



Built environment associates of active school travel in New Zealand children and youth: A systematic meta-analysis using individual participant data

Erika Ikeda^{a,*}, Tom Stewart^a, Nicholas Garrett^b, Victoria Egli^a, Sandra Mandic^c, Jamie Hosking^d, Karen Witten^e, Greer Hawley^f, El Shadan Tautolo^g, Judy Rodda^h, Antoni Moore^h, Melody Smithⁱ

^a School of Sport and Recreation, Faculty of Health and Environmental Sciences, Auckland University of Technology, Auckland, New Zealand

^b Department of Biostatistics and Epidemiology, Faculty of Health and Environmental Sciences, Auckland University of Technology, Auckland, New Zealand

^c Active Living Laboratory, School of Physical Education, Sport and Exercise Sciences, University of Otago, Dunedin, New Zealand

^d Section of Epidemiology and Biostatistics, Faculty of Medical and Health Sciences, The University of Auckland, Auckland, New Zealand

^e SHORE and Whāriki Research Centre, Massey University, Auckland, New Zealand

^f Mackie Research, Auckland, New Zealand

^g Centre for Pacific Health and Development Research, Faculty of Health and Environmental Sciences, Auckland University of Technology, Auckland, New Zealand

^h School of Surveying, University of Otago, Dunedin, New Zealand

ⁱ School of Nursing, The University of Auckland, Auckland, New Zealand

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ABSTRACT

This systematic review and meta-analysis examined the associations between active travel to school and the neighbourhood built environment in children and youth by systematically identifying and collating data from New Zealand studies. Data from five studies involving 2844 children and youth aged 6–19 years were included in the meta-analysis. Data on participant demographics and school characteristics were obtained from each study, and built environment features within 400 m and 1 km buffers around home were calculated in a consistent manner using geographic information systems. A one-step individual participant data meta-analysis was performed in SAS. Using stepwise logistic regression, age, school socioeconomic status, distance to school, dwelling density and intersection density (400 m and 1 km buffers) were taken forward from bivariate analyses into a multiple variable model. Active travel to school was positively associated with intersection density ($p < 0.001$) (1 km buffer) and negatively associated with school socioeconomic status ($p = 0.001$), dwelling density ($p = 0.004$) (1 km buffer), and distance to school ($p < 0.001$), including age, sex, ethnicity and number of siblings as fixed effects in the final model. The findings of this meta-analysis can be used to guide and support the development of policies on school location and catchment, and pedestrian and cycling infrastructure for children and youth to actively and safely travel to school.

* Corresponding author.

E-mail address: erika.ikeda@aut.ac.nz (E. Ikeda).

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1. Introduction

The benefits of physical activity in childhood are significant and widely accepted (World Health Organization, 2010). Regular physical activity is associated with improved cognitive (Donnelly et al., 2016), cardiometabolic (Janssen and LeBlanc, 2010) and musculoskeletal health (Tan et al., 2014), as well as reduced symptoms of depression and anxiety (Biddle and Asare, 2011). Insufficient physical activity is linked to the significant rise in childhood obesity and comorbidities worldwide (Janssen and LeBlanc, 2010; Lee et al., 2012; Molnár and Livingstone, 2000). It is recommended that all children and young people achieve at least 60 min of moderate-to-vigorous intensity physical activity each day (Canadian Society for Exercise Physiology, 2016; Ministry of Health, 2017). Globally, New Zealand fares relatively well in terms of child and youth participation in sufficient levels of physical activity (Tremblay et al., 2016). Despite that a third of New Zealand children and young people remain insufficiently active for health (Maddison et al., 2016), and New Zealand has one of the highest rates of child obesity worldwide (Organisation for Economic Co-operation and Development, 2017).

Several systematic reviews show that children and young people who commute actively (e.g., walk or cycle) to school are more likely to attain recommended levels of physical activity than those who travel by motorised vehicle (e.g., public transport, car or motorcycle) (Faulkner et al., 2009; Larouche et al., 2014). Uptake of active travel in childhood also increases the likelihood of active commuting in later life (Telama et al., 2005). Active travel to school (ATS) permits children to develop navigational and traffic safety skills, identify and manage risks (Mammen et al., 2012), and gain experience in decision making and social interaction (Pooley et al., 2010; Schoeppe et al., 2014). Unsupervised active travel—or independent mobility—can facilitate additional benefits, such as developing and refining resilience and life skills for the adult world, particularly in the context of risk taking (Gill, 2007; Mackett et al., 2007).

The positive implications of active travel go beyond the physical activity and health of individuals. Wider benefits include less noise and air pollution, climate change mitigation, urban vitality, and reduced traffic congestion. The annual economic cost of traffic congestion is estimated to be up to NZ\$1.9 billion in Auckland alone (New Zealand Institute of Economic Research, 2017). Data from 2015 show that New Zealand's gross greenhouse gas emissions have increased 24% since 1990, and road transportation is one of the main contributors to this increase (77.9% increase) (Ministry for the Environment, 2017). Increased uptake of ATS has the potential to reduce overall traffic volume and air pollution, particularly in urban areas around schools at peak commute times (Collins and Kearns, 2010).

Despite these benefits, the prevalence of children's ATS is declining worldwide. New Zealand has one of the lowest rates of ATS internationally, with 28–29% of children aged 5–17 years walking and 2–3% cycling to school (Ministry of Transport, 2015; Tremblay et al., 2016). Understanding the reasons for the low, and declining prevalence of ATS has become a priority for governments, urban planners, public health practitioners, and school and community groups. An interaction of multiple factors operating at several levels affect ATS behaviour. Within a socio-ecological framework, these factors are broadly defined as individual (e.g., demographics, perceptions, skills), interpersonal (e.g., family and cultural norms) and broader environmental factors (e.g., built environment and policy) (Timperio et al., 2006). A collective understanding of these influences is crucial to enhance uptake of ATS among children and youth (Lambiase et al., 2010; Martínez-Gómez et al., 2011).

