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Evaluating the effects of active morning commutes on students' overall daily walking activity in Singapore: Do walkers walk more?

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ABSTRACT

Walking has multiple health benefits. One way to increase students' walking activity is by encouraging active morning commutes. However, students may compensate for active commutes by walking less throughout the day, rendering such initiatives ineffective in increasing overall walking activity. This study aims to assess how morning commuting modes affect students' walking levels, hypothesizing that gains in walking from active morning commutes may not be sustained throughout the day due to compensatory behavior. Our study analyzed objectively measured, sensor-collected data of 5600 children (ages 7 to 18) in Singapore for up to four consecutive weekdays between September and November 2015. Potential confounders of age, socioeconomic status, and built environment characteristics, as well as home-school distance as an effect modifier, were examined. We used linear mixed effects models to analyze differences in step count between students with different morning modes, as well as to analyze 'within students' variations when students switched between different modes over different days.

Students who walked or took public transport walked more than their driven peers during morning commuting hours, by 96.1 steps per hour (95% CI = 71.5, 120.8) and 54.1 steps per hour (95% CI = 32.2, 75.9) respectively. Students who switched morning commute modes from car to public transport took 47.6 more morning steps per hour (95% CI = 10.3, 84.9) when using public transport, compared to when driven. However, the relationship between morning travel modes and step count per hour across the full day was less clear-cut. Both our 'between students' and 'within students' analyses suggest that taking more active morning modes, after controlling for all possible confounders and modifers, was not associated with higher step counts over the entire day. Encouraging students to walk more through more active morning commutes alone may have limited effectiveness in increasing overall daily walking activity.

1. Introduction

Programs such as 'Safe Routes to Schools', 'Walk Safely to School Day' and 'Walking School Bus', which collectively seek to encourage students to adopt active commutes, such as walking or cycling to school, have been initiated in different countries in recent years (Chillón et al., 2011). Advocates of such initiatives see active commutes as a way to boost children's physical activity, which is associated with multiple positive health benefits including lowering risk of depression and anxiety, and improving skeletal and cardiovascular health (Janssen and LeBlanc, 2010; Strong et al., 2005). Physical activity has also been associated with improved academic performance (Rasberry et al., 2011). Active modes, compared to driving, also produce less local and global air pollutants (Rabl and de Nazelle, 2012).

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Both health and transport literatures, however, suggest that the total amount of walking activity one does may be bounded by a set-point. The ‘activitystat’ model posits that when an individual increases physical activity or energy expenditure in one domain, there is a compensatory change in another domain to maintain an overall stable level of physical activity or energy expenditure (Rowland, 1998; Gomersall et al., 2016). A 2012 meta-review of 30 studies on interventions to boost physical activity found strong evidence that physical activity interventions had only small effects on children's overall activity levels. One explanation for why physical activity interventions proved ineffective was that children compensated for imposed increased activity (Metcalf et al., 2012). Relatively few empirical studies have examined activity compensation in children, and findings from these have been mixed. One study found that students from one school with extensive sporting facilities and more hours of scheduled physical education a week were no more physically active than were students from another with much fewer physical education hours. The study thus concluded that students compensated for school physical activity when out of school (Mallam et al., 2003). Other studies however found no evidence of compensation (Dale et al., 2000; Goodman et al., 2011).

In the transport literature, several empirical studies suggest the existence of a ‘walking budget’, whereby individuals trade off leisure walking or other forms of activity with utilitarian walking (Oakes et al., 2007; Rodríguez et al., 2006; Krizek, Handy and Forsyth, 2009). Studies of active school commuting initiatives, however, generally do not reflect evidence of a walking budget or compensatory behavior. Literature reviews focused on active school travel and physical activity conclude that a preponderance of evidence supports associations between active school transport and more moderate-vigorous physical activity over the course of the day (Larouche et al., 2014; Faulkner et al., 2009). However, several studies have also found no gains in physical activity from active commutes to school. A recent study of Australian school children found that active travel modes to school were not associated with children's physical activity, though active travel to non-school destinations had a positive impact on increasing activity (Schoeppe et al., 2015). Research has also examined compensatory behavior in specific sub-groups of students. A 2017 study of 700 Canadian school-children found that the students who spent most time participating in sports were also the ones who spent the most time taking inactive modes of transport, compared to other groups of students, which suggests some degree of trade-off between travel and sporting activities (Mitra et al., 2017).

1.1. The current study

While research on active school travel often focuses on moderate-vigorous physical activity as a study outcome, this study focused on students’ walking activity largely because of the data collection method. The organizers who designed and administered the data collection (see next section of this paper for details) instructed students not to carry their devices during vigorous activity, such as when playing sports. In this case, the data collection method conditioned our particular focus.

Past studies on school commutes and physical activity have largely focused on walking or cycling initiatives. However, commuting via public transport can also boost activity levels, as the need to walk or cycle at each end of a trip generates additional steps (Rissel et al., 2013; Sener et al., 2016). Our study thus examined the relationship between three modes of morning commuting: walking, taking public transport, and being driven – and overall walking activity of school-going children.

Furthermore, most of the studies on active school commutes were conducted in North American, Europe, Australia and New Zealand, with only few studies based in Asia. Our study sought to increase knowledge in this part of the world, by examining active school commutes in Singapore, a high-density Asian city-state.

Our analysis focused on morning travel mode, as initiatives encouraging active morning commutes are more straight-forward compared to those seeking to influence after-school travel, for several reasons. Morning commutes are more constrained, routine and predictable, as they happen within a narrower window of time and subset of possible travel routes, compared to after-school travel that is less restricted to between school and home. These ‘constraints’ allow schools to more easily organize programs such as collective walking from home to school, or even from nearby public transport stops to school, especially for younger students who may need adult supervision. Furthermore, compared to after-school commutes, morning commutes are more likely to be by car, as working parents are more available to drive their children to school before work than in the afternoon (Wong et al., 2011, Faulkner et al., 2010). Encouraging active morning commutes as a policy intervention would thus have a greater scope for change here.

While this study's primary focus was on morning school commutes, we also controlled for the effect of students’ afternoon travel modes, as students who walked to school may have been more likely to walk home after school. Any net positive differences in step counts observed from those who walked to school in the morning may thus partially result from afternoon mode choices as well.

