CHILDREN'S GEOGRAPHIES
2023, VOL. 21, NO. 2, 287–305
https://doi.org/10.1080/14733285.2022.2039901

RESEARCH ARTICLE

OPEN ACCESS

Children's physical activity and active travel: a cross-sectional study of activity spaces, sociodemographic and neighborhood associations

Kamyar Hasanzadeh [a,e], Erika Ikeda [b], Suzanne Mavoa [c] and Melody Smith [d]

[a]Department of Built Environment, Aalto University, Espoo, Finland; [b]MRC Epidemiology Unit, University of Cambridge, Cambridge, UK; [c]Melbourne School of Population and Global Health, University of Melbourne, Melbourne, Australia; [d]School of Nursing, University of Auckland, Auckland, New Zealand; [e]Department of Geography and Geology, University of Turku, Turku, Finland

ABSTRACT

Measures of individual mobility, such as activity space, have been previously used to help improve our understanding of individuals' interactions with their everyday environments. However, such methods have rarely been adopted in studying children's physical activity and active travel behavior. In this study, we use a combination of participatory mapping and accelerometer data collected from children aged 8–13 years living in Tāmaki Makaurau/Auckland, Aotearoa/New Zealand, to describe children's travel behavior and explore associations of active travel, physical activity, and socio-demographic characteristics with environmental attributes. The results from this study reveal complex associations between these different layers. Density of cycling routes was consistently associated with higher levels of physical activity captured via moderate-to-vigorous physical activity (MVPA), prevalence of active travel, and total activity space exposure. Nevertheless, population density, greenspace, and land-use mix revealed varying associations across different activity behaviors including MVPA, number of steps, and prevalence of active travel. The results from this study not only reassert the complexity of person–environment relationships, but also highlight the potential impacts of measurement and analytical methods on the study results. The novel combination of participatory mapping and accelerometer data together with activity space analysis provided new analytical insights which we discuss in this paper. This study concludes by reporting its observations and envisioning future research directions.

ARTICLE HISTORY
Received 16 July 2021
Accepted 4 February 2022

KEYWORDS
PPGIS; activity space; children; physical activity; physical environment

1. Introduction

A growing body of evidence has shown that physical activity (PA) can have significant impacts on various aspects of children's health (WHO 2020). PA guidelines of accumulating the average of 60 min of moderate-to-vigorous physical activity (MVPA) daily have been associated with reduced risk factors for cardiovascular disease and type 2 diabetes, improved bone and mental health, and maintenance of a healthy weight in children (WHO 2020). Active travel is a form of PA and is associated with higher rates of MVPA and improved health outcomes (Tribby et al. 2017). Active

CONTACT Kamyar Hasanzadeh kamyar.hasanzadeh@aalto.fi
Supplemental data for this article can be accessed at https://doi.org/10.1080/14733285.2022.2039901

travel refers to any human-powered transportation such as walking, bicycling, and scootering and it has been previously shown to be associated with higher PA levels among children hence resulting in health benefits (Jones et al. 2019; Cooper et al. 2006; Borghese and Janssen 2018). Despite the many benefits of active travel, its prevalence is low in developed countries including Aotearoa New Zealand (Smith et al. 2019b).

Engagement in PA and active travel can be explained by multilevel interactions between individuals, social and cultural environments, physical (i.e. built and natural) environments, and policies (Mitra 2013). Among these, the physical environment is increasingly recognized as having an important role in supporting or hindering PA and active travel across various age groups (Kajosaari et al. 2021; Laatikainen, Broberg, and Kyttä 2017). This is especially relevant to children whose opportunities for PA and active travel may more directly depend on readily available amenities (Villanueva et al. 2012; Loebach and Gilliland 2016a; Smith et al. 2020a). Some consistent relationships have been observed, despite a largely heterogeneous evidence base. Residing in more 'walkable' physical environments, with characteristics such as higher population/dwelling density, intersection density/street connectivity, and land-use mix (LUM) has been associated with higher children's physical activity and active travel (Pan et al. 2021; Dixon et al. 2021; Ikeda et al. 2018b). Availability of and access to amenities such as safe places to walk or cycle, and recreation settings such as parks and playgrounds are also important (Pan et al. 2021; Davison and Lawson 2006; Smith et al. 2017). The importance of green space for children's PA is an emerging area of research and an increasing amount of evidence shows the importance of greenspace for supporting children's activity (Ward et al. 2016; Lachowycz et al. 2012). However, inconsistent findings have been observed to date and there is some suggestion that greenspace quality and characteristics also play a role (Benjamin-Neelon et al. 2019; Ikeda et al. 2018b).

Most previous research has focused on home and school neighborhoods as representations of the immediate environment where children's PA, active travel and independent mobility typically occur (Smith et al. 2017; Loebach and Gilliland 2016b). This article builds upon the argument that a key reason for the considerable heterogeneity in the evidence base linking children's PA and their environments is due to measurement differences in studies (Smith et al. 2021). Measurement differences exist across all aspects of research, including how PA environments are conceptualized (e.g. areas around the home or school environment, administrative units, or individual-centric approaches) and measured (e.g. estimated using geographic information systems [GIS], child or parent reports, or objective monitoring using global positioning systems [GPS]), and what activity behavior is being assessed (e.g. active travel, total PA). Although to date no agreed-upon best practice exists, there are increasing calls for improved sensitivity and specificity in the evidence base by using PA behavior-specific and population-specific measures (Giles-Corti et al. 2009), and individual-centric approaches that might more accurately capture environmental exposures than researcher-estimated environments (Smith et al. 2021).

