examining workouts that occurred in the study area, with a linked geographic route that is also entirely within the study area, by users who indicate that they live in Winston-Salem. Therefore, this analysis does not include users who live elsewhere but may have traveled to Winston-Salem and logged a route, or who set up their account in a different location then moved to Winston-Salem and did not update their user information to Winston-Salem. We also do not know the time frequency in which GPS points were taken to create the route KML files, limiting our ability to discuss length of time a route may have spent in a park. In some instances, the park shapes (polygons) from the two data sources that we collected park information from did not exactly match. From visual inspection, and based on the names and percent of park area that matched, the same or different park was determined. This method incorporated an element of subjectivity, because we did not visit the park to visually inspect the differences.

ADVANTAGES OF THIS APPROACH

The use of MapMyFitness presents several advantages to potentially advance the field of physical activity measurement. Foremost, MapMyFitness allows for the collection of large-scale objective GPS data on the location of physical activity. GPS data have been widely recognized to be more accurate than self-reported travel surveys and activity diaries in tracking an individual's location (28), but the high participant burden of wearing and charging GPS devices has limited the growth of these data (11). By allowing users to record GPS information through a smartphone application, MapMyFitness provides a platform to collect massive amounts of GPS data. Since data collection is passive, there is no need to ask participants to carry a separate GPS unit, which reduces burden on participants and researchers for data collection. Additionally, the MapMyFitness application is free and available on multiple devices (including iPhone, Android, Blackberry, and Windows). In the United States, where over 60% of mobile phone users own a smartphone (5, 7), this tool is available to a large number of individuals. Additionally, MapMyFitness estimates that in 2013 about 500,000 new workouts are logged around the world each day. The enormous scale of these data creates the potential to explore questions about physical activity in many more individuals, at a much more detailed level than in previous studies. MapMyFitness also alleviates concerns about low adherence, a core limitation of GPS studies (11). Researchers recognize that longer periods of study provide better information on routine physical activity, but a recent review demonstrated that data loss increases substantially after only 4 days (11). Due to low participant burden and the user desire for feedback, adherence for MapMyFitness may be on a time scale of months to years. This type of information has been elusive, and MapMyFitness may represent a breakthrough for researchers, although in Winston-Salem the amount of workouts tracked by each user varied greatly.

DISADVANTAGES OF THIS APPROACH

Despite these major advantages, MapMyFitness does have a number of significant shortcomings for research. Primarily, the generalizability of MapMyFitness data must be thoughtfully considered before use in research. Overall, generalizability is limited by non-random sampling and missingness of: (1) who is included (i.e., using MapMyFitness), (2) which activities are included (i.e., not continual monitoring of GPS), and (3) which points are included in a route (i.e., GPS quality). Users of the application are by definition physical activity conscious, and may not be representative of the general population. Therefore, their patterns and preferences in physical activity may not be generalized to the general population. Within MapMyFitness users, there may be differences between those who use MapMyFitness regularly versus those who use it infrequently. Additionally, users may be different with regard to sociodemographics. In particular, smartphone users may be younger or have more financial resources. Using the Winston-Salem dataset above, we compared Census 2010 and (SMART BRFSS City and County) 2008 data from adult residents of the Winston-Salem Metropolitan Statistical Area (Davie County, Forsyth County, Stokes County, and Yadkin County) to MapMyFitness users' provided information. Compared to the Census data, MapMyFitness users have a narrower age range and are more likely to be female (57.1% compared to 53.0%) (32). MapMyFitness users also had a lower prevalence of obesity (29.6% overweight and 18.6% obese compared to 39.8 and 29.1%, respectively) than identified through population-based samples (33). One further problem is the ability to make inferences on a constantly changing database. As the MapMyFitness database grows exponentially, the users, the routes, and workouts are an ever-shifting target. Thus, determining the extent to which these data are representative is challenging. This problem is compounded in research attempting to identify trends in physical activity; it is difficult to disentangle which patterns are trends in physical activity and which are trends in MapMyFitness users. Additionally, in the MapMyFitness data provided for our example, each user only had one user record. This precludes the ability to look at changes in user characteristics over time at the individual level, since we do not know whether BMI changes within the user.

Beyond the differences in MapMyFitness users compared to a population sample, discontinuous monitoring, and variations in GPS signal could create additional missingness. MapMyFitness is missing data on the location of users when they are not engaged in physical activity (e.g., not tracking a run), and more specifically, when they are not engaged in the physical activities tracked by MapMyFitness or are engaged in physical activity but choose not to track it using MapMyFitness. Therefore, GPS data from the application do not provide a complete picture of overall daily physical activity. In practice, researchers could ask participants to leave MapMyFitness on the entire day. However, due to battery constraints of typical smartphones, MapMyFitness is not intended for use throughout the day. Other apps, including Moves[2], may accomplish this research aim. As with any other GPS device, signal dropout is a concern with MapMyFitness, and the quality of these data may vary, especially in urban areas where GPS signal acquisition can suffer (11). Additionally, GPS accuracy from smartphones may be different than GPS accuracy from a devoted GPS logger. Finally, since users can log routes in multiple ways there are potential measurement differences by GPS device (e.g., Garmin watch compared to smartphone GPS). Additionally, when routes are logged online, this creates a route KML file similar to one logged using GPS. However, a user may not follow the exact path they planned online. The dataset used in our example did not have an indicator as to whether routes were tracked by GPS device, GPS within the app, or manually within the website interface. Teasing apart which routes are logged via GPS and which were logged online through the website would be critical to knowing the accuracy of the mapped route. Furthermore, GPS data may lack some of the objective, contextually rich information that can be gained through direct observation tools, such as SOPARC (34).

The validity of user-input data is also a concern. BMI is based on self-report, which has known issues with misclassification (35). BMI is also entered by the user upon the initial installation of the application; however, it is unlikely that this information is ever updated. Additionally, it is unclear whether age is updated over time or whether the user's baseline age at first download is constant in the dataset.

One of the largest drawbacks of using MapMyFitness for research is the dual role of MapMyFitness as both a tracking technology and a potential behavior-altering intervention. People may choose to run farther or along different routes while they are using MapMyFitness than if they were running without the technology. MapMyFitness' "MVP" users have access to workout plans and suggested routes in order to assist in reaching their fitness goals. Additionally, MapMyFitness encourages users to be more physically active through competitions. We were not provided with the proportion of Winston-Salem users who are MVP or an indicator of which routes may have been logged as part of competitions, so this could not be accounted for in our analyses.

The current MapMyFitness global route database is multiple terabytes (1 TB = 1000 GB) and grows each day, making processing challenging. Even given the limited geographic scope of Winston-Salem, NC, USA we had several computing issues due to the large size of MapMyFitness data. Processing times for combining route information with park information took upwards of 3 weeks using a desktop Windows operating system. Researchers attempting to utilize these types of data may be best suited with an interdisciplinary team that includes contribution from experienced geographers, computer scientists, and biostatisticians.

[2]http://www.moves-app.com

ETHICAL CONSIDERATIONS

As a new avenue of research, utilizing health data from citizens tracking it for personal purposes brings up numerous ethical questions. The Health Data Exploration project is examining these unique scientific, methodological, and ethical issues with support from The Robert Wood Johnson Foundation (36). As of October 2013, when we obtained MapMyFitness data, this project was surveying and interviewing individuals, researchers, and companies in order to understand and convey some of the best practices for handling this type of data. In the absence of guidelines for best practice, we proceeded with caution around the use of this data.

The example in this report was approved and deemed exempt by the University of Michigan Institutional Review Board. However, ethical considerations are a fundamental concern when working with open access GPS data available through MapMyFitness. Although identifying information is not provided, such as user names and addresses, GPS data have the potential to reveal timing patterns of visits to certain locations and even home locations. MapMyFitness is working to ensure that users are protected when researchers access the location of their workouts, and other potentially sensitive personal information, such as BMI and age. It is important to note that MapMyFitness does not currently provide individual data to commercial interests. Therefore, care will need to be taken to confirm that data use is solely within the research domain. Researchers who use MapMyFitness data should take caution to aggregate results before they are presented, published, or shared. Special attention should be paid to identifiability when creating maps of workouts for a given area.

PERSPECTIVES

MapMyFitness is a powerful tool to investigate patterns of physical activity in a broader population across a large geographic and temporal scope. As self-tracking becomes increasingly prevalent across the United States and the world, incorporation of these types of technologies will allow researchers to explore more complex and comprehensive questions. Additional work is needed to understand best practices for data sharing, security, storage, and processing. The large data size precipitates the need for new methods that will only be successful through collaboration with researchers in engineering or computer science. Clarifying the roles of private companies in research and exploring the ethics around user data will be critical for advancement of the use of technology in physical activity research.

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Conflict of Interest Statement: Kyler Eastman works for MapMyFitness, Inc., the company who produces the MapMyFitness suite of apps. His role on the paper was to advise on the data structure, assist with clarifying MapMyFitness data questions, subset the Winston-Salem dataset from the MapMyFitness data, confirm that material in the methods article is accurate, and protect the privacy of MapMyFitness users. The remaining authors declare no conflicts of interest.

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Use of emerging technologies to assess differences in outdoor physical activity in St. Louis, Missouri

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Introduction: Abundant evidence shows that regular physical activity (PA) is an effective strategy for preventing obesity in people of diverse socioeconomic status (SES) and racial groups. The proportion of PA performed in parks and how this differs by proximate neighborhood SES has not been thoroughly investigated. The present project analyzes online public web data feeds to assess differences in outdoor PA by neighborhood SES in St. Louis, MO, USA.

Methods: First, running and walking routes submitted by users of the website MapMyRun.com were downloaded. The website enables participants to plan, map, record, and share their exercise routes and outdoor activities like runs, walks, and hikes in an online database. Next, the routes were visually illustrated using geographic information systems. Thereafter, using park data and 2010 Missouri census poverty data, the odds of running and walking routes traversing a low-SES neighborhood, and traversing a park in a low-SES neighborhood were examined in comparison to the odds of routes traversing higher-SES neighborhoods and higher-SES parks.

Results: Results show that a majority of running and walking routes occur in or at least traverse through a park. However, this finding does not hold when comparing low-SES neighborhoods to higher-SES neighborhoods in St. Louis. The odds of running in a park in a low-SES neighborhood were 54% lower than running in a park in a higher-SES neighborhood (OR = 0.46, CI = 0.17–1.23). The odds of walking in a park in a low-SES neighborhood were 17% lower than walking in a park in a higher-SES neighborhood (OR = 0.83, CI = 0.26–2.61).

Conclusion: The novel methods of this study include the use of inexpensive, unobtrusive, and publicly available web data feeds to examine PA in parks and differences by neighborhood SES. Emerging technologies like MapMyRun.com present significant advantages to enhance tracking of user-defined PA across large geographic and temporal settings.

Keywords: physical activity, parks, MapMyRun.com, socioeconomic status, web data feeds

INTRODUCTION

Obesity has been recognized as a mounting public health challenge, increasing population risk of developing several chronic conditions (1, 2). In the United States (US), obesity is a leading cause of preventable death, second only to smoking (3). Persons of low socioeconomic status (SES) and a minority ethnic or racial background have a higher risk for obesity and related negative health consequences, compared to higher-SES and White populations (4, 5). Missouri has the 17th highest prevalence of adulthood obesity among US states (6). In the St. Louis, MO, US metro region, home to 2.8 million people, 29.8% of adults are obese (7).

Abundant evidence shows that regular physical activity (PA) is an effective strategy for reducing and preventing obesity in people of all SES and racial groups (8). The US National Park Services' Healthy Parks Healthy People Strategic Action Plan 2011 describes health and well-being as an interrelated system linking human health to natural landscapes (9). Urban parks and green spaces provide opportunities for people to engage in various forms of PA (e.g., running, walking, bicycling) while connecting with the natural environment (10, 11). A recent study on PA and park use in five US cities found that up to 50% of weekly vigorous PA and 16% of weekly moderate PA was performed within parks (12). Studies have found that access to parks and green spaces is associated with increased quality of life and well-being (13, 14).

Evidence suggests disparities exist in park proximity, accessibility, and use (10, 15–17), as well as disparities in health outcomes in low-SES communities and among racial and ethnic minorities (18, 19). When controlling for mean neighborhood income, Suminski et al. (20) found that areas with higher percentages of racial/ethnic minorities had the least access to parks and fewest amenities within parks, in comparison with predominantly White neighborhoods. Although access to parks and green spaces is positively related to PA and negatively related to SES (10, 15, 16), the proportion of PA performed in parks and green spaces and how this differs by the proximate neighborhood SES has not been thoroughly investigated. Further, a majority of studies on PA and park use have used self-report surveys, observational audit tools, and activity logs wherein the resource and time-intensive nature of these traditional methods are key limitations (21–25). The present study (1) assesses the use of parks and green spaces for PA (bouts of running and walking) in a Midwestern US city (St. Louis, MO), and (2) examines if this park and green space use differs by the SES of the neighborhood surrounding the park. Understanding possible inequitable utilization of parks and green spaces is essential for public health and urban planning policies related to ameliorating health disparities.

MATERIALS AND METHODS

This study is the first of its kind to use unobtrusive, inexpensive, and publicly available web data feeds along with geographic information systems (GIS) methods to assess the use of parks and green spaces for PA and examine if park usage differs by neighborhood SES. This section provides details on: the study site; measurement of neighborhoods; sources of the data; data collection procedures; and data mapping procedures.

STUDY SITE

The city of St. Louis, MO, US, is rich in terms of number of parks. According to the "2010 City Park Facts," St. Louis has 9.6 acres of park per 1,000 residents, which is 50% more than Los Angeles and more than double both New York City and Chicago (26). St. Louis is far from rich in other ways, for example, data from the 2010 US Census show that St. Louis has a high poverty rate, with 27% of residents living below the federal poverty line (27). St. Louis also has significant adverse health indicators; the death rate is 14% higher than the rest of Missouri, 32% higher than the US, and heart disease mortality is 1.4 times the rate of the US (28). There are also stark differences by race and income between north and south St. Louis (see **Figure 2** for SES distribution). A greater part of St. Louis considered in this study is classified as low-SES, and is primarily concentrated in the north.

Given lack of consensus on what defines a unique neighborhood (29), US census tracts were used as the primary definition of a neighborhood in this study. Census tracts in north St. Louis are 92–99% non-white (primarily African-American) with 38.6% of the population living below the federal poverty line (27). The personal wealth, economic opportunity, living conditions, and health outcomes are all significantly poorer in north St. Louis compared to south St. Louis (27). For example, African-American populations in St. Louis face higher rates of heart disease, cancer, cardiovascular disease, diabetes mortality, and have a life expectancy of 6.3 years fewer than White populations (28).

DATA SOURCES

Physical activity was represented by bouts of walking, jogging, and running in this study. The website MapMyRun.com was the data source for running and walking routes. MapMyRun.com is a route mapping website that provides users worldwide with the ability to plan, map, record, and share their exercise routes, workouts, and outdoor activities like runs, walks, and hikes in an online database (30). Based on built-in geographic positioning system (GPS) technology, MapMyRun.com allows users to record activity using mobile applications compatible with electronic devices (e.g., smart phones), import data from third-party devices (e.g., wearable fitness tracking devices), or enter activity manually from a computer using an interactive map on its website. Users can specify the activity type (walking, running, hiking, dog walking, commuting, etc.) as well as the location. Details such as route start and end points, distance, elevation, points of interest, photographs, and other information of the activity can be recorded. In addition, users have access to a searchable database of over 80 million global routes, online training tools, nutrition tracking, fitness calculators, and event listings, with the ability to share their activities easily with others. For this analysis, we only used publicly available walking and running routes uploaded to MapMyRun.com in St. Louis during calendar year 2012.

Data on parks and green spaces were obtained from a variety of sources including the Environmental Systems Research Institute (31), and park departments in St. Louis City, St. Louis County, and additional municipalities within the jurisdiction of St. Louis County. Missouri census poverty data were obtained from the American Community Survey 2011 (5-year estimates) (27). Census tracts with 20% household poverty or higher were defined as low-SES per US Census Bureau guidelines (27).

DATA COLLECTION AND ANALYSIS

Since 2006, 26,052 runs and walks have been posted on MapMyRun.com in St. Louis. During 2012, 80% of all PA bouts uploaded to MapMyRun.com in St. Louis were runs, with the remaining 20% of PA uploaded as walks. To capture seasonal variation, one route was downloaded per day across the 366 calendar days in 2012. A total of 71 walking routes (representing 20% of dates) and 287 running routes (representing 80% of dates) were systematically selected and downloaded for every day of 2012 from MapMyRun.com. Two dates are missing from walks and six from runs. These missing dates represent days in which the specified activity was not uploaded to MapMyRun.com in our study area.

Starting with the first day of each month, one running route was downloaded for each of four consecutive days (80%; e.g., one running route per day from January 1–4, 2012), followed by one walking route for the following consecutive day (e.g., one walking route from January 5, 2012). The process was repeated cyclically for all months in 2012, maintaining a ratio of four running routes to one walking route downloaded. The number of user uploaded routes for any given day varies on MapMyRun.com; a random number generator method (RANDSELECT in Microsoft Excel) was used to pick which route to download among several routes listed for a particular date.

The interactive map on MapMyRun.com permitted demarcation of study site boundaries within the larger St. Louis metropolitan area. The intersections of major interstate highways (Interstates 270 and 44, 270 and 70) were used to define the western edge of the study site. The Mississippi River, which is also the border between the neighboring states of Missouri and Illinois, defined the eastern edge of the study site. These boundaries captured all of St. Louis City and the majority of the population in St. Louis County (referred to collectively as St. Louis throughout this manuscript). The specific sample area was 903.30 km^2 (348.77 $miles^2$).

The built-in GPS technology on MapMyRun.com allowed for running and walking routes to be downloaded as GPS eXchange

Format, or GPX files, which are a collection of points representing each route. These GPX files were imported into ArcGIS 10.0 (31) and layered over park data and Missouri SES census data (27). GIS spatial analysis was used to identify running and walking routes that occurred tangential to and/or within parks, and identify which of these routes occurred in parks located in low-SES census tracts. Buffers of 30 ft (9.14 m) were created around all parks to capture runs and walks occurring on sidewalks that border parks and to limit potential GPS signal strength error (32). For runs or walks that traversed one or more parks at some point during the route, the clipping tool in GIS was used to extract the length of each individual route segment that traversed a park. A sum total of the length of individual route segments that traversed a park was created for each user.

If a park crossed two or more census tract boundaries, the SES of the census tract with the highest percentage of park area was used to represent the SES surrounding the park. Logistic regression was used to examine the odds of running and walking routes traversing a low-SES neighborhood, and traversing a park in a low-SES neighborhood (dichotomous outcomes: yes/no) using Statistical Package for Social Sciences (SPSS) version 21 (33). Finally, a spatial autocorrelation was conducted in ArcGIS 10.0 (31) to assess the clustering of running and walking routes and parks.

RESULTS

Results show that a large majority of running and walking routes were through or tangential to a park or green space. A total of 1,722.01 miles from 287 running routes and 236.84 miles from 71 walking routes appear in **Figure 1** and **Table 1**. The average lengths of a run and walk in this sample were 6.00 and 3.33 miles respectively. 80.80% of runs traversed a park at some point during their run and 37.50% of these runs took place in parks located in low-SES neighborhoods (**Table 1**). Of the 71 walking routes, 70.40% traversed a park at some point during the walk and 27.43% of those walking routes took place in parks located in low-SES neighborhoods (**Table 1**). **Figure 2** illustrates the availability of many parks across St. Louis, but shows fewer mapped running or walking routes in the northern half of the region that features more low-SES neighborhoods.

The odds of running and walking routes traversing low-SES neighborhoods were significantly higher than the odds of running and walking routes reported in higher-SES neighborhoods (runs: OR = 2.64, CI = 1.58–4.39; walks: OR = 3.18, CI = 1.87–5.44) (**Table 2**). The odds of running in a park in a low-SES neighborhood were 54% lower than running in a park in a higher-SES neighborhood (OR = 0.46, CI = 0.17–1.23). The odds of walking reported in a park in a low-SES neighborhood were 17% lower than walking in a park in a higher-SES neighborhood (OR = 0.83, CI = 0.26–2.61).

The spatial autocorrelation indicated that running routes were significantly clustered (Moran's Index = 1.22, z-score = 5.61, p-value = 0.00). Walking routes were not significantly clustered (Moran's Index = 0.46, z-score = 1.38, p-value = 0.17), but trending toward significance. The distribution of parks (Moran's Index = 0.00, z-score = 0.02, p-value = 0.98) was not significantly different than a random distribution.

DISCUSSION

This study showed that a majority of running and walking routes in St. Louis recorded by users of MapMyRun.com occur in, or at least traverse through, parks. However, this finding does not hold when comparing low-SES neighborhoods to higher-SES neighborhoods in St. Louis. By examining neighborhood-level socioeconomic disparities in the use of parks for PA, this study contributes important evidence to existing literature on PA and park use. The novel use of inexpensive, unobtrusive, and publicly available web data feeds to assess the use of public parks and green spaces for outdoor PA is a main strength of this study.

Community health research has shown that parks have significant roles in supporting up to 50% of the moderate-to-vigorous PA of the local population (8, 12). Findings from this study show a higher percentage of PA in the form of runs and walks occurring in parks, with approximately 80% of running and 70% of walking routes traversing a park at some point. While previous studies refer to total PA (12), this study considered only bouts of walking and running to represent PA. The higher percentage of runs and walks occurring in parks indicate that other types of PA (e.g., hockey, swimming, and weight training) may be occurring in parks at much lower rates than walking and running. The spatial clustering of running routes indicates significant differences from what would be expected by chance, suggesting that specific areas in St. Louis (parks, as evident from **Figure 2**) are more likely to be sought as venues for running. The insignificant spatial clustering of walking routes can be partially attributed to fewer numbers and miles of walking routes considered in this analysis. Overall, findings from this study support and extend the existing knowledge base on the role of parks and green spaces as venues for outdoor PA, particularly running and walking.

Previous studies have shown that low-SES neighborhoods are less likely to have available facilities and locations to facilitate PA, such as parks and green spaces (15, 19). Contrary to the literature, the present results indicate increased odds of running and walking in low-SES St. Louis neighborhoods compared to higher-SES St. Louis neighborhoods (**Table 1**). The high percentage of low-SES census tracts in the St. Louis metropolitan area in this analysis may be a possible explanation for the higher odds of running and walking bouts occurring in low-SES areas in St. Louis (**Table 2**).

The lower odds of running and walking in parks in low-SES neighborhoods compared to parks in higher-SES neighborhoods further corroborates several health and environmental disparities between north and south St. Louis. Previous studies in other metropolitan cities have indicated that low-SES neighborhoods have access to the fewest acres of parks and green spaces (20, 34). On the contrary, this study illustrates that low-SES neighborhoods in north St. Louis have proximate access to several parks and green spaces, equal to higher-SES south St. Louis neighborhoods, yet parks and green spaces in north St. Louis remain underutilized.

Our analysis indicates a random, non-clustered distribution of parks across the St. Louis region. However, many of the parks, particularly those in north St. Louis, remain underutilized for running and walking (**Figure 2**). Perceived constraints to park use may be a possible explanation for the underutilization of parks and green

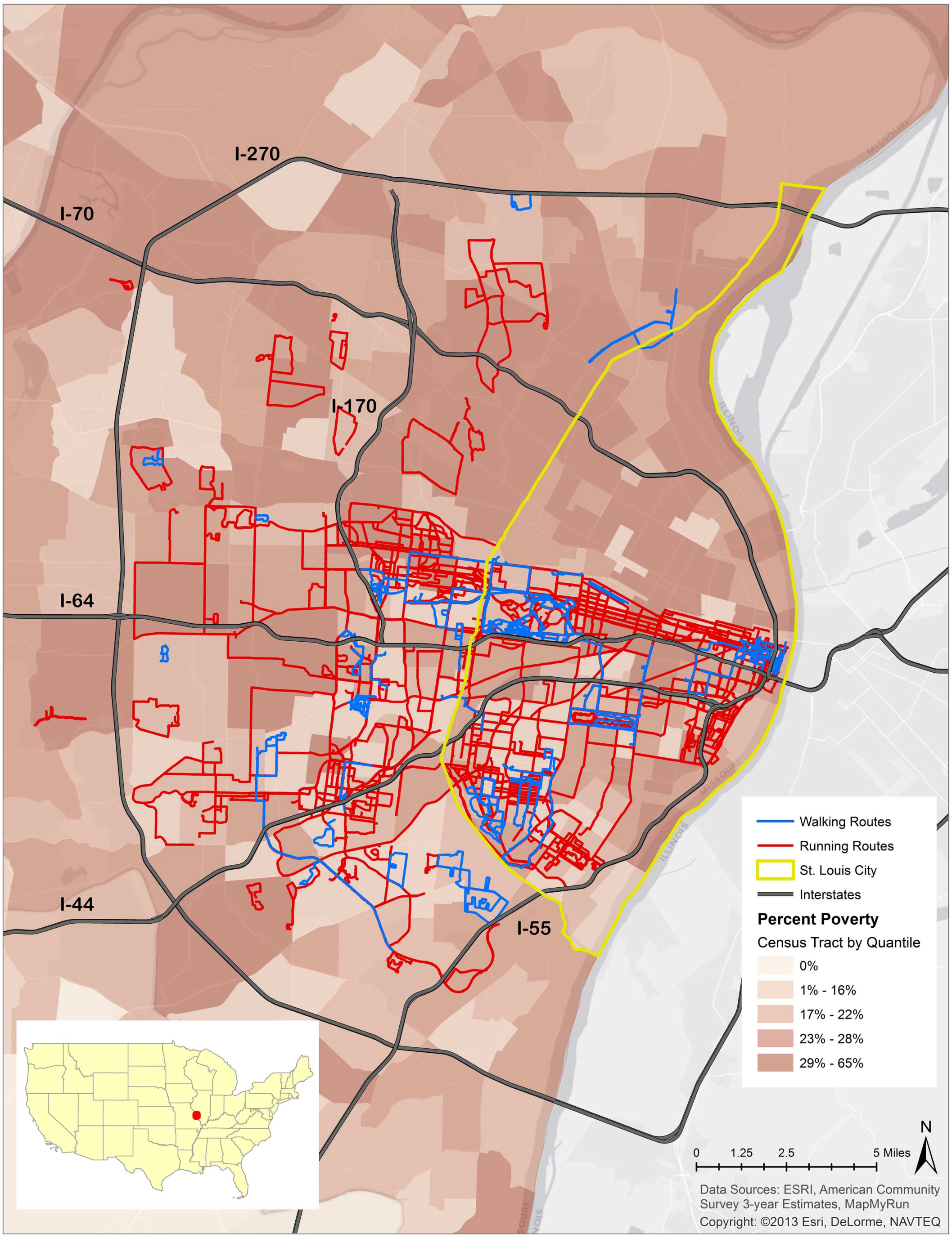

FIGURE 1 | Running routes, walking routes, and poverty rate in St. Louis, MO, USA.

spaces as venues for engagement in PA in north St. Louis. Perceived crime is a common constraint identified by individuals who live near parks but do not use them (17, 34, 35). A qualitative study on perceived constraints to park use in two north St. Louis communities, both within close proximity of a public park, highlighted several issues related to maintenance, safety, and limited amenities that constrained park use and subsequent healthy behaviors (17). Studies have suggested that proximity to parks and green spaces is predictive of nearby residents' PA within the park (11). Decreasing barriers to using parks in low-SES areas like north St. Louis can enhance park-based PA among neighborhood residents. Increased PA in low-SES areas can contribute to reducing disparate rates of obesity and related chronic diseases and improving population health outcomes in these areas.

Table 1 | Use of parks in St. Louis, MO, USA for physical activity in 2012[a].

	Runs	Walks
N	287	71
Total distance (in miles)	1722.01	236.84
Distance (in miles) in parks	519.60	101.00
% in or tangential to parks	80.80	70.40
% in parks in low-SES neighborhoods	37.50	27.43

[a] *Running and walking routes downloaded from MapMyRun.com.*

Increasingly, the demand for infrastructure to accommodate growing populations in many cities and towns has been achieved through the modification or demolition of parks and green spaces (36, 37). Approximately 3,500 acres of parks in St. Louis were recently threatened with closures due to budget cuts (38, 39). Findings from this study show the preference of parks and green spaces as venues for walking and running by a majority of people in this sample, making a compelling case for improved budgetary support toward park conservancy efforts in St. Louis.

STRENGTHS AND LIMITATIONS

The unobtrusive and objective nature of data obtained from MapMyRun.com is an important strength of this study that has the potential to advance PA measurement by placing minimum burden on the sample population. MapMyRun mobile applications can be downloaded free of cost and are supported by a variety of electronic devices and platforms (e.g., Android, Apple, Windows, Blackberry platforms), freely permitting large-scale data collection across widespread geographic areas. The extensive and objective nature of this data has potential for longitudinal studies in future PA research. Additionally, information on routes such as distance, speed, elevation, origin, and destination can allow researchers to conduct further detailed investigation on substantially larger samples of PA behavior across extensive geographic locations.

Existing public health literature on PA in parks focuses on park proximity and use, but little is known about the absolute amount or types of PA they facilitate and demographic and SES characteristics of the populations they serve. An exception to this are studies using direct observation instruments like the System for Observing Physical Activity and Recreation in Communities (SOPARC) (22). Instruments like SOPARC have been able to provide objective, contextually rich information on PA in parks and other open environments, but these data are static since parks are divided into predetermined target areas and then studied by trained observers. Other limitations of direct observation instruments are the time-intensive nature and costs involved in data collection (25). In contrast, data from MapMyRun.com provides a cheaper alternative for precise tracking of PA across larger spatial and temporal settings.

Despite the above advantages, this approach presents several limitations. Data from websites like MapMyRun.com are limited to people with access to some form of GPS technology, those that select to map their running and walking routes, and users who choose to make them publicly available online. Populations who use such technology to monitor their PA may be comparatively more health conscious than the general population.

While a key strength of this study is that it addresses the increasing use of technology to map PA behaviors, it is limited in that certain populations may be more likely than others to use websites like MapMyRun.com. The use of emerging technologies is known to vary by SES, gender, age, ethnicity, and other factors (40). Overall, the use of smartphones and other emerging technologies like MapMyRun.com to monitor and evaluate PA behaviors has been steadily increasing. Telecommunication data shows that 56.80% of US mobile phone users in 2013 were smartphone users, projected to increase by another 15% by 2015 (40).

Several demographic groups have high levels of smartphone adoption. Among low-SES populations, smartphone ownership rates between the ages 18 and 29 are equal to the national average. However, among non-White populations, smartphone usage is less than the national average; only 44% of African-Americans and Latinos are smartphone users (41). Low-SES ethnic minority populations may have limited access to resources and awareness of emerging technologies like MapMyRun.com and other health-related mobile applications to map their PA behaviors. This may be another reason for fewer mapped running and walking routes in north St. Louis. There is no publically available information on SES characteristics of users of MapMyRun.com which limits generalizability of findings.

Pertinent to this study, the occurrence of walking or running routes within or tangential to a park, route origin, and destination points, and the choice of the parks themselves cannot be linked with residential proximity and park use. Users could be relying on a form of motorized transport (e.g., car) to travel to a park located in a census tract different from the one they reside or work in, and then complete a walk or run in the selected park, recording its details using GPS technology. Making assumptions about individual behaviors based on aggregate data from MapMyRun.com is vulnerable to the phenomenon of ecological fallacy. Although this study indicates higher odds of walking and running in low-SES areas compared to higher-SES areas, inferences about the SES characteristics of the population cannot be made; residents from higher-SES census tracts may be running and walking in low-SES areas, thus limiting the ability to generalize these findings. The exclusion of any other PA types that may be occurring in parks (e.g., sports like soccer, golf, tennis, etc.) constrains the estimation of total PA in this study. The lack of data on availability and quality of sidewalks is another limitation of this study since it did not permit comparisons related to sidewalk access, sidewalk connectivity to parks, and subsequent park usage between low-SES and high-SES neighborhoods.

Methodological constraints in the process of downloading routes from MapMyRun.com may also impact generalizability of findings. There is no way of filtering the routes posted on MapMyRun.com by specific users. However, as of April 2014, there were 3,349 unique MapMyRun users who have listed their home as St. Louis, MO, USA. That stated, we are unable to identify the average number of routes created per user which impairs the ability to make generalizable statements.

