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Heterogeneity in distance elasticity of active travel to school

Laya Hossein Rashidi
University of Sydney
laya.hosseinrashidi@sydney.edu.au

Jennifer L. Kent
University of Sydney
jennifer.kent@sydney.edu.au

Emily Moylan
University of Sydney
emily.moylan@sydney.edu.au

Abstract: Children's active transport to school has multiple health, social, economic, and environmental benefits, and the literature on ways to support children's active accessibility is vast. The consistent conclusion from this research is that the distance between home and school is a key determinant of whether a child will walk or cycle to and from the school gate. While distance is undoubtedly of central importance to the active school travel puzzle, our understanding of children's sensitivity to increases in distance remains nascent. How far is too far when it comes to active school access? Using survey data from 6,629 school students in Australia, this paper explores this question through a nuanced focus on the sensitivity of active transport to school (ATS) to changes in trip distance. More specifically, a multinomial logistic regression model is used to analyze the heterogeneity of elasticity to distance, and the nature of the relationship between distance elasticity and land-use and demographic segments. The findings confirm existing understandings that distance and local land use are significant factors associated with ATS. By using a piecewise treatment of distance and estimating point elasticities, the model also shows that mode-choice sensitivity to distance varies across places and populations and is itself non-linear. The turning point of the multinomial logistic regression function with respect to distance is between 1 km and 3 km, indicating that a percentage increase in distance within this range is most likely to deter active school travel. This novel finding provides much-needed clarity to existing understandings of the sensitivity of ATS to distance. Such understandings are central to policy aspirations seeking to design school catchments with active accessibility as a desired outcome.

Keywords: active transport to school, health benefit, distance, heterogeneity of elasticity

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1 Introduction

Children's active transport to school (ATS) is associated with a multitude of health, social, economic and environmental benefits. Children who walk, cycle or scoot to school are more physically active (Barros et al., 2024; Cooper et al., 2005), and there are emerging findings about the link between ATS and mental health (Ramanathan et al., 2014); emotional literacy, cognitive performance (Westman et al., 2017), navigational and risk-management skills (Malone, 2007); and educational achievement (Hassevoort et

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al., 2016). In economic and sustainability terms, the costs associated with the private car chauffeuring of children to and from school are well known, including travel and waiting time; vehicle ownership and maintenance costs; and carbon emissions associated with private car use more generally (McDonald et al., 2016). Finally, ATS provides an opportunity to expose children to less car-dependent lifestyles, endowing the skills, sentiments and appreciations to travel by active modes through the life course (Haustein et al., 2009). These benefits and impacts have not escaped the attention of scholars, the public and professions, and as such, the interest in ways to encourage children's ATS is prolific.

Studies to date include analyses of the socio-cultural attributes of children who walk or cycle (Mammen et al., 2012; Timperio et al., 2017) and evaluations of behavior change and support programs designed to encourage children's modal shift (Curtis et al., 2015; Ermagun & Samimi, 2015; Mammen et al., 2012). Complementing these behavioral foci has been an abundant body of literature examining the built environment determinants of ATS (Figure 1). This paper seeks to extend this body of work through a unique focus on the sensitivity of ATS to changes in trip distance. Using survey data from 6,629 school students, it analyses the heterogeneity of sensitivity to this variable, and the nature of relationships between this sensitivity and land-use and demographic segments.

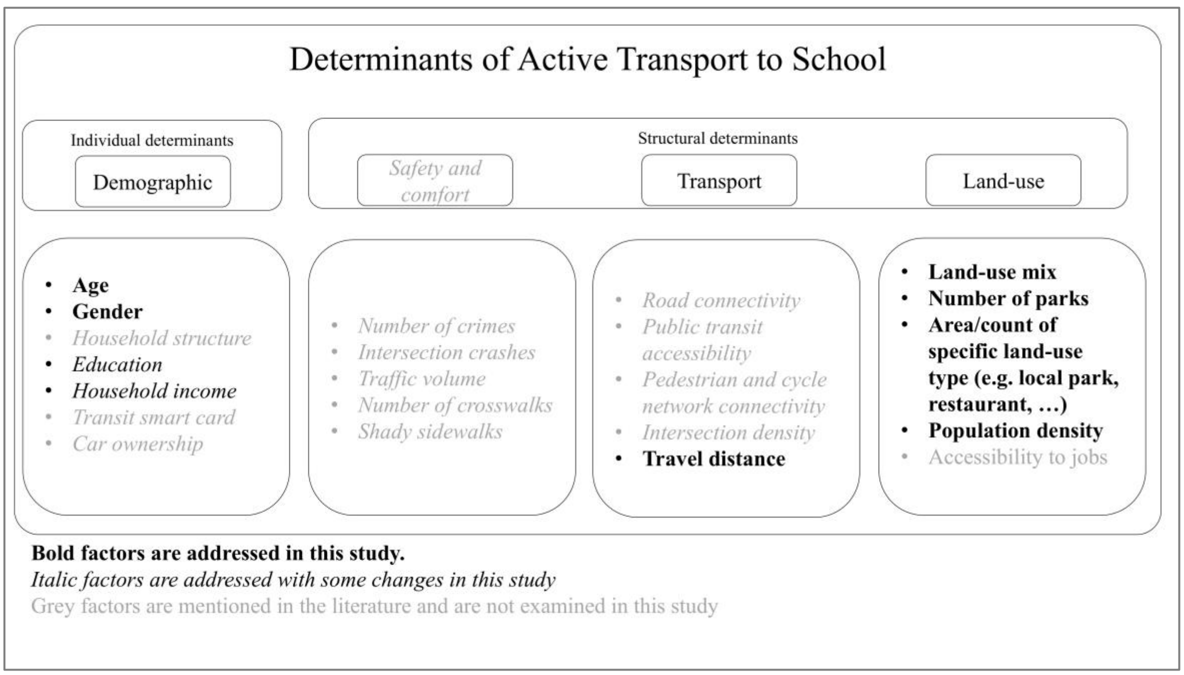

Figure 1. Four categories of factors that affect ATS. Interactions between these determinants shape whether children walk or cycle to school. This study focuses on land-use mix and the distance travelled to school.

The following section reviews existing literature on the built environment determinants of ATS, etching out a space for our contribution to understanding elasticity in the distance. Our approach and method are then outlined, followed by a review of our data and a short description of the explanatory variables informing a multinomial logistic regression model. This model is combined with an elasticity analysis to produce a series of results expressed in tabular formats. The paper concludes with policy implications and recommendations for further research required in this space.

2 Literature review

In many ways, the built environment determinants of ATS are not dissimilar to the structural determinants of active transport more generally. These land-use features can be usefully categorized into a series of variables that all start with the letter "D." The original "three Ds," devised by Cervero and Kockelman (1997), are density, diversity and design, followed later by destination accessibility and distance to public transit (Ewing & Cervero, 2001, 2010). The influence of the Ds on active transport behavior has been tested many times over and in numerous contexts (Kent et al., 2023). They can be applied to children's ATS, albeit with different emphasis on the importance of design for safety and decreased distances reflective of children's developing physical abilities (Mitra, 2013).