An ongoing challenge related to the spatial analysis of such association is the Uncertain Geographic Context Problem (UGCoP), whereby estimated neighborhood delineations (and thus exposures generated) may not reflect an individual's actual environmental exposures (Kwan 2012). The use of administrative units as the spatial unit of analysis is an example of such ill-fitting delineations which are increasingly criticized in the literature (Hasanzadeh, Laatikainen, and Kyttä 2018). To tackle the UGCoP issue, modern research favors ego-centric units of analysis such as activity spaces (Sharp and Kimbro 2021). The activity space (AS) concept has been widely used as a measure of individual mobility by researchers from a range of fields. Given their broad application, ASs have been widely used in empirical research to evaluate various aspects of person-environment relationships. Nevertheless, they have rarely been incorporated in studies of children's mobility (Smith et al. 2021). Given the promising performance of AS models in capturing mobility behavior and place exposure in various age groups (Laatikainen, Hasanzadeh, and Kyttä 2018), this study aims to contribute new knowledge to the evidence base by generating children's AS, exploring its characteristics, and evaluating differences in associations between children's ASs and their PA and active travel.

PPGIS methodology including softGIS and VERITAS has been increasingly utilized in studies with children and youth to capture 'individual-centric' environmental exposure (Broberg and Sarjala 2015; Kyttä, Broberg, and Kahila 2012; Stewart et al. 2015; Smith et al. 2021). However, few studies have used PPGIS data to derive measures of AS and environmental exposure with children (Smith et al. 2021). In a study conducted in Helsinki, Finland, Kyttä, Broberg, and Kahila (2012) generated measures for children's places of importance using PPGIS. However, they did not use these places to delineate neighborhood boundaries, instead using a 500 m network buffer around residential locations. According to the authors, this was a major limitation as only 53% of meaningful places marked by children were within this distance from home. Villanueva et al. (2012) used data on places of importance to generate egocentric neighborhood delineations by making a minimum convex polygon from children's home and actively reached local destinations. AS size was associated with confidence to travel independently and sex differences in relationships were observed.

The paucity of literature using PPGIS with children limits any clear comparability with other measurement approaches. A scoping review of associations between children's PA and environments using GIS suggested some common relationships exist across literature using PPGIS, GPS, and GIS; specifically consistent positive relationships were found between children's PA and destination accessibility, street connectivity, and population density (Smith et al. 2022). Considerable differences were also observed; however, it is unclear whether this was due to the measurement approach (i.e. PPGIS vs. other approaches) or the measures assessed, or other differences in study characteristics.

Studies measuring school routes suggest meaningful differences in environmental characteristics captured when using different approaches. Ikeda et al. (2018a) compared children's drawn routes to school using PPGIS with GIS-derived shortest distance to school using both street and pedestrian networks. Findings showed significant differences in numerous built environment attributes using the different route calculation methods, and varying degrees of overlap in areas measured. Similarly, environmental characteristics differed in children's GPS and GIS-derived school routes in the study of Dessing et al. (2016). Of note, differences in findings across measurement approaches have also been observed by children's travel mode (Moran, Eizenberg, and Plaut 2017; Ikeda et al. 2018a; Dessing et al. 2016). One study reported greater accuracy in child-drawn routes to school (Moran, Eizenberg, and Plaut 2017), and another reported a higher confidence in, and likelihood of, completing mapping tasks (Oliver et al. 2016; Ikeda et al. 2018a) in children who actively traveled to school compared with those who were driven.

Motivated by the existing limitation in how children's mobilities including PA and active travel are analyzed and understood in the literature, this study pursued three aims. First, this study took a new analytical approach to model and understand the individualized AS of children in a major urban city using PPGIS data. The PPGIS data were collected from children aged approximately 8–13 years living in Tāmaki Makaurau Auckland, Aotearoa New Zealand (NZ). Second, this study analyzed AS data to capture both the physical and built environment characteristics of the everyday environments and to explore their associations with sociodemographic and PA characteristics of children. This is complemented with additional PA data collected through accelerometers which not only widened the insight, but also facilitated the third aim, which was to evaluate and discuss the effectiveness of accelerometer based and PPGIS/AS-derived measures of activity.

1.1. Activity space as the spatial unit of analysis

AS can be defined as a set of geographical locations that individuals connect with over the course of their everyday life. Buffers of various shapes and radii, and container geometries such as minimum convex polygons and deviational ellipses are some of the best-known examples of AS delineations in research (Hasanzadeh, Broberg, and Kyttä 2017). Over the last decade, advanced AS modeling methods have also captured the purpose, timing, and intensity of an individual's daily travels (D.

Wang, Li, and Chai 2012; Hasanzadeh, Laatikainen, and Kyttä 2018). These approaches are based on the understanding that the spatial units of analysis should be specific to individuals (Hasanzadeh, Broberg, and Kyttä 2017), unlike static buffers which are often uniformly applied to all individuals (Kyttä et al. 2015).

Places and daily movements, or space in general, are heterogonous between individuals and complex in nature, which should be considered in AS modeling (Wei et al. 2018). An example of such methods, the individualized residential exposure model (IREM) was adopted in this study (Hasanzadeh, Laatikainen, and Kyttä 2018). IREM enables delineating and capturing the relevant geographical context for analysis based on exposure values which are estimated based on the unique mobility patterns of an individual. This not only provides a more realistic spatial unit of analysis, but also a more refined picture of an individual's PA and active travel (Hasanzadeh, Laatikainen, and Kyttä 2018). Compared to other advanced AS models such as the context-based Crystal-Growth model (Wang, Kwan, and Chai 2018), IREM provides a good balance of complexity and accuracy which also suits sparse spatial datasets such as those collected through participatory mapping methods (Hasanzadeh, Laatikainen, and Kyttä 2018).

It is worth noting that ASs do not replace spatial data such as GPS but instead can be a product of them. Historically AS has been modeled using a mobile phone (Zhao et al. 2016) and GPS tracking data (Villanueva et al. 2012), but the use of PPGIS for mapping activity spaces and assessing exposure has also been gradually increasing over the past few years (Hasanzadeh 2021). Compared to GPS data in which actual exposure is measured objectively, PPGIS uses a self-report approach to collect and assess spatial and temporal information on an individual's neighborhood exposure. ASs have been used as a spatial unit of analysis to simply serve as a container to carry out environmental measurements in GIS (Ramezani et al. 2019), or more sophisticatedly as proxy measures capturing the levels and extents of active or motorized travel (Hasanzadeh et al. 2019). The application of AS in this study serves both purposes.