Accuracy of data and signal strength in the use of GPS technology are known to be a weakness, albeit improving. Another major

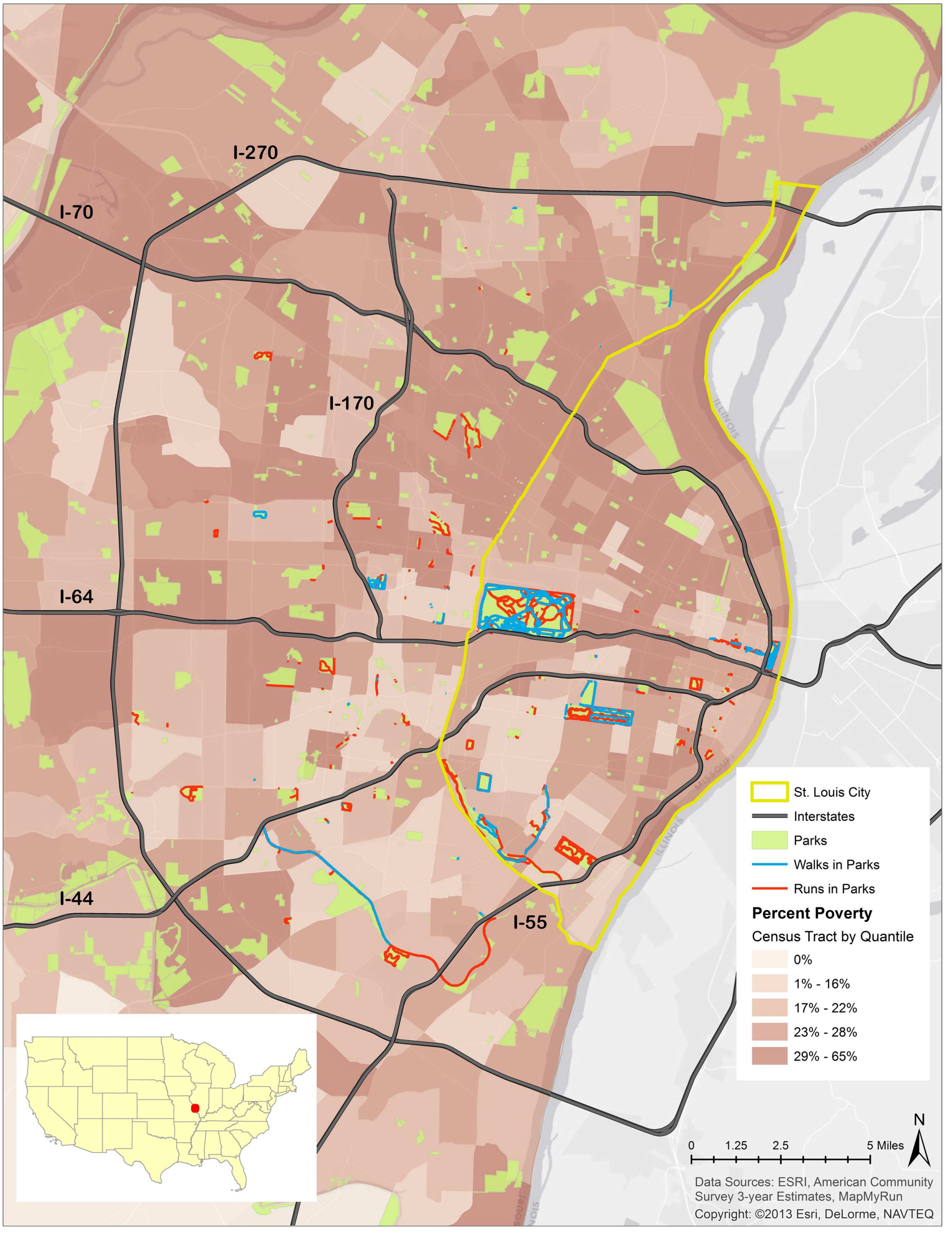

FIGURE 2 | Running and walking routes in parks and poverty rate in St. Louis, MO, USA.

disadvantage in the use of technologies like MapMyRun.com to track PA is its potential to influence behavior among users. For example, users may alter route distance, speed, location, etc., when using GPS technology to track their PA behavior. Results from this study are therefore limited to users of MapMyRun.com, their PA patterns and route selections, and cannot be generalized to the larger population. Despite limited generalizability, data from MapMyRun.com have the potential to reveal distinct patterns of park use and non-park use. Further research is needed to identify underlying reasons for these patterns.

The use of publicly available web data feeds from MapMyRun.com also raises key ethical and privacy considerations.

Table 2 | Logistic regression: odds of running and walking in a low-SES neighborhood and park, compared to higher-SES neighborhoods in St. Louis, MO, USA in 2012.

	N	OR	95% CI	R^2 adj.
Runs in low-SES neighborhood	274	2.64***	1.58–4.39	0.07
Walks in low-SES neighborhood	274	3.18***	1.87–5.44	0.09
Runs traversing low-SES parks	173	0.46	0.17–1.23	0.02
Walks traversing low-SES parks	173	0.83	0.26–2.61	0.00

****$p < 0.001$.*

While user names and addresses are not public on MapMyRun.com, mapped GPS data can reveal underlying patterns in route characteristics such as route origin, time and frequency of occurrence, distance, speed, etc. Researchers using emerging technologies should be cognizant of this and work with ethicists and Institutional Review Boards to ensure privacy and confidentiality of users.

Overall, the unobtrusive nature of data from MapMyRun.com offers several opportunities to provide an unbiased sample of PA patterns in outdoor environments. Next steps include validation of data collected from MapMyRun.com, a detailed examination of park quality and features, and the identification of specific built environment attributes in low-SES neighborhoods that are the most crucial in influencing PA patterns.

CONCLUSION

This study is novel in its use of an emerging technology like MapMyRun.com to track user-defined PA routes in parks and differences in occurrence of these routes by neighborhood SES. Future research could assess additional factors (e.g., quality of parks, neighborhood infrastructure) and their relationship to PA across larger geographical areas and over extended periods of time. A more nuanced understanding of PA in parks is needed for better attribute, policy, and programmatic solutions to increase use of parks for PA, especially those located in low-SES neighborhoods where health disparities are greatest.

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The built environment predicts observed physical activity

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Background: In order to improve our understanding of the relationship between the built environment and physical activity, it is important to identify associations between specific geographic characteristics and physical activity behaviors.

Purpose: Examine relationships between observed physical activity behavior and measures of the built environment collected on 291 street segments in Indianapolis and St. Louis.

Methods: Street segments were selected using a stratified geographic sampling design to ensure representation of neighborhoods with different land use and socioeconomic characteristics. Characteristics of the built environment on-street segments were audited using two methods: in-person field audits and audits based on interpretation of Google Street View imagery with each method blinded to results from the other. Segments were dichotomized as having a particular characteristic (e.g., sidewalk present or not) based on the two auditing methods separately. Counts of individuals engaged in different forms of physical activity on each segment were assessed using direct observation. Non-parametric statistics were used to compare counts of physically active individuals on each segment with built environment characteristic.

Results: Counts of individuals engaged in physical activity were significantly higher on segments with mixed land use or all non-residential land use, and on segments with pedestrian infrastructure (e.g., crosswalks and sidewalks) and public transit.

Conclusion: Several micro-level built environment characteristics were associated with physical activity. These data provide support for theories that suggest changing the built environment and related policies may encourage more physical activity.

Keywords: walkable, micro characteristics, street view, objective measures, policy interventions

INTRODUCTION

Because of physical activity's relationship to health, researchers have been evaluating the association between physical activity and the built environment. Despite increasing evidence suggesting the built environment is associated with increased physical activity, research to date is inconclusive on the exact role of the built environment as it relates to physical activity and which specific aspects of the built environment are most influential (1–3).

One of the current limitations in the field is the inability to directly compare results across different studies due to inconsistencies in the methods or technologies used to measure both the built environment and physical activity (2, 4). For example, using different approaches to measure physical activity (i.e., self-reported or observed) greatly influenced the consistency of associations between environmental attributes and youth physical activity, with observed built environment measures and self-report physical activity measures demonstrating the most consistent associations (2). However, self-report physical activity may introduce recall bias and social desirability issues, potentially leading to over or under estimation of actual behavior (5, 6).

Another limitation is that studies often do not directly link physical activity with specific geographic location (3, 7). A common method is to use surveys that ask respondents to recall their activity for the last week or month. Researchers then either assume that the activity occurred in or near the respondents' homes or work, ask respondents to recall the location (e.g., home or a gym) of that activity, or assume that the activity happened within a certain distance (or buffer) around that location (e.g., 400 m). These methods introduce bias and uncertainty. For example, asking respondents to identify locations of physical activity introduces recall and social desirability biases (8). As Ding and Gebel suggest, studies that do not match the purpose of physical activity with specific environmental attributes where the activity was actually performed may miss important associations (i.e., type-2 errors) (3).

To understand which built environment characteristics are the most significant predictors of physical activity behavior, new methods and emerging technologies allow researchers to assess behavior unobtrusively to circumvent self-report biases and directly link that behavior with attributes of specific geographic locations. Recently, researchers have developed direct observation methods that systematically capture behavior as it is occurring (9–13). For example, the Block Walk Method, an observational method used to identify physical activity as it occurs on streets and sidewalks, provides evidence as to whether the physical activities of interest were performed in the environments being examined (9, 11, 12). Observational methods have several advantages over survey methods. First, they remove respondent bias by unobtrusively monitoring physical activity behavior. Second, they allow researchers to identify the type of physical activity, as well as when, where, and with whom it occurs (13). Recent studies have demonstrated improved estimation of the effects of built environment on physical activity when this type of specificity is incorporated (14). Additionally, using observational methods to evaluate the built environment and for physical activity assessments prevents any opportunity for same-source bias, which could bias the association away from the null (15, 16).

Assessing physical activity behavior unobtrusively directly in the geographic context in which it occurs allows researchers to better understand which characteristics of the built environment predict behavior. Emerging technology using high-resolution omnidirectional imagery is a reliable and efficient method to assess the built environment (17–22). Omnidirectional imagery refers to the simultaneous collection of images in multiple directions from a single location, producing a 360° panoramic view. This imagery provides a permanent visual record of an area and allows the viewer to virtually observe characteristics that are included on many built environment audit instruments. Google Street View[1] and Microsoft Virtual Earth[2] are probably the most well-known examples of publicly accessible omnidirectional imagery. Many built environment characteristics that were previously measured only through direct observation are now revealed in publicly accessible imagery. Recent research by the authors found high agreement between built environment audits conducted with imagery sources (including Street View) and field audits (mean agreement of 0.81), indicating imagery is a reliable and potentially more efficient alternative to field audits for many built environment features (18). Additionally, the authors recently reported substantial to nearly perfect inter-rater reliability when using Street View imagery to audit built environment items included on the Active Neighborhood Checklist (17). Linking these new methods (i.e., built environment audits using publicly accessible imagery and direct observation of behavior) is potentially important for advancing our understanding of the relationships between the built environment, physical activity, and related health outcomes.

PURPOSE

The purpose of this study was to assess the relationship between built environment characteristics using field audits (the gold standard) and imagery audits (emerging technology) and physical activity using a direct observation method, directly linking behavior with the specific geographic location and attributes of the built environment.

MATERIALS AND METHODS

SAMPLING

Four hundred street segments in suburban and urban areas in Indianapolis, Indiana and St. Louis, Missouri were sampled for inclusion in this study. A street segment was defined as the section of the road between two consecutive intersections. Two hundred segments in each city were selected using a stratified random geographic sampling design to ensure representation of neighborhoods with different land use and socioeconomic characteristics. The percent of the total area in commercial land use on each street segment was estimated using parcel-level land use data provided by local government agencies. Segments were classified as above or below the median percent area of commercial land use; medians were calculated separately in each city. A previously established method for socioeconomic stratification using two race categories (>50% African American or >50% White) and two income categories based on the percentage of population in poverty (low poverty <10.0% and high poverty ≥20.0%) was also applied to each segment (18). This sampling method resulted in eight strata; 25 segments in each city were selected randomly within each stratum.

DATA COLLECTION

Characteristics of the built environment were assessed using two objective methods: field audits and imagery audits. While field audits have been the gold standard for assessing the built environment, new methods using high-resolution omnidirectional imagery to assess the built environment have recently been established (17–22).

Field and imagery audits of built environment characteristics were conducted using the Active Neighborhood Checklist (23). The Checklist includes 89 items across six domains assessing presence or absence of land use characteristics, public transportation, street characteristics, quality of the environment for pedestrians, sidewalks and related features, shoulders, and bike lanes.

Multiple teams of two research assistants in each city were trained to conduct built environment audits. Prior to conducting audits, research assistants participated in a 4-h training that included conducting practice audits on segments with varying built environment characteristics (23). Auditors then reviewed their results with each other to discuss any discrepancies. The same process was used to practice built environment audits using Google Street View imagery. Training materials used for the field and imagery audit training are available online at www.activelivingresearch.org/node/10616. The St. Louis team conducted the field audits for street segments in St. Louis, and the imagery audits for Indianapolis blinded to results obtained by the Indianapolis team (and vice-versa for the Indianapolis team) to avoid same-source bias (16).

Two teams of two observers in each city (four teams total) participated in a 5-h training to assess physical activity behavior via direct observation. Observers were trained to use the Block

[1] http://maps.google.com/help/maps/streetview/index.html
[2] http://www.mircrosoft.com/virtualearth

Walk Method, a reliable recording tool and training method (9, 11, 12). This method entails having observers walk both sides of the street at 30.5 m/min pace (with the aid of a metronome), while identifying physical activity behavior that occurs in the observation field (on either side of the street). The observation field was defined as extending to the left and right of the observer's shoulders (9). Physical activity was recorded if the observer crossed a parallel plane of motion to an observed physical activity [i.e., the observer crossed paths with the physically active person(s)]. For more information on the Block Walk Method, see Suminski et al. (9). Physical activity was captured using a multiple-tally denominator click counter with individual counters for each category of physical activity (walking, biking, running, walking a dog, and other). Different teams of two conducted the built environment audits and physical activity behavior observations (i.e., the built environment auditors did not conduct direct observation of physical activity behavior on the same segments).

Direct observation of behavior was conducted on each segment four times on varying days of the week and times of the day. Segments were allotted to each team by first clustering segments based upon proximity to each other (with one to five segments per cluster). The clusters were then divided between the two teams. Each team's clusters were randomly assigned 2 weekday and 2 weekend observations and randomly allocated between hours in the morning to afternoon (between 9:00 a.m. and 3:00 p.m.) and in the early evening (between 4:00 and 7:00 p.m.) using a random number generator. The goal of this random assignment was to spread the assessments across different days and times of day. Teams typically observed three clusters for every 4-h shift, with a half hour allotted for travel time to and from different street segments.

Of the 400 initially sampled segments, 24 segments in Indianapolis and 103 in St. Louis were not covered by Google Street View imagery at the time the study was conducted. To maintain enough statistical power, 62 additional segments were selected in St. Louis using the same sampling criteria. Another 45 segments in both cities were not audited in the field due to safety concerns of the auditors, problems with identifying the specific segment in the field, or scheduling issues with auditors. The final analytical sample included 291 segments (153 in Indianapolis and 138 in St. Louis) with all three sources of data (i.e., field audits, imagery audits, and direct observation of behavior). **Table 1** summarizes the initial streets sampled and the final analytic sample of 291 segments.

STATISTICAL ANALYSES

Consistent with previous studies using the Checklist, items that required auditors to indicate if something was present on one side of the segment, both sides of the segment, or not present were characterized as present (on one or both sides) versus absent (17, 18, 23). Additionally, ordinal items (i.e., none, some, or a lot for litter and tree shading; and flat, moderate, or steep for slope) were dichotomized as present (some/a lot or moderate/steep) versus absent (none or flat). A total of 58 Checklist items had adequate data and were included in the analysis. Segments were categorized as having a particular characteristic (e.g., sidewalk present or not) based on field audit results and again based on image-based results. The following Checklist items were excluded from analyses because of lack of observed variability across the audited segments: presence of large apartment buildings (>4 stories), apartment over retail, basketball/tennis/volleyball court, playground, outdoor pool, entertainment, library or post office, laundry facility, indoor fitness center, college or university, high rise building, big box store or mall, supermarket, bench/shelter at transit stop, sidewalk through a cul-de-sac, public art, off-road trail, alternative places to walk or bike, and sidewalk and shoulder permanent obstructions (≤5 streets with this characteristic). Alternative places to walk and shoulder obstructions were only assessed if there was not a sidewalk, contributing to the lack of variability.

Counts of individuals engaged in different types of physical activity behavior observed on each segment were summed across the four observation periods and by behavior type. This resulted in separate counts of the number of walkers, bikers, runners, individuals with a dog (running or walking), and other (e.g., skateboard and roller blades) for each segment. A total behavior variable was calculated by summing across all types of physical activity behavior categories.

Because the counts of physically active individuals were not distributed normally, non-parametric statistics were used. Mann–Whitney U tests were used to compare median number of walkers, bikers, runners, people with a dog, and total behavior on segments with each built environment characteristic present to segments without such characteristics present (dichotomous variable). Kruskal–Wallis tests were used to compare physical activity behavior on type of land use: all residential, mixed land use, or non-residential land use (categorical variable with three response choices). Additionally, to assess if the results varied by population density, the Kruskal–Wallis test was used to assess if there

Table 1 | Final analytic sample of segments by race, income, and land use stratification ($n = 291$).

	St. Louis	Indianapolis	Total sampled	Streets excluded
1. >50% African American, high poverty, above median commercial land use	15 (11%)	17 (11%)	32	20
2. >50% African American, high poverty, below median commercial land use	18 (13%)	20 (13%)	38	22
3. >50% African American, low poverty, above median commercial land use	18 (13%)	18 (12%)	36	25
4. >50% African American, low poverty, below median commercial land use	17 (14%)	23 (15%)	40	22
5. >50% White, high poverty, above median commercial land use	16 (12%)	18 (12%)	34	22
6. >50% White, high poverty, below median commercial land use	16 (12%)	18 (12%)	34	30
7. >50% White, low poverty, above median commercial land use	20 (14%)	19 (13%)	39	3
8. >50% White, low poverty, below median commercial land use	19 (14%)	19 (13%)	38	3
	139	152	291	147

was a significant difference in built environment characteristics by persons per square mile (US Census data). All analyses were completed separately for field audits and image-based audits.

RESULTS

The number of observed walkers, bikers, runners, individuals with a dog, and other activity are summarized in **Table 2**. Because the prevalence of bikers, runners, and individuals with a dog, and in other activities on each segment was low (median = 0), they were not analyzed separately. However, they were included in the total physical activity behavior category. The remainder of this paper focuses on the total number of physically active persons, regardless of type of activity.

Table 3 shows the relationship between 58 of the built environment characteristics derived from field audits and imagery audits with total physical activity (sum individuals engaged in all types of physically active behavior). There were significantly more physically active individuals observed on segments with certain built environment characteristics. However, because agreement between field and image-based audits was not 100% on all items, some streets were classified as having a built environment characteristic using field audits, while the same street was classified as not having that characteristic when using image-based audits. This disagreement affected the results for 28% ($n = 16$) of the items. For example, when assessing the presence of abandoned homes, medium or large parking lot or garage, abandoned buildings, food establishments, posted special speed zone, amenities, slope along walking area, sidewalk width of at least 5 ft, major sidewalk misalignments, and shoulder width at least 4 ft, there was significantly more physical activity on these streets when assessed by field audits but not when assessed by imagery audits. Similarly, when assessing the presence of undeveloped land, apartments (>4 units), banks, a median/island, and a turn lane, there was significantly more physical activity on these streets when assessed by imagery audits but not when assessed by field audits. However, despite disagreement in significance, the median number of physically active individuals was in the same direction for all of these items (i.e., regardless of auditing method, more physically activity individuals were observed on segments with certain characteristics). However, for one item, sidewalk width at least 3 ft, there was significantly more physical activity observed on streets without this characteristic when assessed by field audits (median = 3.0) but significantly more physical activity observed on streets with this characteristic when assessed by imagery audits (median = 5.0).

The number of individuals engaged in any form of physical activity (total count of physically active individuals) was significantly higher on segments with all non-residential *land use*, including commercial or government buildings (field median = 4.0, $p < 0.05$; imagery median = 4.0, $p < 0.01$), schools and schoolyards (field median = 6.0, $p < 0.01$; imagery median = 7.0, $p < 0.01$), and parks with equipment (field median = 7.0, $p < 0.05$; imagery median = 8.0, $p < 0.05$). However, counts of physically active persons were significantly fewer on segments with only single-family homes and significantly higher on segments with multi-unit homes (2–4 units). Significantly more physically active persons were also observed on segments with a *parking lot or garage* (any size) and *public transportation facilities* (e.g., bus stops).

Table 2 | Number of individuals observed being physically active on 291 segments.

	Mean (SD)	Median	Range
Walkers	3.7 (14.8)	1.0	0–210
Bikers	1.0 (1.9)	0.0	0–14
Runners	0.2 (0.9)	0.0	0–11
With a dog	0.2 (0.6)	0.0	0–4
Other	0.1 (0.4)	0.0	0–4
Total physical activity	5.3 (15.7)	2.0	0–219

When assessing *street characteristics*, there were significantly more physically active individuals on segments that had marked lanes, crosswalks, or a walk signal at the intersection. While there were more physically active individuals observed on segments with a median/island and a center turn lane, this relationship was significant only when the segment was categorized as having these characteristics using imagery audits.

Several characteristics relating to the quality of the built environment were also significant predictors of the number of physically active persons observed during audits. More physically active persons were observed on segments with commercial buildings adjacent to the segment. Segments with more graffiti and litter also had significantly more physically active individuals. When amenities were assessed by field audits, there were significantly more active individuals on streets with amenities than without; however, this was not found when assessing streets with imagery audits.

When assessing *sidewalk characteristics*, significantly more active individuals were observed on segments with sidewalks, buffers between the street and sidewalk, and continuous sidewalks within and between segments. Similarly, there was significantly more physical activity observed on segments with designated *bike* route signs.

When assessing if population density (person per square mile) varied by built environment characteristics, 25 variables varied significantly. Of those 25 variables, 13 also varied by physical activity behavior, suggesting population density may be a confounder in the relationship between 13 built environment characteristics and physical activity. These 13 characteristics are highlighted in **Table 3**.

DISCUSSION

The growing availability of emerging technology (e.g., Google Street View) is allowing researchers to assess the built environment and directly link it with observations of physical activity behavior. Significant relations between several micro-level built environment characteristics and physical activity behavior were observed. Specifically, more active individuals were observed on segments with destinations (e.g., stores, government offices, and schools) than without destinations. The results are consistent with theories suggesting policy changes in zoning and transportation planning that encourages more walkable communities incorporating mixed land use as recommended by the Task Force for Community Preventive Services and the Transportation Research Board-Institute of Medicine (24, 25).

Table 3 | Total individuals engaged in physically active behavior on streets with specific built environment characteristics[a,b].

		Streets assessed with field			Streets assessed with imagery		
		No. of streets	**Mean (SD)**	**Median**	**No. of streets**	**Mean (SD)**	**Median**
LAND USE							
All residential		172	2.8 (4.5)	1.0	173	3.0 (4.7)	1.0
Mixed land use		95	7.5 (22.5)	4.0	88	7.3 (23.4)	4.0
All non-residential		24	13.8 (27.1)	5.0**	30	12.2 (24.5)	5.0**
PREDOMINANT LAND USE PRESENT							
Residential building	No	28	13.1 (25.3)	5.0*	36	16.9 (41.3)	5.0**
	Yes	263	3.0 (13.2)	1.0	255	3.6 (4.9)	2.0
Commercial building	No	219	3.5 (4.9)	2.0	**218**	**3.4 (4.8)**	**2.0**
	Yes	72	10.6 (29.9)	4.0*	**73**	**10.7 (29.7)**	**4.0****
School/school yards	No	**276**	**5.0 (15.9)**	**2.0**	**276**	**5.1 (16.0)**	**2.0**
	Yes	**15**	**9.5 (8.8)**	**6.0****	**15**	**7.8 (7.2)**	**7.0****
Parking lots or garages	No	276	5.2 (16.0)	2.0	267	5.0 (16.1)	2.0
	Yes	15	6.7 (8.5)	4.0	24	7.9 (9.9)	3.5
Park with equipment	No	282	4.5 (9.5)	2.0	286	5.2 (15.8)	2.0
	Yes	9	28.2 (67.2)	7.0*	5	8.4 (5.0)	8.0*
Vacant lots/abandoned buildings	No	270	5.1 (16.2)	2.0	271	5.3 (16.2)	2.0
	Yes	11	6.9 (7.2)	6.0	20	5.3 (5.5)	4.0
Undeveloped land	No	285	5.3 (15.8)	2.0	278	5.3 (15.9)	3.0*
	Yes	6	2.0 (2.1)	1.5	13	3.2 (9.6)	0.0
Designated green space	No	280	4.8 (13.9)	2.0	277	5.2 (16.0)	2.0
	Yes	11	16.0 (39.8)	0.0	14	5.5 (8.2)	1.5
RESIDENTIAL LAND USES PRESENT							
Residential land use	No	266	4.5 (14.1)	2.0	259	4.5 (14.2)	2.0
	Yes	25	13.3 (26.7)	4.0*	32	11.6 (23.8)	5.0*
Abandoned homes	No	265	5.2 (16.4)	2.0	282	5.3 (15.9)	2.0
	Yes	26	5.5 (4.7)	4.0*	9	3.9 (3.4)	3.0
Multi-unit homes (2–4 units)	No	**236**	**5.0 (17.3)**	**1.0**	270	5.1 (16.2)	2.0
	Yes	**55**	**6.2 (4.7)**	**5.0****	21	6.9 (5.1)	6.0**
Single-family homes	No	45	15.4 (37.2)	5.0**	**49**	**14.6 (35.7)**	**6.0****
	Yes	246	3.4 (4.6)	2.0	**242**	**3.4 (4.6)**	**2.0**
Apartments (>4 units, 1–4 stories)	No	261	5.2 (16.4)	2.0	260	4.3 (9.7)	1.5
	Yes	30	6.0 (6.0)	5.0	31	13.6 (38.5)	6.0**
PARKING FACILITIES PRESENT							
Parking allowed	No	273	5.5 (16.9)	3.0	240	5.2 (16.9)	2.0
	Yes	55	3.8 (7.1)	1.0	51	5.4 (7.8)	3.0
On-street parking	No	73	4.6 (7.5)	1.0	82	5.8 (7.9)	3.0
	Yes	218	5.5 (17.6)	2.0	291	5.0 (17.8)	2.0
Small lot or garage	No	236	3.7 (5.4)	1.0	239	5.1 (17.0)	2.0
	Yes	55	12.1 (33.7)	4.0**	52	5.8 (6.6)	4.0*
Medium/large lot or garage	No	264	4.6 (14.3)	2.0	266	4.8 (14.3)	2.0
	Yes	27	12.0 (25.1)	6.0**	25	9.9 (26.1)	4.0
PUBLIC RECREATIONAL FACILITIES PRESENT							
Park with equipment	No	283	5.2 (15.9)	2.0	286	5.2 (15.8)	2.0
	Yes	8	6.4 (4.0)	6.0*	5	7.0 (2.8)	8.0*
Sports/playing field	No	286	5.2 (15.8)	2.0	283	5.2 (15.9)	2.0
	Yes	5	7.0 (6.6)	8.0	8	6.3 (5.6)	7.5
NON-RESIDENTIAL LAND USES PRESENT							
Non-residential land use	No	147	7.3 (21.5)	3.0*	119	8.5 (23.5)	4.0**
	Yes	144	3.1 (4.4)	1.5	172	3.0 (4.7)	1.0

(Continued)

Table 3 | Continued

		Streets assessed with field			Streets assessed with imagery		
		No. of streets	Mean (SD)	Median	No. of streets	Mean (SD)	Median
Abandoned buildings	No	276	5.2 (16.1)	2.0	276	5.1 (16.0)	2.0
	Yes	15	6.3 (5.6)	6.0*	15	7.1 (9.2)	3.0
Small grocery or convenience store	No	278	5.2 (15.9)	2.0	280	5.2 (15.9)	2.0
	Yes	13	6.6 (9.1)	3.0	11	5.7 (8.5)	3.0
Food establishment	No	272	3.7 (5.0)	2.0	276	4.4 (9.3)	2.0
	Yes	19	27.3 (55.1)	6.0**	15	21.8 (55.5)	4.0
Bank	No	286	4.4 (9.0)	2.0	285	4.3 (9.2)	2.0
	Yes	5	51.4 (94.4)	6.0	6	48.2 (84.8)	17.5*
Church	No	264	5.3 (16.4)	2.0	268	5.4 (16.3)	2.0
	Yes	27	4.4 (5.5)	3.0	23	3.3 (4.0)	3.0
Schools	No	**275**	**5.1 (16.0)**	**2.0**	**275**	**5.1 (16.0)**	**2.0**
	Yes	**16**	**7.8 (7.4)**	**5.5***	**16**	**7.6 (7.1)**	**6.5****
Strip mall	No	279	5.1 (15.9)	2.0	279	5.1 (15.9)	2.0
	Yes	12	7.8 (11.0)	4.5	12	7.9 (11.0)	3.5
Large office building	No	261	4.7 (14.4)	2.0	260	4.0 (5.6)	2.0
	Yes	30	10.3 (24.0)	3.5	31	16.0 (44.4)	4.0
PUBLIC TRANSPORTATION AVAILABLE							
Transit	No	261	3.5 (4.9)	1.5	267	4.3 (9.5)	2.0
	Yes	30	20.2 (44.5)	7.0**	22	16.4 (46.0)	5.0*
STREET CHARACTERISTICS VISIBLE							
Posted speed limit	No	210	4.5 (10.5)	2.0	215	4.6 (10.6)	2.0
	Yes	81	7.2 (24.4)	3.0	76	7.0 (25.1)	3.0
Posted special speed zone	No	281	5.2 (15.9)	2.0	280	5.3 (16.0)	2.0
	Yes	10	6.1 (4.2)	6.0*	11	3.9 (3.5)	6.0
Marked lanes	No	**204**	**3.6 (5.4)**	**1.0**	199	3.4 (4.9)	1.0
	Yes	**87**	**9.1 (27.2)**	**4.0****	92	9.3 (26.6)	4.0**
Median or island	No	280	5.2 (15.9)	2.0	280	5.1 (15.8)	2.0
	Yes	11	5.6 (6.0)	5.0	11	9.7 (10.7)	6.0**
Turn lane	No	269	4.4 (9.5)	2.0	270	4.4 (9.6)	2.0
	Yes	22	15.3 (46.1)	4.5	21	15.9 (46.9)	5.0*
Crosswalk	No	246	3.5 (4.8)	1.5	254	3.5 (4.9)	2.0
	Yes	45	15.0 (37.1)	5.0**	36	17.4 (41.1)	6.0**
Walk/do not walk signal	No	272	3.8 (5.3)	2.0	267	3.6 (5.1)	2.0
	Yes	19	26.1 (55.3)	6.0**	24	23.3 (49.3)	6.5**
Traffic calming device	No	281	5.3 (15.9)	2.0	284	5.3 (15.9)	2.0
	Yes	10	3.2 (2.5)	2.5	7	4.1 (3.1)	5.0
Cul-de-sac	No	274	5.3 (16.1)	2.0	279	5.3 (16.0)	2.0
	Yes	17	4.2 (6.9)	0.0	12	4.3 (7.1)	0.0
QUALITY OF THE ENVIRONMENT							
Commercial building adjacent to sidewalk	No	226	3.5 (4.7)	2.0	217	3.4 (4.8)	1.0
	Yes	65	11.4 (31.4)	4.0*	74	10.7 (29.4)	4.0**
Any amenities	No	157	3.6 (4.5)	2.0	204	3.4 (5.7)	1.0
	Yes	27	23.1 (46.6)	7.0**	5	70.2 (100.9)	0.0
Graffiti or broken windows	No	254	5.1 (16.7)	1.5	280	4.7 (14.0)	2.0
	Yes	37	6.3 (4.9)	6.0**	11	19.5 (37.8)	8.0*
Litter or broken glass							
None/a little		237	5.0 (17.1)	1.0	252	5.3 (16.7)	2.0
Some/a lot		54	6.3 (6.2)	5.0*	38	4.8 (4.9)	4.0**

(Continued)

Table 3 | Continued

		Streets assessed with field			Streets assessed with imagery		
		No. of streets	**Mean (SD)**	**Median**	**No. of streets**	**Mean (SD)**	**Median**
Tree shade							
None/a little		179	4.4 (10.9)	2.0	177	6.0 (19.6)	3.0
Some/a lot		112	6.7 (21.2)	3.0	109	4.1 (5.8)	2.0
Slope along walking area							
Flat or gentle		271	5.8 (17.2)	3.0*	255	5.6 (16.7)	2.0
Moderate or steep		57	3.0 (5.7)	1.0	33	2.7 (3.3)	1.0
PLACE TO WALK OR BICYCLE							
Sidewalk	No	**104**	**1.9 (4.3)**	**0.0**	**109**	**2.2 (4.7)**	**0.0**
	Yes	**187**	**7.1 (19.1)**	**4.0****	**181**	**7.0 (19.3)**	**4.0****
Buffer between sidewalk and curb	No	**150**	**3.7 (11.6)**	**1.0**	**158**	**4.8 (18.0)**	**1.0**
	Yes	**141**	**6.9 (19.0)**	**4.0****	**132**	**5.8 (12.4)**	**3.5****
Trees in buffer	No	**205**	**4.7 (18.1)**	**1.0**	**212**	**4.3 (15.7)**	**1.0**
	Yes	**86**	**6.5 (6.8)**	**4.5****	**78**	**7.6 (15.6)**	**5.0****
Sidewalk continuous within segment	No	**122**	**2.0 (4.8)**	**0.0**	**129**	**2.3 (4.6)**	**0.0**
	Yes	**169**	**7.6 (19.9)**	**4.0****	**161**	**7.6 (20.4)**	**4.0****
Sidewalk continuous between segments	No	**128**	**1.9 (4.1)**	**0.0**	**138**	**2.5 (4.9)**	**0.0**
	Yes	**163**	**7.9 (20.3)**	**4.0****	**152**	**7.7 (20.9)**	**4.0****
Sidewalk width at least 5 ft	No	**183**	**2.4 (4.1)**	**1.0**	205	3.9 (5.4)	2.0
	Yes	**108**	**10.1 (24.5)**	**6.0****	84	8.6 (27.8)	3.0
Sidewalk width <3 ft	No	235	5.9 (17.3)	3.0*	231	5.1 (17.4)	1.0
	Yes	56	2.6 (3.7)	1.0	57	6.0 (4.8)	5.0**
Missing curb cuts	No	249	5.5 (16.8)	2.0	237	5.7 (17.2)	2.0
	Yes	42	3.6 (5.4)	2.0	53	3.3 (4.7)	2.0
Major misalignments	No	**221**	**5.2 (17.7)**	**1.0**	240	5.5 (17.2)	2.0
	Yes	**70**	**5.5 (6.1)**	**4.0****	50	3.9 (3.9)	3.0
Bike sign or markings	No	279	4.9 (15.8)	2.0	286	5.2 (15.8)	2.0
	Yes	12	13.4 (11.0)	11.0**	3	13.0 (12.1)	6.0*
On-street, paved, marked shoulder	No	261	5.4 (16.4)	2.0	267	5.1 (16.2)	2.0
	Yes	30	4.0 (5.8)	1.5	23	6.7 (8.9)	5.0
Shoulder width at least 4 ft	No	279	5.1 (15.9)	2.0	282	5.2 (15.9)	2.0
	Yes	12	8.2 (7.0)	7.0**	8	7.4 (8.6)	5.5
Shoulder continuous between segments	No	265	5.4 (16.3)	2.0	269	5.1 (16.1)	2.0
	Yes	26	3.7 (6.1)	1.0	21	7.0 (9.2)	5.0

$*p < 0.05$, $**p < 0.01$.