Although the general principles apply, there have been inconsistent findings when attempts have been made to reveal precise correlations between some D variables and ATS across contexts (McMillan, 2007; Mitra, 2013; Mitra et al., 2010). In relation to land-use mix, some studies have found a positive and significant correlation between land-use mix and ATS (Schlossberg et al., 2006; Timperio et al., 2017), while others have not (Ewing et al., 2004; Mitra et al., 2010). Others have found that land-use mix is associated with increased incidental social interactions within a neighborhood, and augmented perceptions of safety among parents, and that these elements support ATS (Ikeda et al., 2018). Studies have also found that students who live in areas with mixed land-uses are also more likely to enroll in a nearby school, which can promote ATS by decreasing travel distance (Curtis et al., 2015; Nelson et al., 2008).

Population density (Curtis et al., 2015; Ermagun & Samimi, 2015; Ikeda et al., 2018; Nelson et al., 2008), distribution of local parks and playground facilities (Grunseit et al., 2020; Jacobs et al., 2021; Timperio et al., 2017), and destination accessibility (Ewing et al., 2004) are additional land-use variables that have been found to support ATS. Population and dwelling density correlate with living in more urban areas (Curtis et al., 2015; Schlossberg et al., 2006), where destination accessibility is typically higher, which in turn supports ATS. Moreover, the presence of local parks with access to playground amenities can make the neighborhood more livable for families and encourages the use of active mode for all types of trips, including school travel (Timperio et al., 2017).

Safety is also a key determinant of ATS, however emphasis is on parental perceptions of safety, which determines the decision to allow ATS (Curtis et al., 2015; Ermagun & Samimi, 2015; Leslie et al., 2010; Mammen et al., 2012; Sener et al., 2019; Timperio et al., 2006). Perceptions are shaped in part by realities, however, and there are a series of other variables relevant to safety that correlate with ATS. The number of crosswalks, speed limit (Ji et al., 2022), speed humps, intersection density (Mitra et al., 2010; Schlossberg et al., 2006), traffic volume (Mammen et al., 2012; Sener et al., 2019), the number of road crashes, and the number of crimes (Timperio et al., 2017) have all been measured and incorporated into models examining the determinants of ATS. High road volume and dense, complex intersections present significant hazards for children walking or cycling. When children have to cross multiple lanes of traffic or navigate intersections without proper signalization or crosswalks, the risk of a collision increases dramatically (Ikeda et al., 2020). Rail crossings add another layer of risk (Curtis et al., 2015). These crossings can be unpredictable, and if they lack proper barriers, flashing lights, or audible warnings, they become a source of anxiety for both parents and children. Hilly landscapes and vacant lots also contribute to a sense of danger (Müller et al., 2020; Zhu & Lee, 2009). Steep hills can be physically demanding for a child on foot or a bike, which can lead to not using active modes (Müller et al., 2020). More importantly, vacant lands can create areas with a lack of passive surveillance from homes and businesses. This can make children feel exposed and vulnerable to crime, a serious concern for parents deciding whether to let their children travel independently.

Distance is a key determinant of ATS. Numerous studies have demonstrated that increased distances between home and school will decrease ATS (Burke & Brown, 2007; Curtis et al., 2015; Ermagun & Levinson, 2016, 2016; Ewing et al., 2004; Hsu & Saphores, 2014; Ikeda et al., 2018; Lidbe et al., 2020; Mammen et al., 2012; McDonald et al., 2016; Mitra et al., 2010; Nelson et al., 2008; Rodíguez-López et al., 2016; Rothman et al., 2018; Sener et al., 2019). Furthermore, shorter distances are also associated with parents' perception of safety, which in turn relates to whether a child is permitted to use ATS (Curtis et al., 2015; Li et al., 2022; Mammen et al., 2012).

Associations between distance and ATS have been measured in various ways. Some studies have used a continuous (Curtis et al., 2015; Rodíguez-López et al., 2016) or categorical (Mammen et al., 2012) variables, while others have used travel time by a specific mode, such as walking (Ermagun & Levinson, 2016; Ermagun & Samimi, 2015). The studies using travel distance have reported large variations in the threshold for active modes, ranging from 875m to 4 km. For example, Nelson et al. (2008) found that 90% of students citing distance as a perceived barrier to ATS live more than 2.5 miles (4.02 km) from their school. Also, Mandic et al. (2017) examined the perception of walking and cycling among adolescents residing within a 4 km radius of their schools. A study in Oregon. U.S., found that students living within less than 1.5 miles (2.41 km) are more likely to use ATS (Schlossberg et al., 2006). Two studies using United States National Household Travel Survey data in 2009 and 2017 found a 2 mile (3.22 km) threshold for ATS (Lidbe et al., 2020; Sener et al., 2019). An analysis of the Brisbane Household Travel Survey in 2003-04, found primary students' (aged 5-12) average active travel distance to school was 920 m (Burke & Brown, 2007). A study in Spain revealed two thresholds for walking to school of 875 m for children (aged 7-11) and 1.350 km for adolescents (aged 12-18) (Rodíguez-López et al., 2016). Another study in the UK concluded that there are three different threshold distances for students of different ages: 1.421 km for 10-year-olds, 1.627 km for 12-year-olds, and 3.046 km for 14-year-olds (Chillón et al., 2015). Other studies confine their analysis to students living within 2 km of their school, indicating an assumption that this is the distance threshold for ATS (Leslie et al., 2010; Mammen et al., 2012).

Elasticity values, which represent the percentage of change in the active trip propensity resulting from a one per cent increase in the variable of interest, are crucial in evaluating the potential impact of any built environment or policy modification designed to encourage ATS. Yet few studies use elasticity values to discuss the potential impact of hypothetical changes in demographic and built environment attributes on ATS (Ermagun & Levinson, 2016; Ermagun & Samimi, 2015; Ewing et al., 2004; McDonald, 2008; Nelson et al., 2008). Nelson et al. (2008) concluded that the probability of a child using ATS decreases by 71% when the travel distance to school increases by one mile (Nelson et al., 2008). Ewing et al. used elasticity at average to calculate elasticities of three types of modes (bus, walk, and cycle) to household income, car ownership, and walk/cycle travel time (Ewing et al., 2004). Ermagun and Levinson used average elasticity to analyze the sensitivity of ATS to travel distance. They showed that a 1% increase in the distance between home and school reduces the likelihood of walking to school by 2.2% (Ermagun & Levinson, 2016).

