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Linking multi-anchor bus stop accessibility to bus ridership: Evidence from GPS and accelerometer data

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ABSTRACT

Public transport provides well-documented health, environmental, and economic benefits by promoting active travel, reducing car dependence, and enabling efficient land use. However, accessibility analyses often rely on measures defined at static spatial locations (e.g., around residential or zonal anchors), which may not capture the dynamic and context-dependent nature of accessibility across daily mobility. Incorporating accessibility across daily activity locations allows for a more behaviourally grounded assessment, reflecting the spatial and contextual conditions under which travel decisions are made. This study examines how accessibility to bus stops, measured at home, trip origin, and destination, relates to bus ridership in Auckland, New Zealand. Using high-resolution GPS and accelerometer data from 108 participants (835 trips), we applied mixed-effects logistic regression models and tested work status and neighbourhood residency duration as moderators. Results revealed an unexpected pattern: higher accessibility to bus stops around home (*home-based* accessibility) was negatively associated with bus ridership. Accessibility to bus stops around trip destinations (*destination-based* accessibility) showed a positive association with ridership, but only among newer residents. Employed participants were more sensitive to *home-based* accessibility than those who were unemployed. These findings suggest that accessibility–ridership relationships vary across key locations encountered along individual travel trajectories, likely indicating that measures defined at fixed, static locations may provide an incomplete representation of travel behaviour. Trip-specific, dynamic approaches may therefore offer a more behaviourally grounded basis for informing transport planning and policy.

1. Introduction

The health, environmental, and economic benefits of public transport are well documented across urban contexts. Many public transport users, such as bus passengers, achieve recommended levels of physical activity through walking to and from stops, supporting healthier and more active lifestyles (Besser and Dannenberg, 2005; Rissel et al., 2012), whereas private car use is associated with prolonged sitting and increased health risks (Besser and Dannenberg, 2005; Roberts et al., 2018; Saelens et al., 2014; Lachapelle et al., 2011; Frank et al., 2004; Hamilton et al., 2007, 2008). At the societal level, greater public transport ridership reduces car dependency, alleviates congestion, and mitigates adverse externalities including air and noise pollution, greenhouse gas emissions, and road traffic injuries (Litman, 2012). Reduced reliance on private vehicles also enables urban land to be reallocated from roads and parking to more productive uses, such as public spaces, active travel infrastructure, housing, and community amenities (Litman, 2024).

Travel behaviour related to public transport ridership is shaped by a constellation of factors, including socio-demographic characteristics (e.g., age, gender, car ownership, and employment), psychological constructs (e.g., self-efficacy, attitudes, and habits), user perceptions of service attributes (e.g., reliability, safety, and comfort), and perceptions of the built environment alongside its objective features (e.g., street connectivity, walkability, land-use diversity, and population density) (Shoaib, 2025; Wahab et al., 2025; Aston et al., 2021; Wang et al., 2021;

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Pan and Ryan, 2025). Within this multifactorial framework, accessibility to public transport is widely regarded as a critical determinant of ridership, as the absence of nearby stops effectively constrains access to opportunities by public transport (Bree et al., 2020; Chakraborty and Mishra, 2013; Currie, 2004; Jacques and El-Geneidy, 2014; Lindsey et al., 2010; Rahman and Rabby, 2024; Taylor and Fink, 2013; Tsai, 2009).

In this study, built environment characteristics are operationalised through spatial accessibility to bus stops, reflecting the public transport infrastructure dimension of the built environment. Accessibility to public transport, defined as the ease with which individuals can physically reach public transport stops or stations from their location (Murray et al., 1998), does not operate uniformly across travel situations. Daily mobility typically involves movement between multiple locations, and the conditions shaping travel decisions may differ depending on these locations (Chen et al., 2008; Fang, 2017; Givoni and Rietveld, 2007; Azimi et al., 2021; Abdul Sukor et al., 2017). Accessibility can therefore vary across the locations involved in a single trip, meaning measures defined at a static reference point may not fully represent the access conditions influencing observed behaviour.

For instance, individuals may live in well-served areas but travel to destinations with limited access, or experience different tolerances for walking at origins versus destinations. As a result, accessibility encountered across different trip locations may influence public transport ridership in ways not fully captured by static, catchment-based measures. Incorporating observed trip trajectories allows accessibility to be examined with respect to the specific locations involved in individual trips, offering a more behaviourally grounded basis for planning and policy.

Location-specific, high-resolution behavioural data, such as GPS measurements, make it possible to identify where trips begin and end, enabling accessibility to be assessed dynamically at the locations where travel decisions are made. Unlike approaches that infer accessibility from static reference points, these data provide a more detailed representation of everyday mobility and the spatial contexts in which public transport ridership is considered. This perspective allows accessibility to be examined in relation to both residential locations and the origins and destinations encountered across daily travel. Accordingly, this study examines how bus ridership behaviour is shaped by accessibility to bus stops at key locations along individual trip trajectories, including trip origins, trip destinations, and home locations. Furthermore, as the ways in which accessibility is experienced and acted upon may vary across behavioural contexts shaped by time constraints and accumulated experience of the built environment (Gao et al., 2019; Handy et al., 2006a; Olayode et al., 2025; Van Cauwenberg et al., 2018; Yeboah et al., 2019), this study accounts for such contextual variation to provide a more comprehensive basis for understanding heterogeneity in bus ridership.

This work is particularly relevant in the New Zealand context, specifically Auckland, New Zealand's largest metropolitan area with nearly 1.5 m residents (WorldStats, 2026), where empirical evidence on public transport accessibility remains limited compared to the extensive body of research from Europe and North America (Shi et al., 2020). Auckland is characterised by high levels of private vehicle ownership and comparatively low levels of public transport use (Environmental Health Intelligence NZ, 2023). Against this backdrop, the present study uses high-resolution GPS and accelerometer data and applies mixed-effects modelling to inform more nuanced assessments of accessibility to public transport and provide empirical evidence to support transport policies aimed at increasing public transport ridership in car-dependent metropolitan settings. Fig. 1 illustrates the overall flow of the study.

2. Literature review

A substantial body of research has examined the relationship between public transport accessibility and ridership behaviour, with accessibility most commonly operationalised through proximity to stops, stop density, service availability, gravity-based measures, or combinations of these within predefined static spatial catchment areas (Chakraborty and Mishra, 2013; Tsai, 2009; Murray et al., 1998; Kimpel et al., 2007; Prajapati et al., 2020; Nemer, 2024; García-Palomares et al., 2013). These catchments are typically defined around fixed reference points or demand areas, such as residential units or workplaces, reflecting an assumption that static representations of access can reasonably approximate the conditions under which mode choice decision occurs. Bree et al., for example, evaluated several transit accessibility measures, including stop-count, coverage-based, frequency-based, and gravity-based approaches, defined at the level of Dissemination Areas (DAs), Canada's smallest standard geographic units for which detailed census data are available, to examine their relationship with observed transit ridership in Saskatoon, Canada (Bree et al., 2020). Their findings indicated positive associations between accessibility measures and ridership, with variation in magnitude across different accessibility formulations.