Both age and sex are key associates of ATS. The 2014/15 New Zealand Health Survey illustrates that in youth aged 10–14 years, a higher proportion of boys travel actively to school compared to girls (46.9% versus 40.6%) (Ministry of Health, 2015). No meaningful difference by sex was observed for younger children. In New Zealand, more children aged 10–14 years utilised ATS (43.8%), compared to those aged 5–9 years (38.4%) (Ministry of Health, 2015). The relationship between age and ATS is likely to be curvilinear, with an initial age-related increase in ATS among children due to higher degrees of independent mobility, parental allowances, and public transport use. ATS occurs to a small degree; followed by a decrease due to longer distances to secondary (high) schools compared with localised primary (elementary) schools (Gordon-Larsen et al., 2005; Mandic et al., 2017a; Mandic et al., 2015). There is some evidence of ethnic differences in ATS in New Zealand – with children of Māori, Pacific Island, and “other” ethnicities more likely to walk to primary school in Dunedin than New Zealand European children (Yelavich et al., 2008). Household factors such as larger household sizes and having older siblings may also increase the likelihood of ATS (Lin et al., 2017; Mandic et al., 2015). There is a trend towards increased ATS in children and youth residing in more socio-economically deprived neighbourhoods (Ministry of Health, 2015). Boys residing in areas with the highest levels of socio-economic deprivation are significantly more likely to use ATS than their male peers living in areas with the lowest levels of socioeconomic deprivation (Ministry of Health, 2015).

A key principle of socio-ecological theory is that motivating individuals to change behaviour cannot be effective if environments make it difficult or impossible to choose healthy behaviours (Sallis et al., 2008). Rather, creating environments that make it convenient, attractive, safe and economical to make healthy choices (and then motivating and educating people about those choices) will likely be most effective. Built environments comprise all physical surroundings that are constructed through human activity, including buildings, roads, open spaces and infrastructure (Srinivasan et al., 2003). A number of built environment factors have been associated with ATS, which are discussed briefly below.

A convincing body of research in New Zealand as well as worldwide has demonstrated that network distance to school is the most consistent built environmental factor associated with the likelihood of ATS (Davison et al., 2008; Huertas-Delgado et al., 2017; Mandic et al., 2015; Oliver et al., 2014; Oliver et al., 2015; Pont et al., 2009; Schlossberg et al., 2006; Wong et al., 2011). For example, children living within one mile (1.6 km) of school in the US were at least three times more likely to walk or cycle to school than those living outside the one mile radius (McDonald et al., 2011; McMillan, 2007; McMillan et al., 2006). Similarly, McDonald (2008) showed that travel time had the greatest effect on ATS, where a 10% increase in walking time was associated with a 7.5% decline in probability of walking to school in the US. In a sample of 595 New Zealand children and youth aged 8–14 years, a distance

of 1.4 km or less best predicted likelihood of ATS (Duncan et al., 2016). However, threshold distances are likely much further for cycling, with some studies from the US and Spain reporting threshold distances of up to 5 km (Chillón et al., 2016; Nelson et al., 2008; Schlossberg et al., 2006).

Connectivity refers to the directness and availability of travel routes between an origin and a destination (Thornton et al., 2011). Street connectivity offers the potential of increased ways to discover direct and shorter travel routes (Schlossberg et al., 2006). Connectivity is generally measured or assessed using the spacing between streets, the number of three-way or four-way intersections within an area, or the difference between the street and pedestrian network distance and the Euclidean (i.e. 'as the crow flies') distance (Thornton et al., 2011; Wong et al., 2011). For adults, grid-design urban environments are associated with significantly greater physical activity levels (Badland et al., 2008; Hirsch et al., 2014; Sugiyama et al., 2012). Among the few studies investigating associations between street connectivity and physical activity in children, findings showed both positive (Oliver et al., 2015; Schlossberg et al., 2006) and no association (Braza et al., 2004). One study has shown positive associations between street connectivity and active travel to all destinations in children (Oliver et al., 2015).

Population or residential density refers to the number of individuals or dwellings in a particular area. Density is in turn associated with accessibility and increased rates of active travel because housing is closer to a range of destinations (Thornton et al., 2011). Active travel among children living in urban areas (with high population density) in the US was found to be more common than in their rural or suburban counterparts (with sparse population density) (McDonald, 2008). Adolescents living in urban areas have been shown to accumulate most of their physical activity during school travel (Stewart et al., 2017a), whereas those in more rural areas achieve the majority of their activity during school hours (Rainham et al., 2012). However, these findings are not consistent in all geographic regions. In the Otago region of New Zealand youth living in rural areas reported higher rates of ATS compared to their urban counterparts (Mandic et al., 2015).

The diversity of land use within a region (e.g., residential, educational, commercial, industrial, and recreational) can have implications for children and young people's active travel. Mixed land uses within a localised area can reduce the distance to destinations, thereby providing more active travel opportunities (Thornton et al., 2011). Higher land use mix has been associated with ATS (D'Haese et al., 2014; Larsen et al., 2009) as well as overall physical activity and total walking trips in youth (Kerr et al., 2007; Kligerman et al., 2007). These studies allude to the importance of destination accessibility and diversity for active travel in children and youth.

In the New Zealand context, differences in geographic information systems (GIS) approaches across studies have hindered an ability to provide a clear and consistent understanding of the built environment associates of ATS in children and youth nationally. Therefore, the aims of this study were: (1) to systematically identify New Zealand research that had measured ATS, distance to school, and the neighbourhood built environment in children and youth, (2) to collate data from identified studies and combine them in a consistent manner, and (3) to identify associations between ATS and built environment features across the combined dataset. In doing so, this study provides new, robust evidence that has greater statistical power and is more generalisable than the contributing standalone studies.

2. Methods

2.1. Research context

The total population in New Zealand was estimated at 4.8 million in 2017, and a fifth of the population was children and youth aged 5–19 years (Statistics New Zealand, 2017d). New Zealand is also characterised as a highly suburbanised nation. By the end of 20th century, there are 20 main urban areas with a minimum population of 30,000 identified in New Zealand – 16 out of 20 are located in the North Island (e.g., Auckland, Wellington) and the others in the South Island (e.g., Christchurch, Dunedin) (Statistics New Zealand, 2017a). Due to changes in urban form, the population has been shifted towards car-oriented, low density neighbourhoods over the last few decades (Witten et al., 2017) which has resulted in greater urban sprawl and a change in children's mode of school travel and mobility.

In New Zealand, there are more than 180 different ethnic groups including indigenous Māori and migrants from Europe, Pacific Islands and Asian countries. The distribution of the ethnic groups with the majority of European, Māori and Asian varies across regions and cities (Statistics New Zealand, 2017b). In New Zealand, ethnicity is a self-perceived and cultural concept which is considered as a key social factor along with the other demographic characteristics describing the population (Statistics New Zealand, 2017b).