In addition to afternoon mode, we also controlled for other factors that could affect students’ choice of morning mode and their overall walking activity. Specifically, we controlled for age, because older children tend to walk less than younger children (Barreira et al., 2015; Tudor-Locke et al., 2011) and are less likely be driven to school (Mitra and Buliung, 2015). Another factor we controlled for was socioeconomic status, which has been linked to increased walking (Sugiyama et al., 2015) and mode choice differences (Rachele et al., 2015) in adults. Research on the association between family income or parental socioeconomic position, and levels of physical activity in children and adolescents have been more equivocal, with some studies finding positive associations (Drenowatz et al., 2010), and others finding no association (Voss et al., 2008; Ball et al., 2009, Sener et al., 2016). As for school travel mode choice, in Singapore, where car-ownership is very expensive, students from richer families are more likely to be driven to school than those from poorer families (Department of Statistics, Ministry of Trade and Industry, Singapore, 2016)—a pattern observed in studies elsewhere, where lower neighborhood incomes are often associated with more active modes of school travel (Larsen et al., 2009).

We also controlled for the potential impact of neighborhood built environment, which may affect both school mode choice and how much walking one does within an area. Some studies focusing on active school travel have found built environment characteristics such as the density of street intersections, residential densities, and land-use mix to be significantly associated with active school travel (Larsen et al., 2009), while studies focused on overall physical activity found strongest correlations between mixed land use, residential density and higher levels of physical activity among both children and adolescents. (Ding et al., 2011) Overall though, the associations between different built environment characteristics and youth physical activity have been largely inconsistent over different studies (Ding et al., 2011, Smith et al., 2017), particularly for objectively measured physical activity (Ding et al., 2011) and between different ages and genders (McGrath et al., 2015), making it difficult to pinpoint any one environmental variable as an unambiguious correlate of physical activity.

As those who live further from school are less likely to commute via walking (McDonald, 2008), and may have longer commutes which reduce time for activity, or be less likely to use school playground facilities outside of school hours (Hinckson et al., 2014), home-school distance could confound the relationship between step count and mode such that those who travel by car or public transport appear less active. Alternatively, the relationship between mode and step count may be modified by home-school distance instead, since longer distances between home and school would likely generate more steps for those who walk to school than for those who take public transport or the car (Faulkner et al., 2013), and may thus emerge as an interaction effect between distance and mode choice. Our analyses thus tested for these two possible effects of home-school distance.

The primary hypothesis tested in this study was that students with active morning commuting modes walked more during their commutes than those who were driven, net of potential confounders, but that higher step counts would not be sustained over the rest of the day.

While this study did not evaluate a specific program or policy intervention, our observational findings about how commuting modes relate to overall walking activity could facilitate policy assessments of initiatives to increase overall physical activity through active school commutes.

2. Materials and methods

2.1. Study setting and data collection

Between September to November 2015, Singapore's National Research Foundation (NRF) organized a 'National Science Experiment', which deployed approximately 43,000 purpose-built lightweight sensor devices, SENSg, among students from primary schools (ages 7 to 12), secondary schools (13 to 16), and junior colleges (17 and 18). The SENSg devices, developed by the Singapore University of Technology and Design (SUTD), used Wi-Fi signals to identify its user's location, and MEMS accelerometers to compute each user's step counts. Details about the sensors can be found in Wilhelm et al., (2016a). For our study, we obtained de-identified sensor data from NRF. The *Massachusetts Institute of Technology Committee on the Use of Humans as Experimental Subjects* exempted this study.

Given the data collection approach, we used step count as an indicator of each student's amount of walking on a given day. This was not necessarily an accurate measure of a student's actual steps nor total physical activity because SENSg's pedometer function was occasionally insufficiently sensitive to capture small periods of walking (Wilhelm et al., 2016b). Furthermore, prior to using the sensors, students were briefed by their teachers not to carry their devices during vigorous activity, such as during physical education classes, although field observations revealed inconsistent compliance with these instructions across schools.

While the full dataset included data records of close to 40,000 students and over 136,000 days of data, many of the recorded travel patterns were inconsistent with expected movements or location patterns of typical students. For instance, some students logged extremely low step counts that may be explained by inappropriate sensor usage, such as them not wearing their sensors for long stretches. Our analysis thus excluded students who: logged fewer than 200 steps throughout the day, which is far below a reasonable 'basal' level of activity (Barreira et al., 2015; Tudor-Locke et al., 2011); logged fewer than 100 steps within 800 m of their school or home location; or registered no steps before school or after 1 pm.

2.2. Measures

Our study's main outcome variable was step count. We analyzed students' steps counts in two overlapping time periods. The first time period approximated students' morning commute, which started from 4am to when the student's SENSg registered them as reaching school. The second time period captured a full day's worth of walking, and started from 12 midnight to 11.59PM.

As school schedules differed from school to school, and sometimes from day to day, different students had slightly different commuting windows. To standardize our analysis, we used step counts per hour as our primary outcome variable.

Some students registered only a day of data, while others logged more days. We took the average step count of the days where students adopted the same combination of commuting modes for both morning and afternoon travel. For students who had different mode combinations between different days, we picked the most frequently used mode combination. For students without a predominant mode combination, we picked the first combination they used.

The main predictor variable was a student's morning commute mode, as estimated by SUTD's algorithms that compared detailed locational data and travel duration against Google Maps Direction API routes, and that also utilized the accelerometer logs and light and humidity readings recorded by the SENsg devices (Wilhelm et al., 2016a). Students' morning commute modes were coded into three distinct categories: 'public transport', which included travel by public bus, mass rapid transit, or a mix of both; 'walking only'; or 'car'.

Similar algorithms were used to assess students' modes of travel after school from the SENSg data. However, categorizing students' after-school travel modes was less straightforward than categorizing morning travel. While students generally took only one

Table 1
Built Environment Measures.

Category	Measure
Density	• Density of Built Area
Diversity (Landuse mix & Places of Interest)	• Number of Retail, Food and Beverage Outlets within buffer • Land Use Diversity Mix, based on proportion of different uses (Residential, Office, Retail, Industrial, Warehouse, Parks and Open Space, Others)
Access to Public Transit	• Number of bus-stops within buffer • Number of Mass Rapid Transit (MRT) stations within buffer
Design: Street Network	• Length of expressways per unit walk-shed area • Length of major arterial roads per unit walk-shed area • Length of local roads per unit walk-shed area • Number of intersections within walk-shed area • Percent of four-way intersections within walk-shed • Density of four-way intersections • Density of three-way intersections • Length of footpath per walk-shed area • Density of porous walkable space (neighborhood parks and porous grounds of non-gated, public housing estates)
Design: Urban Form	• Average size of building footprint • Average building height

trip from home to school in the morning, they had more flexibility to take multiple trips after school. A student could walk home from school, then take a bus from home to the shopping mall, before hitching a car ride back home. Thus, besides 'public transport', 'car' and 'walking only', we created an additional category 'mixed', which covered students using a mix of public transport and car travel.

Furthermore, we could not easily differentiate between walking trips for transport and for leisure, such as a stroll through the park. Thus, we categorized students who had logged trips by public transport or car as traveling primarily by that motorized mode, even if the SENSg also registered periods of walking between home and school locations. Students who registered no motorized travel, but had logged periods of walking between home and school were then coded as 'walking only'. Finally, a subset of students did not have a clearly identifiable after-school mode that could be discerned from the sensor data. The lack of inferrable modes could be because students removed or turned off their sensors during their travel period.