Average elasticity values are convenient, and they generate welcome generalizations. They may not, however, represent the impact of policies on different demographic, geographic, and land-use segments of society and urban environments in an accurate way. Indeed, interventions based on average elasticity data could over, or under, estimate the expected impacts of specific policies among diverse groups. Recognizing this gap, this study performs analyses of elasticity values in different segments based on age, gender, school sector, distance, and land-use type. We use a large database containing information on children's travel mode to school from geographically and demographically diverse contexts. In doing so, we provide a more nuanced picture of the expected impact of various interventions on different groups.

3 Approach and method

This study aims to examine the heterogeneity in sensitivity of ATS to variations in land-use mix and distance, using data on journeys to school from 6,629 school students aged 4-17 (described below).

Three types of explanatory variables are used in this study: socio-economic/demographic (e.g., age and gender), transport (e.g., distance), and land-use (e.g., density and mixture). These variables are further described in the Data Section. The dependent variable indicates whether children travel to school by car, public transit, or on foot. Since it comprises three alternatives, this study employs a multinomial logistic regression model (Gujarati, 2003). We then calculate the elasticity of ATS to distance and land-use mix, using the coefficient of the model and the numerical definition of elasticity.

The mathematical formulation of a multinomial logitic model is given in Equation 1, in which the probability ($P_{n,i}$) of alternative *i* among a set of available alternatives (*J*) for person *n* is calculated by the observed utility (*V*).

$$P_{ni} = \frac{e^{V_{ni}}}{\sum_{j=1}^{J} e^{V_{nj}}} \tag{1}$$

Elasticity is defined as the percentage of change in the dependent variable (P) as a result of a one percent increase in the variable of interest (x) (Gujarati, 2003). In this study, elasticity is defined as the percentage of change in the propensity to use ATS due to a one percent increase in distance travelled to school. Elasticity values are usually different for each observation since they rely on changes in dependent (P) and independent (x) variables, as illustrated in Equation 2 (Gujarati, 2003).

Elasticity at the average refers to the sensitivity of mode choice with respect to distance, calculated at the average value of the explanatory variables (Equation 2). This approach has been widely used in earlier studies (e.g., Cervero & Kockelman, 1997; Ewing et al., 2004) due to its simplicity, as it requires only a single evaluation of the model at mean values. However, in nonlinear models such as logit, this can be misleading, as the "average" person may not be a good representative of the population. Elasticity depends on the measurement point and may vary due to interactions between variables or non-linear effects, which this method does not capture.

$$\bar{e}_n = \frac{dP}{dx}\frac{\bar{x}_n}{P_n} \tag{2}$$

In contrast, average elasticity, used in more recent work (Ermagun & Samimi, 2015), is calculated by estimating the elasticity for each individual based on their specific characteristics and then averaging the results across the sample (Equation 3). This method captures heterogeneity in behavioral responses and better reflects the distribution of sensitivity to distance changes across the population.

A third and often more informative approach is to compute group-level average elasticities by segmenting individuals (e_n) into meaningful demographic or policy-relevant categories such as age, gender, or income. This retains the individual-level variation within each group while enabling comparisons across segments. It provides valuable insights into which groups are more or less sensitive to changes in distance, informing targeted interventions and equity-focused evaluations.

In the current study, we adopted the third approach. Due to the piecewise specification of the distance variable, conventional derivative-based elasticity formulas were not suitable. Instead, we applied a numerical method: for each individual, we increased the original travel distance by 1%, recalculated the predicted probability of choosing an active mode using the estimated model, and computed the percentage change in probability relative to the baseline. This procedure aligns with the elasticity definition presented in Equation 3 and allows for consistent estimation across individuals and groups.

$$e_n = \frac{dP}{dx}\frac{x_n}{P_n} \tag{3}$$

Then, we estimated the average elasticity of ATS with respect to travel distance in this study. It is possible to address this heterogeneity in the population by calculating the conditional average of the variable of interest. For example, there is substantial evidence that individuals with higher income travel more by automobile (Newman & Kenworthy, 2015), but we do not expect that a group of people with heterogenous incomes will all experience the same income elasticity in their travel demand as a person with the average income. Likewise, the effectiveness of increasing active travel through policies that decrease travel distances will vary within the population.

We first calculated the elasticity of the propensity to use ATS to the distance travelled to the school. Finally, the average elasticity of ATS was calculated at different segments of age, gender, school sector, land-use attributes, and distance. This enabled analysis of the sensitivity of different demographic, transport, and land-use components.

4 Data

We use data from the State of New South Wales (NSW) in Australia. NSW is the most populous of Australia's seven states and hosts the nation's largest city, Sydney. As is characteristic in Australia, the majority of the NSW population live on the coastal fringe and are particularly clustered around the Sydney Greater Metropolitan Region, which houses 4.8 million of the state's 7.5 million inhabitants (ABS, 2016a, 2016b). While the State displays various degrees of demographic, socio-economic and cultural diversity, the built form and transport practices are relatively uniform, characterized by low density and car dependence.

Specifically, we use a subsection of data from a cross-sectional survey of 7,555 primary (Kindergarten, Years 2, 4, and 6) and secondary students (years 8 and 10) aged between 4 and 17 years old, attending 86 different government (66%), Catholic, and independent schools (34%). Known as the NSW School Physical Activity and Nutrition Survey (SPANS), the data was collected in 2015 via questionnaires administered to students/parents and school principals/school liaison officers. Parents completed questionnaires for students aged ≤11. Sampled schools were chosen from all NSW schools, excluding non-mainstream schools (e.g., intellectual disabilities schools), small schools with less than 180 enrolments, and schools in remote areas. Further details about the questionnaire, ethical approval, methodology and sample size are reported in Hardy et al. (2017). As this database is confidential, we do not provide open access to it. This paper uses data on transport mode to school, school type and participant socio-economic/demographic characteristics. Reflecting its robustness, the dataset has been used multiple times to examine children's dietary intake (Boylan et al., 2017) and physical activity participation (Grunseit et al., 2020; Peralta et al., 2019), however, it has not previously been analyzed for the influence of built environment attributes on school travel mode.

Data from the SPAN Survey are combined with data on the locational attributes of each school (obtained from the Australian Curriculum, Assessment and Reporting Authority) (ACARA, 2016) and meshblock population counts (obtained from the Australian Bureau of Statistics) (ABS, 2016c). Meshblocks are the smallest geographical areas in the Australian Statistical Geography Standard, equivalent to census tracks used in the United States. Each residential meshblock contains approximately 30 to 60 dwellings (ABS, 2016d).

4.1 Measures

This section describes the dependent and explanatory variables used for the study.

4.1.1 Dependent variable: Active mode users

The key variable is whether children use ATS. The SPANS dataset records ATS by asking how many days per week in a usual week the student used a specific mode to go to school. The survey also asks the time spent on each mode for each trip. We defined the dependent variable using three alternatives of modes including active mode users as those who exclusively walk, to school at least three days per week. Although the SPANS database captures data on children's trips to and from school, public transit encompasses both bus and train, and private car at least three times per day. We used data for school access based on previous findings that the school egress trip can be confounded by participation in after school activities and parental working practices (Fox et al., 2015). About 19 per cent of students (n=1,239) were defined as active mode users, 24% used public transit (n=1,637), and 57% (n=3,753) drove to school.