2. Methodology

2.1. Data

Data were derived from the Neighborhoods for Active Kids study, which has been described in detail elsewhere (Oliver et al. 2016). A brief overview of the study methods and detail regarding the measures specific to the current study are provided here.

Data were collected through an online mapping survey using softGIS methodology. SoftGIS is a PPGIS method that combines Internet maps with traditional questionnaires (Brown and Kyttä 2014). The result is geocoded qualitative and quantitative data that can be analyzed with GIS.

2.1.1. Participants and setting

Neighborhoods for Active Kids was conducted in Tāmaki Makaurau Auckland in NZ. The overall study aim was to identify relationships between children's health behaviors and their neighborhood environments. Nine intermediate (junior high, years 7–8) schools were selected for invitation based on a matrix of area-level socio-economic status, child-specific destination accessibility (Badland et al. 2015), and child-specific walkability (Giles-Corti et al. 2011). For each intermediate school, a contributing primary (elementary) school in the same neighborhood was also invited to participate. Children in school years 5–8 (approximate ages 8–13 years) were invited with the aim of recruiting approximately 65 children across each neighborhood. Participation required informed consent from the school principal and a parent/caregiver, and assent from the child. Ethical approval to conduct the research was provided by the host institution ethics committees (AUTEC 14/263 3/9/2014, MUHECN 3/9/2014, UAHPEC-019985 9/9/2014).

2.1.2. Protocol

Data were collected at schools, during school time. Trained researchers worked individually with each participant to complete the study protocol, which included fitting of an accelerometer and instructions on wearing the device; measurement of height, weight, and waist circumference; and completion of an online PPGIS survey. Parents/caregivers completed a computer-aided telephone interview (CATI) with trained CATI researchers.

2.1.3. Measures

Spatial information was retrieved from the neighborhood mapping component within the PPGIS survey. Spatial locations of each destination marked for each individual were extracted and used together with travel behavior information to generate the AS measurements (described in 2.2).

Travel behavior was assessed in two ways. Firstly, children were asked to self-report their usual mode of travel to school in the online PPGIS survey with the item '*How do you usually get to school?' Response options were:* walk; bike; scooter (non-motorized); public bus, train or ferry; car, motorbike, scooter or taxi; or another way (e.g. skateboard). Walking, biking, skateboard, or non-motorized scooter was categorized as 'Active Travel to School.' Secondly, children completed a neighborhood mapping exercise in the PPGIS survey where they were asked to mark the places (other than their school) in and around their neighborhood that they go to. For each destination marked, children were also asked to indicate the usual mode of travel to that destination. 'Active travel to destinations' was defined as usually walking, biking, or scootering (non-motorized) to the marked destination.

Physical activity was measured using Actigraph GT3X+ accelerometers worn on a belt at the waist during waking hours for seven consecutive days (excluding water-based activities) (Jarrett, Fitzgerald, and Routen 2015). Specifications included a 30 Hz sampling rate and all download options marked. Evenson et al. (2008) count thresholds were used to determine PA intensity; blocks of ≥60 min of consecutive zero counts were considered non-wear time (Oliver et al. 2011); thereafter, participants with at least three days of data with at least seven hours of data on each day were included in analyses (Mattocks et al. 2008). Variables used for the current study were number of steps and proportion of wear time spent in moderate-to-vigorous physical activity (MVPA).

Socio-demographic information was captured from the parent/caregiver CATI and included child's ethnicity (categorized as Māori, Pacific, New Zealand European/Pākehā, Asian, Middle Eastern/Latin American/African [MELAA], or 'other') (Statistics New Zealand 2005), sex of child (female/male), school year, parent/caregiver current employment situation (generalized to unemployed, part-time or casual work, and full-time employment) and parent/caregiver highest educational qualification (finished primary school, finished high school, University Entrance/Bursary/Scholarship (or equivalent), Apprenticeship, diploma, or trade certificate, Bachelor degree or higher). Both the education and employment measures were treated as ordinal values in the analysis.

Weather information (daily precipitation, hours of daylight, minimum and maximum temperature) was downloaded from the New Zealand meteorological service (cliflo.niwa.co.nz). Daily weather data were matched for each individual to their days of PA measurement. Given the weather conditions at the time of year when data were collected, models were adjusted for average minimum temperature and average rainfall to account for possible effects on the level of activity.

2.2. AS measurements

ASs were modeled using an individualized exposure-based model (Hasanzadeh, Laatikainen, and Kyttä 2018). In this model, exposures are estimated based on everyday locations (i.e. home and destinations), travel routes, modes, and frequency (Hasanzadeh, Laatikainen, and Kyttä 2018). According to this model, an AS comprising frequent travels made using active travel modes has higher exposure than an AS comprising fewer travels driven by motorized travel modes. The modeling was done using a python script (Hasanzadeh 2018). When actual travel route data were available, they were used in the modeling. In other cases, the travel route was estimated using the shortest path based on the indicated travel mode and using Open Street Map route data (2020). For ease of analysis, areas of high exposure were extracted and delineated from the raster files based on the median of individual exposure values (Laatikainen, Hasanzadeh, and Kyttä 2018). This is referred to as the AS throughout this study. An example of the AS model created for an individual and more details on the modeling process are provided in the Appendix.

Space and environmental exposure variables adopted from previous studies were calculated for each AS (Table 1). Additionally, the AS polygons were used as the spatial unit of analysis to calculate the built environment measures. All GIS analyses in this paper were conducted using python scripts and ArcGIS Pro 2.5.