2.2. Eligibility criteria

Experimental studies or interventions (i.e., randomised controlled trials, quasi-experimental studies), longitudinal/cohort studies, and cross-sectional studies were eligible for inclusion. Participants in the included studies were school-aged children between five and 19 years living in New Zealand. In order to be eligible, studies needed to have reported participants' mode of travel to school, and collected objective measures of the neighbourhood built environment using GIS. Travel mode could be self-reported by children, their parents, or obtained by observation.

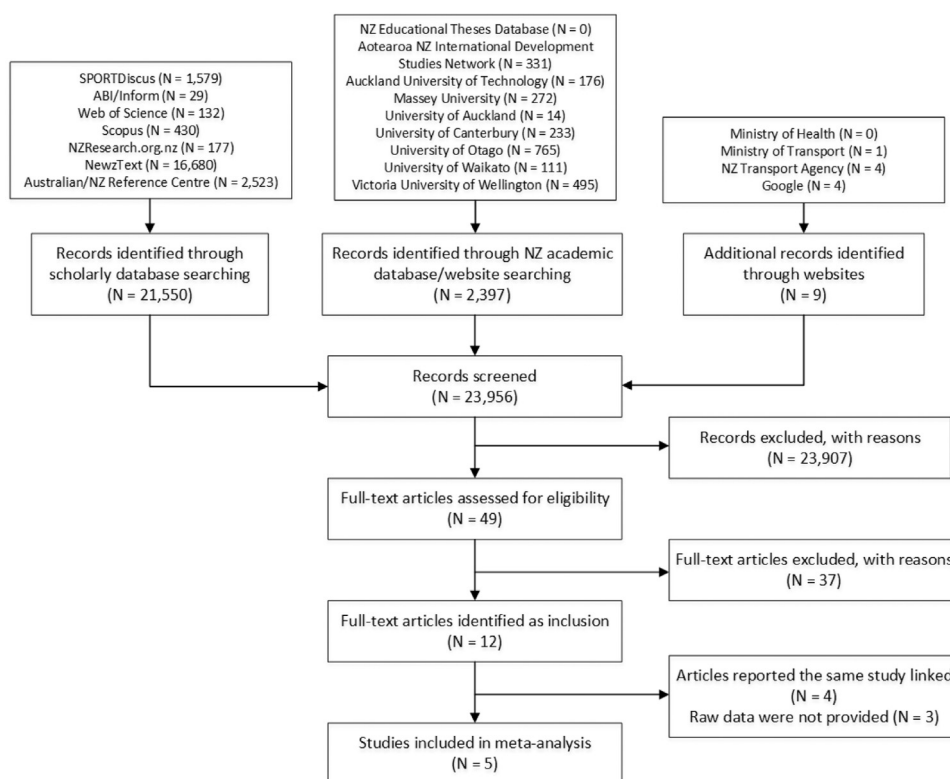


Fig. 1. Flow chart of article identification. N = number. *Note.* Active travel includes walk, bicycle, scooter and skateboard. Passive travel includes car, bus and motorbike.

2.3. Information sources and search strategy

Scholarly published journal articles were searched in the following seven academic databases: SPORTDiscus (via EBSCO Host), ABI/Inform (via ProQuest), Web of Science, Scopus, NZResearch.org.nz (New Zealand theses), NewzText (New Zealand newspapers and commentary sources), and Australian/New Zealand Reference Centre (via EBSCO Host) (New Zealand newspapers and commentary from local sources). Unpublished research (i.e., New Zealand Master's and Doctoral theses) were sought through New Zealand Educational Theses Database (via New Zealand Council for Educational Research), Aotearoa New Zealand International Development Studies Network, and Scholarly Commons/Institutional Repository (i.e. Auckland University of Technology, Massey University, University of Auckland, University of Canterbury, University of Otago, University of Waikato, Victoria University of Wellington). Government and local council related reports were sought through major Government agency websites (i.e., Ministry of Health, Ministry of Transport, New Zealand Transport Agency/Land Transport New Zealand) and generally through Google. Combinations of the following search terms and terms were used: “active travel/transport”, “mode* travel/transport”, “school”, “Zealand”, “walk*”, “bik*”, “trip*”, “car*”. For a full list of search fields refer to Supplementary information. The search was limited to English language and year from January 1990 to June 2016. Searches were conducted between May and July 2016.

2.4. Selection of studies

Fig. 1 shows a flow chart for article identification and selection. The initial search strategy produced nearly 24,000 articles. An initial screening of titles and abstracts was undertaken to remove those which were outside the scope of the review based on the eligibility criteria. The full text were obtained for articles and reports that passed this initial abstract screening process – 49 were considered potentially eligible and were assessed at the full text stage. Full texts of 12 articles and reports met the inclusion criteria. Finally, multiple publications and reports on the same study were linked together ($n = 4$), yielding a total of eight studies identified as eligible. The raw data of primary and secondary outcomes were acquired by contacting the original authors of the included studies. Three authors failed or declined to send raw data and these studies were thus excluded, leaving five studies for inclusion in the meta-analysis.

2.5. Data preparation and synthesis

The following variables were obtained (at the individual participant level) from each study author: participant demographics

(age, sex, number of siblings, household size, body measurements), mode of travel ‘to’ school (excluding ‘from’ school), and GIS-derived distance to school, intersection density, dwelling density, and land use mix using a 400 m and a 1 km street network buffer around each participant’s place of residence. Buffers are boundaries placed around areas or points using a predefined scale, and delineated using straight-line (Euclidean) or street network distance (Thornton et al., 2011). In addition, general information about neighbourhood and participant selection, inclusion and exclusion criteria, individual study analyses, and published results and study protocols were requested. TS liaised with all study authors to ensure consistent approaches to generating neighbourhood buffers and built environment variables were undertaken.

2.5.1. Individual characteristics

Participant age was classified into six groups (< 13, 13, 14, 15, 16, ≥ 17 years): less than 13 years, by age in years between 13 and 16, and more than 17 years in order to detect any possible curvilinearity in relationships, and to ensure sufficient numbers in each age group.

Body mass index (BMI) was calculated from weight and height, and categorised into weight classes (normal, overweight, obese) using growth curve data from the World Health Organization (de Onis et al., 2007). Age was missing for 19 participants, in which case age was imputed using the mean age for the participants from the same school year level.