4.1.2 Explanatory variables

Three categories of explanatory variables are used: socio-economic/demographic, transport network, and land-use. Travel distance is the primary explanatory variable in this study, while socio-economic, demographic, and land-use variables serve as secondary (control) variables. The type, source, and statistical summary of variables of interest are listed in Table 1.

Table 1. Description and statistical summary of explanatory variables. The total number of observations is 6,629.

Variables	Type of variable	Source of variable	Mean	Standard deviation	Max	Min
Age	Continuous	SPANS	10.22	3.32	17.21	3.29
Gender (Female)	0/1	SPANS	0.52	0.50	1.00	0
SES score (divided by 1000)	Continuous	SPANS	1.00	0.07	1.13	0.56
Rural	0/1	SPANS	0.02	0.14	1.00	0
Distance (km)	Continuous	SPANS (Travel time data) and assumption of mode speeds	4.95	4.15	20	0.07
Piecewise distance between 0-1km	Continuous	SPANS	0.93	0.19	1.00	0.07
Piecewise distance between 1-3km	Continuous	SPANS	1.42	0.81	2.00	0
Piecewise distance between 3-5km	Continuous	SPANS	0.97	0.96	2.00	0
Piecewise distance more than 5km	Continuous	SPANS	1.63	2.94	15	0
Government (school sector)	0/1	ACARA	0.63	0.48	1.00	0
Population density (1000 people in a Sq-km)	Continuous	ABS	8.72	7.17	0.23	33.77
Area (Sq-km)	Continuous	ABS	3.38	0.94	5.03	0.74
Number of parklands	Count	ABS	14.90	8.53	43.00	0
Number of local parklands	Count	ABS	10.72	7.53	37.00	0
Top quartile parkland share	0/1	ABS	0.28	0.45	1.00	0
Land-use mix (entropy index)	Continuous	ABS (land-use data)	0.53	0.14	0.91	0

4.1.2.1 Socio-economic and demographic variables

Previous ATS choice models have controlled for gender, age, school year, family income, and parents' education (Curtis et al., 2015; Ermagun & Levinson, 2016; Nelson et al., 2008). In this study, we used participant age, gender, socio-economic status (SES), and whether the student lives in a rural or urban area (Hardy et al., 2017). SES was measured using the Socio-Economic Indexes for Areas calculated by the Australian Bureau of Statistics for each student's home location.

4.1.2.2 Transport network

Distance is a critical variable for ATS (Ermagun & Samimi, 2015; Nelson et al., 2008). This study uses travel time as a proxy for distance by applying mode-specific average speeds to the travel time recorded for each participant (McDonald, 2008). These average speeds were informed by peak time averages by different transport modes in Sydney published by the Australian government via the Bureau of Infrastructure and Transport Research Economics (BITRE) in 2016. The published values for car, bus, train, bicycle, and walking are 33km/h, 14km/h, 24km/h, 14km/h, and 5km/h, respectively (BITRE, 2016). These values are for adults. In recognition of previous research indicating slower walking and cycling speeds for children, we used the average speeds of 13km/h for cycling and 4.5 km/h for walking in this study (David & Sullivan, 2005). The non-linear impact of travel distance is captured using a piecewise specification, following Train (2009). We define three thresholds to create four distance bands (≤1 km, 1–3 km, 3–5 km, and >5 km), allowing the model to estimate distinct marginal effects for each segment while preserving continuity at the breakpoints (Hossein Rashidi et al., 2024).

The final variable relevant to the transport context is the school sector type (government or non-government). In NSW, government schools have specific intake zones (known as catchment areas) (NSW Department of Education, 2022). The geographical size of each catchment area varies based on factors such as the population density and the type of school (NSW Department of Education, 2021). Generally, students attending government schools must live in the catchment area to qualify for enrolment. Students in non-Government schools usually are not subject to catchments and travel further distances to school on average. For example, examining students in Brisbane, Yan et al. (2019) found government school students have a mean travel distance by car of 4.4 km, compared to 7.7 km for non-Government school students.

4.1.2.3 Land use

We hypothesize that the built environment attributes around the school influence whether a child uses ATS. Past studies used school-area buffers ranging from 200m to 2000m (Curtis et al., 2015; Timperio et al., 2006). We defined the area of interest in three distances of 0.5, 1, and 1.5 km on road networks around schools using Open Route Service (openrouteservice, 2022) and QGIS. A sensitivity analysis concluded that the 1.5km buffers result in more significant and interpretable coefficients than the smaller buffers reflecting the typical size of a coherent neighborhood and similar to the 1-mile buffers used in many U.S. studies (Ham et al., 2008; McDonald et al., 2016). Informed by previous literature, we chose to focus on four specific land-use attributes: population density, land-use mix, number of parks, top quartile parkland share. Together, these four attributes are characteristic of a neighborhood that is diverse, convivial, and interesting, particularly from the perspective of a child (Loebach & Gilliland, 2019). These attributes were then quantified within the buffer area using various datasets.

Population density supports active transport use in multiple ways because of its association with shorter distances, land-use diversity and the provision of a critical mass of people to support infrastructure for walking and cycling. Of particular relevance to ATS, higher density areas are generally busier, with more people out and about to provide a sense of safety and conviviality (McMillan, 2007; Mitra et al., 2010). We calculated residential population density using mesh block population data from the ABS.

Previous research has found that the number of parks within proximity of the school is supportive of ATS, presumably because they enhance the aesthetic quality of the route and provide recreational opportunities along the way (Leslie et al., 2010). The number of local parks was defined as the number of parks smaller than 50 hectares in the buffered areas, while the number of all parks contains all types of open spaces. The dummy variable of top quartile park dominant equals one when the buffer is in the top quartile of the parkland density of the school's buffer zone.

Land-use mix supports ATS because it increases the likelihood of there being both origins and destinations within a walkable or cyclable distance (Cervero & Kockelman, 1997; Curtis et al., 2015) and creates an environment that feels safe, convivial and interesting. We followed Cervero and Kockelman (1997), and Frank et al. (2005), and used an entropy mix because it is both quantifiable and flexible across various land-use contexts. The index ranges from 0 to 1, and high values indicate greater mixing of uses. The maximum entropy value (=1) can only be achieved when an area has an equal proportion of all the recognized land-use types. Entropy is symmetric regarding the land-use types; entropy in two neighborhoods with three types of land-use and proportion of 50/25/25 and 25/25/50 is the same. The expression for the entropy mix is given in Equation 4.

$$H = -\frac{\sum_{i=1}^{k} p^i \ln(p^i)}{\ln(k)} \tag{4}$$

H = entropy
P^{i}= Percentage of each land-use in the given area
k = Number of land-use types

The entropy index can be calculated with any mixture of k land-use types. We calculated an entropy index with land-uses of parkland, commercial, and residential (PCR, k=3) (following (Frank et al., 2007; Hinckson et al., 2017).