As our data set included very limited student-level information, we used school level to account for student age, and the average housing sale prices (adjusted to a common base year-quarter) of units sold between 2012 and 2016 that were located within 400 m of students' homes as a proxy for household wealth.

We also hypothesized that local-level built environment characteristics affected how much students walked and their mode choice. Because students travelled primarily between their home and school neighborhoods (Wilhelm et al., 2016b), our built environment covariate was designed to capture the characteristics of the urban environment between each student's home and school. We constructed a neighborhood typology that drew upon 16 built environment measures commonly described in the health and transport literature (Table 1). Given our focus on walking, we defined our areal unit as a 500-meter street network buffer around home or school, which can be interpreted as a 'neighborhood walk-shed'. We used a network-based buffer instead of a circular buffer because the former better reflected the actual spatial area that influences walking, whereas the latter could include blocked-off areas inaccessible by foot (James et al., 2014; Oliver et al., 2007). As walking behavior is likely to vary across cities and countries (Jiang et al., 2012), we picked a buffer distance using available estimates of average walking distances in Singapore. According to a survey of residents in public housing estates (which represent the bulk of Singapore's housing stock), people were willing to walk a maximum distance of 530 m to reach a subway station (HDB 2000). Another survey found that people walked an average of 600 m to subway stations in Singapore (Olszewski and Wibowo, 2005). We thus chose 500 m as a rough, conservative estimate of the likely radius of walking activity typical to Singaporeans.

We calculated all 16 measures using available geospatial land use, building and transport infrastructure data (Le et al., 2016) for over 24,000 'neighborhood walk-sheds' generated from a sample of postal codes (essentially equivalent to a building in Singapore) that collectively covered all built-up areas of Singapore (Appendix A).

Instead of analyzing each built environment measure as an independent variable, which, among other challenges, would introduce problems of multicollinearity, we used a data reduction technique to derive 'neighborhood types' from the 16 measures. Specifically, we applied a K-means clustering algorithm, which has been used in other physical activity and travel-related studies (Gil et al., 2012; Szapocznik et al., 2006), to the 24,000 'neighborhood walk-sheds' and their respective built environment measures. Fig. 1 summarizes the spatial distribution and characteristics of these six neighborhood types.

Finally, we included the Euclidean distance between students' home and school locations as a possible effect modifier of mode, as hypothesized.

2.3. Statistical models

We used two statistical modeling approaches. First we conducted a 'between student' analysis, and estimated a series of nested linear mixed effects models to assess the relationship between morning mode choice and both morning steps and total daily steps. We added the additional control variables progressively to the models, and also tested for interactions between mode and home-school

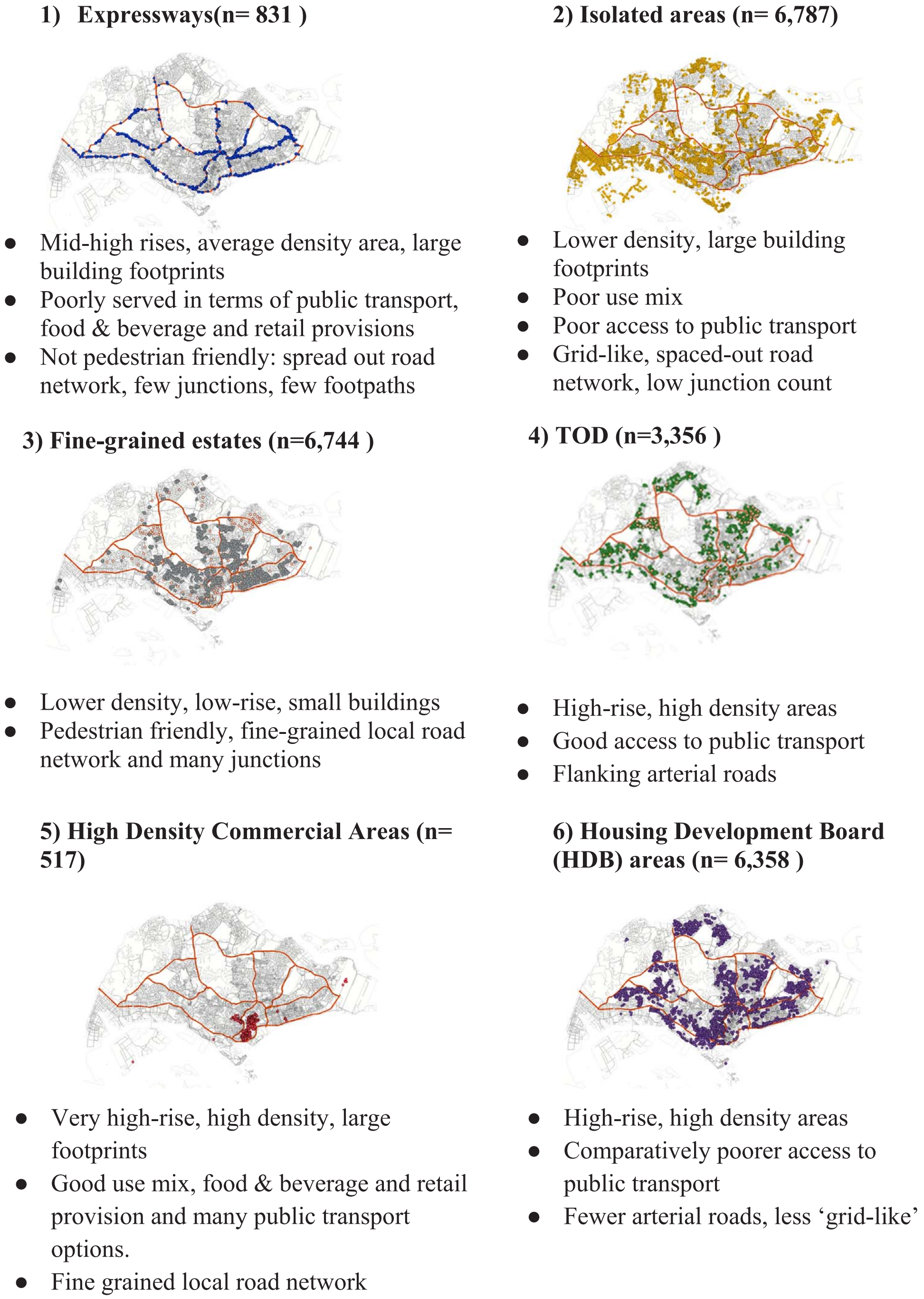


Fig. 1. Singapore Neighborhood Types generated by K-means clustering. This figure summarizes the spatial distribution and built environment characteristics of the six derived neighborhood types.

difference, students' school level, as well as neighborhood property prices to ensure that we factored in potential modification effects, as hypothesized earlier in our introduction section. We also nested the students within their schools as a random effect, to account for any 'between school' differences.