At the stop level, several studies have also analysed accessibility measures defined within buffers surrounding bus stops or stations in relation to boarding counts. Chakour and Eluru, for example, analysed how public transport infrastructure and built environment characteristics within multiple buffer sizes around bus stops relate to boardings and alightings (Chakour and Eluru, 2016). Their findings revealed that the presence of public transport facilities, specifically bus stops and metro stations, within these buffers are strongly associated with higher bus ridership. In contrast, using a similar approach, Cui et al. reported a negative association between the number of nearby bus stops and the number of boardings observed at an individual stop (Cui et al., 2022). Similar stop-level patterns were also reported by Dill et al. and Chu, who identified negative associations between the density of nearby stops and boardings at a given stop (Dill, 2013; Chu, 2004).

While the methodologies employed in prior research have significantly contributed to the understanding of the relationship between accessibility and public transport ridership, they provide only a partial view of travel behaviour because daily mobility is rarely confined to static, predefined spatial buffers. Travel behaviour research has long emphasised that travel decisions emerge from sequences of activity locations encountered across daily mobility, rather than isolated trips, and that accessibility conditions can vary substantially depending on where trips actually begin and end (Miller, 2023; Levinson, 1998; Cui et al., 2019). In particular, growing evidence suggests that accessibility at trip origins and destinations influences travel behaviour through distinct mechanisms, with origin accessibility shaping first-mile access to the network, and destination accessibility determining the extent to which transit enables access to opportunities such as employment and services

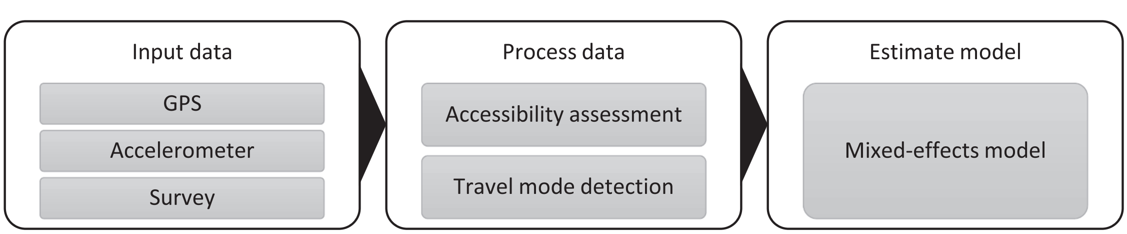

Fig. 1. Framework of the study.

(Tilahun et al., 2016). These differences are critical, as limitations at either end of the trip can independently constrain transit use, and the relative influence of origin and destination accessibility may not be symmetric.

Furthermore, accessibility associated with residential location reflects longer-term structural factors, such as habitual travel choices, that condition overall ridership behaviour (Handy et al., 2005; Manaugh, (n.d.)). As a result, treating accessibility as a fixed location-specific measure may mask these distinct effects and obscure the underlying drivers of ridership behaviour. Distinguishing between origin, destination, and residential accessibility therefore provides a more comprehensive and behaviourally meaningful framework for understanding how accessibility shapes ridership in practice.

Addressing these limitations requires high-resolution data capable of identifying individual trip trajectories and accurately locating trip origins and destinations (Barbosa et al., 2018). Recent advances in data collection, particularly GPS tracking and accelerometer sensors, enable accessibility to be evaluated at fine spatial and temporal resolutions that are unattainable with conventional data sources (Mohammed and Oke, 2023). While census and survey datasets provide broad population coverage and valuable origin–destination and mode information, they are typically limited to work-related travel and coarse spatial units, which can obscure variation in daily mobility patterns (Stopher et al., 2007). In contrast, GPS- and accelerometer-based data offer continuous observation of movement across trip purposes and contexts, allowing accessibility to be assessed in direct relation to observed travel behaviour (Chen et al., 2016). Despite this potential, relatively few studies have leveraged such data to examine dynamic public transport accessibility in relation to ridership (Mohammed and Oke, 2023; Carrel et al., 2015).

Building on this emerging body of work, the present study contributes to the literature by examining dynamic accessibility to bus stops, defined here as accessibility assessed at trip-specific locations identified from observed travel trajectories, rather than relying solely on static catchment-based measures. By using GPS and accelerometer data to identify actual trip origins and destinations across daily mobility, the analysis evaluates accessibility conditions at these key locations where travel decisions are made in practice. Linking home-based, origin-based, and destination-based accessibility measures to observed public transport use, the study extends existing static accessibility approaches and provides new empirical insight into how accessibility across daily activity locations relates to ridership behaviour.

Recognising that daily travel patterns are potentially structured by time availability and constraints, this study incorporates work status (categorised as employed vs. unemployed) to capture systematic differences in responses to public transport accessibility. Although work status has been widely examined in travel behaviour research due to its central role in mode choice (Joyce and Dunn, 2009; Zubair et al., 2024; Beimborn et al., 2003; Garrett and Taylor, 1999; Jacques et al., 2013; Krizek and El-Geneidy, 2007; Pasha et al., 2016), analysing this factor in conjunction with high-resolution, trip-specific accessibility measures enables a more nuanced examination of how behavioural characteristics shape the relationship between accessibility and public transport use, yielding insights that are difficult to capture using static data alone.

Likewise, neighbourhood residency duration, the length of time an individual has lived in their current neighbourhood, has been associated with travel behaviour through its relationship with familiarity, knowledge of local services, and awareness of available opportunities (Yeboah et al., 2019; Anburuvel et al., 2022; Bastiaanssen et al., 2020; Handy et al., 2006b; Jamei et al., 2022). Given its close connection to individuals' perceptions and interpretations of the built environment, analysing neighbourhood residency duration alongside granular, trip-specific accessibility measures provides a more nuanced understanding of how familiarity moderates responses to public transport accessibility in daily travel.

To sum up, this study primarily aims to explore the relationship between dynamic, trip-specific accessibility to bus stops, measured at home locations as well as at observed trip origins and destinations, and bus ridership. As an intermediate objective, it also examines whether work status and neighbourhood residency duration moderate the relationship between dynamic accessibility and bus ridership.

3. Method and material

3.1. Study design

This research is a cross-sectional observational study, grounded in a pragmatic paradigm and employing quantitative modelling approaches to investigate the association between accessibility to bus stops and objectively measured bus ridership behaviour. The study design, data collection, and reporting were guided by the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) framework and the Spatial Lifecourse Epidemiology Reporting Standards (ISLE-ReSt) guidelines (Jia et al., 2020), which provide specific recommendations for studies using GPS, accelerometers, and other location-based data.

3.2. Setting and participants

This study included participants from four regions across Auckland: Aorere, Oranga, Wesley, and Waikōwhai (Fig. 2). These neighbourhoods are located within Auckland, the most populous city in New Zealand with approximately 1.5 million people. The city is characterised by relatively low-density urban form and high levels of private vehicle reliance compared to larger international cities (Besen et al., 2026; Radio New Zealand, 2026). The selected study areas represent established suburban communities with varying levels of public transport provision across Auckland (Mavoa et al., 2012). As such, the findings should be interpreted within the context of these neighbourhood-level characteristics.