[a] Counts of physically activity individuals was not distributed normally; therefore non-parametric statistics were used.

[b] Bolded characteristics also vary by population density.

Additionally, street segments with public transportation facilities (e.g., bus stops) and crosswalks, pedestrian signals, and marked lanes were associated with higher counts of physically active individuals, as were segments with continuous sidewalks or a buffer between the street and sidewalk. These data are also consistent with theories promoting Complete Street policies and Smart Growth principles that encourage transportation planners to design neighborhoods that are accessible for all modes of transportation (26).

In addition to identifying built environment characteristics that predict observed behavior, the results also demonstrate the validity of using omnidirectional imagery technology to audit the built environment. Because agreement between field and image-based audits is not 100% on all items, some streets were classified as having a built environment characteristic using field audits, while the same street was classified as not having that characteristic when using image-based audits (or vice-versa). However, 72% of the characteristics assessed had the same results regardless of auditing method, and there was general agreement regarding which environmental characteristics predicted total physical activity. Items not in agreement (e.g., presence of a turn lane and any amenities) typically demonstrated lower reliability in previous studies (17, 18).

While the results of this study are consistent with the current theory regarding the ways the built environment can be improved to better support physical activity, there are several limitations.

First, we cannot determine causality. Because this was an observational study, we do not know if the built environment characteristics encouraged more people to be active on certain segments or if more active individuals were observed on certain segments for other reasons (reverse causality).

Because of this study design, the generalizability of these results is limited. Behavior was only observed in a specific context, and we do not know anything about the other behaviors in which observed persons might be engaged or where they engage in these other behaviors. We do not know if the same people would behave the same way in a different location. Similarly, we did not measure individual factors or personal correlates that may influence behavior.

Our methods did not allow us to test if activity levels on a segment impact built environment characteristics (e.g., does more activity increase litter?) or if increased pedestrian traffic increases the likelihood of city planners and transportation departments to design streets with these characteristics. However, the sampling method employed ensured that we had a similar number of streets based on racial and poverty composition as well as commercial land use. This stratification allowed us to equally distribute these characteristics across our sample. The results suggest that several of the street characteristics are associated with more observed behavior. However, population density may be a confounder in the relationship between 13 built environment characteristics and physical activity. For example, observed behavior could be higher on some streets because there are more people who live or work in that area, not just because of the features of the streets. Future research should sample by population density as well as commercial land use to better assess how density mediates the relationship between physical activity and the built environment.

While we were able to assess a large number of segments, 44 segments (15%) were not audited due to safety concerns of the auditors, problems with identifying the specific segment in the field, or scheduling issues and another 103 segments initially sampled did not have imagery available at the time of data collection. These 147 segments were fairly evenly distributed across six of the eight strata, with very few excluded from majority white, low poverty areas (**Table 1**). It is unknown how these segments, if included, would have affected the results. However, given the distribution, it is unlikely these streets would have changed the direction of the results.

Additionally, the acquisition date of Street View imagery was not available when the imagery audits for this study were conducted. However, in 2012, Google began providing a stamp indicating the month and year Street View images were acquired. Image dates can change along the same street, and the frequency of image updates is unknown, but researchers implementing these methods in the future are now able to assess the temporal match between observed built environment conditions and physical activity behaviors.

Despite these limitations, there are several strengths to this study. Observational methods for physical activity assessment have several advantages over survey methods. First, they allow researchers to identify the type of activity (e.g., running, walking, and cycling), as well as when and where the activity occurred (13). Second, it removes respondent burden, reduces same-source bias, and places the responsibility for unobtrusive monitoring of physical activity behavior on the researchers. The Block Walk Method used in this study provides data on the number of individuals engaged in different types of physical activity on specific segments, allowing more precise linkage of context and behavior (9, 11, 12). Recent studies have demonstrated improved estimation of the effects of built environment on physical activity when contextual specificity is incorporated (14).

Future research should continue to assess physical activity as it occurs and identify the geographic location of the activity as well as other individual motivators as being active (as exemplified by the recent development of ecological momentary assessments) (27). Additionally, studies that dynamically monitor the intensity and geographic context of physical activity behavior using GPS and accelerometers (14, 28) can integrate the auditing methods used in this study to more closely link behavior to micro-level built environment characteristics that may have a significant influence.

AUTHOR CONTRIBUTIONS

All authors have contributed substantially to the design of this study, data collection and analysis, and manuscript preparation. All authors have given final approval of the manuscript to be published and agreed to be accountable for all aspects of the work.

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Development of a smartphone application to measure physical activity using sensor-assisted self-report

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Introduction: Despite the known advantages of objective physical activity monitors (e.g., accelerometers), these devices have high rates of non-wear, which leads to missing data. Objective activity monitors are also unable to capture valuable contextual information about behavior. Adolescents recruited into physical activity surveillance and intervention studies will increasingly have smartphones, which are miniature computers with built-in motion sensors.

Methods: This paper describes the design and development of a smartphone application ("app") called Mobile Teen that combines objective and self-report assessment strategies through (1) sensor-informed context-sensitive ecological momentary assessment (CS-EMA) and (2) sensor-assisted end-of-day recall.

Results: The Mobile Teen app uses the mobile phone's built-in motion sensor to automatically detect likely bouts of phone non-wear, sedentary behavior, and physical activity. The app then uses transitions between these inferred states to trigger CS-EMA self-report surveys measuring the type, purpose, and context of activity in real-time. The end of the day recall component of the Mobile Teen app allows users to interactively review and label their own physical activity data each evening using visual cues from automatically detected major activity transitions from the phone's built-in motion sensors. Major activity transitions are identified by the app, which cues the user to label that "chunk," or period, of time using activity categories.

Conclusion: Sensor-driven CS-EMA and end-of-day recall smartphone apps can be used to augment physical activity data collected by objective activity monitors, filling in gaps during non-wear bouts and providing additional real-time data on environmental, social, and emotional correlates of behavior. Smartphone apps such as these have potential for affordable deployment in large-scale epidemiological and intervention studies.

Keywords: context-sensitive ecological momentary assessment, experience sampling, smartphone, mobile phone, physical activity, sedentary behavior

INTRODUCTION

One of the most significant continuing challenges in the physical activity field is the need for valid and reliable measures of physical activity and sedentary behavior in adolescents for surveillance, epidemiological, and intervention studies. Concern over the validity of retrospective self-report due to recall errors and biases, especially for youth (1–3), has led to an increase in the use of "objective" measures of physical activity and sedentary behavior, such as accelerometer-based activity monitors, heart rate monitors, and global positioning system (GPS) devices. For instance, a number of studies have found differences in physical activity levels and patterns when comparing self-report and objective (e.g., accelerometers and GPS) assessment methods (4–6). Currently, objective activity monitors are being deployed in large-scale surveillance studies with adolescents (7, 8) and offer a promising opportunity to obtain more accurate assessment of physical activity and sedentary behavior in this age group.

Objective monitors, however, often yield missing, incomplete, or unexplainable data that add complexity and cost to data cleaning and data analysis. Data may be incomplete for a variety of reasons, among them (1) participants forget to wear or carry monitors, (2) participants remove monitors when they do not want to, or cannot, wear them, (3) participants remove monitors during sleep, bathing, and swimming, and (4) device limitations such as low battery life, signal interference, and malfunction. Studies using accelerometers in children and adolescents typically have only about 50% of participants with seven or more complete days of data (9, 10) and 60–80% with four or more complete days (7, 11). Missing data are even more common with GPS monitors, which encounter signal drop inside some buildings or dense urban areas and battery drain after 24 h of use (12, 13). GPS data availability ranges from 11 to 60% of all possible records in recent studies (14–16) with user error as a significant cause of missing data in adolescents (17). A particular concern is that these data are not missing at random (e.g., Actigraph removed during a soccer game), which can result in biased activity estimates from objective monitors.

Objective activity monitors are also unable to capture valuable contextual information about physical activity and sedentary behavior such as activity type and purpose, mood, and social and physical milieu. According to the multilevel ecological framework, interactions between individual, social, physical, and environmental factors in settings in which people live, work, and play are important for predicting physical activity and sedentary behavior (18). A growing body of research suggests that concurrent physical and social contextual exposures (19–22) as well as affective, physical feeling, and motivational states (23) play an important role in determining levels of physical activity and sedentary behavior at any given moment.

Adolescents recruited into objective physical activity and sedentary behavior monitoring studies will increasingly have "smartphones," which are mobile phones with built-in sensors and substantial computing power. Sophisticated programs can be easily installed on the phones (i.e., "apps"). The phones are rarely far from the adolescents, and adolescent affinity for the phones creates new opportunities for activity monitoring in surveillance and intervention studies. Mobile phones are being adopted throughout the U.S. population, including among lower-socioeconomic groups and minority populations (24); these phones expand options for health behavior measurement (25), and phone apps could be used to *supplement* existing data collection methods. In tandem with the peak of the smartphone industry, heightened consumer interest in physical activity measurement has resulted in dozens of devices and hundreds of applications designed to assist individuals in recording their day-to-day activities. While these devices and applications can track objective and subjective reports of physical activity independently, no known application has utilized accelerometry to assist individuals in labeling their day-to-day activities by prompting context-specific questions and showing a visual representation that aids in clustering activity throughout the day using phone motion. The current paper describes the design and development of a smartphone app that seeks to address the limitations listed above by combining objective and self-report assessment strategies to measure physical activity and sedentary behavior using sensor-informed real-time self-report and end of the day recall on typically carried mobile phones. This method utilizes data-driven participant self-report aimed at filling in gaps in objective activity data that result from device non-wear and malfunction. This method also supports the capture of time-sensitive contextual information about physical activity and sedentary behavior episodes that is not available from objective sensors.

METHODS

Mobile Teen is a new software technology ("app") for smartphones that can automatically detect and elicit information about activity and data loss episodes through real-time sensor-informed context-sensitive ecological momentary assessment (CS-EMA) or experience sampling (26) and sensor-assisted end-of-day recall. The Mobile Teen software has two novel features: (1) a component that uses the mobile device's built-in sensors to detect major transitions in type of phone movement or location, after which real-time CS-EMA questions are triggered that collect information about inferred physical activity, sedentary behavior, and data loss episodes, and (2) a second component that allows adolescents to interactively label their own activity data at the end of the day using visual cues from the phone motion and motion transitions to aid in recall of the type, intensity, duration, and start/stop times of those activities. Server-side software also remotely collects data from the Mobile Teen app in real-time and provides researchers with a cost-efficient way to remotely monitor participants during data collection to check for missing data. Following development, the software was tested through alpha and beta testing phases to verify that the app met the requirements that guided its design, worked as expected, could be implemented with the same characteristics as programed, and satisfied the needs of the user. All data obtained by the application was programed to transfer daily from the smartphone to a secure file transfer protocol (SFTP) server. At the conclusion of testing, smartphones were reset to factory settings and local phone data (including personal data) were erased with the participant present to preserve confidentiality. All participants were fully informed of the information gathered by the application, the purpose of the study, and the data purging process; consent and assent was obtained from each participant.

SOFTWARE DEVELOPMENT

The Mobile Teen smartphone app was designed by an interdisciplinary team of researchers consisting of computer scientists, psychologists, epidemiologists, exercise scientists, graphic designers, and users. The app was designed for mobile phones running the Android operating system (OS). The Android OS permits continuous raw data collection and processing from the phone's internal accelerometer; iOS, the OS used on Apple iPhone devices, currently does not; on newer iOS phones summary motion data is provided. The Mobile Teen software was written in Java and targets Android version 2.3.3–4.3, the versions available at the time of the research. The application will run on most Android phones but was tested most thoroughly on LG Nexus 4 model phones, the model used in the pilot testing described in this paper.

Several rounds of iterative technical development and field testing were conducted, starting with storyboarding and low-fidelity paper prototyping exercises (27). The graphic user interface for the surveys was built following a format successfully in use in several other studies. The end-of-day labeling interface was tested on paper with a convenience sample of people in the research group and colleagues, after which a prototype was implemented. Software components were then sequentially added and technical problems resolved. Members of the programing team carried smartphones with the app active for several months to gather data on phone movement and adjust the algorithms used to identify transitions between clusters of the phone's motion, so they map onto transitions between actual bouts of physical activity, sedentary behavior, and missing phone sensor data. Phones were setup to audio prompt (i.e., beep) in real-time when transitions were identified to provide an intuitive sense of the algorithm performance when triggering CS-EMA prompting, and pilot testing was performed in the lab to ensure the system would detect major transitions even when the phone is carried in different configurations (i.e., in various pockets, bags). Short pilot tests consisted of asking individuals to walk at different speeds and sit and stand in various ways to study the motion signals gathered from the phone. Members of the development team also used the app daily to refine the end of the day activity "chunking" interface, simplifying the initial design somewhat in the process and adjusting parameters such as the minimal length of a bout that can be labeled. Initial design ideas aimed at making the end-of-day labeling somewhat like a video game were ultimately revised in favor of a simpler design, due to concerns that the game mechanics would unduly influence participants to enter labels simply to complete the game, versus entering the labels that best captured activity.

ALPHA TESTING

Alpha testing to evaluate internal user acceptance, or feedback concerning typical use of the application, was conducted by four members of the study research team (including two research assistants, one graduate student, and a high school student intern), who did not have a direct role in programing the software. Members of the team carried the smartphone during their daily lives across designated periods of time spanning up to several days each. While carrying the phone, they maintained detailed logs of the dates, exact times, and types of CS-EMA survey prompts that were received. Members of the team also reported technical problems experienced with the Mobile Teen app and provided the programmers with additional feedback in order to refine the prototype application.

BETA TESTING

Limited beta testing with external users was done to assess acceptance, usability, and feasibility of the end of the day recall component of the app. A sample of six high school students enrolled in grades 9–12 (63% male) and living in the Los Angeles metropolitan area participated in this phase. Participants were asked to carry a LG Nexus 4 smartphone with the Mobile Teen app installed for one full day. At the same time, they were also asked to wear an Actigraph GT3X accelerometer on a waist belt. At the end of the 24-h period, a member of the research team guided participants through the completion of the end of the day recall. After completing this component, participants were interviewed to assess their experiences and satisfaction with the software. Sample interview questions included the following: (1) "Could you please explain to me what the Mobile Teen Game[1] does in your own words?" (2) "Did you feel that the instructions were clear on how you start the game and choose what day to begin?" (3) "Did you feel that the instructions were clear on what each part of the user interface does?" (4) "Do you have any suggestions for changes in appearance that would help others better understand or play the game?" Participants were compensated $20 for completing this beta testing component. This research was reviewed and approved by the Institutional Review Board at the University of Southern California.

Out of the six adolescents participating in the beta testing, five were able to label their activities using the end of the day component of the app. Data for one participant were irretrievable due to an application crash during the 24-h wear period. Interview feedback suggested that the app needed a wider range of activity categories, more icons, additional empty space so that each participant could enter their own activity, and the ability to split the activity bout more precisely for labeling. The Mobile Teen software was further refined based on this feedback provided by beta testing.

RESULTS

The Mobile Teen app has two major components: (1) sensor-informed CS-EMA, and (2) end-of-day sensor-assisted recall.

SENSOR-INFORMED CS-EMA COMPONENT

The app uses the mobile phone's built-in motion sensor to automatically detect periods of motion, inactivity, or no-data from the phone. The app then uses these sensor-informed movement transition cues to trigger real-time CS-EMA self-report surveys measuring the type and purpose of activity previously performed, enjoyment of that activity, and social and physical features of the activity setting. EMA is a measurement strategy to elicit real-time self-report responses to electronic surveys in naturalistic settings throughout the course of daily life (28–32). To date, EMA studies have provided useful insight into the role of physical activity determinants such as pain and fatigue (33–35), affective states (36–42), intentions and social support (43, 44), and social and physical contextual influences (20, 21, 45–48).

Activity bout detection

On LG Nexus 4 phones, pilot testing showed that the accelerometer could be monitored continuously and achieve waking-day performance on a single charge (but without extensive additional use of the phone). To increase battery life to allow for typical use of the phone and to increase software reliability on some models of Android phones, the app samples the accelerometer for 20 s each minute[2]. Pilot testing suggested that 20 s/min of monitoring is sufficient to represent activity across the entire minute, for the purpose of triggering questions during the day and labeling activities at the end of the day.

Accelerometer data are captured at 10 Hz. A 1-s summary value is computed by taking the sum of the absolute value of the derivative of the x, y, and z axes. This number approximates the overall amount of acceleration change and can be easily computed in real-time.

Periods of data are then classified into three categories: no-data, low-intensity data, and high-intensity movement. Periods of

[1]The end-of-day activity labeling component of the app was described to participants as the "game" part of the application because it can be used to earn rewards if enough of the day is successfully labeled.

[2]This sampling strategy improves software reliability by permitting the software to run for only 20 s of each minute and then go into a lower-power state for the remaining 40 s. This permits the application to maintain a higher priority on the phone relative to others, thereby reducing the likelihood it will be shut down by app killer software attempting to improve battery life.

no-data are easily identified if the app finds any time spans with missing data because if the app is running, data are recorded. If the phone is turned off or the app shuts down for some reason, when the phone is restarted the app also restarts. Periods of high-intensity data are detected using a set of heuristics that determine if there is a large change in the summary values (i.e., high second derivative of the original signal) or a substantial change in the average summary values around a given point, computed over the previous and next minute (and limited by rules that ensure no more than one chunk is proposed every 2 min). The motion in a high-intensity chunk must be above a threshold that was experimentally determined to represent significant ambulatory motion. All other periods are labeled as low-intensity motion; this category includes periods where the phone is recording data but not moving. The detected transitions, bouts, and motion summary values are stored for later analysis, but they are also used by the software to trigger real-time CS-EMA prompting. The app is designed to detect major activity transitions regardless of body placement of the smartphone on the user (e.g., pocket, hand, purse, and bag). The goal is for the app to function in an environment in which the user carries the phone naturally. For example, even if the user places the phone on a nearby desk or table when sitting, it is likely that he or she will carry the phone when transitioning to another room to keep it accessible for texting, Internet use, and calling (49).

Triggering rules

The app is programed with three rules for triggering CS-EMA survey prompts based on the phone's built-in motion and power sensors (see **Table 1**). These rules were developed to detect automatically the natural end of bouts of physical activity, sedentary behavior or device non-wear, and the device being powered off. The trigger indicators are based on the average activity intensity value computed across a moving window for the timeframes specified in the table. The software is fully customizable and flexible to accommodating different activity thresholds or moving time windows as may be desired in other studies on different populations or circumstances.

Sampling and procedures

The sampling timeframe can be tailored within the software to meet the researchers' needs. Typically, adolescents are asked to carry the phone as usual (either in their pockets, hands, purses, or bags) during waking hours. CS-EMA prompts are triggered during 2-h windows set by the researchers, during non-school hours (3–9 p.m. on weekdays and 7 a.m. to 9 p.m. on weekend days). Upon receiving an auditory CS-EMA prompt (a pleasant but loud 4 s chime), participants are instructed to stop their current activity and complete a short electronic survey question sequence using the touch screen of the smartphone. This process usually requires about 2–3 min. If a CS-EMA prompt occurs during an incompatible activity (e.g., sleeping or bathing), participants are instructed to ignore it. If no entry is made, the phone emits up to two reminder prompts at 3-min intervals. After this point, the electronic CS-EMA survey becomes inaccessible until the next prompting opportunity. Signal or interval-contingent EMA prompts can also be programed within the app. Unlike the CS-EMA prompts, which are triggered automatically immediately after the activity and data

Table 1 | Sensor-informed context-sensitive ecological momentary assessment (CS-EMA) triggering rules.

Type of trigger	Indicator
1. Physical activity bout	15+ min of high-intensity activity followed by 10+ min of low-intensity activity
2. Sedentary behavior bout or device non-wear	60+ min of low-intensity activity followed by 1+ min of moderate intensity activity or greater
3. Device powered off	10+ min of no activity data followed by 1+ min of some activity data

triggers listed in **Table 1**, signal-contingent EMA prompts occur at random times throughout the day based on frequency and boundary rules customized within the program. Combining signal-contingent ("random") EMA prompting schedules with CS-EMA prompting can provide within-person comparison (i.e., "control") conditions (29, 50). For example, they may allow researchers to compare negative mood immediately after physical activity bouts (captured though the CS-EMA) with negative mood occurring at other randomly prompted times throughout the day (captured by signal-contingent EMA).

To avoid excessive prompting, the app enforces a 30-min gap between all prompts. Therefore, if a context-sensitive prompt is presented and there is <30 min to the next scheduled signal-contingent prompt, then the signal-contingent prompt will not be presented for that particular 2-h window of time.

Self-report items

The app is programed with an EMA question sequence that is designed to measure major activity types, smartphone placement on the body, reasons for smartphone non-wear, and other psychological and contextual factors related to behavior. These EMA question sequences can be tailored to the unique hypotheses of the researcher. The app contains features to accommodate item dependencies, branching and skip sequences, and programed item missingness patterns.

The CS-EMA question sequence begins with a basic *activity type* question, "What did you do between (start time) and (stop time)?" where the start and stop times are automatically inserted by the app based on information from the built-in smartphone motion sensor and the particular triggering rule applied (see **Figure 1**). For example, if there was a Rule 2 trigger (60+ min of low-intensity activity followed by 2+ min of moderate intensity activity or greater), the first CS-EMA question would read, "What did you do between 10:33 and 11:48?" Alternatively, the signal-contingent ("random") EMA question sequence begins with the *activity type* question, "What have you been doing for the past 30 min?" For both the CS-EMA and signal-contingent activity type questions, a response structure is used where participants may select multiple activities (i.e., "choose all that apply") to indicate that they were multi-tasking. Response options include "*Reading or doing homework*; *Using technology* (*TV*, *phone*); *Eating/drinking*; *Sports/Exercising*; *Going somewhere*; *Hanging out*; *Other*." This question is followed by a series of branched questions depending on the initial responses. For example, if *Sports/Exercising* is

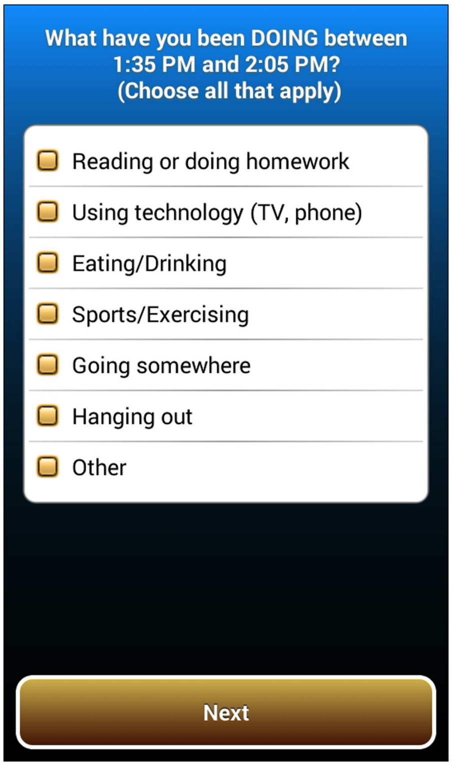

FIGURE 1 | Screenshot of the initial *activity type* question for the sensor-informed context-sensitive ecological momentary assessment (CS-EMA) component.

reported as an *activity type*, a follow-up question asks about the specific type of sports or exercise activity (e.g., *Basketball/Football/Soccer*, *Other running/Jogging*, *Exercise/Dance/Karate class*, *Weightlifting/Strength training*). Branching sequences for other *activity type* question responses are shown in **Table 2**.

After indicating *activity type*, participants were asked, "Approximately how many minutes did you spend [answer from question about *activity type*]?" Next, participants are asked to report their body position (e.g., *Lying down*, *Sitting*, *Standing*) and how the phone was carried (e.g., *On my belt*, *In my pocket*, *Not with me*). If a participant indicates that the phone was not with him or her, the reason for not carrying the phone is asked (e.g., *Forgot it*, *Did not want to damage it*, *Too uncomfortable*). These questions about duration, phone placement, and reason for non-wear are repeated for each *activity type* initially reported and asked 100% of the time.

When "Sports/Exercising" is reported as an *activity type*, a branching sequence is triggered that asks also about what fitness skill was involved (e.g., *Flexibility*, *Strengthening*, *Endurance*), extra weight carried (e.g., None, <5, 5–10 lbs), degree of incline (e.g., *Mainly going uphill*, *Mainly going downhill*, *Mainly staying on flat ground*), perceived pain or soreness during that activity (e.g., *None*, *A little*, *Some*), and the physical context of that activity (e.g., *Home*, *Work*, *School*). Each of these questions is programed to randomly appear in only 40% of the *Sports/Exercising* follow-up question sequences to reduce participant response burden.

Additionally, for each *activity type* reported, a series of follow-up questions asks about the main purpose of the activity (e.g., *Fun/Recreation*; *To get somewhere*; *For work, homework, or housework*), how enjoyable it was (e.g., *Not at all*, *A little*, *Moderately*), intrinsic/extrinsic motivation for that activity (e.g., *You want to do it*, *Your* [*Parents*, *Friends*, or *Teachers*] *want you to do it*), and the social context of that activity (e.g., *Alone or With Friends*, *Parents*, *Siblings*). Each of these questions is programed to randomly appear in only 30% of the *activity type* follow-up question sequences.

SENSOR-ASSISTED END-OF-DAY RECALL COMPONENT

The sensor-assisted end-of-day recall component allows adolescents to interactively label their own activity data each evening using the movement of their mobile phones to cue memory about the type, intensity, and duration of activities. Automatically detected bouts of activity, sedentary activity, or missing data provide activity start/stop boundaries. Participants are instructed to use the application each evening, or more frequently if they prefer, to label the activities for the previous 24 h. Upon launching the application, participants are presented with a horizontal splash screen with a "Begin" button and a "Play Tutorial" button (see **Figure 2**). The tutorial button guides participants through the end-of-day activity labeling procedure. After pressing the "Start Game" button, the app displays a selection of days for the given 2-week period, where each day has three possible status icons: expired and inaccessible (dash), complete and accessible (checkmark), incomplete and accessible (open box), or pending and inaccessible (lock symbol) (see **Figure 3**). Once a day begins, it is open and accessible for 48 h, after which it expires and can no longer be labeled. If the day is fully labeled, it is marked complete, but it can be accessed for corrections for up to 48 h. Pending days in the future are locked and inaccessible.

Activity "chunking"

After the participant chooses a day, the app advances to a visual display screen for that day that is designed to assist the participant in recalling activities. The top half of the screen shows a line graph that represents the intensity of physical activity captured by the built-in accelerometer of the mobile phone (see **Figure 4**). Low and relatively flat lines indicate little phone motion (typically corresponding to sedentary behavior or not carrying the phone) and spikes, peaks, and elevated plateaus indicate substantial phone motion (typically corresponding to body movement). The vertical axis initially used dynamic scaling, but during pilot testing dynamic scaling was found to be confusing; the vertical axis is now fixed so that a typical walking motion with the phone in the pocket will result in the line being one third of the range. The absolute values of the vertical axis are not important as long as typical bouts of ambulation appear as clearly distinct in the graph from no or little movement and are roughly consistent across days. The horizontal axis on this graph is time as indicated by date and time stamps at the bottom of the screen (see **Figure 4**). A participant can navigate across the activity graph using inertia touch scrolling. Section "Activity Bout Detection" described the algorithm used to detect bouts of activity or missing data. The visual display indicates the beginning and end of each activity or

Table 2 | Branching sequence for the activity type ecological momentary assessment (EMA) item.

INITIAL ITEM								
Item	**Item wording**	**Response options (bold-face initiates first branch)**						
Activity type	What have you been doing between (start time) and (stop time)?	Reading or doing homework	**Using technology (TV/phone)**	Eating/ drinking	Sports/ exercising	**Going somewhere**	Hanging out	**Other**
FIRST BRANCH SEQUENCE								
Item	**Item wording**	**Response options (bold-face initiates second branch)**						
Using technology (TV, Phone)	While using technology (TV, phone), were you:	Playing video games	Talking	Texting	Using the internet	Watching TV/ shows movies	Other	
Going somewhere	While going somewhere, were you:	Walking	Biking	Riding in a bus	Riding the metro/train	Riding in a car/ taxi	Other (skateboarding, etc.)	
Other (1/2)	What was this other activity?	Doing chores/ cooking	Showering/ bathing	Sleeping	Working/ part-time job	Getting ready for something	Shopping	Getting dressed
Other (2/2)	What was this other activity?	Class/school	Playing with children	Playing catch	Waiting	**Doing something else**		
SECOND BRANCH SEQUENCE								
Item	**Item wording**	**Response options**						
Doing something else		Write-in						

missing data "chunk" (i.e., bout) with vertical lines (see **Figure 4**). By inserting hypothesized transition points based on the data, the app accomplishes three goals. First, it speeds up data entry when the bout start/stop times are detected accurately from the phone's motion data. Second, if the bouts are not detected properly, having the transition points marked (but so they are easily moveable) will also save time. Finally, third, the application is gently suggesting to the user that certain time periods are sufficiently important to label. The activity "chunking" feature therefore both assists with identifying and recalling discrete activities, including the start/stop timing, and also can make the recall-based labeling task more efficient. Participants are asked to label their day in as much detail as possible, and to label each identified bout. When a bout is selected for labeling, clock face icons and time stamps appear on the vertical bout separation lines to indicate the beginning and end of the activity segment (see **Figure 4**). Also when selected, the bout changes to a yellow color and additional buttons appear that enable activity-frame manipulation.

Merging and splitting activity "chunks"

Green buttons with facing arrows, which sit beneath the clock face icons on the vertical lines, allow the participant to "merge" the selected activity bout with the adjacent bouts to the left or right if the activity contained within the highlighted bout is the same as prior or subsequent bouts (see **Figure 4**). Also, a yellow button with dividing arrows, which is positioned in the middle of the bout, allows the participant to "split" the segment into two equal bouts if two or more different activities were performed within the highlighted bout. A small number of taps therefore allow for efficient splitting, merging, and start/stop time adjustments for bouts. This is important because although the bout detection has been tuned based on the iterative pilot testing, no amount of tuning will lead to a perfect algorithm, and the algorithm often has insufficient information to split or merge certain types of bouts (e.g., a bout of *Eating/Drinking* that transitions without any extended ambulation to *Watching shows/Movies* could look like a single, extended bout based on phone motion).

Participants are told to merge activity bouts that were inappropriately split, and to split activity bouts that consist of more than one type of activity. A user, for example, might need to split a long bout of missing phone data or limited phone motion into different activities. The application allows bouts as short as 2 min.