The second model capitalized on a quasi-experimental, 'pre-post test' opportunity that was an artifact of the data collection method. Some students, over the days which they carried a SENSg device, were coded as taking different modes for the morning journey to school. This allowed us to examine any differences in steps taken by such students associated with mode choice. This model, which assumed an individual fixed effects for each student, sidestepped the need to control for individual-level confounders

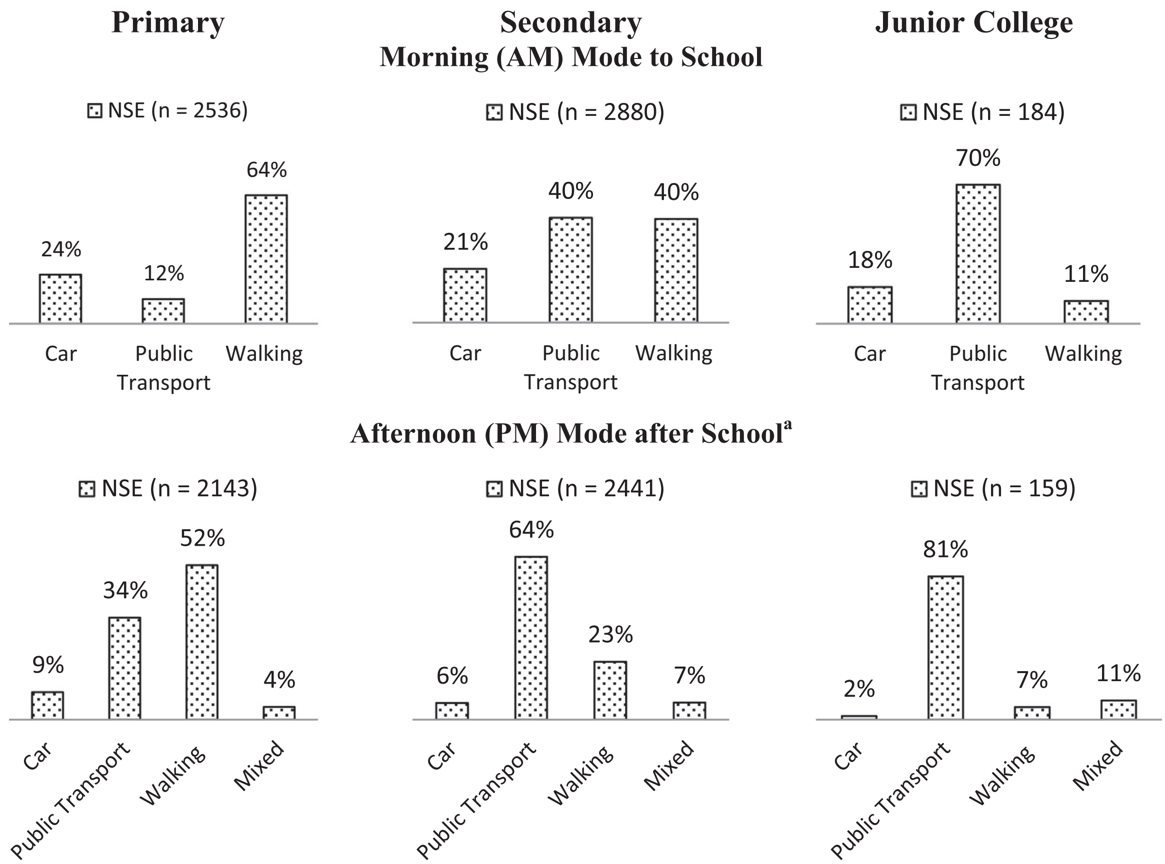
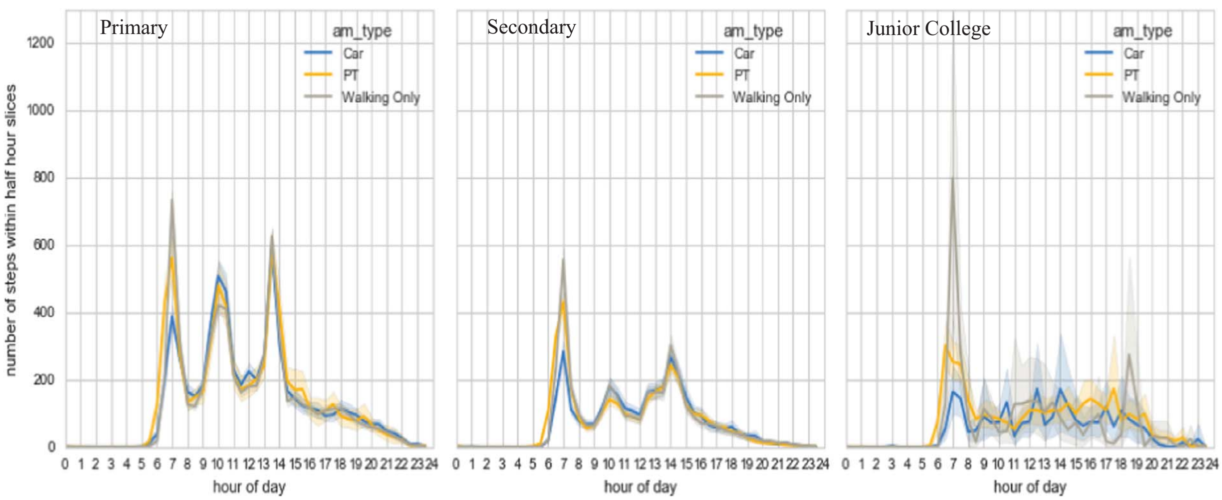


Fig. 2. Students' Journey to School, and After School Mode Shares (by Grade Level). [a]857 students did not have an afternoon travel mode picked up by SENSg. This figure shows the mode share of students' trips, by grade level.



[a] Shaded region around lines indicate 95% confidence intervals

Fig. 3. Average half-hourly step count (by Morning Mode and Grade Level). This figure shows the mean number of steps taken within each half hour of the day, by morning commute type and student grade level.

that would not have changed for an individual across the different days. As with the 'between students' analysis, each student was nested within his/her school. We used the full multi-day dataset in this model.

While the 'between student' models predicted the step counts of groups of students with different commuting modes, the 'within students' model predicted changes in step counts of each individual in relation to changes in their morning commute mode. Having

Table 2
Mixed Effects Model of Morning Steps and AM mode (n = 5600).