The study areas form part of the Te Hotonga Hapori research programme, which focuses on the relationship between urban redevelopment and community wellbeing (Te Hotonga Hapori, 2024). While the broader programme examines a range of social and environmental outcomes, the present study constitutes a transport-focused sub-study that draws on mobility and location-based data to address a specific research question concerning accessibility to bus stops and observed bus ridership.

Data collection within the Te Hotonga Hapori programme was planned at two time points: from May 2023 to April 2024 and from June 2024 to May 2025. As data collection for the second time point was still ongoing at the time this analysis was undertaken, only data from the first completed wave (May 2023–April 2024) were used in the present study.

For the survey component of the study, trained interviewers visited households in the four study regions, explained the study, and invited residents to participate. Eligibility required households to include at least one adult aged 18 years or older who provided informed written consent; one participant per household was included. Participants who agreed to take part completed a face-to-face interview conducted in their home. The interview primarily focused on wellbeing outcomes, along with individual- and household-level characteristics, including age, gender, employment status, and household income. A full copy of the interview schedule is available elsewhere (Te Hotonga Hapori, 2024).

In total, 485 participants were initially approached and interviewed, of whom 108 met the inclusion criteria for this analysis, contributing 835 trips with valid data (described further in subsequent sections). Ethics approval for this study was also obtained from the Auckland University of Technology Ethics Committee, and informed written consent was secured from all participants prior to data collection (AUTEC #21/361).

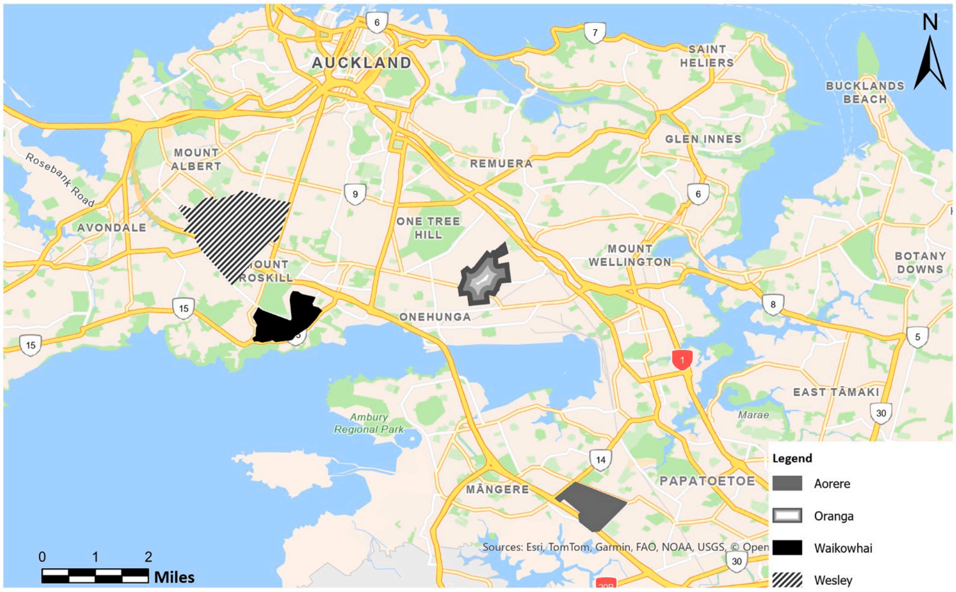

Fig. 2. Neighbourhoods included in this study.

3.3. Equipment and procedure

To collect spatial and activity data, GPS trackers (QStarz BT-Q1000XT) and accelerometers (Axivity AX3) were deployed (Fig. 3) to participants for a continuous monitoring period of seven consecutive days, consistent with thresholds commonly used in prior GPS- and accelerometer-based travel behaviour studies to characterise habitual mobility patterns (Oliver et al., 2010).

Following the face-to-face interview described in Section 3.2, each participant was provided with one GPS receiver and one accelerometer. Participants were instructed to wear the Axivity AX3 on their non-dominant wrist continuously for the full seven-day period, including during sleep. The GPS receiver was worn on the waist using a supplied belt during waking hours and was charged each night using the provided charging cable. After the seven-day monitoring period, interviewers returned in person to retrieve the devices, which were then processed for data download and analysis.

The QStarz BT-Q1000XT, a GPS data logger validated in previous studies (Duncan et al., 2013; Vorlíček et al., 2019), provides real-time positional information. Using the QTravel software (QStarz International Taipei, Taiwan), the GPS units were configured to log latitude and longitude coordinates every 20 seconds. Additional recorded parameters included UTC date/time, GPS fixed mode (VALID), and satellite information-signal-to-noise ratio (SNR) of viewed satellites. The Axivity AX3, a device renowned for its high accuracy in detecting physical activity intensity (Hedayatrad et al., 2020), was also used to measure physical activity behaviour. Using the Open Movement software

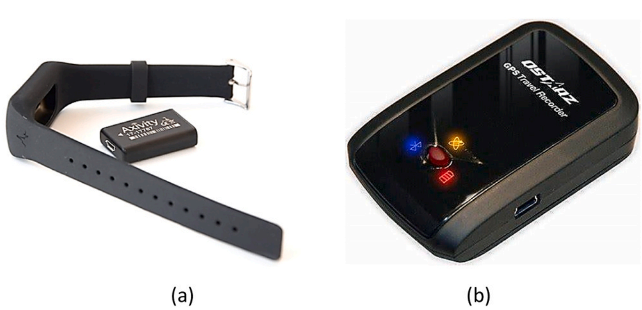

Fig. 3. Used equipment in this study: (a): Axivity AX3 accelerometer, (b): QStarz BT-Q1000XT GPS receiver.

(OMGUI, Newcastle University, Newcastle upon Tyne, UK), the AX3 devices were initialised to record data at 100 Hz with ±8 g bandwidth.

3.4. Travel mode

The QTravel software was used to download data recorded by the GPS devices, while OMGUI was used to retrieve data from the accelerometers. For the subsequent analyses in this study, only participants with at least three days of GPS and accelerometer data, with a minimum of eight hours per day, were included ($n = 108$), resulting in a total of 835 observations (trips). Similar inclusion criteria have been applied in previous studies (Almanza et al., 2012; Stewart et al., 2017a).

The Python package LABDA (version 0.0.12) was employed to preprocess the GPS and accelerometer data. The GPS and accelerometer data were then merged based on the nearest date and time. The LABDA package was also employed to analyse travel patterns and identify travel modes. A trip segment was defined as a series of GPS points uninterrupted by a more than three-minute stationary period within a 25 m radius. The starting point of a trip segment (trip origin) was identified when a participant began moving beyond a 25 m radius after remaining stationary for at least three minutes. Conversely, the ending point of a trip segment (trip destination) was identified when a participant remained within a 25 m radius for at least three minutes. Similar cut points have been utilised and validated in previous studies (Kang et al., 2018; Stewart et al., 2017b). Trip segments in which 60% or more of the GPS points were classified as "indoor" were discarded, as these were more likely indicative of GPS signal fluctuation (jitter) while the participant was stationary inside a building with poor GPS reception rather than actual travel (Heidler, 2024).