2.5.2. School characteristics

Data from the Ministry of Education were used to classify each school into contributing (children aged 5–10 years), full primary (5–12 years), intermediate (11–12 years), or secondary (13–17 years), and to identify school decile values. School decile indicates the socio-economic status of households in a school’s catchment area. Deciles ranging from 1 (being the 10% of schools with the highest proportion of pupils residing in low socio-economic areas), to 10 (being the 10% of schools with the lowest proportion of these students) (Ministry of Education, 2017).

2.5.3. School travel mode

Three studies (Hinckson et al., 2014; Oliver et al., 2014; Rush et al., 2016) collected travel mode data across each of the five school days, and one (Mandic et al., 2016) had a 5-scale response for each travel mode (“never”, “rarely”, “sometimes”, “most of the time”, “all of the time”). The only school travel information available from the final study (Oliver et al., 2011) pertained to ‘usual’ travel mode (e.g., “car”, “walk”, “bike” etc.). For this reason, travel mode data across all studies were dichotomised as 0 or 1, where 0 referred to individuals who used passive modes of travel (i.e., car, bus, motorbike) and 1 represented individuals who used active forms of travel (i.e., walk, bicycle, scooter, skateboard) on three or more school days per week (Ross et al., 2017; Veitch et al., 2017), or “most of the time”. As ATS was a binary response variable, logistic regression (SAS proc logistic) was performed to test whether each variable was associated with (the odds of) active travel to school. Individuals living further than 10 km from school were excluded from analyses. The rationale for this was two-fold: (1) based on visual inspection of the distance to school data, those living further than 10 km from school were considered outliers, and (2) previous New Zealand research suggests this threshold would be sufficiently sensitive to capture most ATS (Duncan et al., 2016; Oliver et al., 2014).

2.5.4. Built environment variables

Dwelling density was calculated as the number of private occupied dwellings per square kilometer. The number of dwellings per meshblock were obtained from the 2013 Census (Statistics New Zealand, 2014), and an area weighted average was used to estimate the number of dwellings within each buffer. Parcel-level zoning data were used to calculate land use mix, which is an indicator of the variety of local destinations close to home. Land use was categorised as residential, commercial, public open space, industrial, recreation, or other. An entropy score was used to calculate the extent of land use mix inside each buffer using the equation (Forsyth et al., 2012) for four studies (Hinckson et al., 2014; Oliver et al., 2014; Oliver et al., 2011; Rush et al., 2016):

$$\text{Land use mix} = - \left(\sum_{i=1}^n P_i \ln(P_i) \right) / \ln(n)$$

where n is the number of different land use categories and P_i is the proportion of land use category i in the region. Entropy scores range from 0, which indicates no mix or homogeneous land use, to 1 which represents heterogeneous land use, or a perfect mix. One study (Mandic et al., 2016) calculated land use mix using a different equation (Cervero and Kockelman, 1997):

$$\text{Land use mix} = \left\{ \sum_k \left[\sum_j P_{jk} \ln(p_{jk}) \right] / \ln(J) \right\} / K$$

where P_{jk} is the proportion of land use category j within a half-mile radius of the developed area surrounding grid-cell k , and K is number of actively developed hectares in each tract. The parcel level land use data used to calculate land use mix was compiled from a variety of sources: territorial authority zoning data, territorial authority points of interest data sourced in 2013/2014 (e.g., parks, libraries), and Zenbu online business directory data extracted in 2014. Lastly, intersection density was calculated as the number of 3 or more-way intersections per square kilometer, using road centerline data obtained from Land Information New Zealand (LINZ; www.linz.govt.nz). The calculation of these variables was consistent with previous work in New Zealand (Badland et al., 2009; Hinckson et al., 2014).

In the first instance, frequency distributions of categorical data were checked and recategorized if necessary (i.e., if a disproportionately low number of responses was observed in one or more categories). Due to logistic regression assuming an exponential relationship for continuous variables and because non-linear and plateauing effects can exist when examining built environment variables, these variables (dwelling density, intersection density, and land use mix) were organised into quartiles.

2.6. Statistical analysis

A one-step individual participant data (IPD) meta-analysis approach was taken. This differs from more traditional meta-analyses where aggregate data (e.g., effect size estimates) are extracted from individual studies and synthesised. In a one-step approach, the original IPD from all studies is modelled simultaneously. All analyses were performed in SAS (v9.4, SAS Institute, North Carolina, NC).

Using stepwise logistic regression, an initial feature selection step was performed to determine what variables were suitable for inclusion in the final model. A criterion of $p < 0.10$ was set for inclusion in the model, and age, sex, ethnicity and number of siblings, were included as fixed effects, being known correlates of ATS behaviour (Chillón et al., 2014; Christiansen et al., 2014; Mandic et al., 2015; Yu and Zhu, 2016). The clustering of observations within studies was accounted for by stratifying the analysis by study (i.e., by estimating a separate intercept for each study) using the STRATA statement (SAS Institute Inc., 2011). Individual study results for the full model were also calculated and presented for each outcome variable using forest plots.

3. Results

Overall, five studies involving 2844 children and youth aged 6–19 years were included in this meta-analysis (Fig. 1, Table 1) (Hinson et al., 2014; Mandic et al., 2016; Oliver et al., 2014; Oliver et al., 2011; Rush et al., 2016). In total, there were 988 active travellers, and 1856 passive travellers. Studies were conducted in three of the largest cities in New Zealand, namely Auckland (urban population of 1.495 million, comprising 32% of the total New Zealand population), Wellington (population 405,000), and Christchurch (389,700) (Statistics New Zealand, 2016). Additionally, one study was conducted in Dunedin, New Zealand's seventh largest city, with a population of 118,500. Detailed information about each study is summarised in the Supplementary information 2.

Participant demographic characteristics, rates of ATS, and the results of the bivariate analyses are presented in Table 2. Descriptive information for the built environment characteristics and results of the bivariate analyses for these variables are presented in Table 3. Age, school decile, dwelling density, intersection density (400 m and 1 km buffer), and distance to school were related to ATS at $p < 0.10$ in the bivariate analyses and were taken forward into the multiple variable modelling, along with the aforementioned fixed effects (age, sex, ethnicity and number of siblings).