	Model 1a (Student Characteristics)				Model 1b (+Home-School Distance)				Model 1c (+Home-School Distance × Mode)			
			CI (95%)				CI (95%)				CI (95%)	
	Coef	**P**	**Lower**	**Upper**	**Coef**	**P**	**Lower**	**Upper**	**Coef**	**P**	**Lower**	**Upper**
Reference	91.48	0.00	76.63	106.34	74.45	0.00	57.64	91.26	102.52	0.00	82.32	122.71
AM Mode (Ref:Car)												
Public Transport	135.36	0.00	121.22	149.51	130.55	0.00	116.26	144.85	96.14	0.00	71.46	120.83
Walking	89.65	0.00	76.92	102.38	102.41	0.00	88.38	116.44	54.05	0.00	32.22	75.89
School-Level (Ref: Primary)												
Junior College	-18.83	0.36	-59.44	21.79	-36.17	0.09	-77.43	5.08	-47.94	0.02	-88.79	-7.09
Secondary	-6.16	0.47	-22.89	10.57	-9.45	0.27	-26.18	7.27	-16.89	0.05	-33.66	-0.12
Home school distance (km)					6.66	0.00	3.55	9.78	-1.41	0.57	-6.26	3.43
Interaction: Home school distance × Public Transport									11.43	0.00	5.28	17.59
Interaction: Home school distance × Walking									38.49	0.00	23.63	53.34
AIC			**74173.28**		**74157.77**				**74129.92**			

Table 3
Mixed Effects Model of Total Day's Steps and AM mode (n = 5600).

	Model 2a(Student Characteristics)				Model 2b (+Home-School Distance)				Model 2c (+Home-School Distance × Mode)			
	Coef	**P**	CI (95%)		**Coef**	**P**	CI (95%)		**Coef**	**P**	CI (95%)	
			Lower	**Upper**			**Lower**	**Upper**			**Lower**	**Upper**
Intercept	251.01	0.00	238.87	263.16	244.19	0.00	230.76	257.62	248.19	0.00	232.36	264.02
AM Mode (Ref: Car)												
Public Transport	14.36	0.01	4.06	24.65	12.36	0.02	1.93	22.79	5.45	0.55	−12.57	23.48
Walking	11.07	0.02	1.78	20.36	16.10	0.00	5.88	26.33	11.69	0.15	−4.26	27.63
School-Level (Ref: Primary)												
Junior College	−119.29	0.00	−153.37	−85.20	−126.24	0.00	−160.75	−91.73	−127.56	0.00	−162.17	−92.94
Secondary	−110.91	0.00	−125.35	−96.47	−112.26	0.00	−126.70	−97.81	−112.46	0.00	−127.10	−97.82
Home school distance (km)					2.69	0.02	0.41	4.98	1.38	0.45	−2.18	4.93
Interaction: Home school distance × Public Transport									2.14	0.35	−2.36	6.65
Interaction: Home school distance × Walking									2.08	0.71	−8.77	12.92
AIC		**70610.53**			**70607.21**				**70610.32**			

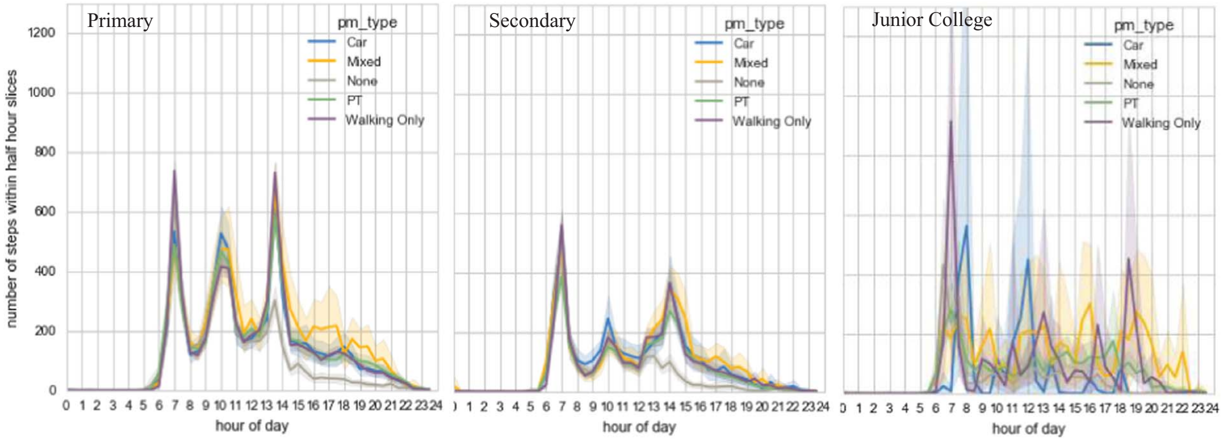
both ‘between students’ and ‘within students’ models provided an analytical robustness check, and thus greater confidence in the findings.

Both models were run in Python version 2.7.11, statistical library scikit.statsmodels 0.8.0, and pandas 0.19.0. All analyses were completed in 2016 and 2017.

3. Results

3.1. Descriptive statistics

Of the 5,600 students studied, 2,536 (45%) were primary school students, 2,880 (51%) secondary school students, and 184 (3%) junior college students. These students were from 103 different schools located all across the country. Older students took fewer steps than younger ones throughout the day, on average. Primary students took on average of 6,305 steps (95% CI = 6163.0, 6446.7) a day, while secondary school students and junior college students took 3,519 (95% CI = 3415.87, 3621.51) and 3,327 (95% CI = 2893.0, 3761.3) steps a day, respectively.



[a] Shaded region around lines indicate 95% confidence intervals

Fig. 4. Average half-hourly step count (by After School Mode and Grade Level). This figure shows the mean number of steps taken within each half hour of the day, by after-school commute type and student grade level.

Older students were more likely to take public transport, while younger primary school students tended to walk or be driven to school. Similarly, the older students were more likely to rely on public transport for their after-school travels, while primary school students relied more on walking. Across all three levels, more students used public transport after school than when commuting to school (Fig. 2). Students who walked to school lived closest to school, with an average home-school distance of 0.8 km (95% CI = 0.75, 0.79), while those who took public transport or were driven lived an average of 3.9 km (95% CI = 3.76, 4.00) and 3.0 km (95% CI = 2.85, 3.09) away respectively.

There were three 'peak periods' in walking activity in a day for primary and secondary school students—one in the morning, corresponding to the morning commutes; one in late morning which likely corresponded with students' recess breaks; and one in the afternoon, for post-school commutes (Fig. 3). For secondary school students who typically have more varied school ending times than primary school students, their PM peaks were more spread out than their younger peers. JC students had much more variability in step count over the course of the day because JC school schedules are usually much more varied, as different course combinations have different class schedules. In contrast, primary and secondary students have much more uniform class schedules.