Trips could be multimodal, involving multiple modes of transport. For each trip segment, travel mode was initially classified broadly as walking (segments with an average speed of $\leq$ 10 km/h) and non-walking ($>$ 10 km/h) (Krenn et al., 2011; Kerr et al., 2011). If the majority of accelerometer data points within a trip segment indicated sedentary behaviour, the segment, even if initially classified as walking, was reclassified as non-walking. This adjustment accounted for slow GPS movement during sedentary behaviour, which likely reflects slow-moving vehicular travel rather than actual walking (Heidler, 2024). Then, consecutive trip segments that occurred within a temporal gap of less than two hours and within a 50 m spatial radius were merged and treated as a single trip. This approach aimed to exclude short stops at locations such as public transport stations or nearby points of interest (e.g., convenience stores and cafes), which were unlikely to represent distinct trips but rather temporary pauses in a continuous travel episode.

In the final classification step, trips were further categorised into bus trips and non-bus trips by overlaying the GPS routes with Auckland Transport bus route data (Auckland Transport, 2025). A 100-m buffer (50 m on each side of the route) was created around bus routes and intersected with the GPS trajectories. Trips with at least 70% overlap with a bus route were classified as bus trips, while those with less than 70% overlap were classified as non-bus trips. The 70% threshold was selected after comparing classifications at overlap thresholds ranging from 50% to 90%. Lower thresholds included many trips that only partially followed a bus corridor, while higher thresholds risked excluding genuine bus trips affected by GPS gaps or minor deviations. Given that speed profiles of buses and private cars are very similar in the Auckland's mixed-traffic environment, classification relied on spatial overlap with bus routes rather than speed. This approach provided a rather balanced classification.

For the purposes of this study, all non-bus modes (walking, cycling, and private motor vehicle trips) were grouped together and contrasted against bus trips. This binary classification reflects the study's primary focus on identifying the factors associated with bus ridership rather than modelling every travel mode. Accurately distinguishing between non-bus modes (e.g., walking and biking) using GPS and accelerometer data alone is particularly challenging in Auckland's mixed-traffic conditions, whereas bus trips could be identified with greater confidence through spatial overlap with bus routes[1] ($\geq$70% overlap). Given the relatively small number of bus trips (n = 104) in the dataset, this binary outcome also ensured sufficient statistical power for the mixed-effects models while keeping the focus aligned with the research aims.

3.5. Accessibility to bus stops

In this study, accessibility to bus stops is conceptualised as a built environment indicator capturing the spatial availability of public transport infrastructure around key activity locations. Although the built environment encompasses multiple dimensions (e.g., land-use mix, density, and street connectivity), this analysis focuses specifically on accessibility to public transport component, as it represents a key determinant of travel behaviour (Jacques and El-Geneidy, 2014; Rahman and Rabby, 2024).

A key feature of this study is the distinction between home-, origin-, and *destination-based* accessibility, which are defined according to the role a location plays within an individual's travel behaviour. Specifically, origin and destination accessibility are trip-specific measures, capturing the accessibility conditions at the start and end of each trip, while home accessibility represents a residential (time-invariant) characteristic reflecting the broader accessibility context of an individual's place of residence. This distinction is important because accessibility at different locations influences travel behaviour through different mechanisms (Tilahun et al., 2016), although they spatially might overlap in some cases.

To clarify the interpretation of these accessibility measures, it is important to note that, over the course of daily travel, the same physical location (e.g., home) may serve as both an origin and a destination across different trips. In this study, accessibility is defined based on the role of the location within each specific trip, rather than being treated as a fixed spatial attribute. Accordingly, *origin-* and *destination-based* accessibility are specified at the trip level and vary with the structure and direction of travel, whereas *home-based* accessibility represents a time-invariant residential characteristic. These accessibility measures are analysed in separate models to examine how accessibility at different spatial anchors is associated with public transport ridership. Consequently, no duplication occurs within a single observation, as each accessibility measure corresponds to a distinct role in the trip-making process. This role-based specification allows accessibility to be interpreted as a context-dependent attribute of the built environment that varies across the sequence of locations encountered in daily travel, providing a more behaviourally meaningful representation of how accessibility relates to mode choice behaviour.

To compute these measures, home locations were obtained from survey data, while trip origins and destinations were derived from GPS trajectories and geocoded using ArcGIS Pro (version 3.4.3). For each home, origin, and destination point, an 800 m service area was generated along the road network using the Network Analyst extension. This threshold reflects typical walking distances to public transport (approximately 400–800 m, or 5–10 min), consistent with established practice in accessibility and catchment-area analysis (Talpur et al., 2024; Taylor and Somenahalli, 2024; NZ Transport Agency Waka Kotahi, (n.d.), and is used here as a walkable distance threshold.

Within each service area, the number of bus stops was calculated and weighted using a distance decay function. Then, accessibility at location *i* was calculated as:

$$A_i = \sum_j \exp(-\frac{d}{\beta}) \tag{1}$$

where d_{ij} is the network distance (in kilometres) between location *i* and bus stop *j*, and $\beta = 0.4$ km is the distance decay parameter. The decay parameter reflects typical walking behaviour to bus stops, where willingness to walk declines rapidly beyond short distances. The selected value therefore represents a relatively steep decay function, consistent with observed pedestrian access behaviour to bus services (Talpur et al., 2024; Taylor and Somenahalli, 2024; NZ Transport Agency Waka Kotahi, n.d.). The negative exponential form is widely used in transport accessibility modelling due to its ability to capture distance deterrence effects (Zhao et al., 2003; Alshalalfah and Shalaby, 2007; Handy and Niemeier, 1997; Geurs and Van Wee, 2004; Koenig, 1980). In this formulation, supply is defined as the availability of bus stops within the service area, and demand is implicitly represented by the locations of individuals (home, origin, or destination points) from which accessibility is measured.

Fig. 4 illustrates examples of locations with high (Fig. 4a) and low (Fig. 4b) *home-based* accessibility to bus stops, for clarity.

3.6. Statistical methods

Descriptive statistics were used to summarise participants' socio-demographic characteristics, built environment attributes, and trip-level information. The primary unit of analysis in this study is the individual trip. Accordingly, all models are specified at the trip level, with trips nested within individuals.

The dependent variable is bus ridership, specified as a binary outcome indicating whether a given trip was made by bus (= 1) or by a non-bus mode (= 0). Independent variables include access to bus stops calculated at different spatial anchors (home, trip origin, and trip destination), which vary at the trip level, as well as socio-demographic characteristics, which are defined at the individual level.

To account for the hierarchical structure of the data, mixed-effects

[1] To assess sensitivity to the spatial-overlap threshold used to classify bus trips, alternative thresholds of 50%, 70%, and 90% overlap between GPS trajectories and bus routes were examined. The number of trips classified as bus trips declined substantially as the threshold increased (257, 104, and 29 trips, respectively), reflecting a trade-off between inclusivity at lower thresholds, where trips by private vehicles travelling along bus corridors are more likely to be included, and increasing classification stringency at higher thresholds, which substantially reduces sample size and estimation precision. A 70% overlap threshold was therefore adopted as a pragmatic compromise that balances these considerations in a mixed-traffic environment.