Table 4 presents the logistic regression results for the final multiple variable model. Accounting for the fixed effects (age, sex, ethnicity, number of siblings) and after removal of non-significant variables at $p > 0.05$, remaining factors in the model were number of siblings, school decile, distance to school, and intersection density and dwelling density within 1 km buffers only. Compared with children who had no siblings, those with one sibling were 30% less likely to use ATS (95% CI 0.48, 0.96, $p < 0.02$). Children and youth attending higher decile (higher socio-economic status) schools were less likely to travel actively compared to those attending lower decile schools (OR 1.18, 95% CI 0.78, 1.79, $p = 0.001$). The greatest odds for ATS were found for distance to school, with the odds of ATS near zero for those living more than 2.3 km from school. Using the 1 km neighbourhood buffer, a linear increase in odds of ATS was observed for intersection density, with those living in neighbourhoods with the highest intersection density almost three times more likely to use ATS than those living in neighbourhoods with the lowest intersection density (OR 2.86, 95% CI 1.95, 4.17, $p < 0.001$). Conversely (and somewhat counterintuitively), a negative relationship was observed between ATS and dwelling density. We conducted exploratory work to examine these perplexing results. These examinations suggested a possible level of interaction between dwelling density and distance to school, with a combination of lower housing density and shorter distance to schools linked with ATS (data available on request).

We further examined distance to school, intersection density and dwelling density as associates of ATS for each individual study. Fig. 2 shows the forest plot for individual study results, comparing quartiles 1 with quartiles 2, 3, and 4 for each variable. Distance to school showed significantly negative associations with ATS with all except one comparison from the Understanding the Relationship between Activity and Neighbourhoods (URBAN) study (Oliver et al., 2014). Within many of the individual studies there were no

Table 1
Frequency of observations in each study.

Study	N	Active Travellers N (%)	Age Range (years)	City
BEANZ (Hinson et al., 2014)	571	254 (44.5)	13–19	Auckland & Wellington
BEATS (Mandic et al., 2016)	1181	384 (32.5)	12–19	Dunedin
KITC (Oliver et al., 2011)	226	120 (53.1)	9–13	Auckland
PIF (Rush et al., 2016)	657	198 (30.1)	13–15	Auckland
URBAN (Oliver et al., 2014)	209	32 (15.3)	6–19	Auckland, Wellington & Christchurch

BEANZ = Built Environment and Adolescent New Zealanders, BEATS = Built Environment and Active Transport to School, KITC = Kids in the City, N = number, PIF = Pacific Islands Families, URBAN = Understanding the Relationship between Activity and Neighbourhoods.

Table 2

Participant demographic characteristics and results of the bivariate analyses for odds of actively travelling to school for each variable.

Variable	Category	N	ATS N (%)	OR	95% CI	p-value
Sex	Male	1440	509 (35.4)	1.00		0.44
	Female	1471	494 (33.6)	0.94	(0.80, 1.09)	
Age (years)	5–12	363	147 (40.5)	1.00		0.05
	13	258	76 (29.5)	0.68	(0.33, 1.37)	
	14	1026	327 (31.9)	0.78	(0.39, 1.56)	
	15	581	208 (35.8)	0.92	(0.45, 1.82)	
	16	313	126 (40.3)	1.03	(0.51, 2.08)	
	17 +	370	118 (31.9)	0.68	(0.33, 1.38)	
Ethnicity	New Zealand European	1438	499 (34.7)	1.00		0.19
	Māori	240	88 (36.7)	1.17	(0.86, 1.58)	
	Pacific	786	238 (30.3)	0.76	(0.55, 1.03)	
	Asian	207	82 (39.6)	0.98	(0.70, 1.35)	
	Other	226	86 (38.1)	1.15	(0.85, 1.54)	
Body mass index (kg/m ²)	Underweight	78	20 (25.6)	1.00		0.61
	Normal	1595	571 (35.8)	1.19	(0.69, 2.02)	
	Overweight	583	193 (33.1)	1.04	(0.59, 1.81)	
	Obese	547	188 (34.4)	1.16	(0.65, 2.05)	
Number of people in a household (n)	< 4	611	239 (39.1)	1.00		0.18
	4	873	289 (33.1)	0.82	(0.65, 1.01)	
	5–6	908	294 (32.4)	0.82	(0.65, 1.02)	
	7 +	181	65 (35.9)	1.00	(0.69, 1.45)	
Number of siblings (n)	0	308	133 (43.2)	1.00		0.11
	1	894	300 (33.6)	0.80	(0.60, 1.04)	
	2	778	267 (34.3)	0.98	(0.74, 1.30)	
	3	449	133 (29.6)	0.88	(0.63, 1.20)	
	4 +	487	171 (35.1)	1.07	(0.78, 1.45)	
School decile	1–3 (lower SES)	715	247 (34.6)	1.00		< 0.001
	4–7	997	388 (38.9)	0.86	(0.62, 1.17)	
	8–10 (higher SES)	1143	357 (31.2)	0.62	(0.44, 0.85)	
School type	Primary/Intermediate	443	161 (36.3)	1.00		0.72
	Secondary	2428	840 (34.6)	0.77	(0.18, 3.22)	

Note. All modelling adjusted for study effects. ATS = active travel to school, CI = confidence interval, N = number, OR = odds ratio, SES = socioeconomic status.

significant findings for dwelling and intersection density. However, studies did show homogeneity in results, which resulted in significant findings overall. With the exception of the Kids in the City (KITC) study (Oliver et al., 2011), individual study findings were relatively consistent with null or negative correlates for dwelling density. For intersection density, greater odds ratios and confidence intervals were observed for the KITC study, and the URBAN study (Oliver et al., 2014).

4. Discussion

The aims of this study were: (1) to systematically identify New Zealand research that had measured ATS, distance to school, and the neighbourhood built environment in children and youth, (2) to collate data from identified studies and combine them in a consistent manner, and (3) to identify associations between ATS and built environment features across the combined dataset. In doing so, this study provides new, robust evidence and greater statistical power that is more generalisable than the previous contributing smaller studies. In total, data from 2844 children and young people were obtained from five studies representing four major cities across New Zealand. Approximately a third of the participants used ATS “usually” or “most of the time”. For the most part, associations between environmental variables and ATS were consistent with previous research (Broberg and Sarjala, 2015; Carlson et al., 2014; Larsen et al., 2016; Pont et al., 2009; Wong et al., 2011) and the individual studies themselves.

4.1. Distance to school

Overall, the relationship between distance to school and odds of ATS had the greatest magnitude of all ATS associations observed even after accounting for all other factors in the final model. This finding is not surprising given the body of existing evidence demonstrating this relationship (Duncan et al., 2016; Ermagun and Samimi, 2017; Larsen et al., 2016; Lee et al., 2013; Mandic et al.,

Table 3

Built environment variable characteristics and results of the bivariate analyses for odds of actively travelling to school for each variable.