Across all three levels, those who walked or took public transport in the morning logged more steps than car users during the first peak, but this tapered off after that peak. For primary and secondary school students, car users appeared to take slightly more steps on average than other students during the middle recess peak.

3.2. 'Between Student' linear mixed effects model results

3.2.1. Mode of morning travel to school

Consistently across all models for morning steps, students who took public transport or walked had higher step counts per hour before school than those who were driven. In our model of best fit (Model 1c, Table 2), students who took public transport walked 96.1 more steps per hour before school (95% CI = 71.5, 120.8) than those who were driven. Walkers took 54.1 more steps per hour before school than those who were driven (95% CI = 32.2 75.9).

While there was no significant relationship between home-school distance and morning steps for car-takers, a 1 km increase in home-school distance was associated with 38.5 more steps per hour before school (95% CI = 23.6, 53.3) for walkers, and 11.4 more steps per hour before school for public transport users (95% CI = 5.3, 17.6).

For total steps per hour measured across the entire day, our model of best fit (Table 3, Model 2b) indicated that those who took public transport had slightly higher step counts per hour (β = 12.4, 95% CI = 1.9, 22.8) than those who were driven, as did those who walked (β = 16.1, 95% CI = 5.9, 26.3). This model also showed that every 1 km increase in home-school distance was associated with 2.7 more (95% CI = 0.4, 5.0) steps per hour.

However, our fuller model (Table 3, Model 2c), fitted based on our *a priori* hypothesis that the relationship between step count and morning mode was modified by home-school distance, indicated no significant effect of mode on daily walking. After factoring in the interaction between mode and home-school distance, the associations between hourly step count, and both home-school distance and morning mode were no longer significant.

Compared to primary school students, secondary school students and junior college students walked less in the morning and throughout the day. None of the other covariates, such as average neighborhood property prices or home or school neighborhood typologies were significantly associated with either total daily or morning steps.

The full sets of nested models for morning and total day's steps per hour are in Appendices B and C.

Table 4
Mixed Effects Model of Total Steps, AM and PM mode (n = 5600).

	Model 3a (Student Characteristics)				**Model 3b (+Home-School Distance)**				**Model 3c (+Home-School Distance × Mode)**			
			CI (95%)				CI (95%)				CI (95%)	
	Coef	**P**	**Lower**	**Upper**	**Coef**	**P**	**Lower**	**Upper**	**Coef**	**P**	**Lower**	**Upper**
Intercept	263.15	0.00	245.74	280.56	258.12	0.00	239.99	276.24	270.51	0.00	246.31	294.72
AM Mode (Ref: Car)												
Public Transport	16.48	0.00	6.31	26.65	14.83	0.01	4.53	25.13	9.78	0.28	−8.04	27.60
Walking	11.67	0.02	1.51	21.82	15.16	0.01	4.41	25.92	11.18	0.23	−7.09	29.44
PM Mode (Ref: Car)												
Mixed (Public Transport & Car)	30.91	0.00	10.21	51.61	28.97	0.01	8.18	49.75	36.35	0.04	1.37	71.32
Public Transport	−12.48	0.10	−27.15	2.20	−13.56	0.07	−28.27	1.15	−24.27	0.03	−46.39	−2.15
Walking Only	0.83	0.92	−14.58	16.25	1.25	0.87	−14.16	16.67	−5.80	0.62	−28.63	17.04
School-Level (Ref: Primary)												
Junior College	−119.14	0.00	−153.20	−85.09	−124.60	0.00	−159.01	−90.19	−126.54	0.00	−161.02	−92.06
Secondary	−109.11	0.00	−123.63	−94.60	−110.00	0.00	−124.49	−95.50	−110.39	0.00	−125.03	−95.76
Home school distance (km)					2.25	0.05	−0.04	4.53	−3.62	0.38	−11.73	4.48
Interactions: Home-School distance & AM mode choice									1.49	0.51	−2.98	5.95
Home school distance × AM PT									2.08	0.73	−9.77	13.93
Home school distance × AM Walking									0.32	0.95	−9.95	10.59
Interactions: Home school distance & PM mode choice												
Home school distance × PM Mixed									0.32	0.95	−9.95	10.59
Home school distance × PM PT									5.42	0.19	−2.71	13.54
Home school distance × PM Walking									2.36	0.70	−9.50	14.22
No PM mode	*−64.31*	*0.00*	*−80.51*	*−48.12*	*−64.38*	*0.00*	*−80.57*	*−48.18*	*−78.06*	*0.00*	*−101.53*	*−54.59*
Home school distance × PM None									*7.44*	*0.10*	*−1.47*	*16.35*
AM PT × PM None												
AM Walking × PM None												
AIC	**70437.72**				**70436.01**				**70442.06**			

Table 5
Within-Student Model of Morning Steps per hour, Total Day's steps per hour and AM mode (n = 165).

	Morning Steps Per Hour				Total Daily Steps Per Hour			
			CI (95%)				CI (95%)	
	Coef.	P	Lower	Upper	Coef.	P	Lower	Upper
Intercept (Ref: AM mode:Car)	127.98	0.00	95.98	159.98	217.07	0.00	182.25	251.90
AM Mode: Public Transport	47.56	0.01	10.25	84.87	−9.55	0.54	−39.83	20.73
AM Mode: Walking Only	12.37	0.48	−22.01	46.75	−3.69	0.79	−31.21	23.83

Table 6
Within-Student Model of Total Day's Steps per hour per hour, and AM & PMmode (n = 45).

	Total Daily Steps Per Hour			
			CI (95%)	
	Coef.	P	Lower	Upper
Intercept (Ref:AM & PM mode: Car)	227.07	0.00	172.29	281.84
AM Car to PM Mixed	32.73	0.50	−61.86	127.33
AM Car to PM PT	−9.31	0.73	−62.71	44.09
AM Car to PM Walking	4.62	0.95	−126.94	136.19
AM PT to PM Car	116.58	0.36	−133.46	366.61
AM PT to PM PT	43.08	0.66	−147.83	233.98
AM Walking Only to PM Car	−94.25	0.49	−362.46	173.96
AM Walking Only to PM PT	35.36	0.78	−208.88	279.59

3.2.2. After school travel

As a robustness check, we examined whether controlling for students' afternoon travel modes affected the observed relationship between morning mode and total daily steps.

Primary and secondary students who travelled by a mix of public transport and car ('Mixed') appeared to walk more than their peers after the third peak in the afternoon, while those travelling only by car in the PM appeared to walk slightly more than their peers during the second recess-time peak (Fig. 4). Similar to that observed for AM modes, average step counts over time varied considerably for JC students. Unsurprisingly, while primary and secondary students with no PM mode maintained a similar distributional pattern of step counts over time as their peers with clear afternoon modes (with three perceptible peaks and a tapering off towards the end of the day), they seemed to walk less on average than their peers in the afternoon.