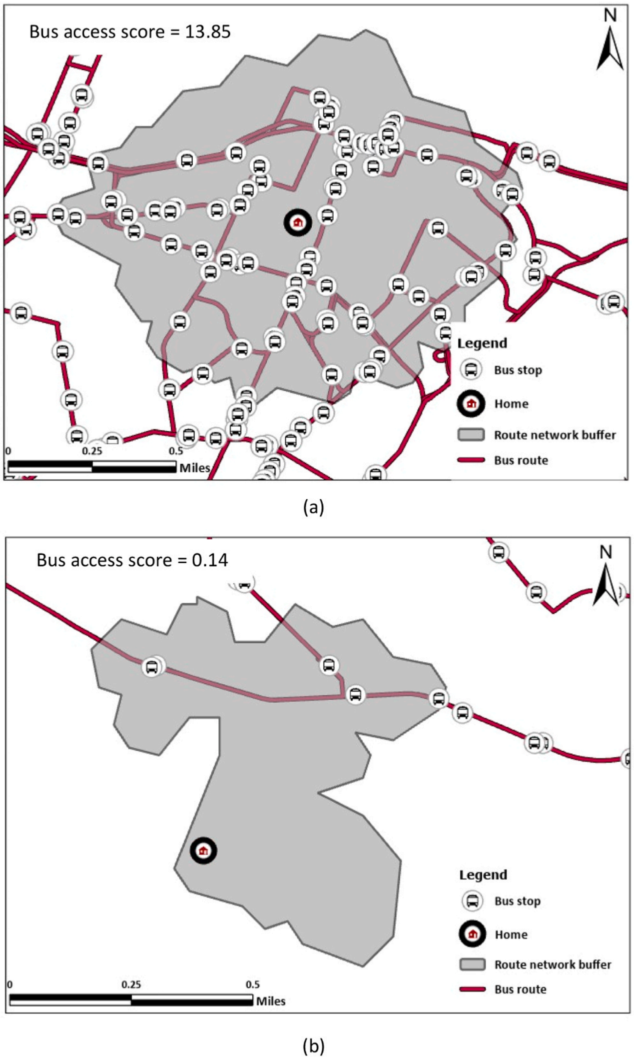

Fig. 4. Home-based accessibility to bus stops; (a) high accessibility; (b) low accessibility.

logistic regression models were employed. Although the dataset is cross-sectional in terms of observation period, each participant contributes multiple trips, resulting in non-independent observations. A random intercept for participant ID was therefore included to account for within-individual correlation in travel behaviour and unobserved individual-specific factors that may influence mode choice.

In the unadjusted models, access to bus stops was included as the primary fixed effect. Adjusted models additionally controlled for socio-demographic variables, including age (18–39, 40–64, $\geq$65 years), gender (male, female), household income (low-to-middle, high), ethnicity (Māori, New Zealand European, Pacific, Other), neighbourhood residency duration (<3 years, 3–10 years, >10 years), and work status (employed, unemployed). These variables were selected based on established evidence linking socio-demographic characteristics to travel behaviour and mode choice.

Neighbourhood residency duration was based on the length of time participants had lived in their current neighbourhood. Responses were categorised into three groups: less than 3 years, 3–10 years, and more than 10 years. Similar categories have been used in the survey instruments in New Zealand official statistics (Te, 2026), which distinguish between shorter-, medium-, and longer-term residence. The thresholds also reflect different stages of familiarity and adaptation to the local environment, distinguishing recent movers, medium-term residents, and long-term residents.

To examine potential heterogeneity in the relationship between accessibility and bus ridership, interaction terms were included between accessibility and (i) work status and (ii) neighbourhood residency duration. These moderators capture differences in temporal constraints and familiarity with the local environment, which may correlate with how accessibility is translated into actual travel behaviour (Handy et al., 2006b; Gim, 2022; Shin, 2019).

Model coefficients are presented as odds ratios (OR). An OR greater than 1 indicates that higher accessibility is associated with increased odds of bus ridership, whereas an OR less than 1 indicates decreased odds. The magnitude of the OR reflects the relative change in the odds of using the bus associated with a one-unit increase in the predictor, holding all other variables constant (Persoskie and Ferrer, 2017).

Although the models include several key socio-demographic covariates, the results may still be affected by residual confounding from unobserved or unmeasured factors. For instance, variables such as individual travel attitudes, car ownership, and perceptions of public transport service quality were not available in the dataset, and may influence both accessibility and mode choice. In addition, the accessibility measures used in this study capture spatial proximity to bus stops but do not reflect service attributes such as frequency, reliability, or travel time, which may also shape travel behaviour.

To partially account for unobserved heterogeneity, random intercepts were included at the individual level, capturing time-invariant differences across participants. However, these models do not fully eliminate potential biases arising from omitted or imperfectly measured variables (Wilms et al., 2021). Accordingly, the findings should be interpreted as associative rather than causal relationships.

Although mixed-effects models can incorporate random effects to account for spatial correlation, in this study a neighbourhood-level random effect was not considered appropriate because the key predictors (i.e., accessibility measures for home, trip origin, and destination) are location-specific and can lie in different neighbourhoods for the same participant. This anchor-specific approach captures spatial variability directly.

4. Results

This section presents the results of the analysis examining the relationship between accessibility to bus stops, measured at home locations, trip origins, and trip destinations, and bus ridership. In this study, accessibility measures were defined separately for each spatial anchor. For example, for a trip from home to a café, *origin-based* accessibility corresponds to the home location and therefore coincides with *home-based* accessibility, while *destination-based* accessibility reflects conditions at the coffee shop. However, for a subsequent trip to a park, the origin shifts to the café and *destination-based* accessibility represents conditions at the park. Thus, accessibility is evaluated for each trip based on its specific starting and ending points. Although these locations may coincide in some cases, their behavioural implications may differ depending on whether a location is experienced as a home, origin, or destination.

4.1. Descriptive statistics

Table 1 provides an overview of the socio-demographic characteristics of the study participants. The majority of participants were aged between 18 and 39 years (44.44%), female (62.96%), and identified as New Zealand European (35.19%), each participant was assigned to a single ethnic group. In terms of household income, most participants were categorised as belonging to low- to middle-income households (54.63%). Furthermore, a significant proportion had resided in their current neighbourhoods for 3–10 years (36.11%) and were employed (62.04%).

The mean bus accessibility scores for home locations, trip origins, and destinations were 4.01 (SD = 1.31), 2.11 (SD = 2.48), and 4.32 (SD

Table 1
Descriptives of socio-demographic, trip, and built environment characteristics.