Variable	Quartile	N	ATS N (%)	OR	95% CI	p-value
<i>1 km buffer:</i>						
Dwellings density (km ²)	Q1 (Low density)	755	185 (24.5)	1.00		< 0.001
	Q2	716	233 (32.5)	1.54	(1.21, 1.93)	
	Q3	718	272 (37.9)	2.04	(1.61, 2.56)	
	Q4 (High Density)	727	314 (43.2)	2.14	(1.7, 2.68)	
Intersection density (km ²)	Q1 (Low density)	743	198 (26.7)	1.00		< 0.001
	Q2	719	222 (30.9)	1.26	(0.99, 1.60)	
	Q3	718	249 (34.7)	1.67	(1.31, 2.11)	
	Q4 (High Density)	736	335 (45.5)	2.97	(2.33, 3.78)	
Land use mix	Q1 (Low Mix)	764	255 (33.4)	1.00		0.61
	Q2	667	230 (34.5)	0.93	(0.72, 1.18)	
	Q3	738	241 (32.7)	0.84	(0.65, 1.08)	
	Q4 (High Mix)	747	278 (37.2)	0.91	(0.70, 1.17)	
<i>400 m buffer:</i>						
Dwelling density (km ²)	Q1 (Low density)	744	199 (26.8)	1.00		< 0.001
	Q2	727	231 (31.8)	1.32	(1.04, 1.66)	
	Q3	716	276 (38.6)	1.73	(1.37, 2.16)	
	Q4 (High Density)	729	298 (40.9)	1.78	(1.42, 2.22)	
Intersection density (km ²)	Q1 (Low density)	751	200 (26.6)	1.00		< 0.001
	Q2	715	237 (33.2)	1.43	(1.13, 1.79)	
	Q3	716	247 (34.5)	1.63	(1.29, 2.05)	
	Q4 (High Density)	734	320 (43.6)	2.37	(1.88, 2.97)	
Land use mix	Q1 (Low Mix)	760	256 (33.7)	1.00		0.29
	Q2	728	245 (33.7)	0.90	(0.71, 1.14)	
	Q3	720	234 (32.0)	0.80	(0.62, 1.02)	
	Q4 (High Mix)	708	269 (38.0)	0.95	(0.73, 1.22)	
Distance to school (km)	Q1 (< 1.3)	767	482 (62.8)	1.00		< 0.001
	Q2 (1.3 to < 2.3)	710	341 (48.0)	0.34	(0.26, 0.43)	
	Q3 (2.3 to < 4.2)	719	152 (21.1)	0.09	(0.06, 0.11)	
	Q4 (≥ 4.2)	720	29 (4.0)	0.01	(0.00, 0.02)	

Note. All modelling adjusted for study effects. ATS = active travel to school, CI = confidence interval, N = number, OR = odds ratio.

2015; McDonald et al., 2011; Schlossberg et al., 2006). Compared to children living within 1.3 km of school, the odds of ATS were reduced by a third among those residing between 1.3 and 2.3 km from school. Beyond 2.3 km, the odds of ATS in this combined dataset reduced to near zero. This distance threshold is in line with earlier research indicating significant and substantial reductions in ATS for distances of 1.4–2.0 km (Mandic et al., 2017b; McDonald et al., 2011; McMillan, 2007; McMillan et al., 2006; Oliver et al., 2014). The results of the individual studies were similar, with the exception of comparing quartile 1 and quartile 2 for the URBAN study whereby the 95% confidence intervals crossed over one, indicating a non-significant association for this comparison only. To some extent, the wider confidence interval may have been a function of the smaller sample size in the URBAN study compared to other included studies (Oliver et al., 2014). Collectively, the evidence shows that shorter school travel distances are significantly associated with increased walking and cycling to school (Wong et al., 2011). Schools located centrally within communities are likely to facilitate children's ATS. Therefore, location of schools and zoning restrictions are important considerations to optimise travel distances and the likelihood for ATS (Mandic et al., 2017b; Oliver et al., 2014).

4.2. Street connectivity

In line with previous research (Schlossberg et al., 2006), a clear positive relationship between street connectivity and ATS was observed when using the 1 km neighbourhood buffer. Children and youth living in neighbourhoods with the highest intersection density were almost three times more likely to use ATS than those living in neighbourhoods with the lowest intersection density. This finding was, however, in conflict with other studies from Australia (Timperio et al., 2006), the US (Carlson et al., 2014) and Canada (Mitra and Buliung, 2012) which reported negative associations between intersection density and ATS. Highly connected streets may be more utilised by motorised vehicles. Consequently, children and youth living in those areas, compared to those living in areas with low street connectivity, could be more exposed to high traffic speed and volume and less likely to use ATS (Sirard and Slater, 2008). Use of pedestrian or walkable networks to calculate intersection density may increase the specificity and sensitivity of results and provide more precise information for active travellers.

Table 4
Final multiple variable model for odds of using active travel to school.

Variable	Category	OR	95% CI	p-value
Age (years)	5–12	1.00		0.26
	13	0.89	(0.39, 2.02)	
	14	0.99	(0.44, 2.19)	
	15	1.20	(0.54, 2.63)	
	16	1.16	(0.51, 2.59)	
	17 +	0.81	(0.35, 1.84)	
Sex	Male	1.00		0.01
	Female	0.79	(0.64, 0.95)	
Ethnicity	New Zealand European	1.00		0.15
	Māori	1.04	(0.71, 1.52)	
	Pacific	0.68	(0.46, 1.00)	
	Asian	0.73	(0.49, 1.07)	
	Other	1.05	(0.73, 1.51)	
Number of siblings (n)	0	1.00		0.02
	1	0.69	(0.48, 0.96)	
	2	0.90	(0.62, 1.27)	
	3	0.76	(0.51, 1.13)	
	4 +	1.08	(0.72, 1.61)	
School decile	1–3 (lower SES)	1.18	(0.78, 1.79)	0.001
	4–7	1.54	(1.22, 1.95)	
	8–10 (higher SES)	1.00		
Distance to school (km)	Q1 (< 1.3)	1.00		< 0.001
	Q2 (1.3 to < 2.3)	0.29	(0.22, 0.37)	
	Q3 (2.3 to < 4.2)	0.07	(0.05, 0.09)	
	Q4 (≥ 4.2)	0.01	(0.00, 0.01)	
Intersection density (km ² ; 1 km buffer)	Q1 (Low density)	1.00		< 0.001
	Q2	1.74	(1.27, 2.38)	
	Q3	2.18	(1.57, 3.02)	
	Q4 (High density)	2.86	(1.95, 4.17)	
Dwelling density (km ² ; 1 km buffer)	Q1 (Low density)	1.00		0.004
	Q2	0.59	(0.42, 0.81)	
	Q3	0.58	(0.41, 0.80)	
	Q4 (High density)	0.56	(0.39, 0.80)	

Note. All modelling adjusted for study effects. CI = confidence interval, N = number, OR = odds ratio, SES = socioeconomic status.