Activity labeling

The center section of the screen functions as the main console for activity labeling. Unlabeled bouts are identified with an orange button with a question mark. After touching this question mark button, an activity selection list appears (see **Figure 5**). It contains a list of 46 common activities performed by adolescents (e.g., jogging, eating/drinking, sleeping) (see **Table 3**) adapted from the 3-Day Physical Activity Recall (3DPAR) (51) and Compendium of Physical Activities (52). Each activity has a corresponding visual

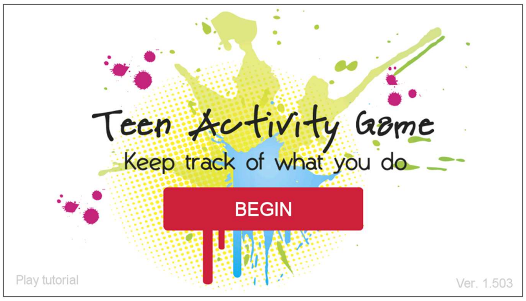

FIGURE 2 | Screenshot of the initial splash screen for the sensor-assisted end-of-day recall component.

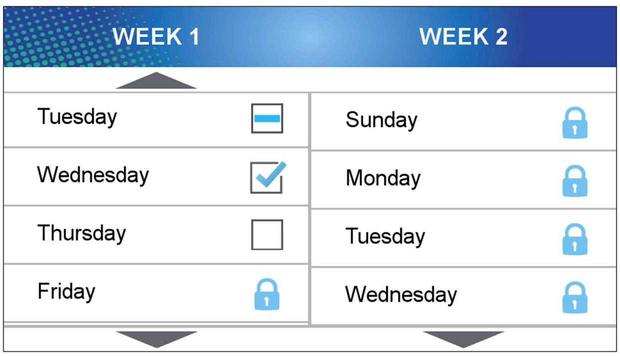

FIGURE 3 | Screenshot of the day selection screen for the sensor-assisted end-of-day recall component.

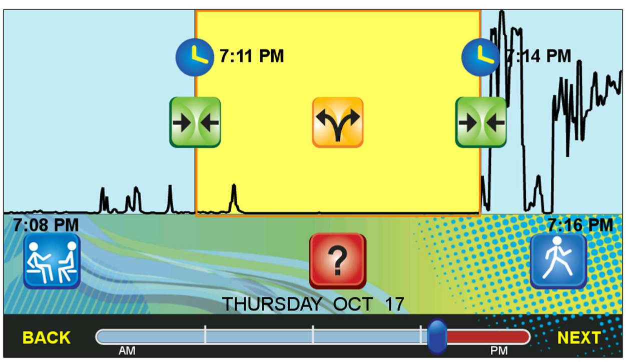

FIGURE 4 | Screenshot of the user interface for the sensor-assisted end-of-day recall.

icon, and the three most recently selected activity choices appear at the top of the list in green[3]. The remainder of the activity list is organized alphabetically. Once an activity label is selected for the highlighted bout, the orange question mark button is replaced

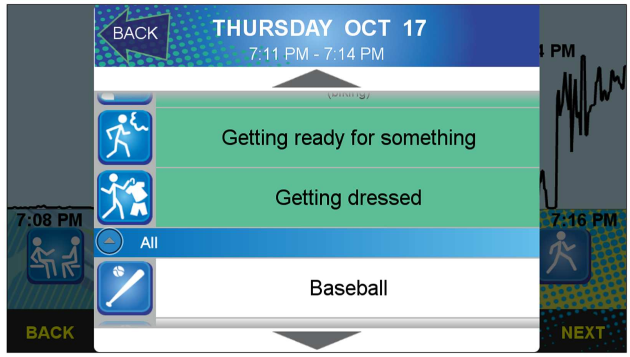

FIGURE 5 | Screenshot of the activity selection list from the sensor-assisted end-of-day recall component.

with the respective activity icon. The participant may change his or her selection at any time by touching any existing icon and choosing another activity via the pop-up activity selection list. If a participant tries to merge two bouts that do not have matching labels, a warning pops up and requests further input to determine whether the new merged bout should contain one of the existing labels or remain unlabeled (see **Figure 6**).

The bottom portion of the screen consists of a red bar quartered with white lines to delineate the day. As the participant advances through the labeling task, the bar changes from a red to a light blue color as a visual aid to indicate progress toward the completion of labeling (see **Figure 4**). A dark blue divider on the bar is used to represent the current visible time frame of the activity graph and functions as a navigation slider that can be moved to advance throughout the day. Additionally, movement between activity bouts is aided by "Back" and "Next" buttons at the bottom of the screen, which advance to the previous or next unlabeled bout, respectively. Periods of time in the future cannot be labeled. A participant who labels once per day in the evening begins labeling the evening of the prior day, completes that day, and then labels from midnight until the current time.

After all activity bouts are labeled for a particular day (i.e., a label is provided for the entire 24 h period) and the participant touches the "Next" button, the app advances to the reward splash screen (see **Figure 7**). The splash screen congratulates the participant for completing the respective day and allows the participant to exit with no action (Done button), fix labels in the previous day (Fix labels button), or obtain the unlocked reward for completing the labeling (Get reward button). The reward is distributed using an Amazon gift code, which can be immediately redeemed for $1 accessed through a redirect to the Amazon website on the phone. An email with the gift code is also sent to participants so that the participant can redeem it at a later time if preferred.

DISCUSSION

The self-reported activity information collected through the Mobile Teen app can be used to augment objective physical activity data collected by externally worn accelerometers or the smartphone's built-in sensor. Data gathered by the app have the potential to enhance physical activity research and practice in a number

[3]Pilot testing raised concerns that some participants may select various *doing something else* options more often than the research team would like. Therefore, these options are excluded from inclusion in the Most Recent list.

Table 3 | Sensor-assisted end-of-day recall activity list.

Activities				
Baseball	Basketball	Bicycling	Cooking/baking	Dance class
Doing chores	Eating/drinking	Fitness class	Football	Getting dressed
Getting ready for something	Going somewhere (biking)	Going somewhere (car/bus/train)	Going somewhere (skateboarding)	Going somewhere (walking)
Hanging out (sitting)	Hanging out (standing)	Jogging	Karate class	Other sports/exercise
Playing catch	Playing with child(ren)	Reading/doing homework	Running	Shopping food
Shopping other	Showering/bathing	Sitting in class	Skateboarding	Sleeping
Soccer	Swimming	Tennis/racquetball	Using computer/tablet	Using phone for anything (sitting)
Using phone for anything (standing)	Waiting (sitting)	Waiting (standing)	Walking	Watching shows/movies
Weightlifting/strength training	Working/job (sitting)	Working/job (standing/walking)	Doing something else (sitting)	Doing something else (standing)
Doing something else (walking)				

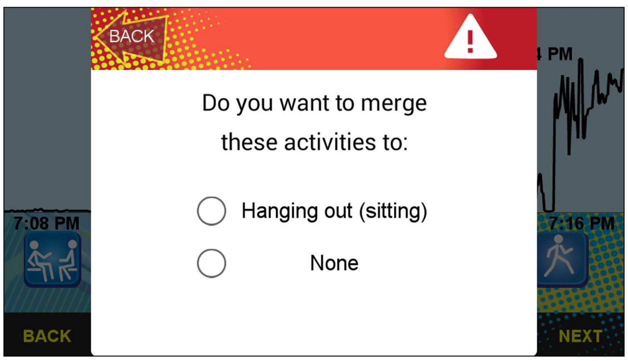

FIGURE 6 | Screenshot of the merging feature of the sensor-assisted end-of-day recall component.

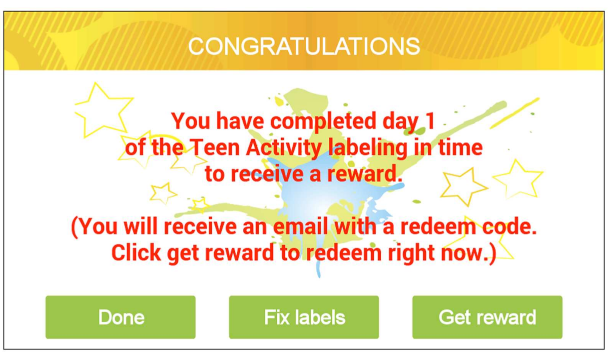

FIGURE 7 | Screenshot of the reward redemption at the end of the sensor-assisted end-of-day recall component.

of areas. First, these sensor-informed self-report data may significantly improve our understanding of objective activity device non-wear. Second, information about how the smartphone is carried (e.g., in my pocket, in my bag, or purse) from the CS-EMA can assist researchers in understanding the importance of smartphone body placement to activity assessment when using the phone's built-in accelerometer. Third, the CS-EMA data can be used to adjust energy expenditure estimates for activities not well captured by waist-worn motion sensors (e.g., cycling, load-bearing, inclined). Fourth, sensor-informed CS-EMA and end-of-day recall data can also be used differentiate between conceptually distinct activity types (e.g., homework versus watching TV or soccer versus football) that may appear identical when examining objective activity intensity data alone. Fifth, contextual and psychosocial information collected by the CS-EMA component can be used to test hypotheses about real-time environmental, social, motivational, and emotional correlates of physical and sedentary activity. Each of these methodological benefits is described in further detail below.

IMPROVED UNDERSTANDING OF OBJECTIVE ACTIVITY DEVICE NON-WEAR

Sensor-informed CS-EMA data from the Mobile Teen app running on a participant's normal phone can allow researchers to more clearly and reliably differentiate between sedentary activity periods and true device non-wear for objective sensors used in research studies. Typically, researchers have defined device non-wear for Actigraph accelerometer (ACT)-based activity monitors by continuous periods of 0 activity counts for up to 60 min or more (53). However, there is some disagreement over the appropriate length of non-activity time (e.g., 20 and 60 min) to be used to define non-wear and whether short interruptions during that non-activity time reliably indicate device wear (54). Detecting non-wear of other types of activity monitors, such as GPS devices, relies on similar monitor-specific heuristics that estimate non-wear from data loss.

Most adolescents are highly motivated to carry and keep charged and operational their own personal phones. The accelerometer data from the phones will therefore capture major transitions throughout the day. Bouts of activity between transitions may correspond to bouts of non-wear of objective activity monitors, but data will still be gathered on these periods in time. This will permit identification of time periods when the objective monitor shows no-data but yet a participant reports meaningful activity, thereby confirming objective monitor non-wear.

Periods of phone non-wear are likely to correspond to periods of objective monitor non-wear. The Mobile Teen app CS-EMA trigger in response to Rule 2 (i.e., 60+ min of low-intensity activity followed by 2+ min of moderate intensity activity or greater) will ask participants how they carried the phone during the low-intensity time period detected by the app; the trigger in response to Rule 3 (i.e., 10+ min of missing phone data) will as well. If a participant responds with *Within reach, but not on me* or *Not with me*, then that particular period of time can be reasonably assumed to be phone device non-wear. The app will then ask about the reason for objective device non-wear (e.g., *forgot it, too uncomfortable*). The more information researchers have available about when and why adolescents are unwilling or unable to wear objective activity sensors, the more able they will be to adjust and improve research protocols to reduce overall non-wear rates. For example, if it turns out that a certain subgroup of adolescents tends to regularly forget to wear a research study objective sensing device, then researchers can devise methods to remind them such as triggering smartphone notifications, sending SMS messages, or enlisting parental assistance (55).

Lastly, self-reported *activity type* information from both the CS-EMA and the end of the day recall components can be used to estimate energy expenditure during device non-wear periods such as while swimming and participation in high-contact sports; most motion sensors are not waterproof and are often prohibited in team sports that involve collision. Activity categories selected through CS-EMA or the end of the day recall to report what the participant did during non-wear periods can be converted to metabolic equivalents (METs) using the Compendium of Physical Activities (52) and multiplied by the duration of known device non-wear (in minutes) to generate an estimate of energy expenditure (in MET minutes) for that period of time. These energy expenditure estimates can then be imputed to fill non-wear holes in objective activity data to obtain a more accurate representation of levels of physical activity and sedentary behavior across that day.

IMPROVED UNDERSTANDING OF THE ROLE OF DEVICE BODY PLACEMENT

The CS-EMA component of the Mobile Teen app will collect information about how the smartphone is carried (e.g., in my pocket, in my bag, or purse). These data can assist researchers in understanding how activity level assessments using the smartphone's built-in accelerometer may differ according to how or where the smartphone is worn on the body. Currently, there is some debate over optimal accelerometer placement (56, 57), and research is ongoing to determine the viability of detecting physical activities directly from mobile phone accelerometer data, regardless of how the phone is carried (58). The Mobile Team app will enable research into the viability of using the phone's motion sensor in lieu of a separate objective monitor worn directly on the body.

IMPROVED UNDERSTANDING OF UPPER BODY, LOAD-BEARING, AND INCLINED ACTIVITIES

Data from the sensor-informed CS-EMA and end of the day components can be used to improve energy expenditure estimates for activities not well captured by waist-worn motion sensors such as those that involve the upper body, cycling, weight bearing, and incline or decline. Objective activity monitors worn on or near the waist (i.e., pocket) may not accurately measure activities that involve the upper body (e.g., hand cycle, rowing) (59). Waist-worn accelerometers may also not adequately capture cycling activities if the participant remains seated the entire time (60). Also, since objective activity monitors measure motion through acceleration, they often do not fully reflect true energy expenditure when the participant is load-bearing (e.g., heavy backpack, pushing a cart, carrying a child) or when motion involves uphill or downhill travel (61). After detected activity bouts (Rule 1), the CS-EMA component of the Mobile Teen app collects self-reported information about whether the activity involved cycling or upper body movements, load-bearing in terms of weight carried (e.g., *None, <5, 5–10 lbs*), and degree of incline involved (e.g., *mainly going uphill, mainly going downhill, mainly staying on flat ground*). These data can be used to upwardly or downwardly adjust energy expenditure estimates obtained from objective activity monitors.

IMPROVED UNDERSTANDING OF ACTIVITY TYPE AND PURPOSE

The sensor-informed CS-EMA and end-of-day recall data from the Mobile Teen app may also be used to differentiate between conceptually distinct activity types (e.g., homework versus watching TV or soccer versus football), which may appear identical when examining objective activity intensity data alone. These distinctions are relevant in the context of behavior change interventions. For example, if the goal of an intervention is to decrease sedentary activity, it would be helpful to know what proportion of one's sedentary activity is discretionary (e.g., TV watching, playing video games) as compared with non-discretionary (e.g., homework, required reading, practicing instruments) (22). This information is important to avoid possible unintended side effects of sedentary activity reduction interventions such as less time spent on homework. Also, the CS-EMA component gathers data about the purpose of the activity (e.g., *Fun/Recreation*, *To get somewhere*, *For work or housework*) that may be useful in assessing the amount of transit- and work-related physical activity performed.

IMPROVED UNDERSTANDING OF CONTEXTUAL CORRELATES OF PHYSICAL ACTIVITY

The CS-EMA questions gather information about where, with whom, and why physical activity occurs; as well as how participants feel during those activities. These data help researchers to understand whether physical activity intensity or duration differs across contexts and to investigate time-varying antecedents and consequences of behavior. For example, using EMA mobile phone surveys, children's moderate-to vigorous physical activity has been found to be greater outdoors than at home or at someone else's house (21, 47). Also, engaging in more moderate-to-vigorous physical activity was associated with higher ratings of positive affect and feeling energetic, and lower ratings of negative affect in the subsequent 30 min (23). Theories of health behavior change could be enhanced by taking into account multilevel interactions between enduring person-level factors and moment-to-moment level fluctuations in contextual factors that may influence physical activity (62).

FURTHER TESTING

Further testing is planned that will compare the performance of the Mobile Teen app relative to that of the ACT in a free-living sample of $N = 40$ low-to-middle income, ethnically diverse adolescents in 9–12th grade. Subjects will be recruited through a Los Angeles area high school using informational flyers, posters, and classroom visits. To simplify the study administration and lower the study costs, we will only recruit adolescents who have a GSM-based mobile provider (AT&T or T-Mobile) so their personal phone SIM cards can be easily switched to temporary LG Nexus 4 smartphones with the Mobile Teen app installed for the duration of the study. Doing so will allow participants to use the study phone to make and receive calls and SMS messages with personal phone numbers. A within-person design will be used with two assessment conditions: (1) Mobile Teen app + ACT (MT + ACT) and (2) ACT, each administered for 14 days. The order of the assessment conditions (MT + ACT first versus ACT first) will be randomly assigned.

This comparison testing will evaluate the performance of the Mobile Teen app plus Actigraph (MT + ACT) versus ACT alone using three primary outcomes: (1) percentage of available activity data, (2) user satisfaction and comfort, and (3) research costs. ACT data collected during this testing will be flagged as *missing activity data* due to non-wear if the number of consecutive minutes with zero activity counts from the accelerometer is ≥ 60 (53). Software will be written to merge data from the ACT data with the data from the Mobile Teen app using internal time stamps generated by the devices. METs generated from the sensor-informed CS-EMA or end of the day recall components of the Mobile Teen app will be imputed where there is missing ACT data, and these episodes will be recoded as *available activity data*.

LIMITATIONS

The Mobile Teen app has undergone iterative development and limited alpha and beta testing. Plans for more extensive testing with adolescents are underway, as described above. One possible concern with the method as proposed is that the Mobile Teen app depends upon adolescents in future activity measurement studies using personal mobile phones. Trends suggest (63–65), however, that within 5 years most adolescents in grades 9–12 will have phones with motion and location sensing. A related concern is that the phones they have will not be the appropriate phones for running the Mobile Teen app. In those cases, some of the adolescents could be switched to appropriate phones by temporarily swapping SIM cards, as proposed for the future Mobile Teen testing. The technology in its current form will only work on Android phones because iOS will not support the required background processing, but over 80% of new smartphone shipments use Android (66), and recent changes to Apple's iPhone line adding a motion co-processor chip may allow continuous movement detection (67) and thereby create opportunities to develop versions of Mobile Teen for new iPhones as well.

As with all EMA, the interruption burden is high with the Mobile Teen app. Participants can theoretically be prompted more than once per hour, although in practice prompting is less frequent than that. However, our prior work (21) and ongoing pilot work with Mobile Teen suggests that high rates of compliance overall can be achieved with this technology. For example, in an EMA study using mobile phones, adults answered 82% of the surveys that were prompted (68). Another concern often raised with EMA is reactivity, the potential for behavior to be impacted by the very act of assessing it (69), but the magnitude of reaction to EMA has been observed to be small for EMA studies (70).

The Mobile Teen app records phone location in addition to accelerometer data, and the application does mark major location changes on the interface, as an additional memory cue. The location data may also be useful when chunking the data into bouts of specific types of behaviors, which we are exploring in current work. One open question is whether the phone can replace the need for other objective sensors entirely. If so, larger scale and longer term, but affordable, studies leveraging the phone technology adolescents will already have would become possible. This may be most feasible if the phone is worn in a consistent way on the body, such as in a holder on the hip, but because our pilot work will ascertain the location of the phone on the body, in a secondary analysis we will compare the quality of output of the Actigraph monitor and phone sensors in our study population.

CONCLUSION AND FUTURE DIRECTIONS

After testing is complete, the source code for Mobile Teen app will be made freely available to other researchers. This new software can be initially deployed in *combination* with other objective activity monitors, working side-by-side with standard activity monitors to improve compliance and quality of data collected. Eventually as smartphones with built-in motion and location sensors are validated for physical activity assessment, the adolescent's own phones loaded with the Mobile Teen app can act as stand-alone activity measurement devices if adolescents will carry them in a standardized way. Overall, sensor-driven CS-EMA and end-of-day recall smartphone programs such as the Mobile Teen app have potential for deployment in large-scale epidemiological and intervention studies to improve the assessment of physical activity and sedentary behavior.

AUTHOR CONTRIBUTIONS

Genevieve Fridlund Dunton made substantial contributions to the conception and design of the work; and the acquisition, analysis, interpretation of data for the work. She also drafted the work and revised it critically for important intellectual content; gave final approval of the version to be published; and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved. Eldin Dzubur made substantial

contributions to the design of the work; and the interpretation of data for the work. He also drafted the work and revised it critically for important intellectual content; gave final approval of the version to be published; and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved. Keito Kawabata made substantial contributions to the design of the work; and the acquisition of data for the work. He revised the work critically for important intellectual content; gave final approval of the version to be published; and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved. Brenda Yanez made substantial contributions to the acquisition, analysis, interpretation of data for the work. She also drafted the work and revised it critically for important intellectual content; gave final approval of the version to be published; and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved. Bin Bo made substantial contributions to the design of the work; and the acquisition of data for the work. He also revised the work critically for important intellectual content; gave final approval of the version to be published; and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved. Stephen Intille made substantial contributions to the conception and design of the work; and the acquisition, analysis, interpretation of data for the work. He also drafted the work and revised it critically for important intellectual content; gave final approval of the version to be published; and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

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A hybrid online intervention for reducing sedentary behavior in obese women

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Sedentary behavior (SB) has emerged as an independent risk factor for cardiovascular disease and type 2 diabetes. While exercise is known to reduce these risks, reducing SB through increases in non-structured PA and breaks from sitting may appeal to obese women who have lower self-efficacy for PA. This study examined effects of a combined face-to-face and online intervention to reduce SB in overweight and obese women. A two-group quasi-experimental study was used with measures taken pre and post. Female volunteers (M age = 58.5, SD = 12.5 years) were enrolled in the intervention ($n = 40$) or waitlisted ($n = 24$). The intervention, based on the Social Cognitive Theory, combined group sessions with email messages over 6 weeks. Individualized feedback to support mastery and peer models of active behaviors were included in the emails. Participants self-monitored PA with a pedometer. Baseline and post measures of PA and SB were assessed by accelerometer and self-report. Standard measures of height, weight, and waist circumference were conducted. Repeated measures ANOVA was used for analyses. Self-reported SB and light PA in the intervention group (I) changed significantly over time [SB, $F(1, 2) = 3.81$, $p = 0.03$, light PA, $F(1, 2) = 3.39$, $p = 0.04$]. Significant Group × Time interactions were found for light PA, $F(1, 63) = 5.22$, $p = 0.03$, moderate PA, $F(1, 63) = 3.90$, $p = 0.05$, and for waist circumference, $F(1, 63) = 16.0$, $p = 0.001$. The intervention group decreased significantly while the comparison group was unchanged. Hybrid computer interventions to reduce SB may provide a non-exercise alternative for increasing daily PA and potentially reduce waist circumference, a risk factor for type 2 diabetes. Consumer-grade accelerometers may aide improvements to PA and SB and should be tested as part of future interventions.

Keywords: computer, accelerometer, inactivity, physical activity, waist circumference

INTRODUCTION

A lack of physical activity (PA) increases the risk of type 2 diabetes among overweight and obese persons and impairs glucose management in those with the disease. Recently, researchers have considered the role of sitting time in cardiometabolic diseases and determined that sedentary behavior (SB) is an independent risk factor (1–4). SB includes time spent sitting at desks, watching television, reading, or commuting (5). Interestingly, breaks from SB have been shown to decrease disease risk (4, 6).

On average, Americans spend 8.44 h a day in SB (4); with obese individuals sitting as much as 2.5 h more than normal-weight individuals (7, 8). A few interventions have been tested to reduce SB and increase light to moderate PA by limiting access to a sedentary activity (9), counting steps (10), or through increased lifestyle PA (11, 12). Lifestyle PA includes tasks of daily living and is less structured than exercise (13), which may be more appealing to overweight or obese women who are not currently physically active.

The hybrid approach combines face-to-face contact with computer-delivered content. This format takes advantage of social influences on behavior and any-time access to the intervention. Computer-delivered interventions appear to be equally effective at increasing PA as traditional methods (14–19). This is a novel approach for reducing SB. Conventional computer use requires participants to sit but also presents an "in-the-act" intervention point. Interest in consumer PA tracking devices such as the Fitbit, Jawbone, or Fuelband, which provide feedback through computer software, makes computer-delivered interventions more relevant.

The aim of this study was to examine the effect of a hybrid intervention for reducing SB on PA, waist circumference, and SB in obese women.

MATERIALS AND METHODS

A quasi-experimental, group × time design was used, with participants assigned to either intervention (I) or waitlist-control (WC) conditions. Time spent in SB, light, and moderate PA was measured by self-report (pre-mid-post) and by accelerometer (pre-post). Weekly pedometer steps were tracked in I group. Height, weight, and waist circumference were measured pre and post intervention.

PARTICIPANTS

Volunteers were recruited from local chapters of a national weight loss support group, Take off pounds sensibly (TOPS™). The chapters were paired and a coin-toss determined I or WC assignments. Four chapters received the intervention ($n = 40$) and three were waitlisted ($n = 24$). No additional chapter was available so the last grouping contained two I chapters and one WC chapter. Women between the ages of 35–85 years, with a BMI > 25 were invited to take part in the study. Participants had to be capable of receiving intervention materials by email and attend all program and data collection sessions. Conditions that prohibited them from standing or walking, such as recovery from surgery, excluded them from the study. TOPS, Inc. is a non-profit organization that offers nutrition, PA, health information, and weight loss tools to members at a low-cost (20). All participants signed the statement of informed consent approved by the university's Institutional Review Board.

MEASURES

Objective measurement of SB and PA

Participants wore an Actigraph model GT3X+ tri-axial accelerometer over the right hip (mid-axillary line) during waking hours for 7 days prior to and 7 days immediately following the intervention. The accelerometer recorded the maximum activity count (vector magnitude) in 60 s epochs, providing data on time in light, moderate, and vigorous PA, SB, and steps. Accelerometer data were analyzed using the ActiLife software, version 5.8.3. The cut points were: sedentary (<100 counts), light (101–1951), moderate (1952–5724), or vigorous (>5725) (21, 22). Participants were retained if they had at least 10 h a day of wear time (23) and at least four valid days (24). Sixty minutes of consecutive zero counts was labeled non-wear time (25) and wear periods less than 1 min were ignored (26).

Participants also wore an Advanced Technologies-82 pedometer over the left hip (mid-axillary line) at baseline. Participants used the pedometer for self-evaluation and goal setting during the intervention. Weekly pedometer step counts were collected at four time points during the study (pre, week 3, week 5, post).

Self-reported SB and PA

Two recall measures were administered pre, mid, and post intervention. The Godin Leisure-time PA Questionnaire (27) asked participants to recall the number of 15 min bouts of light, moderate, or strenuous PA they engaged in over the last 7 days. The numbers are multiplied by MET values (light 3, moderate 5, strenuous 9), to calculate PA scores. Full scale reliability has been reported as $\alpha = 0.74$ with lower coefficients for light (0.48) and moderate (0.46) intensities (28). In this sample, test-retest reliabilities were 0.57 for light and 0.44 for moderate. A weekly sitting inventory, taken from Salmon et al. (29), asked for the number of hours and minutes participants engaged in specific SBs (watching TV or video, using computer or internet, reading, socializing, riding in a vehicle, and doing crafts or hobbies) over the past 7 days. This measure has established intra-class reliability (ICC = 0.79. 0.53) (23, 29). The ICC reliability in the current study was 0.62.

Anthropometric measures

A Registered Nurse, blinded to group assignment took the height, weight, and waist circumference measures pre and post. Height and weight were converted to Body Mass Index (BMI) using the equation, kg/m^2. Waist circumference was measured at the narrowest part of the trunk between the iliac crest and last rib (30) with a Gulick measuring tape. Waist circumference was taken twice and the average was recorded.

PROCEDURE

Due to a limited number of accelerometers, participant chapters entered the study on a staggered schedule. Intervention chapters and WC chapters were paired and observed simultaneously. When possible, chapters were matched according to member and chapter characteristics (email use, meeting schedule, and number of members).

INTERVENTION

On Our Feet was a 6-week intervention framed in the Social Cognitive Theory that targeted self-efficacy for daily PA. Specifically, goal progress was re-enforced with individualized feedback and peers modeled less SB. The intervention was delivered in a combination of face-to-face sessions and email messages. Weeks 1 and 2 were led in-person by the researcher. Weeks 3–6 were conducted by email. **Table 1** shows the contacts and measures for each group.

In week 1 the concept of SB as a cardiometabolic risk factor was introduced and as group participants brainstormed alternatives to sitting. Participants received a workbook with weekly logs for steps and sitting time as well as instructions and suggestions to break up sitting time. In week 2 participants received their accelerometer-determined percentages of SB and PA. This feedback along with their week 1 pedometer data was used to develop two goals: (1) to increase breaks from sitting in the next week, and (2) to increase daily steps by week 5. Participants set the goals while guided by the researcher to list specific actions and cues to help reach the goals.

Seven emails contained the computer-delivered content. The messages consisted of either goal reminders, goal feedbacks, or examples of less SBs. All emails were individualized using information from the participant's goal plan and worksheet. Examples of less SB included short video of a relevant peer modeling the behavior. In week 3 (mid-point), participants completed the Godin Leisure-time Physical Activity Questionnaire and the weekly sitting inventory measures online.

DATA ANALYSIS

Group × Time (pre-post) repeated measures analysis of variance (ANOVA) was used to compare I and WC for accelerometer-determined percentage of time spent in SB, light or moderate PA. Self-reported SB and PA data were also analyzed with a Group × Time (pre-post) ANOVA. Only group I completed SB and PA questionnaires at mid-point and a one-way ANOVA was conducted with those data. WC comparisons were made using a repeated measures Group × Time (pre-post) ANOVA. A one-way ANOVA was performed on the I group pedometer step data. Statistical significance was set at $\rho \leq 0.05$.

RESULTS

Sample characteristics are available in **Table 2**. Participants were mostly White, over age 50, and possessed at least a high school education. Mean BMI at baseline was 36.44 (SD = 7.7). Eighteen participants met the criteria for class I obesity (BMI 30–34.9), 12 for class II (BMI 35–39.9), and 18 were in class III (BMI ≥ 40) (31). Nearly all (96.86%) participants had a waist circumference greater

Table 1 | Study contacts and measures.

	Pre	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Post
I	Accelerometer Pedometer BMI	Group session Godin SB recall	Group session 1 email	2 Emails Godin SB pedometer	1 Email	1 Email Pedometer	1 Email	Accelerometer Pedometer BMI
WC	Waist circum	Godin SB recall						Waist circum Godin SB recall

I, intervention chapters.
WC, waitlisted-control chapters.

Table 2 | Sample characteristics.

	I, $n=40$	WC, $n=24$
Age (years)	56.73 (±12.64)	61.38 (±12.1)
BMI (kg/m^2)	36.37 (±8.19)	36.56(±6.96)
Ethnicity		
White	36 (90%)	21 (88%)
African-American	4 (10%)	3 (13%)
Education		
<High school	1 (2%)	2 (8%)
High school	15 (38%)	12 (50%)
College or trade school	19 (48)	8 (33%)
Graduate school	5 (13%)	2 (8%)
Employment		
Full-time	22 (55%)*	5 (21%)
Part-time	3 (8%)	5 (21%)
Retired	9 (23%)	8 (33%)
Disabled	6 (15%)	6 (25%)
Non-sedentary job	11 (28%)*	5 (21%)
Rural location	18 (45%)	6 (25%)
Membership years	6.31 (±6.91)	4.95 (±5.52)
Cardiovascular disease	16 (40%)	12 (50%)
Type 2 diabetes	16 (40%)	13 (54%)
Arthritis	3 (8%)	4 (17%)
Depression	3 (8%)	4 (17%)
Waist circumference > 88 cm	38 (95%)	24 (100%)

I, intervention chapters.
WC, waitlisted-control chapters.
$^*p<0.05$.

than 88 cm, a level associated with increased risk of cardiometabolic diseases (32). An equal percentage of drop-outs occurred in both groups (14%); drop-outs did not differ significantly in age, health risk, or rural location from those that remained.

SB AND PA

The Group × Time ANOVA showed no significant changes over time or differences between the I and WC groups for the accelerometer-determined SB or PA. The Group × Time ANOVA for self-reported SB and PA, however, did reveal change.

Self-reported SB showed a significant effect for time, $F(1, 63)=4.88$, $p=0.03$, $\eta p^2=0.59$. Intervention participants reported sitting for 57.9 (SD = 29.7) h a week at baseline. This dropped to 45.9 (SD = 28.91) h at the post assessment. The change was not as great in the WC, decreasing from 45.2 (SD = 34.88) to 40.3 (SD = 4.68) h a week. Paired t-tests found the reduction to be significant among I participants, $t(1, 39)=3.08$, $p=0.004$, but not for WC participants (**Figure 1**).

Significant Group × Time interactions were found for self-reported light PA, $F(1, 63)=5.22$, $p=0.03$, $\eta p^2=0.61$, and self-reported moderate PA, $F(1, 63)=3.90$, $p=0.05$, $\eta p^2=0.49$ (**Figure 2**). In each case, the I group reported increased PA while the WC participants reported less PA. Independent t-tests revealed a significant difference in moderate PA at post between the groups, $t(1, 62)=2.27$, $p=0.03$.