Parameters	n (%)	Mean (SD)
Age		
18 – 39	48 (44.44)	
40 – 64	45 (41.67)	
65 and over	9 (8.33)	
Gender		
Male	34 (31.48)	
Female	68 (62.96)	
Ethnicity		
Māori	9 (8.33)	
New Zealand European	38 (35.19)	
Pacific	22 (20.37)	
Other	33 (30.56)	
Household income (NZD)		
Low to middle income (0–100,000)	59 (54.63)	
High income (Over 100,000)	43 (39.81)	
Neighbourhood Residency		
< 3 years	29 (26.85)	
3–10 years	39 (36.11)	
> 10 years	34 (31.48)	
Work status		
Employed	67 (62.04)	
Unemployed	35 (32.41)	
Bus accessibility score		
Home-based		4.01 (1.31)
Origin-based		2.11 (2.48)
Destination-based		4.32 (2.28)
Neighbourhood-based accessibility score		
Aorere		3.55 (0.86)
Oranga		4.05 (1.22)
Waikōwhai		4.58 (1.19)
Wesley		3.51 (1.38)
Used trip modes		
Bus trips	104 (12.46)	
Non-bus trips	731 (87.54)	
Trip duration (min)		
Bus trips		22.40 (15.60)
Non-bus trips		32.50 (26.40)

= 2.28), respectively. The *home-based* accessibility scores ranged from 0.93 to 7.13, *origin-based* scores from 0.14 to 16.70, and *destination-based* scores spanned from 0.15 to 18.20. Neighbourhood-level accessibility scores ranged from 3.51 (SD = 1.38) in Wesley to 4.58 (SD = 1.19) in Waikōwhai. Of the total 835 trips recorded, 104 were made by bus, while 731 were made using non-bus modes (i.e., walking, biking, private cars). Non-bus trips had an average duration of 32.50 min (SD = 26.40). Bus trips had a shorter average duration of 22.40 min (SD = 15.60).

4.2. Home-based accessibility to bus stops and bus ridership

Table 2 presents the results of unadjusted and adjusted logistic mixed-effects models analysing how *home-based* accessibility to bus stops (independent variable) is associated with bus ridership (dependent variable).

In the unadjusted model, no statistically significant association was observed between accessibility and bus ridership (OR = 0.91; 95% CI: 0.68–1.20; p = 0.490), indicating that variations in accessibility were not associated with meaningful differences in the odds of bus ridership.

After adjusting for socio-demographic factors, a significant negative association emerged between *home-based* accessibility to bus stops and bus ridership. Specifically, a one-unit increase in accessibility was associated with a 59% reduction in the odds of bus ridership (OR = 0.41; 95% CI: 0.22–0.78; p = 0.006), after controlling for socio-demographic characteristics. None of the socio-demographic covariates, including age, gender, household income, ethnicity, neighbourhood residency, or work status, showed statistically significant associations with bus ridership.

A borderline significant interaction effect was found between

Table 2
Results of mixed-effects models examining the association between home-based accessibility to bus stops and bus ridership behaviour (n = 108).

Parameters	Odds ratio	SE	95% CI	P-value
Unadjusted model				
Accessibility index	0.91	0.14	[0.68, 1.20]	0.490
Adjusted model				
Accessibility index	0.41	0.32	[0.22, 0.78]	0.006**
Age (ref = 18–39 yrs)				
40–64 yrs	0.77	0.43	[0.33, 1.80]	0.555
65 yrs and over	0.97	0.78	[0.21, 4.44]	0.971
Gender (ref = female)	0.73	0.42	[0.32, 1.67]	0.454
Household income (ref = high income)	0.54	0.45	[0.22, 1.31]	0.169
Ethnicity (ref = Māori)				
New Zealand European	1.31	0.79	[0.28, 6.11]	0.732
Pacific	1.48	0.88	[0.26, 8.25]	0.655
Other	2.23	0.80	[0.46, 10.70]	0.317
Neighbourhood residency (ref = > 10 yrs)				
3–10 yrs	0.34	1.44	[0.02, 5.75]	0.457
< 3 yrs	0.15	1.66	[0.01, 3.82]	0.250
Work status (ref = employed)	0.18	1.35	[0.01, 2.56]	0.207
Interaction – accessibility index * work status (ref = employed)[a]				
Unemployed	1.80	0.31	[0.98, 3.32]	0.058
Interaction – accessibility index * neighbourhood residency (ref = > 10 yrs)[b]				
3–10 yrs	1.65	0.37	[0.80, 3.42]	0.175
3 yrs >	2.05	0.40	[0.93, 4.53]	0.073

[a] Interaction term: effect of accessibility varies by work status.
[b] Interaction term: effect of accessibility varies by neighbourhood residency duration.
Note: * p < 0.05; ** p < 0.01; *** p < 0.001
Unadjusted model: Marginal R^2 = 0.30%; Conditional R^2 = 33%; ICC = 0.33
Adjusted model: Marginal R^2 = 15%; Conditional R^2 = 37.40%; ICC = 0. 26

accessibility and work status (OR = 1.80; 95% CI: 0.98–3.32; p = 0.058). This suggests that the negative association between accessibility and bus ridership may be attenuated among individuals who are unemployed relative to those employed (as depicted in Fig. 5), although this finding should be interpreted with caution due to its marginal

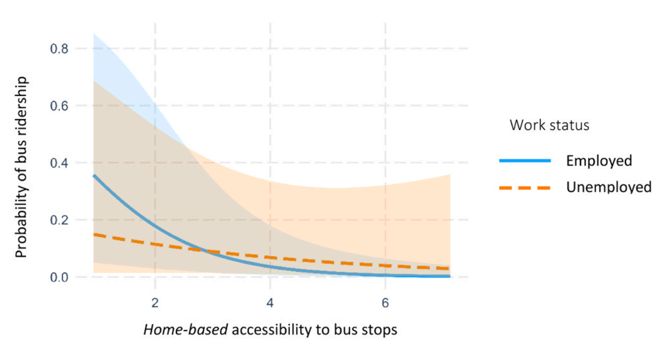

Fig. 5. Home-based accessibility–work status interaction.

statistical significance. No significant interaction was observed between accessibility and neighbourhood residency duration.

4.3. Origin-based accessibility to bus stops and bus ridership

Table 3 presents the results of unadjusted and adjusted logistic mixed-effects models examining the relationship between *origin-based* accessibility to bus stops (independent variable) and bus ridership behaviour (dependent variable).

In the unadjusted model, no statistically significant association was found between *origin-based* accessibility and bus ridership (OR = 1.03; 95% CI: 0.94–1.14; p = 0.502), indicating that variations in accessibility were not associated with meaningful differences in the odds of using the bus.

Similarly, the adjusted model showed no statistically significant relationship between *origin-based* accessibility and bus ridership (OR = 0.79; 95% CI: 0.53–1.16; p = 0.230), after controlling for socio-demographic characteristics. This suggests that changes in *origin-based* accessibility were not associated with meaningful differences in bus ridership behaviour.

None of the socio-demographic covariates, including age, gender, income, ethnicity, neighbourhood residency, or work status, were significantly associated with bus ridership. In addition, no statistically significant interaction effects were observed.

4.4. Destination-based accessibility to bus stops and bus ridership

Table 4 presents the results of unadjusted and adjusted logistic mixed-effects models examining the relationship between *destination-based* accessibility to bus stops (independent variable) and bus ridership behaviour (dependent variable).

In the unadjusted model, a statistically significant positive association was observed between *destination-based* accessibility and bus ridership (OR = 1.13; 95% CI: 1.02–1.25; p = 0.017), indicating that a one-unit increase in accessibility was associated with a 13% increase in the odds of using the bus.