4.3. Dwelling density

A somewhat counterintuitive finding emerged in relation to dwelling density, whereby increased dwelling density (using a 1 km buffer only) was associated with reduced rates of ATS in children and youth. With the exception of the KITC study, all studies showed a trend towards reduced ATS with increasing dwelling density. It is possible the differences observed for the KITC study were due to the comparatively smaller sample size (compared to other included studies), and the focus on medium-to-high density neighbourhoods in this project (Oliver et al., 2011). Overall, the findings for dwelling density are in contrast with earlier research showing positive relationships with ATS (Carlson et al., 2014; Kerr et al., 2006; Larsen et al., 2009). To investigate this further, inter-relationships between the built environment variables were considered in modelling associations with ATS (data available on request). An interesting pattern was observed, whereby there was some evidence for an interaction effect for dwelling density and distance to school. In particular, findings indicated that a combination of low dwelling density and low distance to school may be positively related to ATS. It is likely that the short distance to school overrode the impact of dwelling density on this relationship, so these findings must be interpreted with caution. Further investigation into the links between neighbourhood density, traffic volumes, road safety and ATS is warranted. It is possible that the relationship for dwelling density is curvilinear, with neighbourhoods of extremely low dwelling density (e.g., in rural areas, also characterised as having low walkability overall (Hansen et al., 2015)) and extremely high dwelling density (e.g., apartment blocks in central city areas) offering little in the way of supporting ATS.

4.4. School characteristics

Neighbourhood-level socio-economic status was associated with ATS, with individuals attending higher decile (higher socio-economic status) schools being significantly less likely to travel actively compared to those attending lower decile schools. Economic

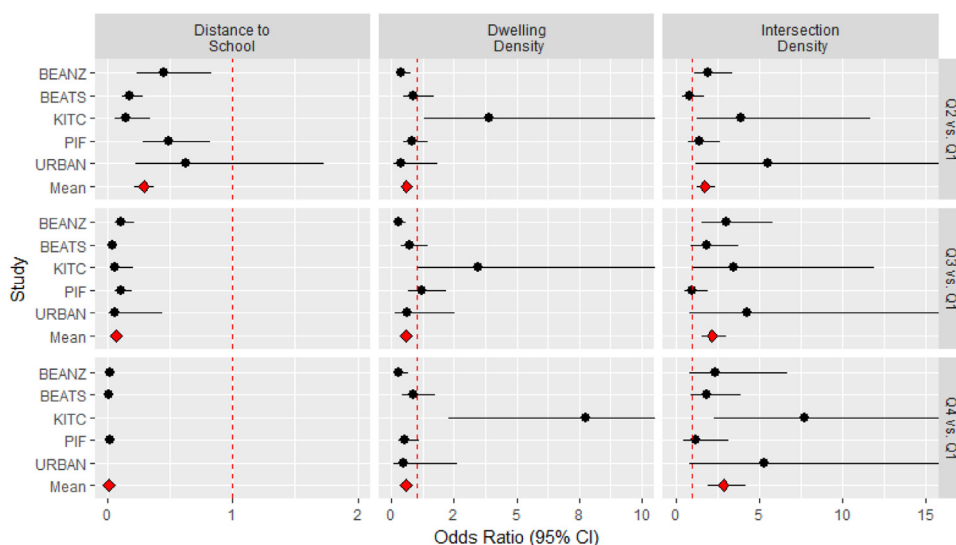


Fig. 2. Forest plot comparing quartile 1 with quartiles 2, 3, and 4 for distance to school, dwelling density (1 km buffer), and intersection density (1 km buffer) associations with active travel to school. BEANZ = Built Environment and Adolescent New Zealanders, BEATS = Built Environment and Active Transport to School, KITC = Kids in the City, PIF = Pacific Islands Families, URBAN = Understanding the Relationship between Activity and Neighbourhoods.

factors contributing to ATS can include car ownership (Mandic et al., 2015) and access, and employment status of parents/caregivers (Lin et al., 2017). It is possible these factors contributed to higher ATS in children and youth residing in lower socio-economic neighbourhoods. However, it was not possible to include these factors in modelling due to differences in measures taken across studies.

4.5. Individual characteristics

Age, sex, ethnicity and number of siblings were retained in the final model as fixed effects, irrespective of statistical significance. Consistent with previous research (Larsen et al., 2016; Yu and Zhu, 2016), females were less likely to use ATS than their male peers. In contrast to our expectations, no significant relationships were observed for the other fixed effects. In the New Zealand context, children of Māori, Pacific Island, and “other” ethnicities have reported higher ATS than their New Zealand European counterparts (Yelavich et al., 2008). This was not the case in the current research. It is hypothesised that socio-economic deprivation (as observed with the school decile being one of the significant associations of ATS) may have a greater impact on ATS than ethnicity. Meaning that when socio-economic factors are taken into account, the effect of ethnicity could be negligible. Compared with participants with no siblings, those with one sibling were less likely to use ATS, and the relationship was not statistically significant for those with two or more siblings. Earlier New Zealand research has shown a positive impact of having older siblings in the household on children's independent mobility (Lin et al., 2017). It is likely that a similar pattern existed in the research included here, but it was not possible to account for age of siblings in this analysis as those data were not measured across all studies.