2.3. Statistical analysis

The associations of AS and environmental exposure measures with built environment measures, sociodemographic characteristics, and travel behavior (including neighborhood destinations and travel to school) were investigated using six hierarchical linear models with random effects at school level. Similarly, the associations between PA variables and AS, built environment, and sociodemographic characteristics were explored using four hierarchical linear models with random effects at three levels: neighborhood, school, and day of data collection (weekday vs weekend). The PA models were additionally controlled for weather conditions using data on average rainfall and average minimum temperature at the time of data collection. A significance level was set at .05. All statistical analyses in this study were conducted with IBM SPSS 27. For all models, multicollinearity was assessed using the variance inflation factor (VIF) and tolerance values.

3. Results

3.1. Participants

In total, 1102 children participated in the study. The geographical distribution of home locations in the study area as well as the detailed characteristics of participants are provided as supplementary materials.

3.2. Associations of AS and exposure with built environment, sociodemographic characteristics, and travel behavior

Table 2 presents the results from the six hierarchical linear models, each made for one of the AS measures.

A higher population density was associated with a more compact and less intense activity space, i.e. generally smaller and with lower exposure. In other words, children living in densely populated areas were more likely to do most of their activities around their home and have a smaller average exposure to their everyday environment. At the same time, a higher availability of green spaces in the AS was associated with increased total exposure.

A higher density of cycling routes was associated with an increase in the overall extents of mobility. Children whose ASs demonstrated a dense cycling network were more likely to have polycentric activity spaces and travel further from home. In contrast, intersection density was negatively associated with the AS variables related to the extent and dispersion. ASs located in areas with a high density of intersections in the street network were more likely to be compact and monocentric.

Children who more frequently used walking to reach their daily destinations were more likely to have a compact AS. In contrast, high car usage as the travel mode was associated with larger, more

Table 1. AS based variables used in the study.

	Variable	Measurement method	Data*	Description
Space and environmental exposure	Area	Geometric measurement (m^2)	–	Captures the overall geographical extent of AS. (Kyttä et al. 2018)
	Total exposure	Measured as the sum of all pixel values from the exposure raster.	–	Captures the overall extent and magnitude of the AS. (Hasanzadeh, Laatikainen, and Kyttä 2018)
	Average exposure	Measured as the average of all pixel values from the exposure raster.	–	Captures the intensity of AS derived from active travel and frequency of travel. (Hasanzadeh, Laatikainen, and Kyttä 2018)
	Elongation	Measured as the length to width ratio of the smallest rectangle enclosing the activity space polygon.	–	Indicates the overall shape of the activity space. A highly elongated activity space may indicate a specialized activity space targeted at a certain location compared to a more balanced and diversely distributed AS resulting in lower elongation (Hasanzadeh, Laatikainen, and Kyttä 2018; Lord, Joerin, and Thériault 2009).
	Centricity	Counting the number of activity clusters yielded from a spatial cluster analysis and categorizing accordingly (Monocentric: one cluster around home; Bicentric: A second cluster beyond home surrounding; Polycentric: two or more activity clusters beyond home surrounding).	–	A high value for centricity indicates a highly polycentric AS whereas a low value indicates a monocentric AS concentrated around the individual's home. (Hasanzadeh 2019)
	Area of minimum convex polygon (MCP)	The area of the minimum convex polygon containing all activity locations was measured in m^2.	–	Captures the geographic extent of an individual's full action space.
Built environments	Greenspace	Measuring the percent of AS area that is in greenspace.	OSM land use data	Captures the percentage of the area that is green.
	LUM	The formula used to calculate the LUM was modified from the formula used by Frank et al. (2005):$H = -1\left(\sum_{i=1}^{n} pi * \ln(pi)\right) / \ln(n)$, where H is the LUM score, *pi* is the proportion of land use *i* among all land-use classes, and *n* is the number of land-use types.	OSM land use data	Higher mix of land use generally indicates a higher versatility and variety of destinations within the AS (Sallis et al. 2016). Included land use types: religious, commercial, entertainment, green, sport, transportation, services, education
	Intersection density	Average number of intersections per km^2	Land Information New Zealand	Widely used as an indicator of street connectivity.
	Cycling routes density	Average length of cycling routes per km^2	Auckland Transport Open GIS Data	Widely used as an indicator of cycling infrastructure availability.
	Population density	Average number of residents per km^2	Stats NZ	Population density is widely used in studies as a key characteristic of the built environment.

*other than data collected in the study.
AS = activity space, GIS = geographic information system.

Table 2. HLM results – AS.