5 Results

Using three categories of explanatory variables, we used logistic regression to predict whether students are either active travelers or non-active travelers on their journey to school. The following section details the model's results and the elasticity of ATS to distance.

5.1 Model results

Model results are provided in Table 2. The total observation of students after data cleaning was 6,837. All explanatory variables were significant at the 99% confidence level. This confirms existing understandings in the literature in those older students (Curtis et al., 2015; Ermagun & Samimi, 2015; Nelson et al., 2008); males (Curtis et al., 2015; Rothman et al., 2018); students from higher SES (Jacobs et al., 2021), and rural areas (Li et al., 2022), are more likely to use ATS. As assumed, government school students are more likely to use ATS than non-government school students.

The result indicates that travel distance correlates negatively with ATS. To test the non-linear effect of distance, the model in Table 2 uses piecewise nested thresholds. The negative correlation between choosing ATS and distance accumulates over the four distance categories so that the impact at the largest distances is captured as the sum of the four distance coefficients shown in Table 2. In the piecewise model, the magnitude of the distance coefficient is larger than that of the continuous variable when it is used alone.

Table 2. Summary of the model result with the demographic, piecewise variable of distance, land-use variables as explanatory variables, and mode users as the estimated variable. The car is the reference mode. Coefficients, standard errors, t-test, and p-values are provided.

Mode	Variables	Coefficients	Standard Error	t-test	p-value
Active	Constant	-1.48	0.83	-1.79	0.07
	Age	0.22	0.02	13.78	0.00
	SES (/1000)	1.01	0.69	1.46	0.15
	Female	-0.29	0.10	-3.02	0.00
	Government	0.62	0.13	4.70	0.00
	Rural	1.08	0.46	2.36	0.02
	Piecewise distance between 0-1km	-2.85	0.25	-11.63	0.00
	Piecewise distance between 1-3km	-1.65	0.09	-18.74	0.00
	Piecewise distance between 3-5km	-0.28	0.13	-2.09	0.04
	Piecewise distance more than 5km	-0.15	0.07	-2.10	0.04
	Population density (1000 People in Sq-km)	0.06	0.01	7.00	0.00
	Number of parklands	-0.11	0.03	-4.29	0.00
	Number of local parklands	0.08	0.03	2.95	0.00
	Top quartile parkland share	0.44	0.14	3.15	0.00
	Land-use mix (entropy index)	2.41	0.52	4.29	0.00
Public transit	Constant	-7.21	0.76	-9.36	0.00
	Age	0.30	0.01	25.04	0.00
	SES (/1000)	2.03	0.48	4.27	0.00
	Female	0.05	0.07	0.69	0.49
	Government	0.22	0.08	2.91	0.00
	Rural	1.34	0.22	6.06	0.00
	Piecewise distance between 0-1km	-0.26	0.58	-0.45	0.65
	Piecewise distance between 1-3km	0.30	0.10	3.05	0.00
	Piecewise distance between 3-5km	0.24	0.05	4.54	0.00
	Piecewise distance more than 5km	0.01	0.01	0.91	0.36
	Population density (1000 People in Sq-km)	-0.02	0.01	-3.82	0.00
	Number of parklands	-0.13	0.02	-6.85	0.00
	Number of local parklands	0.11	0.02	5.45	0.00
	Top quartile parkland share	0.07	0.10	0.67	0.50
	Land-use mix (entropy index)	2.26	0.30	7.63	0.00
	Number of Observations		6,629		
	Pseudo R-squared		0.421		
	AIC		8486.95		
	BIC		8690.93		
	Log-Likelihood		-4213.5		
	LL-Null		-7281.2		

V_{CAR}, V_{PT}, and V_{ACT} (Equation 5 to Equation 7) represent the systematic utility components for car, public transit, and walking modes, respectively. These components are used to compute the probability of choosing to walk to school (P_{ACT}), as shown in Equation 8:

$$V_{CAR} = 0 \tag{5}$$

$$\begin{aligned} V_{PT} &= -7.21 + 0.30Age + 2.03SES + 0.05Female + 0.22Gov \\ &+ 1.34Rural - 0.26dist_{PC1} + 0.30dist_{PC2} + 0.24dist_{PC3} \\ &+ 0.01dist_{PC4} - 0.02Pop_{dens} - 0.13Parkland \\ &+ 0.11LocalPark + 0.07TopQuarPark + 2.26LU \end{aligned} \tag{6}$$

$$\begin{aligned} V_{ACT} &= -1.48 + 0.22Age + 1.01SES - 0.29Female + 0.62Gov \\ &+ 1.08Rural - 2.85dist_{PC1} - 1.65dist_{PC2} - 0.28dist_{PC3} \\ &- 0.15dist_{PC4} + 0.06Pop_{dens} - 0.11Parkland \\ &+ 0.08LocalPark + 0.44TopQuarPark + 2.41LU \end{aligned} \tag{7}$$

$$P_{ACT} = \frac{e^{V_{ACT}}}{e^{V_{ACT}} + e^{V_{car}} + e^{V_{PT}}} \tag{8}$$

The coefficients of the parkland variables indicate that the total parkland in the 1.5-kilometre buffer zone of the school has a negative effect on ATS. This result is inconsistent with previous research on adult populations (Motomura et al., 2022). It could be explained by the fact that the number of local parks, rather than the total area of green open space, positively affects ATS. This implies that the presence of large tracts of green open space (such as golf courses and wildlands) can deter the use of active modes for children, whereas smaller parks break up urban form and provide the interest and opportunity for activity that is associated with ATS. In addition, large green spaces that have limited visibility or are sparsely populated may evoke safety concerns for both children and their parents. Perceptions of these areas as isolated or difficult to supervise can increase parental reluctance to allow independent travel, especially if walking routes pass through or alongside such spaces. In contrast, smaller parks are often perceived as safer and more conducive to active travel, due to their visibility, higher usage, and proximity to residential areas. Also, in neighborhoods matching the top quartile of parkland share (ranking of parkland area), students are more likely to use ATS compared to other neighborhoods. This further supports the initial intuition that parks support active travel. Population density and land-use mix, as measured by the entropy index, also positively correlate with ATS, confirming previous studies (Nelson et al., 2008).

5.2 Distance elasticity analysis

The multinomial logistic regressions presented above generally confirm the conclusions of existing literature on children's ATS. **Questions remain, however, as to how sensitive ATS is to changes in distance variable, and how consistent the response to changes might be across populations and places.** To explore these gaps, we examined the distribution of elasticity and compared elasticities between groups and contexts.