4.6. Limitations and other considerations for active school travel in children and youth

The heterogeneity in study designs and variables measured across included studies limited our ability to consider a range of factors that may have been important in modelling the relationship between ATS and the neighbourhood built environment. Firstly, due to different measures used for mode of travel to school across the studies, only a dichotomous category of active versus passive travel was employed in the meta-analysis, preventing the examination of individual travel modes such as walking versus cycling (Mandic et al., 2017a; Trapp et al., 2011). In terms of the objective built environment, pedestrian and cyclist infrastructure and destination accessibility were not able to be examined in the current study. Pedestrian infrastructure and traffic calming along routes to school, such as constructing sidewalks and cycle lanes have shown promise for increasing children's ATS (Boarnet et al., 2005; Kim and Heinrich, 2016). However, conflicting associations exist—particularly for increasing the uptake of cycling (Pucher et al., 2010). Crossing streets can be perceived as a dangerous activity for children, especially when crossing main or busy streets, and particularly for young children. Indeed, an Australian survey showed that parents viewed road crossings to school and traffic calming around the school entrance as major factors influencing their decision about their child's mode of travel to school (Cole et al., 2007). Children who had to cross a main street on the route to school were more likely to be driven to school than to walk or cycle (Bringolf-Isler et al., 2008). A recent systematic review found strong evidence for the impact of multiple streetscape components (including two or more of: crosswalk/sidewalk improvements, improved/covered bike parking, traffic calming features and safe places to walk) on children's active travel (to school and other destinations) (Smith et al., 2017). Other features such as topography may also impact

decision-making around school travel modes and routes, but little is known in this area (Stewart et al., 2017b; Timperio et al., 2006). In the New Zealand context, cycling to secondary school is less common than walking, is perceived as less safe, and receives less infrastructure and social support compared to walking (Mandic et al., 2017a). However, regional differences exist within New Zealand (Frater et al., 2017). Further work in this area is needed to identify specific environmental factors that generate the greatest impact on children's walking and cycling to school behaviours and active travel in general.

Collectively, population density, street connectivity, pedestrian and cycling infrastructure, and destination diversity affect overall accessibility to destinations, or how easily a range of destinations can be reached on foot or by bicycle (Vale et al., 2016). There are a number of objective (e.g., a spatially-derived indices) or subjective (e.g., questionnaires) measures that have been developed and used to assess the walking potential of an area, such as the Walkability Index and Walk Score (Vale et al., 2016). However, measuring how conducive an environment is for children's walking or cycling is less developed. Most recently a child-specific neighbourhood destination accessibility index (NDAI-C) was developed in New Zealand (Badland et al., 2015) which has been associated with active travel modes on weekdays (Oliver et al., 2015). To some extent, the measure of land use mix used in the current study provides an indicator of diversity of destination types in the neighbourhood, but this does not capture information about destinations of specific importance to children, or the number of destinations within a region. Future research examining destination accessibility in relation to children's and adolescents' travel behaviours is needed.

A number of social and perceived variables such as encouragement and supports for ATS were not included in this study, but may be important in understanding associations between the built environment and ATS. Firstly, neighbourhood self-selection may impact travel behaviours (Cao et al., 2009), but was not measured in the current study. In New Zealand, school choice decisions are influenced by social factors and school programmes/facilities rather than proximity to home (Mandic et al., 2017c) and have important implications for ATS to secondary schools, particularly in higher socioeconomic status areas. One New Zealand study showed that adolescents who enrolled in the closest school to home had five times higher rates of ATS and lower rates of motorised travel to school compared to their counterparts (Mandic et al., 2017b). Thus choice of neighbourhood, and choice of school, assuming families are able to make these choices, can have substantial impacts on the likelihood of ATS in children and young people.

One of the most commonly reported barriers to ATS for children and young people is parental perceptions of neighbourhood safety (Egli et al., *in press*; Hinckson, 2016; Yeung et al., 2008). Research from the US shows parental perceptions of neighbourhood safety and attitudes towards ATS had a greater influence on children's ATS behaviours than physical environment (i.e., presence of sidewalks) (McMillan, 2007). Specific barriers to uptake of ATS, combining the social and physical environment, include high traffic volume and speed, poor visibility, unsafe or inadequate road crossings, dangerous driving and parking, stranger-danger, and fear of crime (Giles-Corti et al., 2009; Kerr et al., 2006; McMillan, 2007). In addition, cycling is perceived to be a less safe mode of travel to school compared to walking by New Zealand adolescents (Mandic et al., 2017a). Giles-Corti et al. (2009) viewed the integral role of parents as 'gatekeepers' of children's travel mode choice and travel behaviours. While crime and stranger-danger in New Zealand have not increased over time (New Zealand Police, 2015), parental concerns about traffic safety are justified, with a substantially increased risk of traffic-related injuries and deaths for child pedestrians and cyclists (Sonkin et al., 2006; Statistics New Zealand, 2017c).

4.7. Strengths and implications

A strength of the current study was the use of consistent approaches to neighbourhood buffer development and subsequent generation of objective built environment measures across studies. The choice of buffers depends on the type of environmental exposures being measured, and the level of spatial interactions (i.e., potential or actual) to capture (Chaix et al., 2012; Thornton et al., 2011). When examining the effects of contextual influences on ATS, fundamental methodological issues arise, namely the modifiable area unit problem (MAUP) and the uncertain geographic context problem (UGCoP). The MAUP and UGCoP refer to the effects of spatial scale and zoning versus spatial and temporal uncertainty of the contextual influences (Clark and Scott, 2014; Kwan, 2012; Openshaw, 1979; Vale et al., 2016). Discrepancies in spatial units across studies may hinder comparisons between research findings because the effects of the contextual variables may change depending on the geographic areas defined in the studies.

Another strength of this study was the systematic approach to identifying studies for inclusion in this meta-analysis. Data could not be retrieved for three of the eight eligible studies, resulting in the potential for bias in terms of geographic and demographic representation. However, we believe the potential for bias was small, with the final dataset for this study including 2844 participants residing in four major cities across New Zealand. Ultimately, this research has enabled greater statistical power than with individual studies, and greater confidence in the representativeness of the findings for children and youth residing in New Zealand cities. Reporting bias of individual studies was negligible, with all included studies having published protocols. Opportunities exist for future research to explore the impact of the built environment on different travel modes such as walking vs. cycling and car vs. public transport (e.g., mixed travel modes (Stewart et al., 2017b): buses, trains, ferries) to profile and understand these associates and behaviours. For example, information on cycling to school may highlight a need for new cycling infrastructure and safety strategies for children and younger people, and develop policy and programmes for this population (Mandic et al., 2018a, 2018b).

5. Conclusion

In this large study of New Zealand children and youth, significant negative relationships were observed between the likelihood of ATS and distance to school, dwelling density and school socioeconomic status. Odds of ATS were positively associated with intersection density. The findings of this meta-analysis suggest that factors that influence distance to school such as school location and