		Area of AS (IREM) β (95% CI)	Area of MCP β (95% CI)	Elongation β (95% CI)	Polycentricity β (95% CI)	Average exposure β (95% CI)	Total exposure β (95% CI)
Built environment measures	Population density	−1.19 (−9.1, 1.3)	−0.64 (−3.9, 0.9)	−1.09 (−2.7, 3.1)	−1.79* (−2.1, 1.9)	−1.74* (−2.0, 7.9)	−1.02 (−7.3, 3.3)
	Greenspace (%)	1.33 (−3.7, 2.0)	0.93 (−1.2, 3.7)	1.03 (-.7, 2.1)	1.04 (−.1, 1.9)	1.55 (−.0, 1.9)	1.99** (0.4, 5.4)
	Cycling routes density	2.98 (1.2, 8.3)	2.63** (0.2, 5.7)	3.07** (1.9, 7.4)	4.51** (2.2, 11.3)	−1.02 (−4.7, 2.1)	1.85* (−5.3, 2.9)
	Land use mix	4.59** (1.7, 6.7)	2.36* (0.1, 2.7)	6.4** (4.3, 7.6)	4.7** (3.2, 6.1)	0.94 (−1.0, 1.23)	4.83** (1.4, 8.3)
	Intersection density	−3.96** (−8.4, −1.1)	−2.63** (−4.2, −1.3)	1.12 (-.5, 2.6)	−2.73** (−7.1, −1.1)	0.16 (−.0, .9)	−4.07** (−10.0, 3.5)
Travel behavior	Walking	−3.59** (−7.7, −1.0)	−3.49** (−6.7, −2.4)	−3.89** (−4.9, −1.1)	−4.52** (−7.2, −3.5)	13.46** (7.1, 18.3)	−2.39** (−3.3, .3)
	Cycling	−0.66 (−2.2, 1.7)	−1.98* (−3.7, −0.4)	−0.35 (−.9, 1.2)	−3.74** (−8.7, −1.5)	−0.35 (−.5, 1.1)	−0.48 (−2.5, 1.5)
	Car	4.24** (1.9, 9.9)	5.79** (3.1, 9.2)	4.13** (2.9, 6.9)	8.90** (2.8, 15.5)	−12.36** (−17.7, −4.9)	2.87*** (.7, 3.9)
Sociodemographic characteristics (H: Household -maternal)	Employment (H)	0.78 (−1.1, 1.8)	−0.08 (−1.2,1.7)	0.51 (−1.3, 1.7)	−2.8 (−4.2, 1.2)	1.54 (−.7, 3.9)	1.88* (−.1, 4.1)
	Education level (H)	0.72 (−.5, 1.7)	.57 (−1.1, 1.9)	−1.92* (−2.9, .6)	−1.70* (−3.2, .4)	0.78 (−2.7, 5.9)	0.69 (−2.1, 2.2)
	Gender (vs. female)	−0.06 (−1.3, 2.2)	−1.55 (−2.6, 2.1)	−1.77* (−2.3, 1.2)	1.23 (−3.4, 3.2)	0.65 (−.7, 1.1)	−0.06 (−16.8, 14.9)
	School year	4.90** (1.9, 9.1)	2.74** (1.6, 5.1)	5.45** (3.5, 7.1)	3.91** (2.9, 5.1)	4.88** (3.2, 6.1)	6.72** (3.1, 8.6)
	Ethnicity (vs. NZ European)						
	Maori	−0.23 (−2.2, 3.1)	−1.28 (−3.1, 1.7)	0.22 (−.9, .6)	−1.34 (−2.2, 3.7)	1.49 (−.5, 1.6)	0.39 (−1.1, 2.7)
	Pacific people	−0.49 (−3.2, 4.1)	−1.52 (−3.3, 2.8)	1.12 (−1.9, 1.8)	−1.58 (−3.2, 2.6)	2.30* (.5, 3.8)	0.19 (−.1, .7)
	Asian	0.63 (−1.2, 3.3)	−.42 (−4.2, 3.1)	3.69** (1.0, 5.2)	−2.24* (−2.9, −.6)	1.34 (−.7, 2.2)	1.18 (−2.3, 3.7)
	MELAA	1.11 (−1.7, 5.7)	1.89 (−5.1, 2.7)	0.08 (−1.0, 1.1)	0.27 (−.4, .5)	−0.45 (−.9, 2.1)	0.45 (−5.1, 2.9)
	Other	−0.25 (−4.2, .8)	−0.51 (−2.0, 0.7)	−0.55 (−2.5, .5)	−1.18 (−2.4, 1.5)	1.47 (−.2, 3.6)	−0.05 (−1.8, 4.7)

* Significant at $p < 0.05$.
** Significant at $p < 0.01$.
Note: There is no multicollinearity between variables ($VIF_{max} =$ 3.436, Tolerance < 1).

polycentric AS. Children who more often used bicycle as their mode of transport were more likely to have monocentric activity spaces.

3.3. Associations of PA and active travel with AS and sociodemographic characteristics

Table 3 presents the results from the four hierarchical linear models, each made for one of the PA measures.

Population density was negatively associated with all PA measures suggesting that children in denser areas were generally less active. The amount of green areas within the AS was positively associated with number of steps and MVPA, but negatively associated with the use of active travel modes to reach destinations. In areas with a higher density of cycling routes, children were more likely to use walking and cycling as their mode of travel and have a higher MVPA. LUM was positively associated with higher use of active travel modes.

There were also statistically significant associations between the PA measures and some of the socio-demographic variables. For example, being older was associated with higher step counts and being male was positively associated with all three PA measures. Additionally, compared to the NZ European ethnic group, being of Asian or Māori ethnicity was associated with being less active according to some of the measures. Being of Māori ethnicity was associated with less active travel to school. Similarly, being of Asian ethnicity was negatively associated with MVPA and share of active travel to school.

4. Discussion

4.1. Individualized ASs for studying children's mobility and PA

In this study, we used an exposure-based AS model, namely IREM (Hasanzadeh, Laatikainen, and Kyttä 2018) to model and analyze the individual activity and travel behavior of children. As reviewed in an earlier study (Smith et al. 2021), such approaches have been rare in children's PA studies leaving research gaps in how we conceptualize, operationalize, and scrutinize children's ASs.

Using the individual AS models, we made two sets of GIS measurements which enabled the statistical analysis conducted in the following step pursuing the second objective of this study. The first set of measurements focused on the space and environmental exposure of individuals. The measures in this category enabled us to capture the extent and magnitude of mobility in a quantitative and individually sensitive way. The second set of measures focused on the physical and environmental characteristics of the children's everyday environments. Based on evidence from previous studies (Laatikainen, Hasanzadeh, and Kyttä 2018; Kwan 2012), the use of an individualized AS model for this purpose helped mitigate the effects of UGCoP in the analysis.

4.2. ASs and associations with personal and environmental characteristics

Results showed that population density had an inverse association with 'how active' the AS is. In other words, in more densely populated areas children generally had less exposure to their environment. That could be the result of less frequent travels and/or higher use of motorized travel modes. This pattern was even more consistent in the second set of hierarchical linear models where activity measures were used as the outcome variable. This somewhat counterintuitive negative relationship was also reported in an earlier study (Ikeda et al. 2018b). Exploratory work by Ikeda et al. (2018b) showed that a possible level of interaction between dwelling density and distance to school, with a combination of lower housing density and shorter distance to schools, is linked with active travel to school.