A one-way ANOVA for the I group revealed significant time (pre-mid-post) effects for SB, $F(2, 39)=3.81$, $p=0.03$, $\eta p^2=0.09$, and for light PA, $F(1, 2)=3.39$, $p=0.04$, $\eta p^2=0.09$. I participants reported decreasing their weekly sitting time from $M=57.99$ (SD = 29.70) hours to $M=49.56$ at mid-point and to $M=45.99$ (SD = 28.91) at post. Self-reported light PA increased from $M=9.2$ (SD = 11.92) METS per week to $M=18.79$ (SD = 23.92) by mid-point and regressed to $M=12.66$ (SD = 15.26) METS at the post assessment. I participants increased their weekly pedometer steps significantly, $F(1, 3)=4.3$, $p=0.006$, $\eta p^2=0.10$. Follow-up t-test showed a significant increase in steps from baseline to week 3, $t(1, 39)=-4.74$, $p=0.001$, and from baseline to week 5 $t(1, 39)=-4.91$, $p=0.001$. Pedometer steps were not significantly different from week 5 to post (**Figure 3**).

ANTHROPOMETRIC MEASURES

A significant Group × Time interaction was found for waist circumference, $F(1, 63)=16.0$, $p=0.001$, $\eta p^2=0.21$. The I group dropped significantly from 108.5 (SD = 15.91) cm to 106.24 (SD = 15.82) cm, $t(1, 39)=5.09$, $p=0.001$. A non-significant increase (105.40 ± 13.52 to 107.01 ± 13.07 cm) was seen in the WC group (**Figure 4**). Twenty-nine of the 40 (72.5%) I participants experienced a reduction in waist circumference. The mean decrease was 2.25 (SD = 2.84) cm. BMI was unchanged over time (36.44 ± 7.70 to 36.48 ± 7.85) and did not differ between the groups.

DISCUSSION

Self-report data and I pedometer steps point to an increase in PA and reduction in SB over the intervention. Weekly sitting decreased in the I participants at the mid-point with no significant differences between the mid-point and post assessments. Self-reported

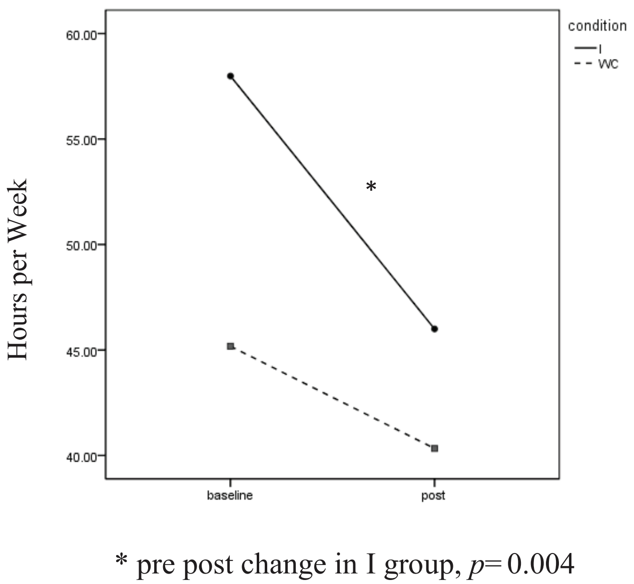

FIGURE 1 | Self-reported sedentary behavior. *Pre post change in group, $p = 0.004$.

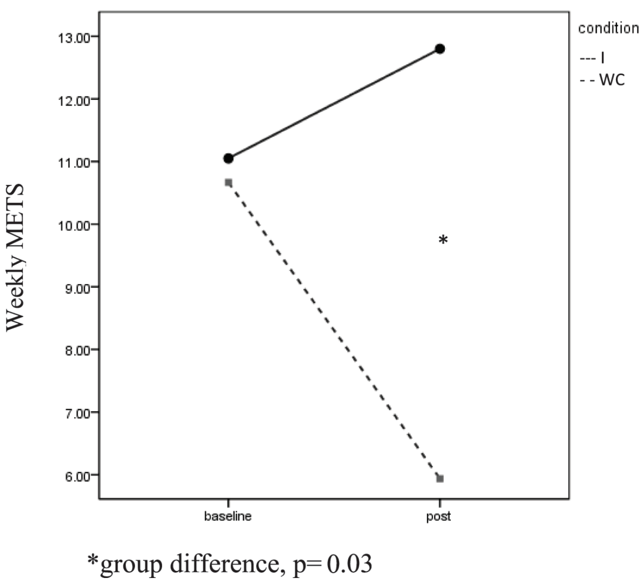

FIGURE 2 | Self-reported moderate physical activity. *Group difference, $p = 0.03$.

light PA peaked at mid-point and regressed by the post assessment. While it's unfortunate that a pre-post change was not seen in the accelerometer counts, it does not mean that the hybrid intervention was not effective. It's reasonable to conclude that behavior changes were made prior to the post assessment and missed because the accelerometer was only used pre and post intervention.

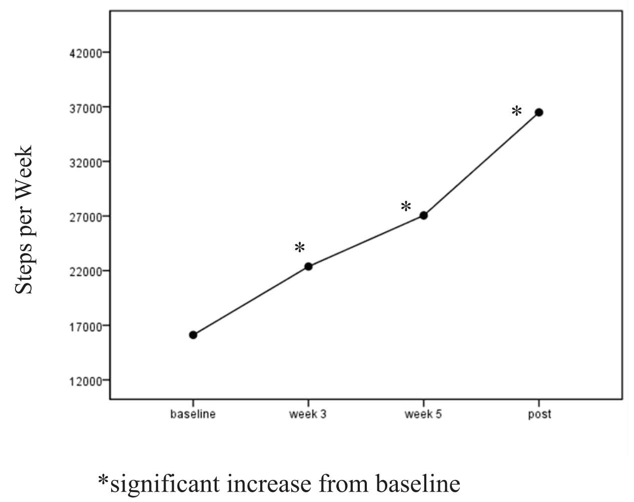

FIGURE 3 | Intervention pedometer steps. *Significant increase from baseline.

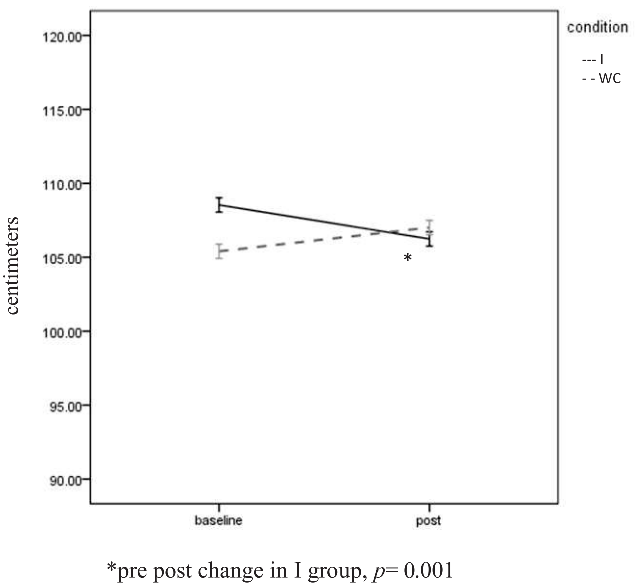

FIGURE 4 | Waist circumference. *Pre post change in I group, $p = 0.001$.

The significant reduction in waist circumference is further evidence of increased movement in the I group. Since no change in body weight occurred, the decrease in waist circumference was likely due to increased PA rather than calorie restriction. This finding reflects increased energy expenditure over the course of the intervention, whereas the accelerometer data only reflects the last 7 days of the intervention. Body fat redistribution, resulting in reduced waist circumference has been reported without significantly decreased body weight following aerobic exercise training (33).

The improvement in waist circumference is promising. While a small effect, the change came without increases in structured PA, aka exercise. Interventions that encourage more energy expenditure, whether through exercise, household chores, or standing, are a priority for health educators and researchers. The barriers to regular PA are many for obese women, including time, higher rates of perceived exertion, low self-efficacy, and lack of enjoyment (34). Suggesting that inactive persons sit less may overcome these. In follow-up surveys, participants reported high levels of satisfaction with *On Our Feet*, and the combination of face-to-face sessions and email messages was viewed positively.

The ability to self-monitor movement and structure the built-environment is important to changing SB. Participants were frustrated by the inaccuracy of the pedometer; for many the pedometer did not rest vertically on the waistband and steps did not register. *On Our Feet* used pedometers, but a consumer PA tracking device, such as the Fitbit, Jawbone, or Fuelband would have been a better choice for self-monitoring. These PA tracking devices are low-cost accelerometers that detect changes in speed and direction rather than hip vertical displacement as a pedometer does. These devices are more versatile and can be worn at the wrist or clipped to the waist or bra. Particularly for overweight and obese populations, the accelerometer offers more precise measurement of PA (35). An additional benefit of the Fitbit, Jawbone, or Fuelband is the constant feedback that is provided via their software programs. Users are able to sync their device to a computer and track multiple PA variables. They receive messages that positively reinforce improvements, much like the intervention tested here. Unfortunately, these PA tracking devices do not detect standing (versus sitting) and therefore do not help people that wish to monitor their SB.

Also worth noting, both groups engaged in less SB than expected for their age and BMI. Tudor-Locke (36) and colleagues found that obese adult women sat 57.6% of their monitored day. Prior work by Matthews (37) showed that the average daily SB for U.S. Caucasian women aged 40–59 years is 7.74 h (37). At baseline, participants were sedentary for 6.03 (±1.95) h out of 11.65 (±2.16) h or 52% of their monitored time. The fact that 18 I participants improved an average of 6.1% is remarkable given the low prevalence of SB. More research is needed to determine what the rates of SB are for obese persons specific to their occupations and urban or rural environments. Thirty-eight percent of participants lived in rural settings as categorized by the US Department of Agriculture (38) and could explain, in-part, the different levels of SB.

In terms of behavior change, participants found it hard to stand in environments where sitting was the norm. Working at a desk, attending a meeting or being in a waiting room were seen as non-negotiable barriers. More research is needed to determine if offering standing options, especially in the work environment, impact SB. Computerized alarms, that alert workers to the need stand and move are another area to pursue.

LIMITATIONS

Due to accelerometer availability, PA counts were only assessed during the first and last weeks of each intervention period. Had all participants worn the accelerometers over the entire course of the study, a better picture of their SB and PA would have emerged. The self-report measures and pedometer data point to an increase in PA in the I group.

Accelerometer wear time was lower in this study than in the cited research. Participants in the Tudor-Locke (36) and Matthews (37) cohorts wore the accelerometer for an average of 13.8 and 13.9 h a day. Wear time in this study was about 2.25 h short of these standards. While 10 h of daily wear is considered valid (23), lower wear times have been shown to impact SB, both inflating and deflating accelerometer estimates (25). Possibly the lower wear time in this study accounts for the differences in SB noted between this sample and the national data.

Another limitation is that no dietary measures were used to ensure similar pre and post calorie intakes. While no change in weight was observed, as members of a weight loss program, participants could have altered their diet and contributed to the reduction in waist circumference. Alternatively if participants increased their intake, any energy expenditure from increased PA would have been offset so that weight would remain constant. Study participants were long-time members of TOPS ($M = 5.8$ years) and were less likely to make dietary changes than new members.

SUMMARY

A short trial of a hybrid intervention to reduce SB in obese women was promising. Intervention participants increased self-reported PA and reduced self-reported SB as compared to the waitlisted-control group. They experienced the additional health benefit of reduced waist circumference. New PA tracking devices that combine accelerometers with real-time feedback may be useful in future SB and PA interventions. The role of the built-environment and programmable alerts should also be tested.

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Development and implementation of a smartphone application to promote physical activity and reduce screen-time in adolescent boys

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Purpose: To describe the development and implementation of a smartphone application (app) designed to promote physical activity and reduce screen-time in adolescent boys considered "at-risk" of obesity.

Methods: An app was developed to support the delivery of a face-to-face school-based obesity prevention program known as the "Active Teen Leaders Avoiding Screen-time" (ATLAS) program. ATLAS was guided by self-determination theory and social cognitive theory and evaluated using a cluster randomized controlled trial with 361 boys (12.7 ± 0.5 years) in 14 secondary schools. Following the completion of the study, participants in the intervention group completed a process evaluation questionnaire and focus groups were conducted with 42 students to explore their general perceptions of the ATLAS program and their experience with the smartphone app. Barriers and challenges encountered in the development, implementation, and evaluation of the app are also described.

Results: Participation in the study was not contingent on ownership of a smartphone, but 70% of participants in the intervention group reported having access to a smartphone or tablet device. Focus group participants reported an enjoyment of the program, and felt that it had provided them with new skills, techniques, and routines for the future. However, their engagement with the smartphone app was limited, due to a variety of reasons. Barriers to the implementation and evaluation of the app included limited access to smartphone devices, technical problems with the push notifications, lack of access to usage data, and the challenges of maintaining participants' interest in using the app.

Conclusion: Although participants reported high levels of satisfaction with the ATLAS program in general, the smartphone app was not used extensively. Additional strategies and features may be needed to enhance engagement in adolescent boys.

Keywords: physical activity, obesity prevention, sedentary behavior, behavior change, self-determination theory, social cognitive theory, technology, fitness and exercise

INTRODUCTION

Physical inactivity has been described as a global pandemic (1). Recent estimates suggest that approximately 80% of young people internationally are not meeting the physical activity guidelines of 60 min of moderate-to-vigorous physical activity (MVPA) each day (2). It is of additional concern that children and adolescents are spending a large proportion of their day engaged in screen-based recreation. Both physical inactivity and high levels of screen-time are associated with a range of adverse physical and psychological health outcomes in young people, including obesity, metabolic syndrome, and poor mental health (3–5). Although adolescent boys are typically more active than girls (2, 6), they report significantly higher levels of screen-time (7), making them susceptible to unhealthy weight gain and poor social and emotional well-being.

Schools have been identified as ideal settings for physical activity promotion and obesity prevention, as they have access to the majority of youth, appropriate facilities, and qualified personnel to achieve these outcomes (8). Numerous school-based interventions delivered in the primary-school setting with children have been found to be effective in promoting physical activity and preventing obesity (9, 10). In comparison, the evidence for effective school-based interventions targeting adolescents in secondary schools is limited. Indeed, the most recent Cochrane review of obesity prevention interventions found that primary school-based interventions were twice as successful as interventions targeting adolescents (9). The challenges of achieving health behavior change in this cohort has prompted researchers to explore novel and engaging intervention strategies. One such approach has involved the use of eHealth technology (e.g., internet, mobile phones, etc.) to encourage young people to develop physical activity behavioral skills (i.e., self-monitoring and goal setting) (11–13) and prevent the decline in physical activity typically observed during adolescence (14).

Mobile phone ownership is increasing at a rapid rate and recent data suggest that 77% of US adolescents (15) and 90% of Australian adolescents over the age of 15 own mobile phones (16). Not surprisingly, there has been a proliferation of mobile phone-based interventions using apps and short messaging service (SMS) to prompt physical activity and healthy eating in adults (17, 18). The evidence suggests that SMS-delivered interventions can have positive short-term behavioral outcomes in adults, but little is known regarding their utility for increasing activity levels in adolescents. A recent systematic review of smartphone apps for pediatric obesity prevention (19) found that very few apps included features recommended by the Expert Committee for Pediatric Obesity. The authors suggested that future apps should include comprehensive information about health behavior change and opportunities for goal setting. Although interventions are beginning to emerge in the published literature (20), little is known regarding the efficacy and practicality of mobile phone apps to promote physical activity and reduce sedentary behavior in young people.

Therefore, the primary objective of this paper is to describe the development and implementation of a smartphone app designed to support the delivery of the Active Teen Leaders Avoiding Screen-time (ATLAS) obesity prevention program (21). A secondary objective is to explore participants' perceptions of the program in general. ATLAS was a multi-component school-based intervention targeting adolescent boys attending schools in low-income communities, who were considered to be "at-risk" of obesity based on their physical activity and screen-time behaviors.

MATERIALS AND METHODS

STUDY DESIGN

Ethics approval for this study was obtained from the University of Newcastle, Australia and the New South Wales (NSW) Department of Education and Communities. School principals, teachers, parents, and study participants all provided informed written consent. The rationale, study protocol and intervention description have been reported previously (21). Briefly, ATLAS was evaluated using a cluster randomized controlled trial (RCT) conducted in state-funded co-educational secondary schools within low-income communities of NSW, Australia. The socio-economic indexes for areas (SEIFA) of relative socioeconomic disadvantage (scale 1 = *lowest* to 10 = *highest*) was used to identify eligible schools. The SEIFA index is derived from multiple indicators of socioeconomic disadvantage within an area (e.g., education, employment, etc.). Public secondary schools located in the Newcastle, Hunter, and Central Coast regions of NSW with a SEIFA index of ≤5 (lowest 50%) and an enrollment of at least 100 students in the targeted year group were considered eligible. Twenty-two eligible secondary schools were identified and 14 agreed to participate.

PARTICIPANTS

A power calculation was conducted to determine the required sample size for detecting changes in the primary outcomes [i.e., Body Mass Index (BMI) and waist circumference]. Assuming a drop-out rate of 20% by the primary endpoint, it was calculated that 350 participants (i.e., 25 from each school) would be required to detect a between-group difference in BMI of 0.4 $\mathrm{kg\,m^{-2}}$ and 1.5 cm in waist circumference. All male students in the targeted year group at the study schools completed a short screening questionnaire to assess their eligibility for inclusion in the study. The questionnaire aimed to identify those "at-risk" of obesity based on their physical activity and screen-time behaviors. Based on their responses, students failing to meet national physical activity or sedentary behavior guidelines (22) were considered eligible and invited to participate. Students with a medical condition that would preclude them participating in the program were also excluded. In total, 361 adolescent boys (mean age, 12.7 ± 0.5 years) in Grade 7 (first year of secondary school) consented and completed baseline assessments.

INTERVENTION

Active Teen Leaders Avoiding Screen-time was informed by the Physical Activity Leaders (PALs) pilot study, a successful trial conducted in four secondary schools in the Hunter region, NSW, Australia (23–25). A detailed description of the ATLAS intervention is reported elsewhere (21). The multi-component intervention was designed to increase physical activity, reduce screen-time, and reduce intake of sugar-sweetened beverages among adolescent boys attending schools in low-income areas. The intervention, which was delivered over 20 weeks (February–June, 2013) and was underpinned by self-determination theory (SDT) (26) and social cognitive theory (SCT) (27). ATLAS focused on the promotion of lifetime (e.g., resistance training) and lifestyle (e.g., active transport) physical activities and was aligned with current physical activity guidelines, which include a recommendation to engage in muscle and bone strengthening physical activities on at least 3 days/week (22, 28). The intervention promoted four behavioral messages: (i) *walk whenever you can*; (ii) *get some vigorous physical activity on most days*; (iii) *reduce your recreational screen-time*; and (iv) *drink more water and less sugary drinks.* Briefly, the school-based intervention involved the following components: teacher professional development, researcher-led seminars, enhanced school sport sessions, lunch-time physical activity mentoring sessions, provision of fitness equipment to schools, pedometers for self-monitoring, parental strategies to reduce screen-time, and a smartphone application (app) and website. To assist in facilitating the intervention as intended, participating teachers at the study schools attended two full-day professional development workshops (pre- and mid-program) designed and delivered by the research team. While the other intervention components have been described previously (21), a detailed description of the app is provided below:

Smartphone application and website

A smartphone app was developed as a supplement to the intervention and was made available to participants on both iOS (i.e., Apple app store) and Android (i.e., Google Play) platforms at no cost to participants (**Figure 1**). A website was also developed so that the same features were available to participants without access to a smartphone or handheld device with similar capabilities. Data for both apps (i.e., iOS and Android) were stored on the device, but the iOS version could be backed up to a secondary location (i.e., iTunes or the Cloud). Consistent with the face-to-face components of the ATLAS intervention, the apps were operationalized

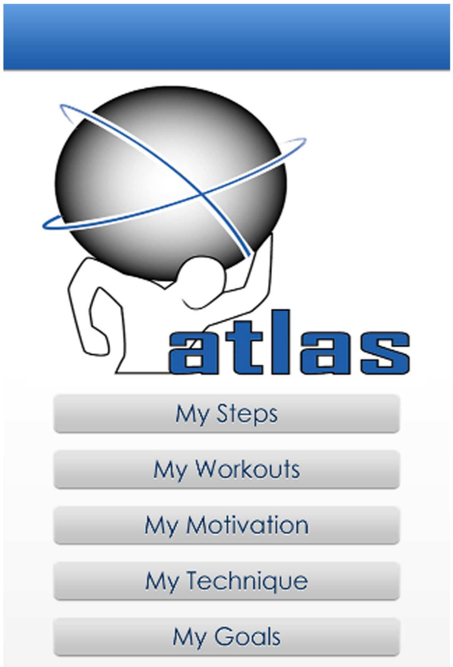

FIGURE 1 | ATLAS app welcome screen.

using SDT (29) and SCT (27, 30) (**Table 1**). More specifically, the app was designed to satisfy participants' needs for autonomy and to increase their autonomous motivation for physical activity. It was also designed to enhance their self-efficacy to be physically active and increase their outcome expectations regarding the benefits of physical activity and the consequences of excessive screen-time and sugared beverage consumption. Prompting of goal setting and behavioral monitoring were also encouraged. The five functions (**Figure 1**) of the app/website are described below.

Physical activity monitoring. *My steps* – participants were able to record their daily step counts measured using their personal pedometer which was provided by the research team. They could then review their "date-stamped" step count entries or select the graph view which allowed a visual representation (i.e., bar graph) of their entries over time. The graph view could be converted to show entries over a daily, weekly, or monthly time scale.

Pre-designed fitness challenges. *My workouts* – during the school sport sessions participants were introduced to CrossFit-style fitness challenges (henceforth referred to as workouts), which involved a series of resistance training (e.g., push-ups) and aerobic exercises (e.g., shuttle runs) with a predetermined number of repetitions (see **Figure 2** for example). The workouts were also included in the app to encourage participants to complete them outside of school hours. Ten separate workouts of "easy," "moderate," and "hard" rating were designed for the study and participants were encouraged to select workouts based on their perceived fitness levels. The time taken to complete the circuit was considered the result, with decreases in the time taken indicating improvements in performance. Using the app/website, students were able to select a workout, and then once completed, record their result (i.e., completion time). "Date-stamped" entries could be reviewed and entries could also be viewed in a bar graph format as described above.

Assessment of resistance training skill competency. *My technique* – the performance criteria for resistance training exercises from the Resistance Training Skills Battery (RTSB) (31, 32) were provided on the app/website. The RTSB is an assessment tool for appraising *technique* during the performance of six skills (i.e., squat, lunge, push-up, overhead press, suspended row, and front support with chest touches), which are considered to be the foundation for more complex movements used in resistance training programs (33–35). The app/website allowed users to assess their own (or others) technique, with the assistance of a peer or family member, during the performance of each resistance training skill. The performance criteria for each skill that were successfully demonstrated could be selected from a list of all criteria and then submitted following the completion of the exercise. The number of performance criteria successfully demonstrated is saved as the user's score. "Date-stamped" entries could be reviewed and the graph view, using the format previously described, could also be used to track progress in correct performance of the resistance training skill over time.

Goal setting. *My goals* – the app/website allowed users to set and review goals related to physical activity and screen-time. This function enabled users to select either (a) the number of daily steps they would like to achieve; (b) the number of workouts per week they would like to complete; or (c) the amount of screen-time (in minutes) they would like to limit themselves to each day. The user could then select the date on which they would like the achievement of the goal to be reviewed. On the date selected by the user, a *push notification* was sent asking the user to verify achievement of the goal. Previously achieved goals were retained and displayed on the screen for user review.

Tailored motivational messaging. *My motivation* – this function was available on the app only. After the initial download of the app, users were asked to select two of four physical activity outcome expectations that were personally important to them, relating to (i) appearance (i.e., to look good), (ii) health and well-being (i.e., to improve my health), (iii) school performance (i.e., to do better at school), and (iv) social interaction (i.e., to spend time with friends). Based on their responses, informational and motivational messages developed in reference to SDT and SCT were sent twice weekly via *push notifications* through the app (see **Figure 3** for example). The informational messages related to the ATLAS behavioral messages (e.g., *exercise helps u look fit and feel good. How much exercise have u done 2day?*) and the motivational messages were based on the user's initial responses to the motivation question. (e.g., *Do u want to look good and feel gr8? Well u won't get there sitting down!*). As recommended in the literature, messages were simple and written in vernacular "*text speak*" to engage teenagers (36).

Table 1 | ATLAS smartphone app features, behavior change techniques, and potential mediators.

Feature	Description	Behavior change strategies	Potential mediators
Physical activity monitoring *(My steps)*	This feature enabled participants to record their daily step counts measured using a pedometer and review results over a daily, weekly, or monthly time scale	Prompt self-monitoring of behaviors Prompt specific goal setting	Autonomous motivation for physical activity Behavioral capability Self-efficacy Self-control
Pre-designed fitness challenges *(My workouts)*	This feature listed 10 pre-designed CrossFit-style workouts including resistance training and aerobic exercises. Participants could enter and review results over a daily, weekly, or monthly time scale	Prompt self-monitoring of behaviors Set graded tasks	Self-efficacy Self-control Behavioral capability Autonomous motivation for physical activity Autonomy support
Assessment of resistance training skill competency *(My technique)*	This feature enabled participants to assess their resistance training skill competency with the assistance of a peer or family member. Results could be reviewed over a daily, weekly, or monthly time scale	Prompt self-monitoring of behaviors Prompt practice	Behavioral capability Self-efficacy Autonomous motivation for physical activity
Goal setting *(My goals)*	This feature allowed participants to set and review goals related to physical activity (steps/day), workouts (sessions/week), or screen-time (min/day). Push notifications were automatically sent to participants to confirm if goals were achieved	Prompt specific goal setting Prompt intention formation Prompt self-monitoring of behaviors	Self-efficacy Self-control Autonomous motivation for physical activity Motivation to limit screen-time Autonomy support
Tailored motivational messaging *(My motivation)*	Informational and motivational messages were sent twice weekly via push notifications through the app	Information on consequences Provide information about behavior–health link Provide general encouragement	Outcome expectations Outcome expectancies Social support Autonomous motivation for physical activity Motivation to limit screen-time

PROCESS EVALUATION

Baseline and post-program assessments were conducted in November–December, 2012 and July–September, 2013, respectively. Trained research assistants completed data collection at the study schools. A process evaluation was conducted to determine participants' usage of, and satisfaction with, the ATLAS app. Evaluation questionnaires were distributed to study participants at mid- and post-program periods. The mid-program questionnaire included items on the type of app/website usage (i.e., iOS, Android, or website usage) and the frequency of use (i.e., 1 = *Never* to 5 = *5 or more times*). The post-program questionnaire included more detailed items regarding user enjoyment of the app/website (1 = *Strongly disagree* to 5 = *Strongly agree*) and frequency of use for each specific function (1 = *Never* to 4 = *Often*).

Participants were also asked their behavioral intentions to (i) *limit recreational screen-time*, (ii) *limit consumption of sugary drinks*, (iii) *participate in at least 60 min of MVPA each day*, and (iv) *participate in muscle strengthening physical activities on 2–3 days each week* (1 = *Strongly disagree* to 5 = *Strongly agree*). To assist researchers interested in the use of smartphone apps for obesity prevention research, barriers and challenges encountered in the development, implementation, and evaluation of the app are described.

FOCUS GROUPS

A series of focus groups were conducted to gain insights into participants' experiences in and perceptions of, the ATLAS program. Consenting students took part in separate focus groups, each consisting of six participants. Each focus group included three participants who failed to meet MVPA guidelines and three participants who achieved MVPA guidelines (using baseline accelerometer data). These group meetings lasted between 42 and 58 min and were conducted in a separate classroom during school hours by a research team member who had not been directly involved in the delivery of the ATLAS program. The structured discussion framework was developed by the research team to facilitate discussion and reflection on the program. Specifically, the questions asked of the students were designed to explore their general perceptions of ATLAS and their experience with the ATLAS smartphone app. Views were also sought of the participants as to the perceived impact of the program on a range of attitudes and behaviors relating to physical activity and nutrition. Prompts were used as needed to explore topics in depth.

Qualitative data analysis

The focus groups were digitally recorded with the participants' consent and transcribed verbatim. A computer program (NVIVO 10) was used to assist with the organizational aspects of data

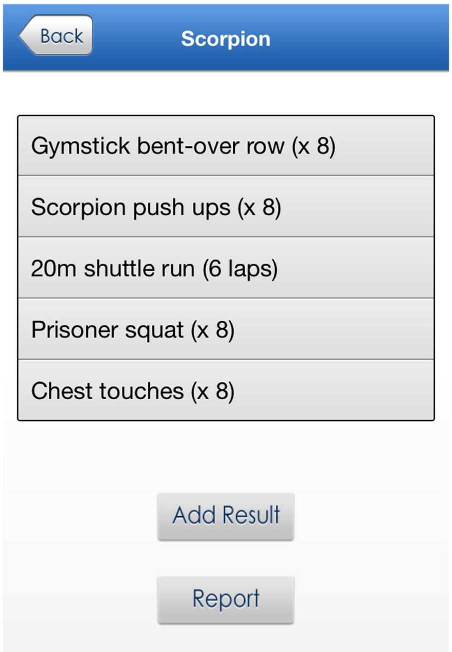

FIGURE 2 | Sample challenge workout.

FIGURE 3 | Example-tailored motivational message.

analysis. Analysis was conducted by an independent qualitative researcher using a standard general inductive approach to qualitative analysis. Initially, inductively derived codes or labels were attached to the meaning units arising from the data. The developing hierarchical coding scheme was continually revised and further expanded after coding of additional transcripts. Following coding of all the transcripts, emerging themes were identified and elaborated. Due to the structured format of the discussion framework, these themes were closely aligned with the research aims. The following reports on these inductive analyses and explores the impact that the program has had on the lived experiences of the students taking part in the ATLAS program.

RESULTS

DEMOGRAPHICS

Participants were 361 adolescent males (mean age = 12.7 ± 0.5 years) attending schools in low-income areas of NSW, Australia. The majority of boys (i.e., 95%) were born in Australia and most (i.e., 96%) reported speaking English at home. Ninety two percent of boys reported their cultural background as Australian or European. Furthermore, 13.5% of boys indicated they were of Indigenous descent (i.e., Aboriginal or Torres Strait Islander). The sample was predominantly of low socioeconomic position with 91.4% of boys residing within areas with a SEIFA population decile ≤5 (i.e., bottom 50%). Twenty-nine percent of boys resided in areas with a SEIFA population decile ≤2 (i.e., bottom 20%).

APP/WEBSITE USAGE

Participation in the study was not contingent on ownership of a smartphone, but 70% of participants in the intervention group reported having access to a smartphone or tablet device (including iPod Touch). At the mid-program evaluation, 49 and 15% of participants had used the iPhone and Android apps, respectively (**Table 2**). At the end of the intervention period, the majority of participants (70%) reported using the goal setting function to increase their physical activity or reduce their screen-time. Fewer participants used the app to monitor their resistance training technique (62%), pedometer steps (49%), and fitness challenge results (49%). Approximately, 20% of participants did not engage with the app at all.

APP/WEBSITE SATISFACTION AND BEHAVIORAL INTENTIONS

After completing the program, almost half of the group agreed or strongly agreed that the push prompt messages reminded them to be more active, reduce their screen-time, and drink less sugary drink (**Table 2**). Forty-four percent of participants agreed or strongly agreed that the ATLAS app was enjoyable to use. Alternatively, 95% of participants agreed or strongly agreed that the ATLAS program overall was enjoyable. Participants' intentions to limit their recreational screen-time (mean = 3.95 ± 1.07), limit their consumption of sugary drinks (mean = 4.01 ± 0.82), participate in regular MVPA (mean = 4.16 ± 0.81), and muscle strengthening activities (mean = 4.08 ± 0.76), were high following the completion of the program.

FOCUS GROUP RESULTS

A total of 42 male students from year 8 participated in 7 focus groups. Each group consisted of students attending the ATLAS program from the same school. The thematic analysis revealed a range of emerging themes surrounding the participants' general

Table 2 | Mid- and post-program process evaluation questions and responses.

Questions	*N* (%)
Mid-program questions	
I have used the iPhone app	53 (48.6)
I have used the Android app	14 (14.7)
I have used the website	25 (25.3)
Frequency of use	
≤2 times	70 (58.8)
≥3 times	49 (41.2)
Post-program questions	
I enjoyed using the app/website	
Strongly disagree	3 (2.8)
Disagree	13 (8.5)
Neutral	46 (43.4)
Agree	36 (34.0)
Strongly agree	12 (11.3)
The app messages reminded me to be more active, reduce my screen-time, and drink less sugary drinks	
Strongly disagree	6 (5.7)
Disagree	13 (12.4)
Neutral	35 (33.3)
Agree	38 (36.2)
Strongly agree	13 (12.4)
I used the "my goals" setting function on the app	
Often	20 (19.0)
Sometimes	54 (51.4)
Rarely	15 (14.3)
Never	16 (15.2)
I used the "my technique" function on the app	
Often	22 (20.8)
Sometimes	45 (42.5)
Rarely	21 (19.8)
Never	18 (17.0)
I used the "my steps" function on the app	
Often	13 (12.4)
Sometimes	39 (37.1)
Rarely	26 (24.8)
Never	27 (25.7)
I used the "my workouts" function on the app	
Often	16 (15.1)
Sometimes	37 (34.9)
Rarely	25 (23.6)
Never	28 (26.4)
How often did you wear your pedometer?	
Often	34 (30.1)
Sometimes	50 (44.2)
Rarely	20 (17.7)
Never	9 (8.0)

119 and 114 participants completed the mid- and post-program evaluations.

perceptions of the program, key messages, and ATLAS app, as well as clusters relating to the students' perceptions and evaluations of the physical activity sessions, as well as relationships with teachers and peers. The overarching theme relating to the perceived impact of the ATLAS program contained a number of sub-themes representing the changes to behaviors, knowledge, and attitudes relating to school, diet, and physical activity which were felt to have followed on directly as a result of involvement in the ATLAS program.