Figure 2 shows the distribution of elasticity of ATS to distance with consistent negative values, mostly suggesting a strong tail of highly elastic individuals. This suggests the average elasticity of ATS would be misleading because there is substantial variation.

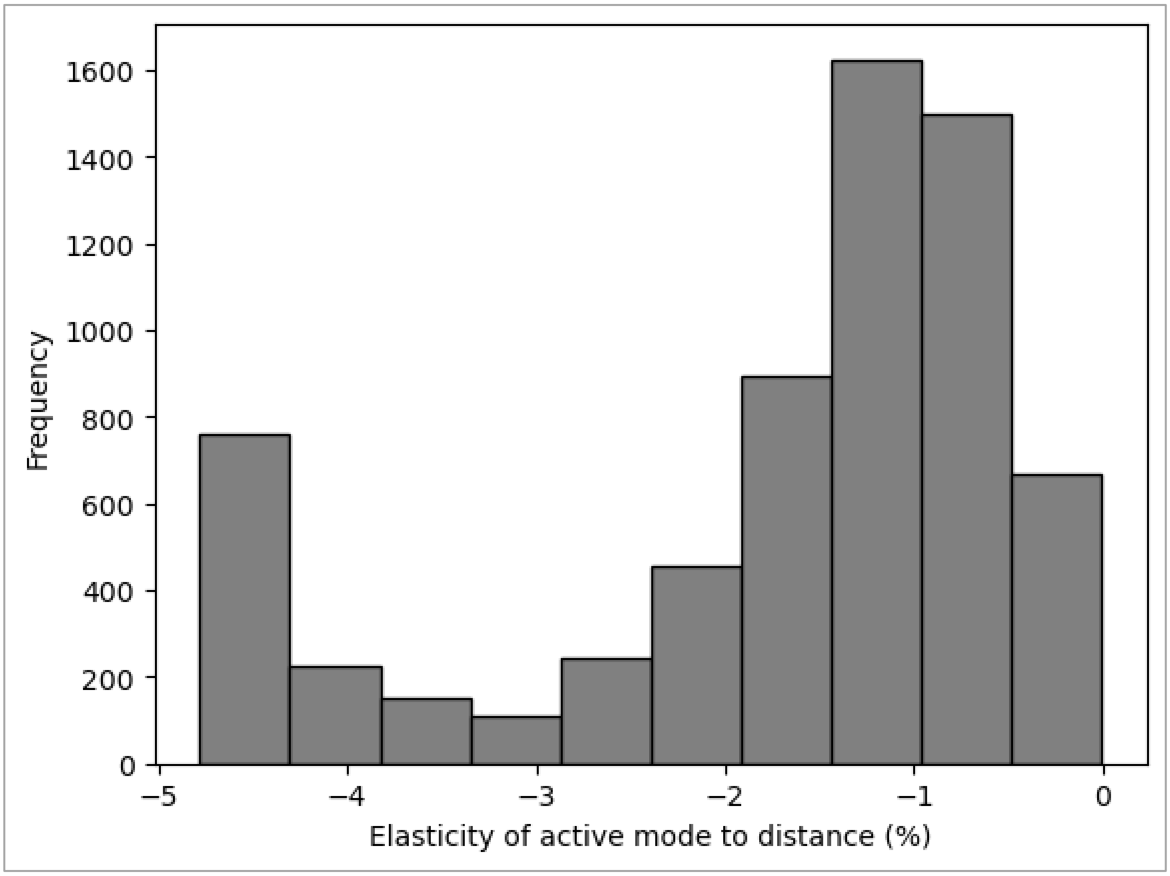

Figure 2. The distribution of distance elasticity of ATS at the student level. 4,427 students (66%) are highly elastic to distance ($|e_n|$>1), 1,582 students (24%) are moderately elastic (0.5=<$|e_n|$<=1) and 694 students (10%) are inelastic ($|e_n|$<0.5). This shows that the elasticity at the average (-1.01) would mislead policymakers by ignoring the substantial number of highly elastic individuals that should be targeted.

The distribution of ATS elasticity across the sample may indicate patterns across different demographic groups. Table 3 compares average ATS elasticity to distance by categories of gender, area type, school year, school sector, SES score, and land-use dominance. Elasticity values show that with a 1% increase in travel distance, the probability of active travel decreases by 1.74% on average. However, students who live near the school are inelastic (- 0.35%), and students with a travel distance between 1 and 3 km are highly elastic (- 2.98%). These differences have important implications for the overall level of active travel. Consider that 14% of students have travel distance of less than 1 km, and 77% of them uses active transport. In contrast, 32% of students live in the highly elastic distance category (1-3 km) and 20% of them utilized ATS.

Referring to rows marked "All" in Table 3, as the travel distance increases, the absolute value of elasticity of ATS to distance increases. However, there is a decrease in the absolute value to -1.36 in average elasticity among students travelling more than 5 km because these students have low rates of ATS and are less sensitive to changes in distance than students who live a bit closer to school. In Table 3, some comparisons between groups of students show values that are intuitively reasonable but small enough to question their importance.

Across a number of demographic categories, there are small but statistically significant differences in elasticity (Table 4). Females are 0.06 per cent more sensitive than males. The elasticity of active mode to distance is 0.08% percent higher among students who study in kindergarten and year 2 (Stage 1) compared to older students, with a distance elasticity of -1.72. Furthermore, students in Years 4 and 6 exhibited ATS distance elasticities that were 0.02% lower than those of older students. Students who study in commercial-dominant areas have the highest elasticity (-1.65%). These differences suggest that policy interventions to promote ATS should be tailored to different groups and contexts.

Table 4, however, shows that not all categories are worth differentiation in policy design. For instance, there are no statistically significant differences between students living in urban versus rural areas, government versus non-government schools, different socio-economic statuses, or among various land-use dominances, except for commercial areas. Moreover, while some differences between groups are statistically significant, their small magnitude may limit their practical importance for policy decisions.

Table 3. The elasticity of active mode to distance by land-use and demographic groups in percent. The differences between travel distances, school year groups and commercial land use dominance are notable. This result implies that policymakers may focus on students with travel distances between 1-3 km for possible policy implications.