At the same time, the amount of greenspace was almost consistently positively associated with different activity measures. Individuals with higher amounts of greenspace available within their AS generally had higher MVPA, number of steps, and total amount of environmental exposure. This is

Table 3. HLM results – PA.

Category		MVPA (%) β (95% CI)	Steps β (95% CI)	Active travel to school β (95% CI)	Active travel to destinations β (95% CI)
Activity space measures	Population density	−3.10** (−6.3, −2.1)	−2.63** (−6.1, −1.2)	−3.9** (−4.1, −3.3)	1.8 (−0.9, 3.2)
	Greenspace (%)	2.18* (1.7, 4.3)	1.72* (−1.0, 5.3)	−2.8** (−3.3, −1.8)	1.1 (−2.9, −1.1)
	Cycling routes	2.20* (−.5, 4.5)	1.15 (−0.1, 1.5)	3.4** (2.0, 5.3)	2.69** (1.7, 6.9)
	LUM	−0.20 (−.4, .4)	−1.30 (−7.3, 5.6)	2.99** (2.1, 6.1)	−4.55** (−7.3, −2.2)
	Intersection density	1.20 (−1.2, 1.4)	−1.53 (−15.0, 2.6)	0.50 (−1.0, 2.3)	1.7* (0.5, 3.8)
	Elongation	0.76 (−.5, 2.5)	−1.14 (−7.3, 3.5)	−4.17** (−4.9, −3.6)	−2.6** (−3.9, −.5)
	Area	−1.15 (−2.8, 7.4)	−.31 (−.5, .5)	−4.13** (−5.4, −3.3)	−4.1 (−7.7, −3.1)
	Polycentricity	0.86 (−.39, 1.0)	0.29 (−.12.1, 13.3)	−1.67* (−2.1, 3.3)	−7.80** (−12.3, 1.1)
	Average exposure	4.06** (1.2, 7.3)	2.89** (1.2, 4.7)	1.95 (−0.0, 2.0)	12.26** (2.5, 15.7)
Sociodemographic characteristics (H: Household -maternal)	Employment (H)	0.15 (−.3, .6)	1.31 (−10.4, 11.2)	−1.11 (−2.0, 1.7)	1.5 (−2.1, 2.3)
	Education level (H)	−0.21 (−.3, −.7)	−0.99 (−5.9,1.3)	−0.05 (−.1, .06)	−2.84** (−3.3, 2.7)
	Gender (vs. female)	4.95** (3.1, 5.6)	5.43** (2.6, 6.7)	3.32** (2.1, 4.6)	1.0 (−1.1,3.4)
	School year	0.11 (−0.2, 0.4)	2.76** (0.5, 3.2)	−0.85 (−1.0, 1.2)	5.2** (−2.3, 2.4)
	Ethnicity (vs. NZ European)				
	Maori	0.33 (−.9, 1.2)	0.80 (−.3, 1.3)	−1.68* (−3.0, 2.3)	−0.3 (−1.1, .6)
	Pacific people	−0.55 (−1.3, .7)	0.97 (−1.3, 1.0)	−0.22 (−.7, 1.9)	−0.7 (−2.1, 1.6)
	Asian	−2.16* (−2.7, 5.7)	−1.54 (−2.2, 1.3)	−1.7* (−1.9, 3.3)	−0.4 (−1.2, .6)
	MELAA	−1.1 (−4.9, .32)	0.05 (−.3, 1.7)	−1.37 (−2.0, .7)	−1.3 (−2.1, 1.6)
	Other	0.25 (−4.1, 6.9)	0.34 (−2.3, .5)	0.50 (−.7, 1.1)	−0.3 (−2.1, 1.1)

Note: There is no multicollinearity between variables ($VIF_{max} = 3.007$, Tolerance < 1).

in line with previous studies reporting associations between green areas and PA (Ward et al. 2016; Benjamin-Neelon et al. 2019). Conversely, the amount of greenspace was negatively associated with the share of use of active travel for reaching school. This can be due to an increased sense of unsafety which has previously been shown to impede active travel among children (Smith et al. 2020b). Further, this contrast may be attributable to how children accumulate their activity. While the overall activity can include play, sports, or walking and cycling for leisure, active travel is specific to walking and cycling between destinations. It is worth noting that this negative association contradicts most of the findings from studies of adults (Ramezani et al. 2019). This may suggest significant differences on how exposure to similar built environment characteristics can affect children compared with other age groups. Children, especially those who are transported by their parents (Herrador-Colmenero, Villa-González, and Chillón 2017), might have less autonomy over travel routes and hence factors such as esthetics may have less impact on children's choice of route. Understanding such mechanisms may significantly deepen our understanding of travel behavior in children. This demonstrates the importance of conducting child-specific research rather than extrapolating adult findings to children.

The density of cycling routes available within the AS was positively associated with PA and active travel. This is consistent with previous findings that a better availability of cycling infrastructure is associated with increased PA and active travel (Pan et al. 2021; Ramezani et al. 2021). At the same time, density of cycling routes was positively associated with polycentricity and elongation of ASs. This is interestingly in contrast with what we would expect from adults as a better availability of cycling routes may encourage higher use of active travel modes and hence result in a more compact activity space (Ramezani et al. 2021). Among children, a better availability of cycling routes may increase accessibility and increase the geographical extents of active travel.

It is noteworthy that the prevalence of children cycling in New Zealand is low (i.e. six percent based on the New Zealand Household Travel Survey) (Smith et al. 2019b). Moreover, the availability of child-friendly cycling infrastructure was extremely low across Auckland at the time of data collection. Earlier examinations in the Neighborhoods for Active Kids study revealed parental license for independent mobility was negatively associated with cycling infrastructure and positively associated with parent-reported need for safer places to cycle (Smith et al. 2019a). Hypotheses for these somewhat counterintuitive findings were that parents who allow their children greater independence also have a greater awareness of their traffic environments, and a preference for allowing walking more than cycling in children due to inadequate infrastructure. The results suggest that a large polycentric AS can result from increased active mobility opportunities for children, but also can be driven by motorized travel. Hence, measures of AS dispersion alone cannot yield conclusive results regarding active travel in children.