General perceptions of ATLAS

While a number of students had some suggestions for how the program could have been improved (mainly in terms of less repetitive activities and more variety), all expressed an enjoyment of the program, and felt that it had provided them with new skills, techniques, and routines for the future, while learning about the importance of reducing sedentary behavior, adopting a healthy diet, and limiting sugary drinks also generally having been received well by the students;

> "I felt the ATLAS program opened a lot of opportunities in the future; taught me a lot of things that I would not really do and helped me find my physical peak"

For the majority of the students, one of the most beneficial and important aspects of the program had been the learning of "how to do things right" and adding to their repertoire of techniques and activities which they could do with friends or by themselves. Many students, who reported engaging in various out of school sports, felt that the newly acquired skills, techniques, and fitness benefits arising from the program were highly transferable, such that they had gained an additional competitive edge. The particular techniques and activities most often referred to in this context were squats, lunges, and CrossFit.

Another frequently mentioned positive aspect of the ATLAS program had been the sense of achievement gained from the evidential gradual improvement in fitness throughout the duration of the program, with many commenting on the enjoyment they had gained from the regular testing of their performance against oneself and their peers;

> "At the start of the program in the CrossFit challenges, I was really, really puffed by the end but then at the end of the program I was still getting puffed by them but nowhere near as much and I could run a lot further for a lot longer"

while yet others (albeit a minority) commented favorably on the social aspects of ATLAS;

> ". . . having a training partner, having someone beside you, to slap you across the back of the head and tell you to get up and stop being lazy."

Engaging in activities which were not usually part of the school curriculum was perceived as a special treat for some students who for instance had been doing boxing as part of their program. Not only did this present a welcome change from normal routine, but also appeared to have aided in feelings of empowerment and improved standing compared to students not involved in ATLAS.

Key messages

Students had perceived a range of different key messages being conveyed by the ATLAS program. However, the most frequently mentioned related to the importance of reducing sedentary behavior and in particular screen-time, and reducing the consumption of sugary drinks while increasing water intake. This was closely followed by the importance of staying fit while increasing general physical activity and increasing incidental or opportunistic exercise (e.g., running to the school bus in the morning instead of walking). While many students had taken away several key messages, these four main areas accounted for over 80% of individual comments made.

Other less frequently mentioned key messages were the importance of attending to a healthy diet, with this mostly being associated with reducing overall caloric intake and fat, and the significance of learning and employing the correct technique over sheer strength. Finally, only one student had taken away from the program quite a profound message alluding to the importance of individual capacity and achievement.

> "It's all about going at your own pace and achieving your own goals."

ATLAS app

The reception of the ATLAS smartphone app was somewhat mixed. While approximately 80% of the students participating in the focus groups reported owning a smartphone or iPad, approximately 60% reported having downloaded the ATLAS app. Of those who had not done so, the reasons given were mostly that they had forgotten, were not aware of it, or had neglected to download it due to issues or problems with their device. Of "non-smartphone owners," only a few students reported having used the Web app. This was exclusively accessed on home PC, and the use of it was in most instances limited to a single viewing.

Of the remaining students, over half reported short-term, once-only or very occasional use of the app, while the remainder (approximately eight students) had used it quite frequently (i.e., three times/week or more). Three students particularly commented that their little usage of the app was due to being unsure how to use it.

In terms of the utility of the specific functions within the app, the My workouts, My steps, and My goals functions were the most frequently used. While the feedback relating to the My workouts function was mostly positive, being described as challenging and enjoyable, a few students had felt it had been boring and repetitive. The My steps function was also a high-use function, but mostly only short-term (limited by accessibility to pedometers), with some reporting simply forgetting about it. However, one student had particularly liked the graphing function to visualize his own performance while, for others, the My steps function had increased their awareness of physical activity or lack thereof. Generally, the use of pedometers was erratic and short-term.

The My goals function had received moderate use and reports were generally good (albeit not very elaborate). Only one student had used my technique function, and had found it very useful. The function which certainly received the most critical feedback was My motivation, which almost exclusively had been considered a nuisance by students. Mostly, the messages had been considered too frequent, too repetitive, or received at inappropriate times (e.g., midnight) and therefore not perceived to fit in with the rhythm of their day. However, one student had found self-programed messages very useful as reminders to engage in physical activity.

The vast majority of students taking part in the focus groups reported having successfully reached the goals which they had set for themselves at the outset of their participation in ATLAS. The most frequently mentioned of these goal accomplishments related to having achieved increased fitness levels including reaching sporting goals;

> "My goal was just to get fitter be able to get a place in cross country which I had never done. Well, mostly I'd come 10th. But after the ATLAS program, I actually came 3rd or 4th, so I finally got into zone"

followed by enhanced self-confidence, including higher expectations of oneself, and feelings of mental stamina;

> "Before the ATLAS program, I underestimated myself and set my goals pretty low, but during I set them a lot higher and felt I could reach them a lot more easily"

Yet others, who reported having reached their goals, had entered the program with the expectation of becoming more physically active, improving their knowledge of health and nutrition, achieving weight loss, achieving a general improvement in their physical or mental strength, or simply, as one student put it, perform to the "best of [his] ability."

Of the seven students who reported not having reached their goals, four had not set any specific goals at the outset of the program, while two felt they may have reached their goals had the program continued, while one student, very introspectively, noted that while he had failed to reach his goal of a certain number of steps per day, he had learnt the importance of realistic and progressive goal setting.

Diet and sugary drinks

In terms of dietary changes resulting from participation in the ATLAS program, a little over half of the students reported changes to their dietary habits as a direct result of what they had learnt in the ATLAS program. This had taken the form of attempts to purchase and consume healthier foods (less junk foods), reduce amount of food eaten, eating more of the healthier foods served up at home, healthier snacking options and, most commonly, increased fruit intake. There was clear evidence that students had increased their awareness of healthy nutrition, leading to a "think before you buy" approach and a conscious decision to improve long-term health outcomes;

> "Yeah it has [changed my attitude to sugary drinks] because after seeing the stuff they showed us about it. It's just like terrible all the caffeine in like Monsters and all the energy drinks and that, so I'm just sticking with water now."

Of the remainder of the students, who did not perceive any changes to their diets, most reported already adhering to healthy balanced diets, containing little junk foods, which not surprisingly appeared to stem from healthy family dietary routines. A similar pattern was observed in the students' attitude toward sugary drinks. While five students reported no changes to their consumption of sugary drinks, three of these indicated that such drinks had not been part of their diet in the first place. The remainder of students described changes to their knowledge and behavior relating to the consumption of sugary drinks, with most having cut down their consumption, and some having either switched to sugar-free soft drinks, or cut out sugary drinks from their diet altogether and as a result increased their water consumption, with one student commenting on the positive effects it has had on his energy levels;

> "I like to drink water and [it has] sort of helped me keep going outside, whereas before I [would] get tired and go inside and sit down but now, because I don't drink as much soft drink and that, I can sort of stay outside for a bit longer"

Physical activity

The discussions around the students' attitude and behaviors relating to physical activity provided strong evidence of the profound impact that the program had exerted, not only on actual behavior, but also on the cognitions accompanying the choices which the students make. The vast majority reported having replaced sedentary behaviors (mainly some form of screen-time) with physically active behaviors such as outside play or intentional fitness activities such as jogging, bike rides, chin-up's, push-up's, etc. In many instances, the students talked about these changes having occurred in personal realms as well as social contexts, such that the increased physical activity had extended to friendship circles and family members as well;

> "I used practically every afternoon be on my Xbox just playing video games and when the ATLAS program started like now I like practically out every afternoon shooting hoops with my brother and all of that, doing sport and kicking a ball and everything."

Not surprisingly, there was strong evidence that increased motivation was one of the key factors behind their behavior changes. This motivation appeared to stem from greater enjoyment in physical activity, a more serious approach to fitness, as well as greater knowledge and skill. Indeed, quite a few students talked about the ATLAS program having equipped them with skills and techniques to improve their sporting performance and stamina;

> ". . . with surfing it's helped, like I got heaps more arm strength now or paddling power, like I'd paddle for like 2 h and I'd be tired. Now I can paddle like the entire day and I'm fine."

Another of the more profound impacts of the ATLAS program were changes to students' routines. While some had made just minor changes to everyday routines, such as running to school bus instead of walking, some had adopted an impressive daily fitness routine;

> "Well, every time I used to walk home and I used to go for a jog but now I do a little bit more extra; like I'd go for a jog and come home and we've got this tree out the back and its kind of like a chin up pole and I'd do chin ups and before I'd go to bed, I do about 50 sit ups."

BARRIERS AND CHALLENGES TO THE DEVELOPMENT, IMPLEMENTATION, AND EVALUATION OF THE ATLAS APP

As described previously, the ATLAS app was developed to support the delivery of a school-based obesity prevention program for adolescent boys. However, due to the timing of school terms and the conditions of funding, we were unable to conduct a usability study of the ATLAS app prior to the RCT. Consequently, the app was launched and was made available to participants before we were able to rectify minor technical glitches. More specifically, in the original version of the app, the tailored motivational messaging function did not send the push prompts to the participants' phones. The function was subsequently fixed by the technical team and participants were encouraged to update their app to access this feature, but this did not occur until 5-weeks into the intervention period.

The diversity of the ATLAS platform and device servicing (i.e., iOS, Android, and web) was designed to provide greater access for users, but came at the cost of higher maintenance and data dispersion issues (**Figure 4**). The web-based application was primarily written in *Hypertext Preprocessor* and hosted in a data center in India. It included a distributed architecture model traditionally used in standard *n*-tier web applications, in that the client layer, business, and data access layer, and data layer all reside in different locations. Platform decisions were solely based on the two most dominant market shares at the time of development. As shown in **Figure 4**, each platform has it merits and drawbacks, but both use local device storage; the iOS version can also be backed up to a secondary location such as iTunes or the Cloud. This created problems for the evaluation of the ATLAS app as we did not have access to user data to determine the utility and usage of the five different functions (i.e., *My steps, My workouts, My technique, My goals*, and *My motivation*).

DISCUSSION

The primary objective was to describe the development and implementation of the ATLAS smartphone app designed to promote physical activity and reduce screen-time in adolescent boys attending schools in low-income communities. Although we were unable to collect objective usage data, the majority of participants reported having access to a smartphone device and utilized the ATLAS app functions to some extent. The focus group findings indicated that the participants benefited from the ATLAS program in general, but did not engage extensively with the smartphone app. Lack of engagement may in part be due to the technical glitches experienced by the research team.

To our knowledge, ATLAS is the first smartphone app designed to supplement an obesity prevention program for adolescent boys. The app included five major features, guided by behavioral theory to promote physical activity and reduce sedentary behavior and the consumption of sugary drinks. A unique aspect of the ATLAS smartphone app was that it included push prompt messages (e.g., to set goals), based on information entered by participants. After completing the program, almost half of the participants agreed or strongly agreed that the push prompt messages reminded them to be more active, reduce their screen-time, and drink less sugary drinks. Interestingly, the messaging was considered a nuisance by many students in the focus groups. However, it is possible that messaging still had its desired effect, as participants' intentions to adhere to the ATLAS behavioral messages were high at the completion of the study. The content of the push prompt messages used in the ATLAS intervention was guided by the Nutrition and

FIGURE 4 | Original ATLAS infrastructure architecture.

Enjoyable Activity for Teen Girls intervention (11, 12, 37). Similarly, the format and style of messages was guided by formative work conducted with adolescents (36), which found that young people desired SMS that were (i) informative providing relevant new information), (ii) simple (limited to small words and phrases), and (iii) sociable (could be shared easily with friends). The optimal messaging format for promoting health behavior in young people is not known and additional formative research may help to create messages that are meaningful and long-lasting.

Due to the structure of the ATLAS architecture, we were not able to determine the degree to which participants engaged with the app or if they continued to use the app after the completion of the study. It is possible that the novelty of the app wore off quickly, as participants may have found more attractive mobile apps to use. In adults, self-monitoring behaviors diminish over the duration of an intervention (38). While there is evidence to suggest that behavioral skills, such as goal setting and self-monitoring are important for adolescents' physical activity levels (13, 39–41), evidence for their sustained impact is limited. It is plausible to suggest that adolescents also find it challenging to adhere to physical activity self-monitoring protocols. Few studies have explored the ways that young people use apps to monitor their health behaviors and a number of questions have emerged from our findings. What are the apps most commonly used by adolescents? What are the features of these apps? How many apps do young people have on their phones? Do push prompts encourage young people to engage with specific apps? What other strategies can be used to enhance goal setting and self-monitoring in adolescents? Young people have notoriously short attention spans (42, 43) and can be a challenging group to keep engaged. "Gamification" or "social media linkage" might provide some entertainment value and encourage prolonged use of the app in future versions. These questions could be explored in future research including analyses examining app usage and its association with behavior change along with qualitative research to explore adolescent perceptions and beliefs around these issues.

In the current study, participants were provided with pedometers to self-monitor their physical activity. A recent systematic review concluded that pedometers could be used to increase physical activity in young people and highlighted the importance of individually tailored goals (44). Although these strategies were employed in the ATLAS intervention, only 30% of participants wore their pedometers regularly. In a previous study, Scott and colleagues (45) found that many young people did not enjoy wearing objective monitoring devices such as pedometers and accelerometers and it is possible that participants in the current study were reluctant to wear the devices for self-monitoring purposes. While not feasible in the current study, apps that take advantage of a phone's inbuilt accelerometer (e.g., "Moves") may have more utility for promoting self-monitoring in young people. These apps do not require the user to wear an additional activity monitor or regularly enter values, but the user must carry their phone, which can also be considered a limitation. Furthermore, evidence for the validity and reliability of smartphone apps to measure physical activity is only starting to emerge in the literature and acceleration values from phones may not always provide a reliable estimate of a person's physical activity.

Over two-thirds of participants in the intervention group reported access to a smartphone or tablet. Although access is not equivalent to ownership, there is a growing trend in the ownership of smartphone devices in youth populations (15). To cater for participants who did not have access to a smartphone, a website was developed. While the initial multi-versions of ATLAS were suitable for testing and evaluation in the intervention, the challenges of maintaining all three versions for use in future studies and for dissemination to schools was not considered to be feasible. Therefore, at the completion of the study it was decided that the ATLAS app would evolve into a single web services-based architecture. The research team is currently working on a revised ATLAS app including native mobile applications written for both iOS and Android devices. This model will allow the ATLAS app to be serviced on multiple mobile devices and computing platforms due to it becoming effectively a web-based mobile application. Through the use of custom-developed web services, coupled with a centralized data source (**Figure 5**) we will have significantly more control and access to the application data for research and analysis purposes. With the new architecture, users of all types of smartphones, including Apple, Android, Windows, and Blackberry will be able to consume the service.

Active Teen Leaders Avoiding Screen-time is the first obesity prevention program targeting adolescent boys to be supplemented with a purpose built smartphone app. Despite these strengths, there are some limitations to the current study. First, it was not possible to determine the unique contribution of the app to behavior change, as it was one component of a multi-component school-based intervention. Second, due to the original software

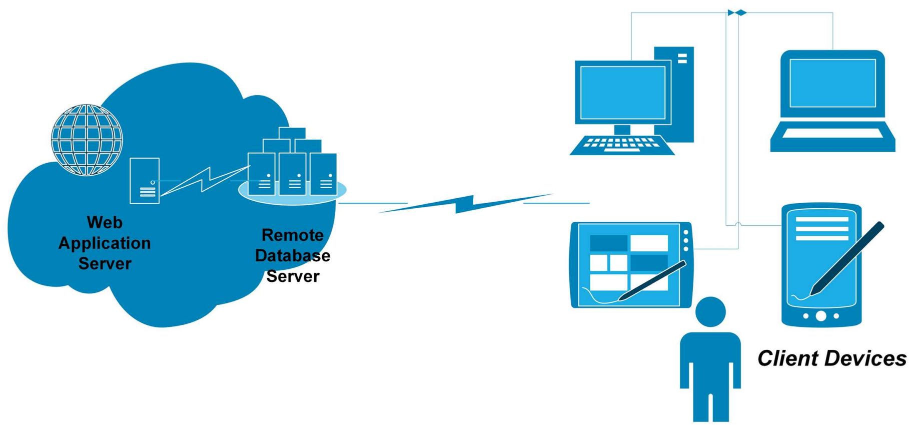

FIGURE 5 | Proposed ATLAS data storage arrangements.

architecture we were not able to access participants' usage data. Alternatively, participants self-reported their use of the app features, which introduces self-report bias. Third, our study was conducted in a sample of adolescent boys attending schools in low-income communities and therefore our findings cannot be generalized to other populations. Finally, the timing of the school-based intervention prevented us from conducting a usability study before implementation and minor technical problems were experienced.

CONCLUSION

In this study, we have described the development and implementation of a smartphone app designed to supplement a school-based obesity prevention program for adolescent boys. The majority of participants reported having access to a smartphone or tablet and many engaged with the ATLAS app features. Participants reported moderate satisfaction with the app, but were more positive of the intervention in general. Findings from our focus groups suggest that additional training on how to use the app may be necessary to improve usage in future studies. In addition, the technical glitches experienced by the research team highlight the importance of allowing sufficient time to conduct a usability study before conducting a full-scale RCT.

Although eHealth interventions hold promise for behavior change in youth, it is unlikely that they will provide the "silver bullet" to the global physical activity pandemic. Physical activity is a complex behavior that can take place in a wide variety of settings and is influenced by various psychological, social, and environmental factors. Future studies are encouraged to explore the utility of technology-based intervention strategies, such as smartphone apps, to determine if they are appropriate stand-alone strategies or adjuncts to face-to-face behavior change interventions.

AUTHOR CONTRIBUTIONS

David R. Lubans and Philip J. Morgan obtained funding for the research. All authors contributed to developing the protocols and reviewing, editing, and approving the final version of the paper. David R. Lubans, Philip J. Morgan, and Jordan J. Smith developed the intervention materials. All authors have read and approved the final manuscript.

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The HEART mobile phone trial: the partial mediating effects of self-efficacy on physical activity among cardiac patients

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Background: The ubiquitous use of mobile phones provides an ideal opportunity to deliver interventions to increase physical activity levels. Understanding potential mediators of such interventions is needed to increase their effectiveness. A recent randomized controlled trial of a mobile phone and Internet (mHealth) intervention was conducted in New Zealand to determine the effectiveness on exercise capacity and physical activity levels in addition to current cardiac rehabilitation (CR) services for people ($n = 171$) with ischemic heart disease. Significant intervention effect was observed for self-reported leisure-time physical activity and walking, but not peak oxygen uptake at 24 weeks. There was also significant improvement in self-efficacy.

Objective: To evaluate the mediating effect of self-efficacy on physical activity levels in an mHealth delivered exercise CR program.

Methods: Treatment evaluations were performed on the principle of intention to treat. Adjusted regression analyses were conducted to evaluate the main treatment effect on leisure-time physical activity and walking at 24 weeks, with and without change in self-efficacy as the mediator of interest.

Results: Change in self-efficacy at 24 weeks significantly mediated the treatment effect on leisure-time physical activity by 13%, but only partially mediated the effect on walking by 4% at 24 weeks.

Conclusion: An mHealth intervention involving text messaging and Internet support had a positive treatment effect on leisure-time physical activity and walking at 24 weeks, and this effect was likely mediated through changes in self-efficacy. Future trials should examine other potential mediators related to this type of intervention.

Keywords: mobile phones, exercise, behavior, self-efficacy

INTRODUCTION

The ubiquitous use of mobile phones offers important new opportunities to bring self-management support directly to people with long-term conditions such as cardiovascular disease (CVD) (1). Mobile health (mHealth) programs offer several advantages for supporting patient self-management, compared with traditional office-based approaches: (1) they can be delivered anywhere at any time and for extended periods, facilitating regular communication and behavioral maintenance; (2) they can be designed to send messages in a time-sensitive manner that fits with the individual's lifestyle; (3) they are proactive and do not require prompting by the user before support is offered; (4) they can be personalized and tailored to suit specific demographic and health needs; (5) they increase access (e.g., less travel); (6) they allow cheaper provision of services than face-to-face contacts; and (7) they provide a way of reducing inequalities due to their widespread adoption by all cultural and socioeconomic groups.

Research on the use of mHealth for delivering healthcare and improving disease self-management (2) has increased in recent years (3). This research has targeted a wide range of health conditions (4) and a number of systematic reviews support the delivery of mobile phone text messaging interventions (3–5) for achieving behavior change. However, a recent (2014) meta-review highlighted that the quality of future studies needs to be improved and interventions should employ behavior change theory (4).

A recent randomized controlled trial of a mobile phone text messaging and Internet intervention (HEART) showed a statistically significant treatment effect on self-reported leisure-time physical activity and walking (secondary outcomes) but not on peak oxygen uptake (PVO_2; primary outcome), which favored the intervention group at 24 weeks (6). In response to the lack of theoretical basis of many mHealth interventions to-date (4) the HEART intervention content development was

Abbreviations: PVO_2, peak oxygen uptake.

grounded in self-efficacy theory (7–10), which is a key psychosocial determinant of exercise and physical activity behavior (11–13).

Self-efficacy refers to an individual's beliefs in his/her capabilities to execute necessary courses of action to satisfy situational demands (9). Self-efficacy is theorized to influence the activities that individuals choose to approach, the effort expended on such activities, and the degree of persistence demonstrated in the face of adverse stimuli (9, 14). Within the cardiac setting, self-efficacy has been the most examined psychological variable and has consistently been shown to be related to exercise behavior (15), exercise intentions (12, 16), and treadmill test performance (13, 17). Furthermore, self-efficacy based interventions have been shown to have a positive effect on exercise behavior (18, 19), adherence to exercise regimens (19–21), and effort expended during bouts of exercise testing (13). There is however, a lack of empirical evidence on the impact of mHealth interventions on efficacious beliefs and the potential mediating effect of self-efficacy on exercise behavior. Understanding potential mediators of mHealth interventions is needed to increase their effectiveness (22). In this paper, the mediating effects of self-efficacy on secondary outcomes of the HEART trial were examined. Mediators identify possible mechanisms through which a treatment might achieve its effects, and represent the causal links between treatment and outcome (23).

MATERIALS AND METHODS

A two-arm, parallel, randomized controlled trial was conducted in Auckland, New Zealand between 2010 and 2012. One hundred seventy-one adult participants, with a diagnosis of ischemic heart disease (IHD) were randomly assigned to either receive the HEART mHealth intervention in addition to usual cardiac services ($n = 85$), or to usual cardiac services alone (control group; $n = 86$).

Full details of recruitment, participant flow through the study, and measures have been published elsewhere (24). In brief, participants were recruited from two metropolitan hospitals, and were identified by cardiac nurses as inpatients, through outpatient clinics and existing databases. After screening for eligibility, nurses referred interested participants to the research team to schedule baseline data collection procedures.

Eligible participants were adults aged >18 years, with a diagnosis of IHD (defined as angina, myocardial infarction, revascularization, including angioplasty, stent, or coronary artery bypass graft) within the previous 3–24 months. All participants were clinically stable as outpatients, able to perform exercise, able to understand and write English, and had access to the Internet (e.g., at home, work, library, or through friends or relatives). All participants owned a mobile phone. Participants were excluded if they had been admitted to hospital with heart disease within the previous 6 weeks; had terminal cancer, or had significant exercise limitations other than IHD.

All participants were free to participate in any other cardiac services or support that they wished to use. In addition, participants in the intervention group received a personalized, automated package of text messages via their mobile phones aimed at increasing exercise behavior over 24 weeks. The primary goal of the intervention was to have all individuals participate in moderate to vigorous aerobic-based exercise for a minimum of 30 min (preferably more) most days (at least 5) of the week (25). Intervention content was grounded in self-efficacy and consisted of (1) regular exercise prescription, (2) provision of behavior change strategies, and (3) technical support. Additional information was provided via a secure website that participants could log on to, and included role model video vignettes, an opportunity to self-monitor progress, as well as information on various forms of physical activity and exercise, energy expenditure, healthy eating advice, and links to other websites (e.g., local exercise programs and cardiac clubs). Full details of the intervention are described in the protocol (24).

MEASURES

All outcomes were measured at baseline and 24 weeks. The primary outcome (PVO_2) was determined using respiratory gas analysis during a standardized treadmill exercise testing protocol (26). Self-reported physical activity levels were assessed using the international physical activity questionnaire long form (IPAQ-LF) (27). Self-efficacy (task) was assessed using a valid measure on a scale of 0 "no confidence to 100% complete confidence" (28). An example item is, "how confident are you that you can complete 30 min of physical activity at a moderate effort on most days of next week?" Scores were summed with greater values indicating greater efficacy to exercise for longer periods of time and at a greater level of intensity. For barrier efficacy, participants rated their confidence to overcome seven common reasons (e.g., bad weather, lack of time, pain, or discomfort) preventing people from participating in exercise sessions (12). Efficacy strength was calculated by summing the scores and dividing by total number of items.

In accordance with the recommendations of Kraemer et al. (23) for testing mediators of treatment effects in randomized clinical trials, hierarchical regression analyses were conducted on the observed participants' data with post intervention physical activity (leisure-time and walking) at 24 weeks as the criterion measures. According to Kraemer et al., a mediator measures an event or change occurring during treatment, and must correlate with the treatment choice, hence possibly be a result of treatment, and have either a main or interactive effect on the outcome. Their analytic approach differs conceptually from that of Baron and Kenny (29) in several important ways. According to Kraemer et al. with mediation, demonstration of precedence is required, thus a mediator occurs during treatment. Similarly, demonstration of correlation is required. In the absence of such criteria, they argue that the interpretation of whether a relationship is mediating or moderating is often arbitrary. The analytic model, in contrast to the several linear model proposed by Baron and Kenny, is exactly the same for moderators and mediators. The difference lies in how M (Mediator or Moderator) is defined in terms of time relation to treatment onset and correlation with treatment choice (23).

RESULTS

All statistical analyses were performed using SAS version 9.3 (SAS Institute Inc., Cary, NC, USA). Statistical tests were two-sided at 5% significance level. Treatment evaluations were performed on the principle of intention to treat (ITT), using observed data collected from all randomized participants. Analysis of covariance (ANCOVA) regression model was used to evaluate the main treatment effect on the outcome measured at 24 weeks, adjusting for the baseline outcome, age, sex, ethnicity (Māori vs. non-Māori), and exercise history. Change in self-efficacy at 24 weeks was added

Table 1 | Treatment effects[a] with and without self-efficacy as the mediator.

Outcome at 24 weeks	Intervention	Control	Difference in groups	Lower 95% CI	Upper 95% CI	*P*-value
LEISURE-TIME PA						
Main model	1394	968	426	16	836	0.042
Model with mediator[b]	1363	994	369	−37	775	0.075
WALKING						
Main model	1690	1191	500	91	908	0.017
Model with mediator[b]	1681	1199	481	68	894	0.023

[a] *Linear regression model adjusting for: baseline outcome, age, sex, Māori, and exercise history.*

[b] *Mediator: change in self-efficacy at 24 weeks.*

as the mediator of interest to the main model for evaluation of its mediation effect.

Significant main treatment effects were observed in favor of the intervention for leisure-time physical activity [group difference: 426 MET-min/week, 95% confidence interval (CI) (16, 836), $P = 0.04$] and walking [group difference: 500 MET-min/week, 95% CI (91, 908), $P = 0.01$] at 24 weeks (see **Table 1**).

Change in task self-efficacy significantly mediated the treatment effect on leisure-time physical activity ($P = 0.021$) by 13% [group difference: 369 MET-min/week, 95% CI (−37, 775), $P = 0.07$], but not on walking ($P = 0.51$) with only 4% relative reduction in treatment effect [group difference: 481 MET-min/week, 95% CI (68, 894), $P = 0.02$]. Barrier efficacy did not meet the conditions for mediation and was not included in the analysis (see **Table 1**).

DISCUSSION

The main findings from this study can be summarized as follows. A theory-based mHealth intervention involving text messaging and Internet support had a positive effect on physical activity levels. The effect was most likely mediated through increased self-efficacy to undertake more physical activity at increasing intensity. Self-efficacy can be targeted in mHealth interventions and has potential to increase physical activity behavior.

In the present study, the HEART intervention had a positive effect on task efficacy but not for barrier efficacy. Task efficacy referred to participants' confidence to exercise for greater intensity and increasing duration. Intervention content (messages and Internet) targeted all sources of self-efficacy, including mastery experiences, social modeling, social persuasion, and physiological responses, which may have had a stronger impact on participants' confidence to perform exercise, but not for overcoming barriers to exercise. The lack of effect on barrier efficacy was surprising given that the text messages and role models vignettes did address this construct. While items were drawn from a previous study of New Zealand patients with CVD; (12) it is possible that the barriers (e.g., weather, discomfort/pain, work commitments) assessed in this study were not salient for this population. Future studies might need to consider identifying more relevant barriers (30).

Notwithstanding the issues above, this study does provide some support for the intervention successfully manipulating key constructs of Social Cognitive Theory. This is important as it is unclear whether existing behavior change theories are relevant for mobile delivered interventions (31). While mHealth behavior intervention development could benefit from greater application of health behavior theories, Riley et al. (31) argued that current theories appear inadequate to inform such mHealth intervention development as these interventions become more interactive and adaptive. They suggested that consideration be given to the development of more dynamic feedback system theories of health behavior, utilizing longitudinal data from mobile devices and control systems engineering models.

This study has several strengths and limitations that should be considered when interpreting the findings. Data were obtained from an adequately powered RCT, which used computer randomization to ensure allocation concealment, and an objective measure for the primary outcome, with blinded assessors. The HEART intervention was also developed using established theory. The main limitation was the use of a self-reported measure of physical activity behavior, which is associated with recall bias. Objective assessment of physical activity (e.g., accelerometry) was not feasible in this study due to logistic reasons; but should be used in subsequent research.

Opportunities for future research exist. First, the use of alternative theoretical frameworks or embedding key behavior change strategies common to many behavior change theories may enhance the impact of future mHealth interventions (31). Second, other potential mediators (including attitudes to or preferences for physical activity) and moderators (age, sex, ethnicity) of mHealth interventions should be considered. Third and finally, while the HEART intervention utilized text messaging and a website, it was predominantly unidirectional and did not include many interactive features. Future interventions should harness many of the existing native smart phone features including application to enhance participant interaction and encourage behavior change. These could include self-monitoring features such as recording activities and visual representation of progress, passive collection of physical activity data, social media features, as well as opportunity to interact with health practitioners.

CONCLUSION

An mHealth intervention had a positive effect on physical activity levels, which was most likely mediated through increases in self-efficacy. Future trials should examine other potential mediators related to this type of intervention, including attitudes to, or preferences for physical activity.

AUTHOR CONTRIBUTIONS

Ralph Maddison provided study oversight. Leila Pfaeffli, Karen Carter, and Jonathan Rawstorn conducted the research and undertook data collection. Yannan Jiang performed the statistical analyses. Ralph Maddison, Robyn Whittaker, Ralph Stewart, and Andrew Kerr designed the research (project conception and development of overall research plan). Ralph Maddison wrote the paper. All authors assisted in interpretation of the analyses and revision of the paper. All authors read and approved the final manuscript. Ralph Maddison takes primary responsibility for final content. Ralph Maddison has had full access to all of the data in the study and takes responsibility for the integrity of the data and the accuracy of the data analysis.

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Active gaming as a mechanism to promote physical activity and fundamental movement skill in children

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Insufficient physical activity is a global health issue (1). Australian physical activity guidelines recommend children engage in 60 min or more of moderate- to vigorous-intensity physical activity every day (2). In 2011–2012, only 19% of Australian children met these recommendations (3). Fundamental movement skills (FMS; e.g., run, jump, catch, kick, hop) are the building blocks of physical activity and underpin successful participation in sports games. FMS are not, however, naturally acquired (4). Less than 50% of Australian school aged children demonstrate competence of key FMS (5, 6) and trends across the last decade are no better (7).