Variable	Group		<1km	1-3km	3-5km	>5km	Total
Gender	Female		-0.40	-3.00	-1.41	-1.35	**-1.77**
	Male		-0.32	-2.97	-1.40	-1.37	**-1.71**
		All	**-0.36**	**-2.98**	**-1.41**	**-1.36**	**-1.74**
Area Type	City		-0.31	-3.31	-1.51	-1.31	**-1.87**
	Rural		-0.36	-2.98	-1.40	-1.36	**-1.73**
		All	-0.36	-2.98	-1.41	-1.36	**-1.74**
School Year	K and 2		-0.47	-3.27	-1.19	-1.24	**-1.80**
	4 and 6		-0.26	-2.83	-1.35	-1.33	**-1.70**
	8 and 10		-0.33	-2.82	-1.58	-1.48	**-1.72**
		All	-0.36	-2.98	-1.41	-1.36	**-1.74**
School Sector	Government		-0.36	-2.88	-1.38	-1.31	**-1.74**
	Non-Government		-0.35	-3.30	-1.44	-1.40	**-1.74**
		All	-0.36	-2.98	-1.41	-1.36	**-1.74**
SES Score	<800		-0.01	-3.75	-1.32	-1.29	**-1.79**
	800-1000		-0.33	-3.04	-1.42	-1.37	**-1.76**
	>1000		-0.37	-2.93	-1.38	-1.34	**-1.72**
		All	-0.36	-2.98	-1.41	-1.36	**-1.74**
LU Dominance	Commercial		-0.28	-2.96	-1.44	-1.41	**-1.65**
	Residential		-0.38	-2.97	-1.40	-1.37	**-1.79**
	Park		-0.40	-2.88	-1.38	-1.29	**-1.76**
	No dominance		-0.35	-3.09	-1.40	-1.35	**-1.75**
		All	-0.36	-2.98	-1.41	-1.36	**-1.74**
Percentage Using Active Modes			77%	20%	5%	1%	**19%**
Share of Students			14%	32%	11%	43%	**100%**

Table 4. Difference in average elasticity of active mode to distance within the land-use and demographic groups. The grey values indicate the deviation from the base group.

Variable	Group	average elasticity	std err	P>|t|
Gender	Female (base)	**-1.77%**	0.02%	0.00
	Male	**0.06%**	0.03%	0.07
Area Type	City (base)	**-1.87%**	0.11%	0.00
	Rural	**0.13%**	0.11%	0.25
School Year	K and 2 (base)	**-1.80%**	0.03%	0.00
	4 and 6	**0.10%**	0.04%	0.01
	8 and 10	**0.07%**	0.03%	0.03
School Sector	Government (base)	**-1.74%**	0.02%	0.00
	Non-Government	**-0.01%**	0.03%	0.87
SES Score	<800	**-0.07%**	0.23%	0.75
	800-1000	**-0.05%**	0.03%	0.15
	>1000 (base)	**-1.72%**	0.02%	0.00
LU Dominance	Commercial	**0.10%**	0.04%	0.02
	Residential	**-0.05%**	0.04%	0.29
	Park	**-0.05%**	0.04%	0.83
	No dominance (base)	**-1.75%**	0.03%	0.00
Distance	<1km (base)	**-0.36%**	0.03%	0.00
	1-3km	**-2.63%**	0.04%	0.00
	3-5km	**-1.05%**	0.05%	0.00
	>5km	**-1.10%**	0.03%	0.00

6 Discussion

This study applied logistic regression to a dataset of 6,629 records to examine various built environment attributes associated with ATS. The model showed that distance, number of local parks, ranking of parkland area, and diversity of land-uses within the vicinity of the school, are associated with ATS. These findings generally confirm the conclusions of existing literature on children's ATS— situating schools in catchments of mixed land uses and minimizing the distances between home and school are associated with more children walking and cycling to school.

But what size should these catchments be? How far is too far for children's ATS? We progressed to explore the sensitivity of ATS to *changes* in distance, and how heterogeneous the sensitivity to distance of ATS is across people and places. As discussed in the review section, previous studies have suggested children will walk/cycle anywhere between 875m to 4 km to get to school. We have found that the distance at which any increase in distance most dramatically deters ATS is somewhere between 1km and 3km. This finding provides unprecedented clarity to understandings of the distance thresholds for ATS.

More specifically, the elasticity analysis indicates that the probability of students' active trips to school decreases by 1.74% when travel distance increases by 1%. This average elasticity is higher than the often-reported elasticity at average (-1.01%) due to tails in the distributions of and interactions between the independent variables. Both average elasticity and elasticity at average, however, mask considerable heterogeneity across distances, demographics and land-use categories. Logically, students living closer to school, i.e., within 1 km, have the least active mode elasticity, with a value of 0.36% because a 1% change in distance is less than 10m. Moreover, students with travel distances less than 1 km are already the most likely to use active modes 77%), and so this low elasticity is relevant to a group with little need for intervention. However, students with travel distances between 1 and 3 km have the highest elasticity, with a value of 2.98%. Students who travel distances to school between 1 and 3 kilometers are therefore extremely sensitive to further increases in distance. The implications of these findings for scholars, policy makers and others seeking to encourage children's ATS are multiple.

From a methodological standpoint, this study demonstrates the extreme heterogeneity in changes to ATS in response to built environment variables. Elasticity at average, which dominates past studies (Ewing et al., 2004), does not reflect the diverse behavioral response observed in this analysis. Calculating the average elasticity across the range of observed places and populations supports estimations of the impacts of tailored potential interventions. This work presents conditional averages across different demographic and geographic groups, revealing that targeted, context-specific policies will be more effective.

More practically, our findings suggest care must be taken when considering school catchment zones that include students living between 1 and 3km of the school. Drawing catchments with approximately this radius are likely to include students who may well willingly walk or ride to school, if their school were slightly closer. Likewise, schools where most students live within 1km of the school gate could increase their drawing catchments without reducing the likelihood of ATS. School catchments, however, are only effective in shaping children's active accessibility if parents and carers are compelled to use their local school. This may include better enforcement of catchment zones or, more radically, increased investment in public education to reduce the incentive for parents to enroll their children in private schools outside their designated catchments.

Finally, our results draw attention to the various geographical scales relevant to interventions to encourage children's walking and cycling to school. Focus to date in many jurisdictions has been on creating a safe walking and cycling environment for children within the immediate vicinity of the school. In Australia, for example, traffic speeds around schools are slowed within 200m of the school gate each morning and afternoon. To get children walking and cycling to school, however, we need to attend to the environment within a 1-3km network radius of the school gate. This would mean a genuine commitment to slowing streets, providing infrastructure and raising awareness of the presence of vulnerable road users across the entire neighborhood precinct, as opposed to paying attention to a convenient and neat slice of roadway that flanks the actual school grounds.

Figure 3 provides a schematic overview of the determinants influencing active school travel across three distance regions. Distances less than 1 km are classified as the walking zone, 1-3 km are compatible with cycling, and 3-5 km are more associated with car and transit. Within the walking zone, factors such as the provision of active modes, friendly infrastructure, higher population density, improved land-use mix, availability of local green spaces, and enhanced traffic safety strongly encourage walking to school. In the 1-3 km cycling buffer, these same determinants moderately promote active travel tempered by the higher distance burden. Conversely, factors such as high traffic volume, adverse weather conditions, and hilly terrain negatively impact active travel for distances under 3 km. In the 3-5 km zone, which is typically dominated by motorized modes, these determinants generally have minimal or neutral effects on the increasingly rare choice of active travel.