There were associations between the physical structure of ASs and some of the built environment and PA variables. Intersection density was found to be positively associated with active travel to destinations. This is consistent with previous research (Ikeda et al. 2018b; Jia et al. 2021b), solidifying the case for the important role of connected streets in supporting resident active travel behaviors in the neighborhoods. In more densely populated areas with a higher density of intersections, children's ASs were more monocentric, meaning that destinations were concentrated around a fewer number of clusters. This is in line with a number of empirical studies from various age groups reporting the presence of more compact ASs in areas of higher density largely due to the fact that points of interest and amenities are generally located closer to individuals' homes (Hasanzadeh et al. 2021). Given that monocentricity of AS was associated with more active travel, this may be interpreted as a desirable outcome of urban planning ideals, such as a compact or walkable city (Ramezani et al. 2021). At the same time, LUM was positively associated with polycentricity. This could mean that a more diverse land use was associated with a more geographically diverse AS among the participants.

LUM was positively associated with most of the AS and activity measures. This suggests that ASs located in areas with more land-use diversity, and therefore more diverse destination possibilities, generally comprise more frequent and more active travel. This is in line with many previous studies reporting a positive link between LUM and children's PA level (Jia et al. 2021a). Nevertheless, similar to what is seen in the literature (Jia et al. 2021a), the associations found with LUM were not consistent across all PA measures. According to our results, while LUM was positively associated with active travel to school, a negative association emerged with active travel to destinations. Neighborhoods with land-use diversity in which people perform various activities are likely to facilitate safety and opportunities for children to be active, and facilitate social interactions (Smith et al. 2019a; Bahadure 2012). A previous New Zealand study showed that children (aged 8–13 years) of parents who perceived their neighborhood as more cohesive and connected had higher levels of independent mobility (Lin et al. 2017), which is positively associated with children's active travel and PA (Marzi, Demetriou, and Reimers 2018). It is worth mentioning that the observed discrepancy can be due to measurement differences in both the activities and the LUM itself. As previously reported in a number of studies, the way LUM is measured can affect the findings (Mavoa et al. 2018; Song, Merlin, and Rodriguez 2013; Duncan et al. 2010).

Among the sociodemographic variables, gender and age seem to be most relevant to PA and are consistent with previous research (Smith et al. 2018). Potential ethnic inequities also exist, with New Zealand Europeans having higher PA and active travel than other ethnic groups.

4.3. Measurement methods and potential effects on results

Results show that different measures of activity derived from PPGIS and AS models or accelerometer data may affect findings. While generally congruent, the associations yielded from different sets of activity measures were not always consistent. For example, active travel as measured directly from the survey ('to school') or retrieved from travels mapped in the survey ('to destinations') revealed considerably different and even contrasting associations. LUM revealed strong and positive associations with activity measures derived from ASs whereas its associations with accelerometer-measured MVPA were statistically insignificant. Further, the AS measure of the average exposure was positively associated with accelerometer-measured steps and MVPA but did not always result in the same kind of associations with other variables.

There are two ways to interpret such discrepancies: the differences may be originated from measurement biases and inaccuracies, or different measures may be capturing different things. We suggest it can be both. Active travel and PA are related concepts, but they are not the same. Additionally, active travel and PA have different aspects which may be captured through different measures (Laatikainen, Hasanzadeh, and Kyttä 2018). Thus, differences in results may not necessarily be due to inconsistency or inaccuracy but it could merely be because they are capturing different aspects of the same phenomenon or some closely related phenomena (Davis et al. 2021). Nevertheless, these findings warrant further investigation. In the meantime, it is important to acknowledge that our findings can be impacted by the choice of data and measurement of variables.

4.4. Contributions, limitations, and future study

This study took a fresh methodological approach to study the PA and active travel as well as their personal and environmental associates among children aged 8–13 years living in Tāmaki Makaurau/Auckland. To the authors' best of knowledge, this was a first example of how an exposure-based AS model can be used to study PA in this age group. As discussed above, the combination of AS analysis and accelerometer data led to empirical findings shedding new light on the complicated associations between the physical environment and the PA and relevance of active travel in this age group and study area. Further, by taking this dual approach this study tried to draw scholarly attention to the impacts of data and measurement choices on empirical findings by discussing the results in light of two different analytical methods. However, this is a one-case observation and a more conclusive result would require a more systematic and comprehensive approach.

There are also other limitations in this study that need to be discussed and addressed in future research. Firstly, and most importantly, this study used cross-sectional data, meaning that the causality of relationships might not be confidently determined. Further, as a common limitation of all data collected through map-based surveys including PPGIS, individual differences in engagement in mapping among participants as well as differences in their level of mapping skills, may have introduced some biases to the study (Brown 2016). Additionally, self-reported bias, social desirability bias, and recall bias are particularly relevant to this data collection method. While involving children in determining neighborhood environment measures through mapping activities can be time-consuming and susceptible to self-report errors (Stewart et al. 2017), these approaches can provide detailed insights in ways that estimated measures cannot (Smith et al. 2021). There is a need to advance these techniques and the evidence base through considering relative importance and role of key destinations in children's lives.

To our knowledge, this was the first study to employ PPGIS with children as young as eight years old. Accordingly, the protocol was pilot tested with a class of children prior to field implementation. A number of adaptations were made to the protocol including the need for one-to-one assistance with the PPGIS survey completion (Oliver et al. 2016). Accordingly, these potential biases may have been mitigated through in-depth researcher support. There are also limitations related to the AS modeling implemented in this study. The model used in this study does not consider the temporal aspect of mobility. The absence of the temporal aspect from the model is largely due to the data constraints. To this point, time has not been successfully integrated with PPGIS data (Hasanzadeh 2021; Fagerholm et al. 2021).