Low levels of physical activity and FMS are coupled with ubiquitous electronic media use in the Australian home. Nearly all households with children (98%) have access to computer games (8). By 2014, it is predicted 87% of 6–10 year olds and 96% of 11–15 year olds will be playing computer games, with sessions typically occurring every 2 days and ranging in duration from half an hour (6–10 year old girls) to over 2 h (in 11–15 year old boys) (8). Incentives for game play include playing for the fun, challenge, and stimulation, with exercise benefits rated last (8). Since the chances of removing screen based behavior from children's twenty-first century lives is virtually nil, developments that integrate computer gaming with opportunities for physical activity and FMS may elicit beneficial changes in these outcomes and overall health.

A strategy for introducing physical activity into gaming has been through the development of active video games (AVG). Technologies such as the Microsoft Kinect and Nintendo Wii deploy sophisticated controllers which sense whole body motion through depth cameras, accelerometers, and pressure sensors. However, these are constrained to a finite but controlled indoor environment which may limit opportunities for physical activity and FMS practice. For example, whilst review evidence suggests AVG play can result in light-to-moderate intensity physical activity (9, 10), it is likely the modest physical activity provision is inadequate for helping children meet national recommendations (11, 12). There is some evidence that AVG play is associated with higher movement skill proficiency in young children (13), and while children believe they are developing skill (14), few demonstrable skill components have been observed (15).

An interesting development in AVG play are mobile active games that allow game play to become pervasive (through continuous tracking via a personal mobile device) (16), accumulative (encouraging multiple informal physical activities on an ongoing basis) (17), and persistent (through logging and scoring over an extended duration) (18), whilst removing game constraints that limit games to a fixed location. Smartphones are particularly universal devices that can be used to support and facilitate mobile active games, especially as they are well integrated into an individual's daily activities, have sufficient processing capability to present a personalized experience to the user (19), and can utilize a range of in-built sensors (e.g., WiFi, GPS) and features (e.g., audio, camera).

An example of AVG play using smartphones is through overlaying synthetic visual content above images of the real world (augmented reality; AR). Existing AR mobile applications fall into two categories. In the first, specially designed reference images are provided as posters or cards in the physical world. Digital content is generated relative to these reference points with the combined result shown on the mobile device's screen. Live processing of the video stream from the camera allows control of the overlaid digital images. For example, the mobile game "Rolling Dead" overlays virtual zombies over a view of a player controlled robotic ball viewed through the camera and screen of the mobile phone (accessed 7/11/2013)[1]. Several AR games use sport inspired themes, such as AR Soccer (accessed on 7/11/2013)[2].

The second approach employs location-based gaming, which exploits position tracking of the player through GPS and other location measures. Location sensitive games provide a novel yet underutilized opportunity to promote physical activity and FMS in children whilst achieving game outcomes. For example, children can engage in active yet unrelated movements to earn game play time (20) and to correctly perform exercises (21, 22). Indeed, general physical activity during play can be encouraged and rewarded (23). The game elements introduced through AVG provide persuasive motivation to continue the activity long enough to gain benefit from the physical activity (16, 19, 24, 25), provide purposeful action in support of narrative and game mechanics (26),

[1] http://www.gosphero.com/tag/rolling-dead/
[2] https://itunes.apple.com/us/app/arsoccer-augmented-reality/id381035151?mt=8

and encourage thinking and problem solving skills at the same time as physical activity (27).

Whilst there are benefits to such techniques, limitations do exist. For example, many active mobile games distinguish activities using only thresholds on acceleration variance and device orientation (18, 21), or classifiers such as artificial neural networks or hidden Markov models (17). Misclassification or failing to register valid actions is significantly demotivational (19), particularly if the player is erroneously reprimanded. The designers of mobile games must consider these issues if they are to use different sensor perceptions to encourage engagement in physically active behaviors in the physical environment.

To date, few studies have examined the use of location-based games in the promotion of physical activity. Suggestions for design elements to motivate physical activity in games include music integration, facilitation of short and long term fitness goals, and the ability to form groups, though these have not been validated (27). One study in children explicitly attempted to build in FMS practice opportunities using AR concepts such as embedding an accelerometer into a ball with direct feedback on the throw provided to children by colored LED's (28), however, this study did not use location-based techniques. No studies have examined the impact of such games on children's FMS development, despite the potential of these games in real world settings.

In summary, using AVG technology away from the constraints of the home environment may provide an opportunity for children to engage in physically active behaviors and practice and develop their FMS. Collaborations that use the skills of games designers and public health researchers could help to design mobile active games. Whilst research is needed to examine the efficacy of such techniques in real world settings, mobile active games may change our perspective of the potential of technology for enabling children's physical activity and FMS.

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Do personally tailored videos in a web-based physical activity intervention lead to higher attention and recall? – an eye-tracking study

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Over half of the Australian population does not meet physical activity guidelines and has an increased risk of chronic disease. Web-based physical activity interventions have the potential to reach large numbers of the population at low-cost, however issues have been identified with usage and participant retention. Personalized (computer-tailored) physical activity advice delivered through video has the potential to address low engagement, however it is unclear whether it is more effective in engaging participants when compared to text-delivered personalized advice. This study compared the attention and recall outcomes of tailored physical activity advice in video- vs. text-format. Participants ($n = 41$) were randomly assigned to receive either video- or text-tailored feedback with identical content. Outcome measures included attention to the feedback, measured through advanced eye-tracking technology (TobiiX 120), and recall of the advice, measured through a post intervention interview. Between group ANOVA's, Mann–Whitney *U* tests and chi square analyses were applied. Participants in the video-group displayed greater attention to the physical activity feedback in terms of gaze-duration on the feedback (7.7 vs. 3.6 min, $p < 001$), total fixation-duration on the feedback (6.0 vs. 3.3 min, $p < 001$), and focusing on feedback (6.8 vs. 3.5 min, $p < 001$). Despite both groups having the same ability to navigate through the feedback, the video-group completed a significantly ($p < 0.001$) higher percentage of feedback sections (95%) compared to the text-group (66%). The main messages were recalled in both groups, but many details were forgotten. No significant between group differences were found for message recall. These results suggest that video-tailored feedback leads to greater attention compared to text-tailored feedback. More research is needed to determine how message recall can be improved, and whether video-tailored advice can lead to greater health behavior change.

Keywords: physical activity, health promotion, web-based, eye-tracking, tailoring

INTRODUCTION

Physical activity improves physical and mental health, and significantly lowers the risk of non-communicable disease including cardiovascular disease, diabetes mellitus, and cancer (1). It is estimated that individuals who are physically active have a 30–50% lower risk of non-communicable diseases and a 20–50% lower risk of mortality than inactive individuals (2–4). The World Health Organisation recommends 30 min of moderate intensity activity on 5 days of the week to receive health benefits and reduce the risk of non-communicable disease (5). Despite this, more than 50% of Australians fail to meet these recommendations (6), which is estimated to cost the Australian economy 13.8 billion each year in healthcare, loss of productivity, and mortality costs (7). Hence, there is an urgent need for effective physical activity interventions with a broad reach.

Innovative web-based physical activity interventions have been developed to take advantage of the high percentage of Australians (79%) with access to the Internet in their homes (8). Not only do health interventions delivered via the Internet have the potential to reach a large audience at low-cost, they are convenient for the participants and enable the content to be delivered in a non-confrontational way (9–11). Although the short-term effectiveness of web-based physical activity interventions is well established, participant retention and engagement have been identified as a challenge with many web-based interventions reporting high dropout rates or low use of the websites (12, 13). As exposure to the intervention content is strongly linked to behavioral outcomes, low participant retention and engagement may be limiting the effectiveness of the web-based interventions (14, 15).

Web-based health interventions that provide personalized advice improve engagement and behavioral outcomes compared to interventions that provide generic advice (16, 17). Computer-tailored advice is the personalized feedback that is automatically produced using a computer-based expert system that delivers feedback based on participant's responses to a questionnaire (17). Computer-tailored feedback is commonly delivered in text-based format on intervention websites, despite users tending to skim and scan text on the Internet rather than engage in concentrated reading (18). The use of rich media content, including graphics and videos, has become very common on the Internet, and users have become accustomed to this (19). Furthermore information presented in video-format has been found to result in improved recall of website content (20, 21), improved engagement, and to facilitate a stronger emotional response than text in educational settings (22, 23). Information presented through videos in web-based health interventions may therefore be an effective way of engaging users and be more effective in producing behavior changes.

To date, only a small number of web-based health interventions have used videos to deliver program content, and only one provided video with personalized content to participants (24, 25). Vandelanotte and colleagues (24) developed and conducted the pilot testing of a physical activity intervention with two modules of either text- or video-tailored feedback. Video-group participants received their activity feedback in video-format with a presenter and animated graphical images, whilst text-group participants received their feedback in text-format, which included static graphics. Results demonstrated that inactive participants who received computer-tailored physical activity feedback in video-format had greater improvements in physical activity levels than participants receiving traditional computer-tailored feedback in text-based format with identical content; however a more conservative intention-to-treat analysis found no significant differences between the two groups (26). A study conducted by Lee (27) found that participants in a web-based health intervention, which delivered content through videos had greater levels of self-reported attention, interactivity, overall website evaluation and preference than participants assigned to a static intervention site. These results suggest that videos may be more effective at engaging participants in web-based tailored health information, and have the potential to improve the behavioral outcomes of text-tailored feedback. Further research is required to understand how participants process video- and text-delivered information and to determine whether video-tailored physical activity feedback leads to greater observed engagement, understanding, and recall than traditional text-tailored physical activity feedback.

Eye-tracking technology can be used to objectively measure participant's attention and engagement in web-based health interventions. Eye-tracking technology has been used in marketing and educational research to record users eye-gazes on web-delivered information (28, 29). The eye-tracking data provide a physiological measure that is directly linked to the cognitive processing (30), and has been beneficial in understanding how people attend to and process information on a web-page (28). Past health studies have used eye-tracking data to determine what types of health promotion advertisements attract attention. These studies also found that eye-gaze predicted correct recall of the advertisements, demonstrating the importance of attention for learning (30, 31). To our knowledge no web-based physical activity interventions have used eye-tracking technology to understand the way users interact with and attend to personal activity information. Eye-tracking technology can therefore improve our understanding of how user's process health advice delivered through text and video on the Internet. Such findings will enable health promotion workers and researchers to make adjustments to the delivery of information on web-based behavior change interventions and improve participant's engagement in the intervention content.

The aim of this study was to examine, with the use of an eye-tracking device and a recall questionnaire, the differences between video-tailored and text-tailored physical activity feedback in terms of participant attention to and recall of the intervention content. It was hypothesized that participants receiving video-tailored feedback would spend more time paying attention to the feedback, be less distracted and have improved recall of their personal physical activity feedback in comparison to those receiving text-tailored feedback.

MATERIALS AND METHODS

PROCEDURE

A two group randomized trial was conducted to compare participant's processing of text- and video-tailored physical activity feedback. Participants were recruited via e-mail from staff and students of Central Queensland University Noosa campus. To be eligible participants had to be English speaking, be over 18 years of age and be familiar in using the Internet for general purposes. Data were collected from each participant in one 20–25-min session from March to June 2012. To begin the session, participants were seated at a computer in a quiet research room where they were uninterrupted. Participant's eyes were calibrated with an eye-tracking device connected to the computer. Participants were then invited to complete a demographic questionnaire on the computer. Next participants were provided with access to the "My Physical Activity Advice" website where they completed two modules of tailored feedback in either video- or text-format. The intervention website automatically assigned participants at random to receive either text- or video-tailored physical activity feedback as they signed into the website. The researcher supervising the session was unaware of the randomization sequence. While participants were completing the intervention, the eye-tracking device video recorded and produced data of their eye movements. After completing the intervention the researcher asked participants nine brief questions to test their recall of the intervention content. Ethical clearance was obtained from the Central Queensland University Human Ethics Committee (project number H13/04-044).

INTERVENTION

The two module web-based physical activity intervention with video- and text-tailored advice was previously developed by Vandelanotte and colleagues (24). The intervention has been found to be effective at increasing participant's physical activity levels (26). The content and structure of the text-based and video-based feedback was identical, only the method of delivery was different. The computer-tailored content was tailored to participant's physical activity levels, as assessed by the "Active Australia Questionnaire

(AAQ)" (32), participant demographics (age, body mass index (BMI), work environment, and the distance to often-visited places) and psychosocial correlates of physical activity that were based on the theory of planned behavior (attitudes, subjective norm, perceived behavioral control, and intention) (33). The intervention provided normative feedback by comparing participant's physical activity to the minimum and optimal physical activity guidelines in a bar graph. Participant's perceived benefits and barriers to becoming more active were also discussed. The intervention consisted of two modules. Participants can receive up to 7 sections of feedback in the first module, which focuses on the benefits of physical activity, and up to 10 sections of feedback in the second module, which focuses on creating an active lifestyle. A more detailed description of the intervention can be found elsewhere (26).

MEASURES

Demographics

The pre-test demographic survey collected information on: gender, age, height and weight (to calculate BMI), highest level of education, current employment status, household income level, and motivation to increase physical activity through the question "do you want to increase your physical activity?" with two response options, yes and no.

Attention

Participant's visual attention to the personalized video- and text-tailored feedback was measured with a TobiiX 120 eye-tracking device. The TobiiX 120 tracks eye movements at a resolution of 1,280 pixels and at a controller refresh rate of 60–75 Hz. It allows 15° of head movement 60 cm from the screen (Tobii Technology AB, 2008). Eye-gazes on the screen including fixation, when participant's eye-gaze focuses on one point, and saccades, when participant's eye-gaze moves from one fixation to fixate on another point, were recorded at 15 ms. The eye-tracking software, Tobii studio can be set to record fixations and saccades in a selected area of interest. The area on the computer screen in which the feedback was displayed (the video or text) was chosen as an area of interest. Tobii studio software calculated data on gaze-duration (the total time of both fixations and saccades), and fixation-duration (the total time of all fixations) for the area of interest as well as the total computer screen (Tobii Technology AB, 2008). Gaze-duration in areas on the screen outside the area of interest was calculated as a measure of distraction. The video recording of participant's eye movements was used to measure the focusing-duration, by measuring the duration of actually reading by text-group participants or watching key parts of the video (e.g., presenter, graph) by video-group participants. Due to the potential measurement error when recording focusing-duration, a second researcher re-timed the focusing-duration of 10 (24%) randomly selected participants to test the inter-researcher reliability. The video was also used to record the number of feedback sections participants skip before they have finished reading or watching the advice in full. Gaze-duration outside the feedback area of interest was recorded as a measure of distraction. The proportion of gaze-duration in the feedback area compared to gaze-duration in the entire screen and the proportion of fixations compared to gaze-duration in the feedback area were also calculated as measures of distraction.

Recall

The post intervention recall interview was conducted immediately after each participant received their physical activity feedback. The interview consisted of nine open-ended questions. The questions assessed participant's understanding of the goal of the feedback they received, their memory of the feedback they received (including the recommendations for physical activity, their own physical activity levels, and the benefits of physical activity) and their understanding of the graph comparing their physical activity levels to the recommendations. The interview duration was approximately 5 min. Participant responses were recorded using an audio digital recorder (Livescribe Pen), and transcribed in Microsoft Word. Each question was coded as correct or incorrect. A total recall score was also calculated for each participant by summing the total number of correct recall responses the participant gave on all questions. Possible scores ranged from 0 to 9.

ANALYSIS

Data screening

All analyses were conducted using SPSS version 19. Significance level was set at $p < 0.05$. Descriptive statistics were calculated for participant demographic information. A chi square analysis was conducted to compare group baseline participant characteristics. All continuous variables were screened for outliers and normality using Fisher's skewness coefficient. The proportion of time participants spent viewing the feedback compared to the entire screen, and the number of feedback sections skipped were found to have a significantly skewed distribution. Square root, logarithm, and inverse transformations were unsuccessful to transform these variables. Therefore Mann–Whitney U tests were used to analyze the data from these variables.

Attention

A series of four one-way between groups Analyses of Variance (ANOVA's) were conducted to compare video- and text-participants on attention, which included gaze-duration, fixation-duration, and focusing-duration in the feedback area, and number of sections skipped. Bonferroni correction was applied to control for the risk of a false positive arising from the four comparisons of attention and group. A p value score of $p < 0.01$ was therefore required for any of the attention and group analyses to be deemed significant. Three Analyses of Variance were also conducted to compare video- and text-participants on distraction (gaze-duration in the areas outside the feedback), the proportion of gaze-duration spent in the feedback area compared to other areas on the screen, and the proportion of fixation-duration compared to gaze-duration. Bonferroni correction was applied to control for the risk of a false positive arising from the three comparisons of distraction and group. A p value score of $p < 0.017$ was therefore required for any of the distraction and group analyses to be deemed significant. The number of feedback sections participants read or watched was entered as a covariate in all attention analyses.

Recall

A chi square analysis was conducted to determine whether there was a between group (video and text) difference in the mean number of correct responses to each question. An Analysis of Variance was conducted to compare the total recall scores in video- and text-participants. Next, the total recall score was dichotomized using a median split in order to examine the relationship between group, recall, and attention. An Analysis of Variance was conducted to compare gaze-duration in the feedback area and recall (high total recall score vs. low total recall score) with the covariates group (video vs. text), and number of feedback sections.

RESULTS

The demographic details of the participants are documented in **Table 1** below. Data were collected from 41 participants. Participants were randomly assigned to the video- ($n = 21$) or text-group ($n = 20$). There were no baseline differences between the two intervention groups for participant characteristics.

Table 1 | Participant demographics for total group and for video- and text-groups.

		Total *n* (%) ($n = 41$)	Video *n* (%) ($n = 21$)	Text *n* (%) ($n = 20$)
Gender	Males	14 (34)	7 (33)	7 (35)
	Females	27 (66)	14 (67)	13 (65)
Age	18–30	12 (29)	8 (38)	4 (20)
	31–50	15 (37)	5 (24)	10 (50)
	>50	14 (33)	8 (38)	6 (30)
BMI	Normal (<25)	23 (57)	11 (55)	12 (60)
	Overweight (≥25)	17 (43)	9 (45)	8 (40)
Motivation	Motivated	31 (76)	16 (76)	15 (75)
	Not motivated	10 (24)	5 (24)	5 (25)
Education	Secondary school	9 (22)	5 (24)	4 (20)
	TAFE	7 (17)	3 (14)	4 (20)
	University	25 (61)	13 (62)	12 (60)
Employment	Full time	13 (32)	7 (33)	6 (30)
	Part time	17 (42)	8 (38)	9 (45)
	Unemployed	3 (7)	1 (5)	2 (10)
	Student	8 (20)	5 (24)	3 (15)
Income	<30,000	16 (39)	9 (43)	7 (35)
	30,001–70,000	11 (26)	5 (24)	6 (30)
	>70,001	14 (35)	7 (33)	7 (35)

ATTENTION

As shown in **Figure 1** and **Table 2**, Gaze-duration within the feedback area was significantly higher in the video-group than the text-group, $F(1, 36) = 30.39$, $p < 001$. Furthermore, video-group participants had a significantly greater fixation-duration and focusing-duration, $F(1, 36) = 13.09$, $p < 001$; $F(1, 36) = 20.85$, $p < 001$ respectively. The inter-researcher reliability of the focusing-duration variable was very high, as indicated by a Krippendorff's alpha of 0.99. Researcher 1 timed the 10 participants who were measured by both researchers to have a mean of 4.8 (SD = 2.9) minutes focusing on the feedback and researcher 2 timed these participants to have a mean of 4.9 (SD = 3.0) minutes focusing on the feedback. Video-group participants finished 95% of their feedback sections ($M = 0.75$, SD = 2.2) compared to the text-group participants who finished only 66% of their feedback sections ($M = 4.6$, SD = 3.9), this difference was significant at $p < 0.001$.

As seen in **Table 2**, distraction, measured by the length of gaze-duration within areas on the screen other than the feedback area was significantly higher in video- compared to text-group participants $F(1, 36) = 29.33$, $p < 0.001$. The proportion of gaze-duration within the feedback area compared to gaze-duration within the total screen was significantly lower in video-group participants ($M = 82\%$, SD = 8.83%) than text-group participants ($M = 87\%$, SD = 16.15%; $p < 0.01$). The proportion of time participants spent fixating on the feedback from the total time they spent viewing the feedback was 76.28% (SD = 11.07) in the video-group and 83.27% (SD = 9.02) in the text-group. This difference was not significant $F(1, 36) = 4.01$, $p = 0.053$.

RECALL

The percentage of correct responses for each of the recall interview questions for total group and the video- and text-groups are presented in **Table 3**. A chi square analysis revealed that there were no between group recall differences for any of the questions.

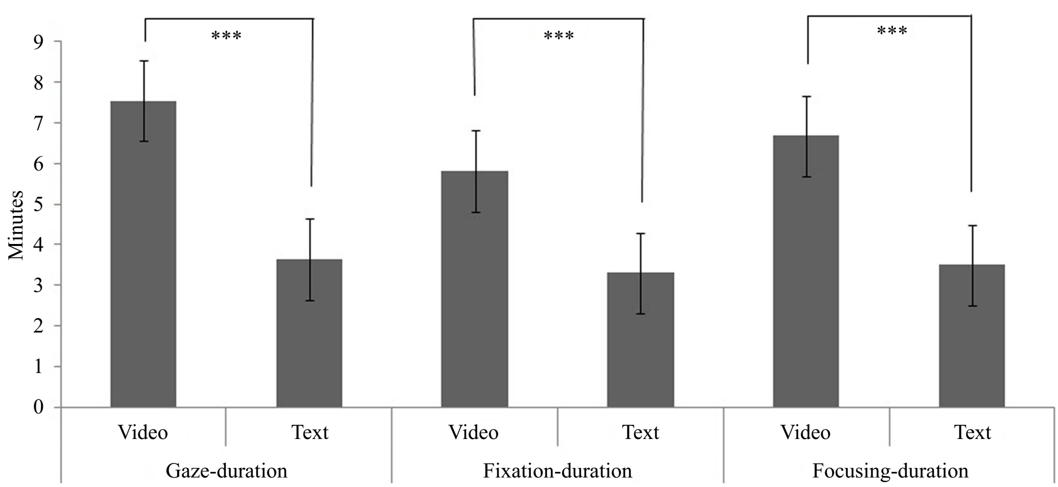

FIGURE 1 | Gaze-, fixation-, and focusing-duration in the feedback area by group (video, $n = 20$; text, $n = 17$).

Table 2 | Descriptive statistics for gaze-, fixation-, and focusing-duration in the feedback area and distraction by group (video and text).

		Attention						Distraction	
		Gaze-duration feedback area (min)		Fixation-duration feedback area (min)		Focusing-duration on feedback (min)		Gaze-duration other areas on screen (min)	
Group	n^a	$M \pm$ SD	F	$M \pm$ SD	F	$M \pm$ SD	F	$M \pm$ SD	F
Video	20	7.72 ± 2.00	30.39***	5.96 ± 1.93	13.09***	6.82 ± 1.94	20.85***	1.56 ± 0.68	29.33***
Text	17	3.63 ± 2.43		3.30 ± 2.19		3.50 ± 2.38		0.42 ± 0.56	

****p < 0.001.*

Adjusted for number of feedback sections.

[a] Eye-tracking data was missing from one video and three text-participants.

Table 3 | Correct responses for each recall question by group and chi square comparison of correct responses in video- and text-groups.

	Correct response			Chi square χ^2
	Total group *n* (%)	Video-group *n* (%)	Text-group *n* (%)	
Q1. What is the goal of the advice?	33 (80)	15 (71)	18 (90)	2.25 ns.
Q2. What is the recommended amount of physical activity?	25 (61)	12 (57)	13 (65)	0.27 ns.
Q3. What is the optimal amount of physical activity per day?	21 (51)	11 (52)	10 (50)	0.02 ns.
Q4. Are you meeting the physical activity guidelines?	36 (88)	18 (86)	18 (90)	0.18 ns.
Q5. Exactly how many minutes of physical activity do you do on a weekly basis?	35 (85)	17 (81)	18 (90)	0.67 ns.
Q6. What was presented in the graph	14 (34)	7 (35)	7 (33)	0.01 ns.
Q7. What was each of the bars in the graph showing?	15 (37)	8 (38)	7 (35)	0.04 ns.
Q8. How will meeting the physical activity recommendations benefit you?	34 (83)	17 (81)	17 (85)	0.12 ns.
Q9. What chronic diseases can be prevented?	33 (80)	18 (86)	15 (75)	0.75 ns.

ns., not significant.

The mean total recall response was 5.86 (SD = 2.26) in the video-group and 6.15 ($SD = 1.63$) in the text-group. No significant relationship between total recall and group (video vs. text) was found $F(1, 36) = 0.22$, $p = 0.639$. Based on the total recall scores 17 participants were assigned to the low recall category, and 21 to the high recall category using a median split. The mean gaze-duration in the feedback area for participants with high recall was 5.51 (SD = 2.83) minutes, and 6.28 (SD = 3.20) minutes for participants with a low recall score. No significant relationship was found between attention and recall.

DISCUSSION

The findings demonstrate that video-tailored advice is more effective at gaining participant's visual attention than text-tailored advice in a web-based physical activity intervention. Video-group participants spent significantly longer viewing their feedback, had a higher sum of fixations on the feedback, and spent longer focused on the key parts of the feedback than text-group participants. Furthermore, video-group participants finished a significantly greater amount of feedback sections than the text-group participants despite both groups having the ability to navigate through their feedback and finish sections prematurely. The objective eye-tracking data confirms the findings from Lee (27) of improved self-reported attention to video-presented health information compared to identical text-presented information. The findings also demonstrate that the improved engagement toward video-messages compared to text-messages observed in marketing and educational settings applies in a web-based health behavior intervention setting (22, 23). The finding of improved attention in video-group participants is important for the development of web-based health interventions as high exposure to the intervention content is associated with improved behavior change (14, 15). Presenting health advice through video may be an effective strategy to improve the low levels of participant engagement and therefore exposure to web-based health interventions.

There might be several reasons to explain the improved attention to the message in the video-group participants. Firstly, the improved attention in the video-group participants could in-part be a result of participant's expectations. Website users have come to expect interactive websites with rich media content due to the current Internet environment where popular websites are employing rich media content to engage users (19). Secondly, the higher attention in video-group participants could be due to participant's social and emotional connection to the feedback. The presenter delivering the feedback and the images of active people in the video may produce a greater emotional and social connection to the feedback. This is in line with previous research that found students to have a greater emotional response to information delivered in video compared to text (23). Thirdly, the improved attention in video-group participants could be due to the lower level of mental effort required from the video-group participants. Text requires users to actively read in order to comprehend the text, whilst watching a video requires a lower mental effort (34). This might also be the reason why text-group participants skipped more feedback sections than video-group participants. Lastly, the higher level of attention seen in the video-group participants may be due to the perceived control video- and text-group participant's have to move through their feedback. Although both video- and text-group participants were able to click over to the next section of the feedback at any time, text-group participants more frequently clicked over to the next section before they had finished their current section. Internet-users typically have less control over the pace of information they receive through video compared to text (35), and could therefore be in the habit of watching videos to the end, without navigating through them. Furthermore, text-group participants were forced to click to read the next section, whereas transitions through the video sections were automatic. As such video-group participants may have been less aware of their ability to fast-forward through the video-feedback.

Although video-group participants spend longer viewing their feedback than the text-group participants, they demonstrated greater levels of distraction than text-group participants. Video-group participants spend significantly longer viewing other areas on the screen whilst the feedback was being presented and viewed the feedback area on the computer screen for a significantly lower percentage of time than text-group participants. This may also have resulted from the difference between groups in perceived control to move through the feedback faster (35). It is likely that text-group participants clicked through to the next section immediately when they chose not to read any more of the section they were on. Whereas video-group participants tended to continue watching each section until it finished. It is likely that video-group participants were looking outside of the feedback area when they had brief moments of distraction or when they perceived some sections of the feedback as less interesting. Alternatively, they could have been listening to the audio of the video without paying close attention to what was on the computer screen. The measure of attention produced by the eye-tracking device is based upon visual attention only, and does not account for the audio of the video. Whilst it is important to note the increased distraction in the video-group participants, it is more important that video-group participants spent longer viewing the feedback, as they were less likely to skip to the next section when momentarily distracted.

Although video lead to a higher level of attention, no group differences were found for the number of correct responses on each of the recall questions, or the total number of correct responses for all of the recall questions. This is incongruent with past research findings of video leading to a greater recall in marketing and education settings (20, 21). Furthermore, the lack of relationship between attention and recall was not expected as past research demonstrated a significant positive relationship between attention and recall (30, 31). It is possible the questionnaire used did not adequately measure recall, as many participants might have had prior knowledge of some answers such as their level of physical activity, the benefits of physical activity, and the diseases associated with inactivity. Furthermore, participants in both groups had a very high number of correct responses, which may have been due to the interview being conducted immediately after the intervention. This might have created a ceiling effect where the low variability in participant's responses made it difficult for any group differences to be detected. If there was a greater time gap between the intervention and the recall questionnaire group differences resulting from participant's attention to the feedback may have been detected. Further research is needed to determine whether increased attention to video leads to greater recall and behavior changes, with the use of a pre-post test design, and a comprehensive recall questionnaire conducted with a longer time gap after the intervention to adequately assess recall.

Finally, the recall questionnaire outcomes revealed that participants remembered the main messages of the advice very well, but the details were much less well retained. The majority (at least 80%) of participants knew what the goal of the advice was, could remember if they were meeting the guidelines or not, knew how many minutes of physical activity they did on a weekly basis, could list how physical activity could benefit them and could recall the diseases physical activity helps to prevent. However less than half of participants could recall that the recommendations and their own activity levels were presented in the physical activity graph, and just over half of participants could correctly recall the minimum and optimal physical activity recommendations.

LIMITATIONS

Although eye-tracking technology has improved our understanding of how to engage participants in online health interventions, the nature of the eye-tracking data poses some limitations. The eye-tracking technology only measures visual attention, not auditory attention. Furthermore, it is possible that the longer gaze- and fixation-duration in the video-group were because it took longer to watch the videos than it would take to read the same information in text-format. Another limitation with the eye-tracking technology is the use of eye-gaze as an attention measure. It is possible that participants were looking within the feedback area but are not actually processing the feedback, however given the outcomes on focusing-duration (which was much higher in the video-group) this is doubtful. Finally, there may have been error in the measurement of BMI due to the use of self-reported data.

CONCLUSION

The findings support the hypothesis that video-delivered content is an effective way of improving participant's attention to tailored health information in a web-based physical activity intervention. This is important for the development of future web-based physical activity interventions as attention and engagement are strongly linked with behavioral outcomes. Future research is required to evaluate the effectiveness of video-tailored advice in producing long-term behavior changes in comparison to standard text-tailored advice. Furthermore, future research with a larger sample size is needed to conduct analyses on the two-way interactions between participant demographics (gender, BMI, motivation to become more active, and age) and group (video and text) on attention. It is, for example, important to determine whether personalized video content is effective at increasing activity levels in older or overweight participants, as they are at higher risk for developing chronic diseases. The findings did not support the hypothesis that video-group participants would have a higher recall of the intervention content. Due to the high percentage of participants in both groups with correct responses to many of the questions, further research with more sensitive measures is needed to confirm this finding. However, the low levels of recall, especially for the physical activity recommendations highlight a need for future research to evaluate ways of improving recall of the key parts of physical activity advice. Overall, this research using eye-tracking data demonstrates that video-tailored advice leads to a higher level of attention compared to text-tailored advice in a web-based physical activity intervention.

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Jump In! An investigation of school physical activity climate, and a pilot study assessing the acceptability and feasibility of a novel tool to increase activity during learning

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Physical activity (PA) benefits children's physical and mental health and enhances academic performance. However, in many nations, PA time in school is decreasing under competing pressures for time during the school day. The present paper argues that PA should not be reduced or seen as incompatible with academic learning. Instead, the authors contend that it is critical to develop tools that incorporate PA into content learning during the school day. To facilitate the development of such tools, the authors conducted 6 focus group discussions with 12 primary school teachers and administrators to better understand the school climate around PA as well as school readiness to embrace PA tools that can be used during academic content learning. In addition, a pilot test of a new health promotion tool, the *Jump In!* educational response mat, was conducted with 21 second-grade students from one classroom in Northern Colorado in 2013. The results of both studies demonstrated acceptability and feasibility of incorporating PA into classroom learning, and suggested that tools like *Jump In!* may be effective at overcoming many of the PA barriers at schools. Teachers and administrators valued PA, believed that students were not getting enough PA, and were receptive to the idea of incorporating PA into classroom learning. Students who used *Jump In!* mats during a math lesson reported more interest in the class material and rated themselves as more alert during the lesson, compared to students who did not use the response mats. In addition, incorporating PA into the lesson did not impair performance on a quiz that assessed learning of the math content. *Jump In!* mats were successfully integrated into the lesson plan and were well-received by teachers and students. Together, the results of these studies suggest that, given the right tools, incorporating more PA into classroom learning may be beneficial and well-received by students, teachers, and administrators.