However, after adjusting for socio-demographic characteristics, this association was no longer statistically significant (OR = 0.95; 95% CI: 0.78–1.16; p = 0.623), suggesting that *destination-based* accessibility was not independently associated with bus ridership when accounting

Table 3
Results of mixed-effects models examining the association between *origin-based* accessibility to bus stops and bus ridership behaviour (n = 108).

Parameters	Odds ratio	SE	95% CI	P-value
Unadjusted model				
Accessibility index	1.03	0.05	[0.94, 1.14]	0.502
Adjusted model				
Accessibility index	0.79	0.20	[0.53, 1.16]	0.230
Age (ref = 18–39 yrs				
40–64 yrs	0.68	0.49	[0.26, 1.79]	0.431
65 yrs and over	1.02	0.82	[0.20, 5.06]	0.985
Gender (ref = female)	0.94	0.45	[0.39, 2.27]	0.892
Household income (ref = high income)	0.57	0.50	[0.22, 1.52]	0.261
Ethnicity (ref = Māori)				
New Zealand European	1.01	0.84	[0.20, 5.21]	0.994
Pacific	1.21	0.92	[0.20, 7.39]	0.833
Other	1.94	0.82	[0.39, 9.68]	0.420
Neighbourhood residency (ref = > 10 yrs)				
3–10 yrs	1.43	0.63	[0.42, 4.90]	0.569
< 3 yrs	0.98	0.72	[0.24, 4.01]	0.973
Work status (ref = employed)	1.42	0.61	[0.43, 4.67]	0.566
Interaction – accessibility index * work status (ref = employed)[a]				
Unemployed	1.16	0.13	[0.90, 1.51]	0.264
Interaction – accessibility index * neighbourhood residency (ref = > 10 yrs)[b]				
3–10 yrs	1.16	0.20	[0.78, 1.73]	0.467
3 yrs >	1.43	0.21	[0.95, 2.16]	0.087

[a] Interaction term: effect of accessibility varies by work status.
[b] Interaction term: effect of accessibility varies by neighbourhood residency duration.
Note: * p < 0.05; ** p < 0.01; *** p < 0.001
Unadjusted model: Marginal R2 = 0.10%; Conditional R2 = 34%; ICC = 0.34
Adjusted model: Marginal R2 = 8.90%; Conditional R2 = 37%; ICC = 0.31

Table 4
Results of mixed-effects models examining the association between *destination-based* accessibility to bus stops and bus ridership behaviour (n = 108).

Parameters	Odds ratio	SE	95% CI	P-value
Unadjusted model				
Accessibility index	1.13	0.05	[1.02, 1.25]	0.017*
Adjusted model				
Accessibility index	0.95	0.10	[0.78, 1.16]	0.623
Age (ref = 18–39 yrs				
40–64 yrs	0.92	0.43	[0.40, 2.14]	0.856
65 yrs and over	1.28	0.76	[0.29, 5.65]	0.741
Gender (ref = female)	0.78	0.39	[0.36, 1.68]	0.520
Household income (ref = high income)	0.59	0.44	[0.25, 1.40]	0.230
Ethnicity (ref = Māori)				
New Zealand European	1.25	0.75	[0.28, 5.47]	0.769
Pacific	1.25	0.84	[0.24, 6.55]	0.794
Other	1.73	0.75	[0.40, 7.62]	0.461
Neighbourhood residency (ref = > 10 yrs)				
3–10 yrs	1.13	0.78	[0.25, 5.16]	0.876
< 3 yrs	0.60	0.86	[0.11, 3.29]	0.559
Work status (ref = employed)	0.82	0.76	[0.19, 3.63]	0.794
Interaction – accessibility index * work status (ref = employed)[a]				
Unemployed	1.17	0.13	[0.90, 1.52]	0.220
Interaction – accessibility index * neighbourhood residency (ref = > 10 yrs)[b]				
3–10 yrs	1.13	0.15	[0.85, 1.51]	0.394
3 yrs >	1.34	0.14	[1.01, 1.77]	0.045*

[a] Interaction term: effect of accessibility varies by work status.
[b] Interaction term: effect of accessibility varies by neighbourhood residency duration.
Note: * p < 0.05; ** p < 0.01; *** p < 0.001
Unadjusted model: Marginal R^2 = 1.60%; Conditional R^2 = 31%; ICC = 0.30
Adjusted model: Marginal R^2 = 8.50%; Conditional R^2 = 32%; ICC = 0.26

for individual-level factors. None of the socio-demographic covariates showed statistically significant associations with bus ridership.

A statistically significant interaction effect was observed between *destination-based* accessibility and neighbourhood residency duration among newer residents (< 3 years) (OR = 1.34; 95% CI: 1.01–1.77; p = 0.045). This indicates that, compared to long-term residents (=> 10 years), the positive association between accessibility and bus ridership is stronger among newer residents. In other words, increases in *destination-based* accessibility are associated with a greater increase in bus ridership among individuals who have more recently moved into the neighbourhood. This pattern suggests that newer residents may be more responsive to accessibility conditions at trip destinations, as illustrated in Fig. 6.

To better reflect the multifaceted nature of travel behaviour in relation to bus ridership, a model incorporating objective *home-*, *origin-*, and *destination-based* accessibility to bus stops was estimated (Table A.1 and Table A.2). Including all three spatial anchors simultaneously allows for the assessment of distinct accessibility contexts encountered during a single trip. The adjusted model indicated that *home-based* accessibility remained significantly and negatively associated with bus ridership (OR = 0.44; 95% CI: 0.23–0.84; p = 0.012), suggesting that higher accessibility at the place of residence is associated with lower odds of bus ridership, holding other factors constant.

5. Discussion and conclusion

Using GPS and accelerometer data to capture actual travel behaviour, this study primarily intended to investigate how accessibility to bus stops, measured from multiple spatial anchors (i.e., home, trip origin, and destination), relates to bus ridership. By incorporating accessibility measures derived from observed trip trajectories, the analysis moves beyond conventional approaches that rely on static buffers around fixed locations, enabling a more behaviourally grounded representation of accessibility as experienced across daily mobility. As an intermediate goal, this study also examined how individual factors, such as work status and neighbourhood residency duration, moderate the association between accessibility and ridership behaviour. The findings contribute to the literature by suggesting that accessibility–ridership relationships are context-dependent, with statistically significant associations observed for some spatial anchors but not consistently across all contexts, within the characteristics of the study sample and settings considered.

Across the models, accessibility measures alone accounted for only a small proportion of the observed variability in bus ridership. This likely indicates that the associations between accessibility to bus stops and bus ridership are mainly shaped by unmeasured individual-level characteristics, such as travel habits, personal attitudes, or lifestyle preferences (Handy et al., 2005; Cao et al., 2009). Regarding that individual-level factors are typically more internally consistent, being collected from the same respondent, they may therefore exert a stronger influence on travel behaviour than externally measured environmental attributes. However, this does not negate the importance of built environment attributes, which may be underrepresented when measured solely through objective indicators (van der Vlugt et al., 2019). For instance, objective measures may indicate high accessibility, but individuals accustomed to driving might continue using cars regardless; vice versa, those with strong pro-transit attitudes may choose bus travel even in less accessible areas (Cao et al., 2009; Bamberg et al., 2003; Verplanken et al., 1997). Residential self-selection may further contribute, as housing decisions often reflect broader lifestyle preferences, including school access, housing features, and neighbourhood amenities, which may also shape the composition of observed participants and their travel behaviour.