Additional research in diverse populations is essential to move the field forward, alongside longitudinal approaches to determine causality, and with clear reporting of methods to improve the evidence base (e.g. using the ISLE-REST statement (Jia et al. 2020). Improved confidence in the measures generated could be achieved through simultaneous use of GPS, accelerometry, and PPGIS. Approaches that have not yet been explored include having participants cross-check/validate generated ASs. This could be achieved through providing generated ASs and bringing them back to participants. As spatial modeling approaches and technology advances, ASs could be generated in real time during the PPGIS mapping process, enabling children to cross-check/validate maps during the data collection process.

Acknowledgements

KH is supported by Academy of Finland as part of PLANhealth Project (13297753). KH would also like to acknowledge FinEst (H2020 grant 856602) for supporting this study. SM was supported by an Australian National Health and Medical Research Council Early Career Fellowship (#1121035) and a University of Melbourne Faculty of Medicine, Dentistry and Health Sciences Research Fellowship. EI is supported by the Medical Research Council [MC_UU_12015/7, MC_UU_00006/5]. MS is supported by a Health Research Council of New Zealand Sir Charles Hercus Research Fellowship (Grant number 17/013). Neighbourhoods for Active Kids was funded by the Health Research Council of New Zealand (grant number 14/436). Authors would like to acknowledge prof. Marketta Kyttä her contribution to this research.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work was supported by Academy of Finland [grant number 13297753]; Economic and Social Research Council; Health Research Council of New Zealand [grant number 14/436,17/013]; Medical Research Council (MRC) International Centre for Genomic Medicine in Neuromuscular Disease [grant number MC_UU_12015/7, MC_UU_00006/5]; National Institute for Health Research; University of Melbourne Faculty of Medicine, Dentistry and Health Sciences Research Fellowship; Australian National Health and Medical Research Council Early Career Fellowship [grant number 1121035]; Wellcome Trust.

ORCID

Erika Ikeda http://orcid.org/0000-0001-6999-3918
Kamyar Hasanzadeh http://orcid.org/0000-0002-0705-7662
Suzanne Mavoa http://orcid.org/0000-0002-6071-2988
Melody Smith http://orcid.org/0000-0002-0987-2564

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Appendix: Activity space modeling

The exposure-based model was created using the following steps:

Step 1: The initial extent of activity space was defined using a convex polygon enclosing home location, activity places, and routes.

Step 2: Where actual routes were not present in the data for an individual, shortest path between each participant's home location and destination was estimated using network analysis while considering the reported mode of transportation in the survey.

Step 3: In this step the place exposures were estimated. To quantify the level of exposure, weights were assigned to each feature (home, activity point, and travel route). The weights for point features were calculated in terms of frequency of visit per month. A weight for each path was determined by its frequency of use and the used travel mode. This was operationalized as the geometric mean of destination and origin weights divided by the ratio of transportation mode's speed to walking speed. The average speed for each transportation mode was obtained from local transportation authorities. It should be noted that the transit timetables were not considered in calculation of transportation mode speeds.

Step 4: Areas of high exposure were extracted from overall activity space and used as the main activity space used in this study. High exposure areas delineated from the raster files based on the median of individual exposure values for each individual (high exposure: exposure in pixel > median of exposure in all pixels for the individual).

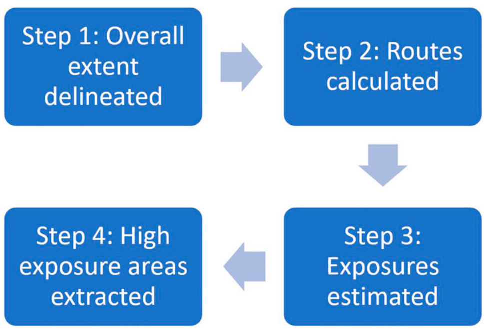

Figure A1. AS modeling process.

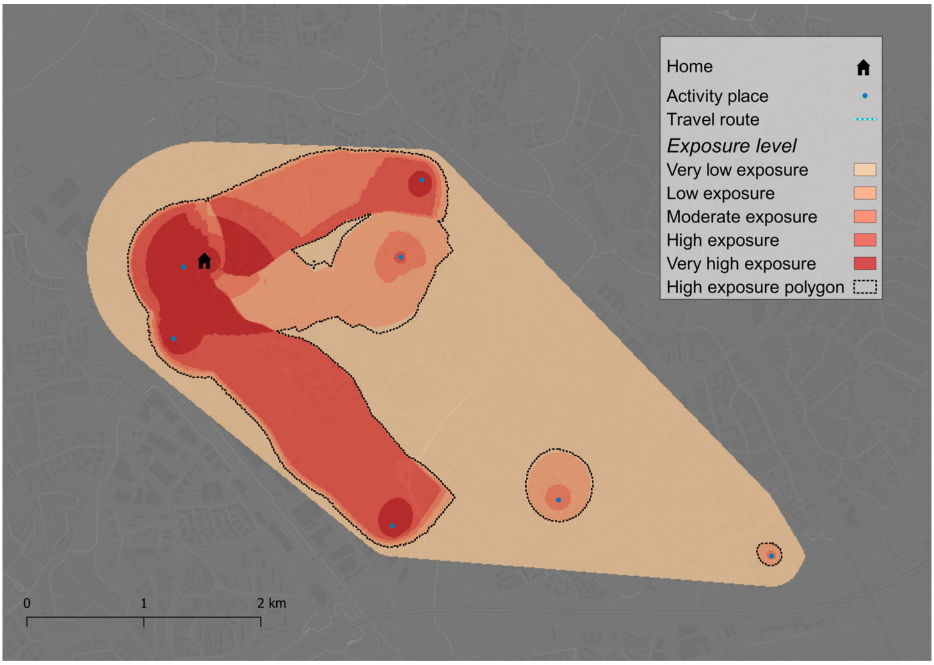

Figure A2. An exemplary individual AS modeled by IREM (Hasanzadeh, Laatikainen, and Kyttä 2018; Laatikainen, Hasanzadeh, and Kyttä 2018).