Keywords: physical activity, focus groups, primary school children, health promotion, sitting reduction

INTRODUCTION

The physical health benefits of regular physical activity (PA) for individuals of all ages (e.g., greater quality and length of life, reduced incidence of acute and chronic mental and physical illness) are well-established (1–3). Thus, PA comprises a critical element of health promotion among youth. In addition, PA can also enhance learning (4, 5). Bouts of PA augment cognition (6), and the effects of PA on the brain, induced by increased flow of blood, norepinephrine, and endorphins can "reduce stress, improve mood, induce a calming effect after exercise, and perhaps as a result improve achievement" [Ref. (7), p. 214]. A 2005 review of the effects of PA on health and behavior outcomes for youth reported that a variety of research types have demonstrated links between PA and gains in academic performance, concentration, memory, and classroom behavior (8). Although these benefits have largely been linked with moderate-to-vigorous PA, it has recently become clear that PA of lighter intensity may also produce similar benefits, particularly if the light-intensity PA replaces sitting (9).

These various physical and cognitive benefits provided by PA suggest that PA would be of considerable benefit for all people, certainly including school-aged children and adolescents for whom daily learning is their primary task. In the United States of America (USA), 94–98% of school-aged children and adolescents are enrolled in school for an average of 35 h per week (10). Despite these indications that PA can benefit both student health and academic performance, most children in the USA do not achieve the recommended 60 min of daily PA and PA in schools is declining (11); internationally, many countries have rates of child and adolescent PA that are even lower than in the USA [e.g., Ref. (12)], and rates of in-school PA are also declining internationally (13).

In the USA, physical education (PE) time has been reduced in many schools due to efforts to increase time spent in content-area learning (14), despite recommendations from international working groups that increasing PA at school is a high-leverage target for promoting health worldwide (15). Preparing students to achieve specific standards for content-area courses, but not PA, has meant reduced incentive and thus reduced time for PA at school. In many countries, PA on the way to and from school (i.e., active commuting) has also decreased in recent years [e.g., Ref. (16–22)]. Social and environmental changes have made actively commuting less attractive for many and not possible for some (e.g., due to safety concerns and constraints imposed by the built environment).

As a result, at a time when meeting academic standards is being greatly emphasized, PA in schools is decreasing despite its demonstrated ability to enhance cognitive and physical health outcomes (8). Research demonstrating that PA can benefit learning suggests that removing PA time from the school day to make room for more academic time may not only be harmful to students' physical health, but may also fail to improve (or actually worsen) academic outcomes. Indeed, spending more, rather than less, time being physically active may provide a greater boost to academic outcomes while also improving student health. In addition, students allowed to move around more during the school day may be better able to focus on learning. A 2010 CDC executive summary of research on school-based PA and academic performance reported that of nine studies that had explored PA in the classroom, eight of the studies suggested that more classroom-based PA was related to more-positive cognitive and academic behaviors and attitudes, and none of the studies suggested that more PA was detrimental to cognition and achievement (23).

Due to the prevailing primary school educational atmosphere in the USA being largely focused on achieving specific educational standards, elements not included among those standards (e.g., PA) may be viewed as non-essential; thus, it is important to devise PA tools that can be used during academic content learning, without taking away time from instruction. To facilitate the development of tools that can be incorporated by teachers into content learning, it is essential to better understand the school climate around PA, as well as school readiness to utilize such tools. Broadly, "school climate" refers to the overall quality of the school environment, and more specifically: the quality of interactions between students, as well as between students and teachers, and the extent to which students have autonomy in decision-making and rules and guidelines are fair and clearly communicated to students (24); school climate is very strongly related to student success and adjustment (24). The school climate construct has recently been applied to PA specifically, and encompasses issues related to adequate facilities, interpersonal relationships that are respectful of physical and social changes that occur during childhood and adolescence, and norms that support PA (25). There is increasing evidence that the school climate around PA is an important predictor of student engagement in PA (25, 26). Because incorporating PA into classroom learning would require a qualitative shift in thinking about PA at school, we considered it necessary to first assess attitudes of teachers and school administrators about PA at school, as well as their openness to incorporating PA into content learning. Therefore, our first step was to conduct a health promotion needs assessment surrounding the current PA climate in primary schools in one school district in Northern Colorado. We aimed to determine: (a) when, where, and what types of PA, teachers currently see occurring in their schools (to identify possible needs and opportunities for PA to be increased), (b) whether teachers and administrators believe that PA is beneficial to students and whether greater rates of PA would benefit students (to determine if school staff have attitudes that would support or hinder increasing PA), (c) what the school-based obstacles to PA are (to understand what barriers new PA tools would need to overcome), and (d) how school staff responded to a health promotion tool that increases PA in the classroom (to understand openness to qualitative shifts in thinking and acting in relation to PA in the classroom). In addition, we conducted a pilot test of a health promotion tool that increases PA during content learning in the classroom, a device called the *Jump In!* educational response mat.

Jump In! educational response mats, created by the study team for use in a classroom environment, are 2 × 2 ft mats that can fit behind or next to student desks in a classroom setting. Mats are comprised of four equally sized and differently colored squares lettered "A," "B," "C," and "D" (see **Figure 1**). The mat design was chosen with several considerations in mind: (1) the presence of four answer choices allows the mats to be used with multiple-choice questions that employ a common number of answer choices (i.e., four); (2) the squares are large enough for children to jump into them with room to spare, so that it is clear which answer choice is being selected; (3) the use of both colors and letters permits mats to be used by even very young children who have learned colors, even before they can read letters.

Students jump on the lettered sections of the *Jump In!* mats to respond to teacher queries (e.g., multiple-choice questions with different letter or color response options), to answer mathematical questions (e.g., answering "what is 10 divided by 2?" by jumping 5 times on the mat), to volunteer answers in class (like a

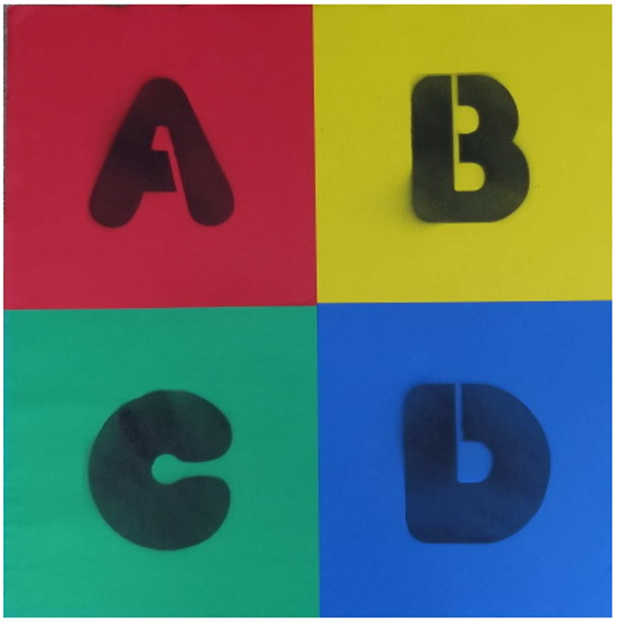

FIGURE 1 | *Jump In*! educational response mat.

more active hand raise – teachers can ask students to "Jump in when you know the answer," rather than "Raise your hand when you know the answer"), or for countless other educational purposes. Easy-to-use, durable "Jump In" mats placed on classroom floors allow students to jump to answer questions in class, rather than remaining sedentary during content learning. Mats can incorporate response clicker technology already in place in some classrooms (e.g., iClickers™), but replace handheld response boxes with a floor-based mat format that encourages PA.

The present research is comprised of two studies: Study 1, a health promotion needs assessment that included focus group discussions with school teachers and administrators regarding the current PA climate, school and school personnel readiness to change, and perceived benefits and barriers to increased PA in general as well as with *Jump In!* in particular. Study 2, a process and impact evaluation of a health promotion pilot project that tested the effects on academic performance of *Jump In!* educational response mats used *during* classroom learning, and assessed student outcomes including evaluations of these mats. These mats allow PA to be undertaken simultaneously with content learning, as a complement to course material, as opposed to the predominant view of PA as a break from learning and a supplement to be added on top of the many essential curricular elements competing for teacher and student time during the school day. This view of PA as something extra, rather than as an activity that can coincide with, and indeed contribute to, content learning has enabled PA to be reduced and even removed from many schools despite the high percentage of youth in many countries failing to meet PA recommendations (11, 27, 28).

STUDY 1: FOCUS GROUPS WITH TEACHERS AND SCHOOL ADMINISTRATORS

PARTICIPANTS AND PROCEDURE

The following protocol was approved by Colorado State University's Institutional Review Board (approval ID 13-4120H). Teachers and school administrators were recruited to participate in focus groups about PA in the classrooms via emails that were sent to individual principals (who then distributed them to teachers), as well as flyers that were posted in several schools in Fort Collins, CO, USA. Eleven teachers and one principal participated in these focus groups (8% male). Each focus group was scheduled with a very small group of participants (each of them provided written consent) in order to gather as much data as possible from each individual respondent without requesting that participants devote more than an hour to these discussions. Within each group, a semi-standardized set of questions was designed to be consistent with the needs assessment portion of an Adapted Intervention Mapping approach to public health issues (29). First, participants reported on their beliefs about the benefits of PA for themselves personally and also for students; second, participants reported on their beliefs about how much PA students should get at school, as well as how much PA students actually do get. They were then asked questions about times during the day when students were physically active and what their schools did to support PA. Then, attention turned to whether and how PA could be increased at schools. Participants were asked to describe when and why students were inactive at school, including discussion of specific barriers to PA at school. Finally, teachers were given a description of *Jump In!* educational response mats and then were asked to describe their reactions to this specific tool, the barriers to incorporating such a tool in their school/classroom, and their ideas for how the mats could be incorporated into their teaching.

Paralleling a more recent acceptance and value placed on mixed methodology, qualitative research in public health fields may illuminate phenomena not otherwise captured by purely quantitative methods (30); therefore, focus groups were chosen for the present study for several reasons. First, focus groups are effective for understanding exercise and exercise programs (31, 32), and in particular, in school health exercise research [e.g., Ref. (33)]. In addition, small focus groups were used to facilitate discussion across different participants and different schools in the northern Colorado area. For example, on several occasions, the research team noted that one participant was able to build off of the ideas of the other participant(s). Finally, although the study team was aware of the risk for participants to converge in agreement in a focus group setting, it was deemed of greater importance to approximate venues in which school health issues are discussed and decisions are made (e.g., a school health and wellness committee). Although focus group participants did frequently express agreement about PA in their schools, each focus group with multiple participants also included disagreement about one or more policies or trends at participants' schools, suggesting that false convergence was not likely occurring.

Six focus groups were conducted with 12 participants; 4 groups had 2 participants, 1 group had 3 participants, and 1 teacher participated alone. Data saturation was achieved with this number of participants. Teachers taught a range of grade levels, although all were elementary school educators. Two teachers taught music, one taught PE, and one taught integrated services; the remaining teachers were primary educators. Teachers and principals represented six schools from in and around Fort Collins, CO, USA; schools represented demographically and geographically (i.e., both urban and rural) different areas.

Data from the focus groups were audio recorded. Consistent with the framework analysis approach to qualitative research (34), the study team used a theme-based approach to analyze results. Upon conclusion of the six focus groups, results were analyzed by: (a) identification of key ideas, (b) classification of typologies, and (c) explanatory analysis with focus on the study's primary objectives: to better understand school climate around PA, assess school readiness to implement PA initiatives, and explore readiness to use *Jump In!* The research team met on several occasions to reach consensus.

RESULTS

Teacher descriptions of the school climate related to PA

Overall, participants agreed that students were not getting ideal amounts of PA on most school days, although the actual estimates of average daily PA varied from school to school. Most teachers (roughly 75%) estimated that on average students accumulated approximately 30–45 min of PA during the school day, and the majority of this active time was during recess. Participants reported that younger children (kindergarten through third grade) had more opportunities for PA than did older children (in fourth and fifth grade); again, this primarily meant more time spent in recess for the younger children. For instance, one teacher noted that teachers and principals "agree that little kids need time to be active and run around and play but then you reach a certain period like fourth and fifth [grade] and those are the highly, you know, standardized tested grades and it's like, well, all of the sudden we think they don't need that . . . which, you know, obviously I disagree with."

Several participants reported that there was much more active time on days that students had PE classes, but the frequency of those classes was not consistent among the schools represented by focus group participants, ranging from three times over 4 weeks to approximately every other day. In addition, many teachers spoke very highly of the ability of PE teachers to get all of the children moving for most of the time spent in the class; however, other teachers reported that students spent less than half of the time in PE classes actually being physically active.

Interview participants reported a wide range of percentages (ranging from approximately 10–33%) when asked what percent of students at their schools commuted actively (e.g., walking or bicycling to school), but only teachers at one school described having a lot (but still a minority) of children who commute by bike or by foot. However, the majority of teachers talked at some point in the focus groups about PA occurring frequently during classroom transitions. They reported using many different strategies frequently referred to as "brain breaks" to get children moving for just a few minutes every hour; when asked whether these breaks were used widely by teachers throughout their schools, all teachers reported that they were relatively typical.

Although participants reported that most teachers used brain breaks to encourage PA during the day, they agreed that most students were inactive during classroom learning. However, when these periods of inactivity were problematic, especially for particularly high-energy/fidgety students, most teachers reported using strategies to encourage healthy outlets for energy, rather than punishing hyperactivity (e.g., allowing students to stand in the back of the classroom rather than sit at a desk, allowing students to sit on exercise balls rather than typical chairs).

Overall, participants reported that their school environments and policies were generally supportive of PA. Most typically, this support came in the form of providing playground and sports equipment (the latter was often provided by parent groups or PE teachers). In addition, several teachers reported school-wide initiatives (e.g., bike to school programs, competitions to encourage PA); however, roughly half of the participants reported that there were no official policies to support PA, beyond the district-mandated Wellness Committee at each school. Finally, several schools were moving to celebrating events like birthdays with PA rather than food; when there were policies in place about this issue, teachers reported they were often motivated by food allergies rather than by encouraging PA, *per se.* Taken together, these results suggest that teachers and school administrators believe that students should be more physically active during the school day than they currently are, and that school climates are generally supportive of PA.

BELIEFS ABOUT BENEFITS OF PA FOR STUDENTS

Across the board, focus group participants believed that there were benefits of PA across multiple domains for their students. Most frequently, participants highlighted cognitive and mental health improvements for students. Interestingly, participants did not discuss physical health benefits.

Overwhelmingly, focus group participants highlighted that PA during the school day allowed students to focus more effectively and, likewise, that the absence of PA led to a diminished ability to focus. One participant made a behavioral observation regarding recess and focus. She stated, "I notice a difference on the days they get to go out [for recess]. They are a lot more ready to settle down and work [afterwards]." Another individual made an argument about the importance of PA by observing behavior in the absence of PA. She noted, "What I have observed is when students don't get the opportunity to exercise, they are not able to focus as well." Many participants also highlighted the relationship among PA, the brain, and learning. One teacher stated, "[PA] activates a different part of their brain. I can get them thinking with a different part of their brain through PA." Similarly, another participant stated, "[PA] gets blood into their brain, helps them to retain information."

In terms of mental health, several participants highlighted the mental health benefits and positive mood changes observed in their students resulting from PA. Broadly, they observed positive effects on student mood. One teacher noted, "They are happier. They need that time to be unstructured and free." Another individual discussed PA as a protective factor in clinical mental health issues. She stated, "There are certain individuals who are prone to depression, and I know that exercise helps." Finally, one administrator discussed PA as an intervention strategy. She stated, "We can use PA to change their emotional state – get them out of that stressed state so they have a chance to think."

OBSTACLES TO PA IN SCHOOL

Teachers identified several barriers to in-school PA at the state/federal level, at the school level, and at the individual level. Several of these barriers are particularly relevant to a discussion of how to incorporate PA into classroom learning, and are detailed below. However, other barriers would remain even if these new tools were utilized; these include inadequate equipment, money (e.g., only being able to hire PE teachers part-time), and perceptions that students are getting enough PA outside of school time (particularly students who come from wealthier families).

Time (related to federal and state mandates/standards and testing). Endorsed nearly unanimously across all of the study participants was the barrier of time, and more specifically, lack of time to devote to PA due to federal and state mandates, standards, and testing. One teacher described this barrier and its impact on PA during the school day. When asked about barriers, she stated, "Curriculum. There's so much. At the elementary school level, they are giving us more and more and more stuff to do. We got rid of afternoon recess because there wasn't enough [contact time] to meet required times. Those are minutes that are standard." Another highlighted how pervasive and distressing the issue is: "Teachers are constantly feeling the crunch time. It's always hanging over your head that you have all of these things to get done." One participant, in particular, succinctly described the dilemma between classroom instruction time and opportunities for PA. She noted, "When you rob Peter to pay Paul, are you going to take it from writing or take it from movement?"

Buy-in from administration/school culture. Another related barrier described by multiple participants was the importance of administrative buy-in for PA initiatives. Several participants described that their participation in programing that included PA was directly related to the emphasis administration did (or did not) place on such activities. One participant highlighted the relationship between PA, administrative emphasis, and lack of teacher time. She described a barrier as "... definitely values of the administration. Buy-in from administration. A lot of what we don't do is based on the administration in our building. A big initiative across the board won't happen from teachers – they have so much on their plate." Furthermore, one PE teacher highlighted his own frustration with bureaucratic and school level barriers. He stated, "Why can't there be a mandate for PA? We have study after study and it's proven over and over again that more active kids perform better, but there are blinders put on at the administrative level." Clearly, the adoption of new PA tools would require buy-in from school administration.

Student characteristics. Individual characteristics of students were also discussed including natural inclination toward PA, student choice, and medical concerns, especially respiratory problems. Many teachers discussed that some students seemed "naturally" less inclined toward movement. In addition, some teachers described experiencing a dilemma about whether they should discourage a sedentary, but otherwise desirable activity (e.g., reading at recess) in order to promote PA at recess. Finally, student health and invisible disability were noted barriers. In fact, one participant described it as the most significant barrier to PA during the school day. She stated, "This is the biggest one: Asthma. Students with asthma. So many students on inhalers..." The adoption of tools that incorporate PA into learning would require sensitivity to individual health issues, but could overcome individual differences in inclination toward movement, and tools like *Jump In!* could reduce health risks associated with sitting even for students who used the mats in a low-exertion way (e.g., standing, stepping onto mats), if more vigorous activity was not feasible.

Thoughts on Jump In!

Focus group participants reported enthusiasm for *Jump In!* as a tool that students would greatly enjoy using and that would contribute to increased activity during the school day without detracting from time spent learning. One teacher thought *Jump In!* could be implemented in her classroom in several ways: "It would be easy: With math ... Have them solve a problem and say 'here's four choices.' Reading: We do multiple-choice tests for reading so instead of filling in bubbles we could use that [*Jump In!*] instead. I could see it used for the formal assessments so they are not sitting there for a long time. Informal assessments, too."

Echoing these sentiments, several teachers indicated that they would find *Jump In!* particularly useful for math lessons and for multiple-choice quizzes in other areas, but that other uses would be possible as well. In fact, despite talking specifically about the mats for only approximately 10 min during each of the focus group sessions, the teachers were able to come up with numerous uses for *Jump In!* in their own classrooms and schools during this brief span of time. One teacher comment reflected these multiple possible uses well: "I think it's really adaptable," she said, and described a few of the ways she could use the mats in her classroom: "It would be cool if they used their hands and feet ... or if you could hang it on the wall. Or throw a ball on it." "Or in teams. They have to decide on an answer and run over and click it."

Teachers thought that given more time and more teachers they could come up with many different ways to use *Jump In!* "I think teachers if they were given enough time to explore it, they would be using it... Once you show it, demonstrate, let them try it, you will come up with a million more ideas..." In addition to the favorable responses to using *Jump In!* with younger students, and the many possible uses for the mats with this age group, one teacher indicated that *Jump In!* could be useful and enjoyable not only for younger students but among high school students as well.

In addition to the positive feedback, focus group participants were asked to discuss what roadblocks they might encounter in using *Jump In!* in their classrooms. The primary potential barrier reported by participants to using *Jump In!* in the classroom was space, both for storing the mats and for using them in the classroom. Many teachers thought that given the amount of space currently occupied by the desks/tables in their classrooms there would not be sufficient space for all of the students to simultaneously place a mat next to or behind their seat without moving furniture around. A minority of teachers also expressed concerns about how much time would be required to get the mats out and ready to use during class. An additional concern included teachers having to modify existing lesson plans to include questions with discrete outcomes (e.g., multiple-choice questions) in order to be compatible with *Jump In!* mats, rather than using open-ended questions as they preferred to use for many topics. Teachers were also worried that the mats may not be sturdy enough to withstand frequent jumping or that there may be breakable parts, given the electronic communication system used to gather response data and communicate it wirelessly to the teacher's computer/tablet. One participant also wanted to clarify that the mats would not have wires connecting them to one another, as she foresaw such a design could produce a tangled mess of mats and wires in her classroom. Teachers expressed a desire to have different answer choices appear on the mats themselves, rather than A, B, C, D, as the prototypes were marked. Finally, some participants were concerned that students could "cheat" by waiting to answer questions until a classmate had jumped on his or her answer choice, as it would be possible to see the answers classmates were selecting.

DISCUSSION

Teachers' perceptions of the benefits of PA align well with existing research on the relationships between PA and mental health, physical health, and cognition (1–6). Although this was a sample of teachers' from one region in the USA, participants' perceptions were in line with data from across the world that students do not engage in ideal amounts of PA (11, 12). Consistent with national trends indicating that PA tends to decrease with age (35), the amount of time allocated to recess and PE by school policy was reported to decrease with increasing student age, such that the kindergarteners, first graders, and second graders in some of the schools represented by focus group participants were afforded the opportunity to participate in nearly twice as much daily PA as fifth grade students.

Physical education time has been reduced in many schools in the USA and internationally to allow for more time spent focusing on content-area learning (13, 14), an issue reflected in the focus group results. The focus group participants agreed that, due to current academic demands, the emphasis on standards, and prescribed amounts of time each day devoted to particular curricular components, it would be very difficult to increase levels of student PA at school. Indeed it was clear that adding PA to the school day would not be possible without extending the school day *or integrating PA into content learning*. Some teachers (i.e., the music teachers who participated in the focus group discussions) mentioned already combining movement with content learning in their classrooms. Most other teachers conceived of PA as a "break" from learning, and had not conceived of PA integrated with classroom learning as a possibility. Thus, none of the subject-area primary educators had yet attempted to integrate PA into learning in her classroom, but after viewing the *Jump In!* mats, all were open to the idea of "killing two birds with one stone" by combining PA with classroom instruction. *Jump In!* would allow these teachers to add PA to the school day without taking away from time spent teaching curriculum, and may very well bring about enhancements in student cognition, achievement, and physical and mental health. In addition, the use of such tools would overcome other barriers related to PA, including individual differences in students' inclinations toward engaging in PA.

The specific feedback about *Jump In!* provided by the focus group participants underscored many strengths and weaknesses of the initial mat design. The set of prototype mats created for this pilot testing did indeed have design limitations (e.g., sturdiness) that will be addressed in future versions of *Jump In!* intended for longer-term use. Some of the mat characteristics that will be enhanced in forthcoming iterations (e.g., the electronic communication between mats and teacher's computer, the ability to change the images displayed on the surface of the mats from A, B, C, D, to other letters, words, numbers, and pictures) will require a larger budget than was available for prototype design. Encouragingly, nearly all obstacles described by focus group participants can be overcome with modifications to the mats and creativity on the part of teachers and the study team.

As an example of how even seemingly intractable problems may be solved through mat modification and creativity in the classroom, the space constraints described by many participants as a potential roadblock to adopting *Jump In!* could be addressed by reducing the size of the mats, by pairing *Jump In!* mats with standing desks that allow more space behind them for jumping, by placing mats around the periphery of the room, rather than next to desks, or even by imbedding mats into flooring material so that the mats need not to be stored and moved on a regular basis. As one teacher stated in regard to the potential problem of finding classroom space for using *Jump In!*, "Everyone could find a space. We could push desks together to get more floor space. It would just be creative thinking, but it would be manageable."

In addition, *Jump In!* users concerned that some students could copy the answers provided by their classmates could rearrange the mats in the classroom such that students were facing away from classmates (e.g., in a circle around the periphery of the room), rather than toward them (as in classrooms set up with traditional rows of desks), or the teacher could count down (e.g., 3 . . . 2. . . 1. . . Jump In!) when requesting an answer so that all students jumped simultaneously. This problem could also be addressed technologically, by identifying those responses provided more than X units of time later than a response was requested.

STUDY 2: IN-CLASSROOM ASSESSMENT

PARTICIPANTS AND PROCEDURE

The following protocol (13-4120H) was approved by Colorado State University's Institutional Review Board. To recruit students for the in-classroom assessment, the district wellness coordinator emailed teachers directly to evaluate interest in having classrooms participate in the current study. One teacher responded in enough time to complete the following assessment before the end of the school year. All children in her classroom were sent home with parental consent forms; the teacher tracked consent forms and followed up with parents until the day of the assessment, by which time all but one child's parents had provided consent. Children provided written assent the day of the assessment.

Jump In! was tested in a second-grade classroom in Fort Collins, CO, USA. There were 23 students (21 participated; 52% male) in this inclusive classroom, in which two students were deaf and/or hard of hearing. Authors worked with the teacher of this classroom to help her incorporate *Jump In!* into her existing class plans. In this classroom, students were divided into three groups that rotated through various stations (independent work, game play related to curriculum, and math). Two of these three groups were assigned to use *Jump In!* during the math lesson ($n = 13$); the other group did not use *Jump In!* during this lesson ($n = 8$). The only demographic information available on students was gender; the experimental and control groups (i.e., *Jump In!* users and non-users, respectively) were comparable in terms of gender breakdown, $\chi^2(1) = 2.65$, $p = 0.10$; the teacher reported that the mean achievement of students was comparable between the experimental and control groups.

At the end of the lesson, each student was individually given a short quiz on the math material covered during their lesson; the number of correct answers was used in analyses. Then, students answered four questions about their experiences during the math lesson: (1) How easy was it for you to pay attention in class today? (four answer choices ranged from 1 = "really easy" to 4 = "really hard"); (2) How interested were you in the math lesson you just did? (four answer choices ranged from 1 = "not at all" to 4 = "extremely"); (3) How much fun was this period of class today? (four answer choices ranged from 1 = "not at all" to 4 = "extremely"); and (4) How alert (or full of energy) did you feel? (four answer choices ranged from 1 = "not at all" to 4 = "extremely"). Happy and sad faces accompanied the answer choices (e.g., for the question about interest, a sad face was printed below "not at all" and a happy face was printed under "extremely") and the authors as well as the teacher were available to help students if they had trouble understanding the questions.

For analyses, the two groups of students who did use *Jump In!* were combined and compared to the students who did not use the response mats in terms of their performance on the math quiz and their answers to the questions about their experience during the math lesson for the day; these analyses were conducted using t-tests to answer research questions about whether the use of the *Jump In!* mats affected: (a) academic performance and (b) student experiences of the math lesson.

RESULTS

There were no differences in performance on the math quiz, $t(18) = 0.51, p = 0.62$ ($M_{\text{Jump In}} = 4.08$, SD = 0.73; $M_{\text{No Jump In}} = 4.25$, SD = 0.71) or in terms of student-reported attention or fun during the day's lessons, $t\text{s} < |1.54|$, $p\text{s} > 0.14$. However, students who used *Jump In!* were significantly more interested in the class material, $t(19) = -2.32$, $p = 0.03$ ($M = 3.69$, SD = 0.48) and also rated themselves as significantly more alert, $t(19) = -2.16$, $p = 0.04$ ($M = 3.85$, SD = 0.38) compared to students who did not use *Jump In!* (interest: $M = 3.13$, SD = 0.65; alert: $M = 3.25$, SD = 0.89).

DISCUSSION

Study 2 demonstrated the feasibility of using *Jump In!* in a primary school classroom in the USA. Those students who used the mats found class material more interesting, reported feeling more alert, and were also observed to be moving around more than their classmates who were not using *Jump In!* These results suggest that there may be benefits to *Jump In!* and that the use of such a tool will not detract from classroom learning. Indeed, the greater interest in curricular material and greater alertness reported by students could lead to improved classroom learning over a longer period of time than we observed in the present study. The enhanced alertness, along with the potential learning gains it could produce over time, is consistent with previous research supporting longitudinal cognitive benefits from engaging in PA [e.g., Ref. (6)]. However, it is important to acknowledge that, although the two groups were comparable in the indices we were able to examine in the current study, it is possible that there were unmeasured differences between the groups that may explain some of these findings.

In the pilot classroom, the mats were placed around semi-circular tables where the students would otherwise sit, and the students stood while reading math questions and jumped to indicate their answers. Students were not observed to "cheat" by looking at other students' mats, and the scores on the math quiz indicated that the students using *Jump In!* did not perform differently from the control students taking the quiz without the mats. The teacher who welcomed *Jump In!* into her classroom reported that her students enjoyed the mats, and that she did not have to make significant modifications to her lesson plan for the day in order to incorporate these tools. This classroom test suggests that student activity levels can be increased during content learning by using *Jump In!* without increasing teacher burden or impairing short-term student performance or concentration (indeed, interest in course content and alertness was increased among the pilot participants compared to seated control participants). Longer-term testing of *Jump In!* is necessary to determine what effects this tool may have on student learning and health over time.

GENERAL DISCUSSION

Despite the many benefits to be gained through PA (1–6), activity time is being reduced in schools in the USA and worldwide in deference to time spent learning content, particularly given the emphasis on standardized testing (13, 14). The present research was undertaken to determine whether incorporating an innovative tool into the classroom to encourage PA *during* content learning would be acceptable and feasible. Taken together, the results of these two studies demonstrated both acceptability and feasibility of this tool. Primary school teachers and administrators reported valuing PA as an asset to learning as well as mental and physical health, and were receptive to the idea of building more PA into the classroom. *Jump In!* was seen by focus group participants as a fun way to incorporate movement into content learning and avoid prolonged periods of sitting [which, in addition to causing students to become "antsy," as noted by teachers, may itself be detrimental to health; (9)]. Finally, in a second-grade classroom, *Jump In!* was successfully integrated into a typical lesson plan without necessitating significant modification, and was well-received by both teacher and students.

Along with the strengths of including both focus group discussions with teachers and administrators along with an in-class test of *Jump In!*, the present research had limitations as well. First, although it seemed that saturation of themes was achieved across the focus groups, it is possible that a different sample of teachers and administrators may have demonstrated a lower-level of readiness to adopt new PA techniques in their schools and classrooms. Despite potential generalizability concerns, information from the focus groups may be useful for other school personnel and researchers to examine similarity between the schools represented in this study and their own schools of interest. Such between-school comparisons would be helpful to determine if *Jump In!* would be similarly well-received and utilized in other schools and to explore whether populations different from the group investigated here might also enjoy and benefit from *Jump In!*. These participants had agreed to come discuss their school environments, and part of the description they were provided included PA specifically, so it is possible that these teachers knew more about PA in their schools, had a greater interest in the topic, or were stronger proponents of the benefits of PA than teachers who chose not to participate in the focus groups. In addition, it should be reiterated that, although the purpose of the in-class test of *Jump In!* was to demonstrate feasibility, this test occurred in only one classroom, which may not be representative of all classrooms in the tested school or district. Although *Jump In!* demonstrated success objectively and subjectively in the pilot classroom, it is not yet possible to infer that this tool will be easily adopted by all primary teachers and classrooms.

Future research with *Jump In!* will expand testing into more schools and classrooms, and will objectively measure PA among students using accelerometry. Observation of students using *Jump In!* in Study 2 suggests that while, on occasion, PA using these mats could meet the threshold for moderate-to-vigorous PA (e.g., when students answer math questions by jumping many times consecutively), the mats will more frequently produce intermittent, low-intensity activity; therefore, many of the health advantages may be obtained due to reduction of sitting (36, 37) and also due to weight-bearing activities (i.e., standing and jumping) that strengthen bone during formative years (38, 39). Additional testing will reveal how other teachers and other classrooms use *Jump In!*, as it is possible different teachers will elicit different levels of PA from their students when using the mats. Reduction of sitting time is a benefit that is expected to be reaped by all users of *Jump In!*, as it is not anticipated that students would sit on these mats.

As testing of *Jump In!* continues, the mats will be modified to meet the needs of teachers, administrators, and students. A goal of the present line of research is to make *Jump In!* mats commercially available for any school interested in utilizing them, but further research and development will be necessary before this goal becomes a reality. Further research will also investigate the amount and intensity of PA necessary to improve student academic performance, and how *Jump In!* contributes to meeting these critical levels of PA among students of various ages.

Finally, it should be noted that *Jump In!* is just one possible mechanism for combining PA and learning in a way that both can occur simultaneously and synergistically. One of the primary take-away messages from this research is that PA need not serve solely as a break from learning, and is not necessarily incompatible with content-focused classroom lessons. Many teachers and administrators are ready and willing to challenge the *status quo* of PA and content learning as mutually exclusive entities. The present results suggest that the time may be ripe for a qualitative shift in the way in-school PA is conceptualized and undertaken.

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