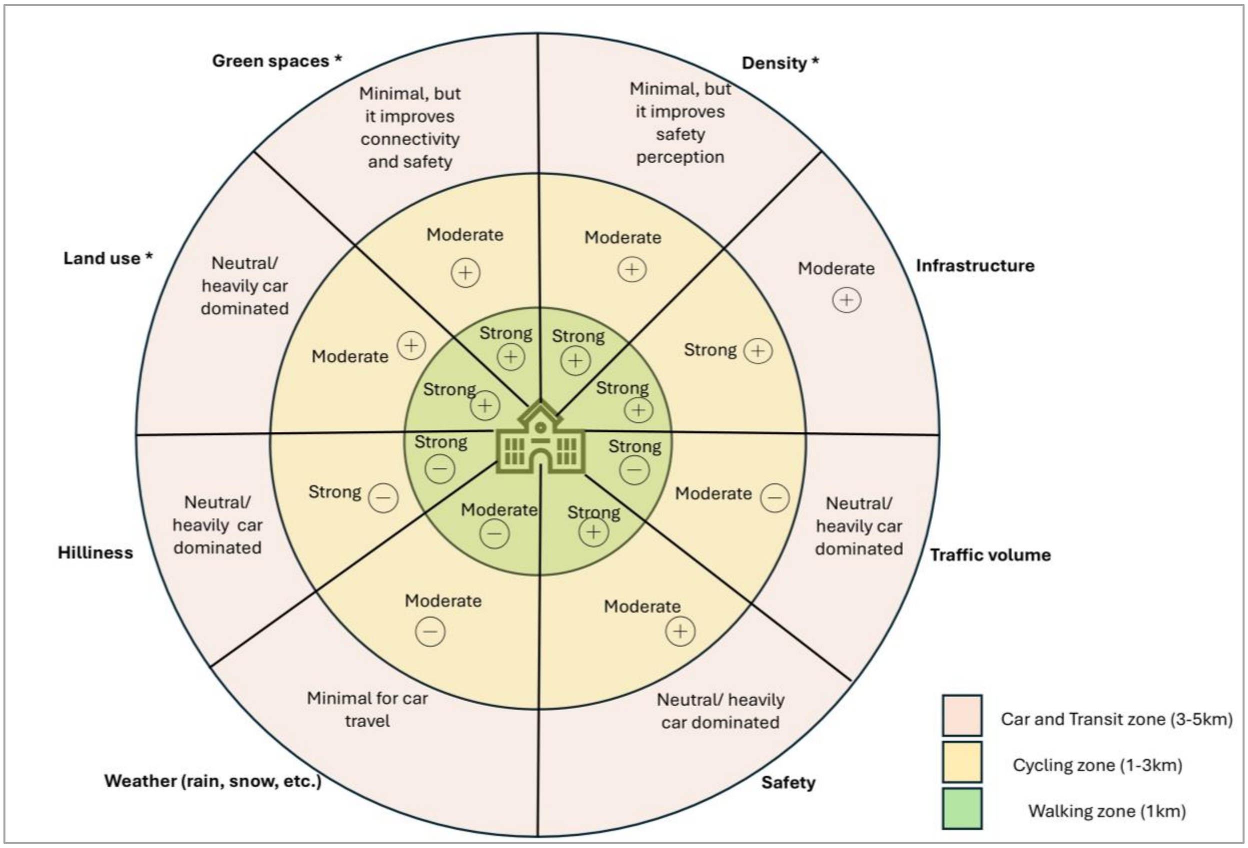

Figure 3. Schematic of the determinants that affect active school travel in three distance regions characterized by a matched potential mode. The determinants analyzed in this study are marked by a star (*). This schematic conveys that the roles of the determinants vary with travel distance and mode, and that travel distance and mode are interdependent.

7 Conclusion

The aim of this paper is to extend the prolific body of work on structural determinants of ATS through a unique focus on the sensitivity of ATS to changes in trip distance. Our key finding is that the impact of built environments on ATS is more nuanced and contextual than previously intimated by both research and practice in this space. It by no means infers that the relationship is inconsequential. Instead, it simply demands that professionals, policymakers and researchers in this space continue to avoid assumptions and tailor interventions to build, cultural, social and practical contexts.

This study highlights the significant impact of distance and environmental exposure on students' propensity to walk to school, suggesting that policy implications should extend beyond a narrow focus on improving or constructing infrastructure in the immediate vicinity of schools. Policies aimed at enhancing safety, reducing traffic speeds, and expanding pedestrian infrastructure should consider a spatial range approximately 1–3 km from schools, which is larger than typical school catchment sizes in this study. Accordingly, the findings provide an empirical basis for informing school boards and local governments about the potential benefits of targeted investments in safer streets and improved walking environments beyond the conventional catchment area.

The analysis has several limitations. First, although the dataset we used is comprehensive, it did not contain information on all of the known and potential influences on children's travel behavior. For example, ATS is notoriously shaped by parental attitudes and behaviors, and we did not have information on these attributes. Nor did we have data on participants' residential address, household income, ethnicity or parents' educational status. This means that some variables known to be important in mode choice decisions had to be estimated or proxied. We anticipate that access to this information would have reduced unexplained variation in ATS in our model by capturing additional explanatory variables.

There are several avenues for future research in this space, which could extend our understanding of ways to encourage more children to walk to school. To some extent, the limitations of the data could be addressed with informed inferences. For example, comparing students' active mode trips both to and from school would expose variations in family and student behavior at different times of the day and allow us to infer the availability of certain modes for each student. Using a richer and more detailed database that includes metrics such as access and egress time, waiting time, in-vehicle travel time, car travel time, and toll costs allows for a more nuanced distinction between car and transit modes. With this expanded dataset, it becomes possible to apply more advanced choice models, such as nested logit or cross nested logit, to better represent travel mode decisions. This approach can improve the accuracy of predicting choices among active travel, public transit, and private car use for school trips, and also enables the classification of transit modes involving reasonable walking as semi-active travel.

Furthermore, conducting a multilevel regression at city/urban area or neighborhood level would provide a more comprehensive understanding of the various factors that locally influence the model's outcomes. Also, future research could examine the underlying sources of variation in distance elasticity across demographic and geographic groups. This could involve the use of interaction terms or latent variable models to explore how individual preferences, travel behavior, and contextual factors contribute to observed elasticity differences. Finally, there is a desperate need for research in this space to step outside of the allure of quantification, and seek to explore the detailed habits, assumptions, appreciations and histories of the parents and children who travel to and from school each day.

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Author contribution

The authors confirm their contribution to the paper as follows: study conception: J. Kent and E. Moylan; study design, data analysis and modelling, and first draft: L. Hossein Rashidi; data interpretation and final draft: L. Hossein Rashidi, J. Kent, and E. Moylan.

None of the authors have any interests to declare.

Data availability

This study used the School Physical Activity and Nutrition Survey (SPANS), which is funded by the NSW Ministry of Health. As this database is confidential, we do not provide open access to it.

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