Including afternoon travel modes as an additional control variable in our models of total steps per hour yielded results consistent with our earlier models without afternoon travel modes (Table 4). In the model of best fit for total steps (Model 3b, Table 4), those who walked or took public transport logged 15 more steps per hour in a day (95% CI = 4.4, 25.9 for walkers, 4.5, 25.1 for public transport users) than those driven. However, similar to Model 2c, the fuller Model 3c that included home-school distance and its interaction with mode showed no significant difference in total steps per hour between students with different morning modes.

Across all models, students who travelled by both public transport and car after school walked more steps per hour than those driven around after school. In Model 3c, those who travelled by public transport after school took about 24.3 fewer steps per hour compared to those driven, over the course of the day (95% CI = −46.4, −2.2).

We also tested for the interaction effects between morning and afternoon modes, which were largely non-significant. While the interaction between morning public transport use and afternoon walking was statistically significant ($\beta = -57.4$, 95% CI = −113.4, −1.5), after accounting for the model coefficients associated with morning public transport modes ($\beta = 41.3$, 95% CI = −0.8, 83.3) and afternoon walking modes ($\beta = 13.3$, 95% CI = −30.8, 57.4), the resultant magnitude of the overall association of taking public transport in the morning and walking in the afternoon with total daily steps was negligible.

As in main models, none of the other covariates, such as average neighborhood property prices or home or school neighborhood typologies, were significantly associated with total daily steps per hour.

The full set of nested models for total day's steps and both morning and afternoon travel modes is in Appendix D.

3.2.3. Interactions with school level and property prices

To test whether neighborhood wealth modified how mode related to walking activity, we also tested interactions between travel modes and property prices. While most of the interactions were not significant, there was a small positive relationship between steps per hour and the interaction between neighborhood property prices and afternoon walking mode choice ($\beta = 3.4$, 95% CI = 0.7, 6.1). The positive relationship here suggested that those who lived in wealthier neighborhoods and who relied on walking only after school walked slightly more than their peers.

We also tested the interactions between travel modes and school level, to examine whether the relationship between mode and walking activity differed by different age groups. While most of the interactions were not significant, the results suggested that secondary students in particular walked less than their primary school peers if they took public transport after school ($\beta = -30.8$, 95% CI = −60.8, -0.8), or a mix of public transport and car ($\beta = -43.6$, 95% CI −87.2, −0.2) (Appendix E).

3.3. 'Within Students' model results

The 'within students' model examined changes in step counts of students (n = 165) who switched journey-to-school modes across the days they wore the SENSg. By comparing different travel days for the same student, this modeling approach benefitted from a stronger quasi-experimental design, by controlling for individual-level characteristics likely to affect step count.

Our results suggested that on days students were driven to school, they walked fewer morning steps per hour compared to the days they took public transport ($\beta = 47.6$, 95% CI = 10.3, 84.9). Students' total day's steps, however, had no significant relationship with school commute mode (Table 5).

Similarly, for students who switched from traveling by car in both the morning and after-school periods to any combination of modes that included more active ones (either public transport or walking), there was again no significant relationship between modes and total daily steps per hour (Table 6).

3.4. Sensitivity analysis

We conducted sensitivity analyses that included students with very low step counts throughout the day and within their school and home environments, as a robustness check. Results from the 'between student' sensitivity analyses of morning mode and morning steps were consistent with the more restricted main model. However, the sensitivity analyses of total day's steps using the larger dataset showed that students who walked to school took 22.6 more steps per hour (95% CI = 7.3, 37.9) throughout the day than students who were driven(Appendix F), which differed from our main models' results. 'Within students' models that relied on both on the larger dataset for the sensitivity analyses and filtered dataset for the main analyses both consistently found that changing to more active commute modes did not affect students' total daily step counts (Appendix G).

4. Discussion

4.1. Significance of findings

Our results show that while more active commute modes were clearly associated with more morning steps per hour, this positive relationship between morning mode choice and steps became less clear when we considered the full day of walking. These findings suggest that students with active morning commuting modes may be compensating for their early morning activity by walking less the rest of the day, as per our original hypothesis.

In our 'between students' model of best fit, students who walked or took public transport recorded 54.0 or 96.1 more morning steps per hour respectively than those driven, who took about 102.5 steps per hour. Students who walked or took public transport thus walked almost 50% to 100% more intensely in the period before school. On average, students in our sample arrived at school around 7.30am, which translates into a 3.5 hour window in the morning for when their early morning steps were calculated. Students who walked or took public transport thus logged roughly 200 to 300 more steps respectively, before they reached school, compared to those who were driven.

Whether these additional morning steps carried through the rest of the day was ambiguous. Our model of best fit for total day's steps per hour (Model 3b) suggested that those who took public transport or walked to school walked about 15 more steps per hour than those driven, which translated to a difference of about 360 steps over the course of a full day. However, the model that we fitted based on our initial hypothesis that home-school distance modified the relationship between morning mode and steps per hour (Model 3c), which we believe is more theoretically sound than our best-fit model, suggested that morning mode choice was not associated with differences in a day's average hourly step counts.

Results from the 'within student' model showed that when students took public transport to school, they took about 47.6 more morning steps per hour than when they were driven, but not more total daily steps. Furthermore, students who switched from travelling solely by car, to any other combination that included at least one walking only or public transport trip throughout the day did not log significantly more steps on the days they used more active modes. Collectively, our findings from both the 'between student' and 'within student' analyses suggested that there was not a clear, positive relationship between more active travel modes and more walking activity throughout the day.

Interestingly, students who switched from being driven to walking in the morning did not walk more during the morning commute period. One possible explanation is that many of these students lived relatively close to school (25% lived within 600 m of school, while 50% lived within 800 m), such that walking to school might not have generated many steps. Another possible explanation is that on the days students were driven to school, they could have used the time they saved from not having to walk to school to participate in other activities.

We found that students who travelled by a mix of public transport and car after school walked more steps per hour compared to those who were driven. Given that this group of students was taking two or more trips in the afternoon to participate in different activities outside of home or school, it was not surprising that they logged significantly more steps than their counterparts. It is reasonable to also attribute their higher hourly step counts to the activities they were travelling to, and not just the modes of these trips.

In our ‘between students’ analysis Model 3c, we found that those who travelled by public transport after school logged fewer steps than those who travelled by other modes. One explanation for this observation may be because students travelling by public transport had less time after school for activities that would boost their step counts, compared to their counterparts travelling by car, since taking public transit is slower and more time-consuming compared to car-travel.

As hypothesized, we found that home-school distance modified the relationship between mode and morning steps: living further from school was associated with a greater increase in morning steps among walkers than public transport users. However, the same effect modification was not observable for total daily steps. Once the interactions between home-school distance and travel modes, whether morning or afternoon, were factored into the models, neither home-school distance nor its interaction with mode was significantly associated with step count.

From our ‘between students’ analysis, we conclude that both average property prices and built environment characteristics had little significant association with the amount of walking being done. The only association we found was a positive relationship between total day's hourly step count and the interaction between property prices and after-school walking mode, suggesting that those who lived in wealthier neighborhood and walked home after school walked more than their peers. While we cannot infer a reason for this behavior solely from our data, we speculate that those who travelled by walking only after school spent their after-school hours within a limited, walkable radius of their school and home environments, which likely overlapped. Students living in a neighborhood with high property prices would thus spend their after-school hours mostly within rich neighborhoods, compared to their counterparts spending their time in less wealthy areas. In contrast, those who travelled after school by public transport were more likely to experience a greater mix of socioeconomic environments, regardless of whether they lived in a more or less expensive neighborhood. One could hypothesize that the unobserved characteristics of a more expensive neighborhood, such as better amenities, more pleasant streetscapes or more opportunities for activity, may be driving this positive interaction between property prices and after-school walking mode. It is also possible that this finding was due to chance.

The lack of significant association between neighborhood property prices and walking levels here supports similar findings from other studies that found no association between family income and levels of physical activity among the young (Voss et al., 2008; Ball et al., 2009, Sherar et al., 2016).

As for the lack of association between neighborhood built environment types and levels of walking, we suggest three possible reasons as to why our findings differ from other studies. Firstly, our approach to cluster discrete objective built environment measures into six different neighborhood types may have masked some of the variation in walking activity that could have been associated with each individual measure. Secondly, we speculate that students may have been time-constrained during the regular school week, and thus may have had limited leisure time to interact with their immediate neighborhood built environment. A different relationship between the built environment and walking activity may have emerged if students were observed over the weekends. Finally, given the lack of a clear consensus between other studies on which neighborhood environment characteristics are associated with objectively measured physical activity among children and adolescents (Ding et al., 2011), our findings could very well be an accurate reflection of the lack of any strong relationship between neighborhood characteristics and activity levels of the young.

Compared to estimates in published literature, our sample of Singaporean students were more sedentary. International studies suggest that the average range of step counts for children range from 10,000 to 16,000 per day, and 8,000 to 9,000 for adolescents (Tudor-Locke et. al, 2011). A recently published analysis of physical activity of over 700,000 users of a smartphone application from 111 countries found that male users aged 15 to 20 logged about 5,600 steps per day, while female users walked about 4,500 steps (Althoff et al., 2017). In comparison, our sample of primary school students averaged 6,305 steps daily, while the older secondary and JC students took just 3,519 and 3,327 steps daily. However, step counts in our study were likely to be underestimations of actual walking activity, given SENSg's occasional insensitivity to small periods of walking. More importantly however, our study's step counts excluded steps logged during vigorous exercise, and thus cannot be directly compared to step counts from other studies without adjustment. Assuming a 157 step per minute cadence for vigorous activity (Tudor-Locke et. al, 2011), the difference in step counts between young Singaporean and the averages cited above translates into approximately 20 to 60 min of vigorous activity for children, and about 30 to 35 min for adolescents. Taking into consideration Singapore's Ministry of Education's current guideline that schools should provide two hours of physical education per school week (MOE, 2017), or 24 minutes per weekday, Singaporean students may still be less active than their peers elsewhere even after factoring in physical education classes, especially for those that do not participate in additional exercise outside of scheduled classes.

4.2. Limitations and strengths

While this study sought to understand the relationship between active school commutes and walking activity, the observational nature of our data precluded any causal inferences. Our study also did not directly examine health outcomes, but rather focused on a health-related behavior.

Furthermore, although we cannot be sure that the sensors were consistently removed during vigorous activity due to reports of non-compliance, given that many students did not wear their sensors during vigorous activity, we were limited in our ability to directly study how active commutes affected overall physical activity. We could not examine potentially longer set-points that extend over a week or more, as we had only up to four days of data per student. Future rounds of data collection where students wear activity sensors consistently throughout the day and over a longer period of time would thus help improve understanding of how students' active commutes relate to their overall physical activity.

This study also relied on the SUTD researchers' mode-identification algorithms, which were estimated to have an accuracy of 70 to 85%, to be accurate and unbiased. Details about these methods, their accuracy and limitations can be found in a previous publication (Wilhelm et al., 2016a). Further analysis of these mode identification methods was beyond this study's scope.

Finally, our main findings may not be generalizable to very sedentary students. Results from our sensitivity analysis of our 'between students' full model, which included students with very low step counts, suggested that those who walked to school in the morning walked more throughout the day, unlike results from the filtered dataset, which excluded low step count students. While we treated extremely low step counts as sensor usage errors in this study, they could potentially represent truly sedentary behavior. To resolve this uncertainty, further study of how students with low step counts utilize their SENSg devices would be necessary.

Despite these limitations, our study had several strengths. We utilized a large sample of students and objective measures of both walking activity and built environment characteristics. This study was also situated in a high-density Asian city, which distinguished it from most other studies on active commutes and physical activity.

5. Conclusions

Students who travelled to school by public transport or by walking walked significantly more during morning commutes than did peers who were driven. However, our data did not unambiguously support a positive association between active morning commutes and higher total daily steps. Thus, while encouraging students to walk or take public transport can have multiple benefits such as reducing emissions and morning traffic congestion, boosting overall walking activity may not be one such benefit. More research is needed to test if active commuting interventions can indeed lead to increased walking activity in a city like Singapore. Before then, policy-makers should be circumspect when considering such initiatives to boost activity.

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Conflict of interest

The authors declare there is no conflict of interest.

Appendix A. Categorizing Neighborhoods by Built Environment Characteristics

To characterize each student's home and school neighborhood environment, we identified the following 16 different built environment measures.

Density:
- Density of Built Area

Diversity: (Land use mix & Places of Interest)
- Number of Retail, Food and Beverage Outlets within buffer
- Land Use Diversity Mix, based on proportion of different uses (Residential, Office, Retail, Industrial, Warehouse, Parks and Open Space, Others).

Access to Public Transit
- Number of bus-stops within buffer
- Number of Mass Rapid Transit (MRT) stations within buffer

Design: Street network
- Length of expressways per unit walk-shed area
- Length of major arterial roads per unit walk-shed area
- Length of local roads per unit walk-shed area
- Number of intersections within walk-shed area
- Percent of four-way intersections within walk-shed
- Density of four-way intersections
- Density of three-way intersections
- Length of footpath per walk-shed area
- Density of porous walkable space (neighborhood parks and porous grounds of non-gated, public housing estates)

Design: urban form
- Average size of building footprint
- Average building height