Of the three measures of accessibility to bus stops (i.e., *home-based, origin-based,* and *destination-based*), only *home-based* accessibility to bus exhibited a statistically significant association with ridership behaviour in the adjusted model. Although the limited sample size might have impacted this outcome, this finding is broadly consistent with prior research suggesting that residential environments play an important role in shaping travel behaviour, particularly where longer-term decisions and routines are formed (Handy et al., 2005; Manaugh, (n.d.)). Studies have shown that the built environment around the home, including public transport services, can shape travel mode choices, particularly when individuals choose neighbourhoods that reflect their transport preferences (Handy et al., 2005; Krizek, 2003; Salon, 2009; Van Acker and Witlox, 2010). However, the strength of this relationship may vary across populations and depends on the socio-spatial characteristics represented in the sample.

Notably, the association between *home-based* accessibility and bus ridership was negative, indicating that higher local stop density is associated with lower levels of bus ridership in this context. While this contrasts with some findings in the literature (Lucas Albuquerque-Oliveira et al., 2024; Welch and Mishra, 2013; El-Geneidy et al., 2014), it may reflect the complex interplay between accessibility, service characteristics, and alternative travel options. Areas with dense bus stop coverage are often more walkable, with shorter distances and better pedestrian infrastructure, potentially encouraging walking or cycling in place of public transport. In this sense, lower bus ridership in highly accessible areas may reflect substitution toward active modes rather than a lack of transport options, although such patterns may also reflect locally specific conditions, including the characteristics of the suburban environments examined as well as the participants captured in the dataset.

At the same time, high stop density does not necessarily correspond to efficient or reliable services. Closely spaced stops can contribute to slower travel speeds and reduced service reliability, particularly in mixed-traffic conditions (Manaugh, (n.d.)). Recent evidence from Auckland's bus network, which operates within a predominantly low-density and car-oriented urban context, illustrates this point. Despite abundant stops and frequent services, buses have been reported to experience substantial delays (1News, 2025; Hancock and journalist, 2025). Furthermore, official performance metrics, measuring punctuality primarily at initial stops and excluding missed services, may not

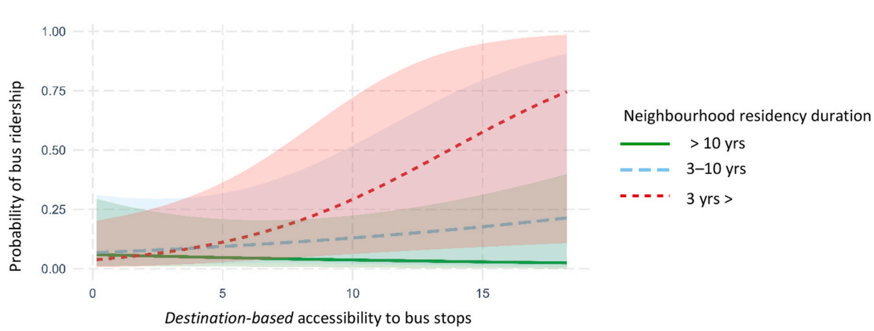

Fig. 6. Destination-based accessibility–residency duration interaction.

fully capture users' real-world experiences, potentially affecting perceptions of reliability and trust (F. H. of RNZ, 2025). While these patterns provide a plausible explanation for the observed relationship in this study, they are likely to be context-specific and may differ in cities with higher service reliability or stronger public transport priority, as well as in populations with different mobility resources or travel preferences.

The above discussion is further supported by the positive interaction between *home-based* accessibility to bus stops and work status in relation to ridership behaviour, although the correlation is only borderline significant. The findings suggest that individuals who are unemployed may be less sensitive to variations in *home-based* accessibility than their employed counterparts. One possible explanation is that individuals outside the workforce may have greater temporal flexibility, allowing them to adapt more easily to longer travel times or less reliable services (Rasouli et al., 2015). Alternatively, some individuals may rely on public transport regardless of its quality due to limited access to alternative modes (Mengedoth, 2025). In contrast, employed individuals, who might face stricter time constraints, may be comparatively more responsive to differences in accessibility and service reliability (Wang, 2025; Lu et al., 2023).

This finding broadly aligns with travel behaviour research demonstrating that work-related travel is associated with public transport accessibility, although the moderating role of employment status in the relationship between accessibility and ridership behaviour remains virtually underexplored. The interaction effect observed in the present study was relatively modest (OR = 1.80, 95% CI = 0.98–3.32) and characterised by statistical uncertainty (P-value = 0.058), suggesting a weaker relationship than those reported in some previous accessibility studies (Ewing and Cervero, 2010). For instance, Tilahun et al. (2016) examined the role of last-mile constraints in public transport use while distinguishing between *origin-* and *destination-based* accessibility (Tilahun et al., 2016). Their analyses revealed that higher accessibility at destinations was strongly associated with work-related public transport use, with substantial increases in the odds of choosing transit-related modes (63% increase in public transport use for each unit increase in walk-accessed transit).

Destination-based accessibility showed a different pattern, with its association with bus ridership appearing to depend on neighbourhood residency duration. Specifically, a statistically significant relationship was observed only among newer residents. While this finding should be interpreted in light of the characteristics of the study sample, one possible explanation is that longer-term residents are more likely to rely on established travel routines, reducing their sensitivity to contextual differences across locations. In contrast, individuals who have more recently relocated may experience a period of behavioural adjustment, during which accessibility at destinations such as workplaces or service locations becomes more influential in shaping travel decisions (Bamberg et al., 2003; Clark et al., 2016; Kim et al., n.d.). While destination environments are varied for all individuals, their influence may be more pronounced when habitual patterns are less established.

Taken together, these findings suggest that associations between accessibility and bus ridership vary depending on the spatial anchor at which accessibility is measured and are not consistently statistically significant across contexts. This suggests that accessibility, when operationalised at a single static location, may not fully capture the spatial and behavioural complexity of daily travel. Approaches that incorporate multiple spatial anchors may therefore offer a more comprehensive and behaviourally grounded understanding of accessibility in relation to observed travel behaviour. These findings should be interpreted in light of the study's sample composition and geographic focus, including the characteristics of Auckland's urban form and public transport system, and should not be assumed to generalise uniformly beyond comparable contexts.

Limitations and future research

This study has several limitations. First, identifying bus trips involved segmenting travel episodes using GPS and accelerometer data, where uninterrupted movement exceeding three minutes of stationary time was classified as a distinct trip segment. These segments were then merged if separated by less than two hours and within a 50 m buffer, assuming these represented continuous travel episodes. However, this merging may have combined distinct trip segments involving different travel modes (e.g., walking, bus, private vehicle). Trips were subsequently classified as bus trips if the merged trajectory overlapped with a bus route by at least 70%. In cases where walking, cycling, or private vehicle segments followed a bus corridor or occurred near bus infrastructure, this classification rule may have resulted in mislabelled trips. Because buses and private vehicles in Auckland's mixed-traffic environment often travel at very similar speeds, speed data alone were not sufficient to distinguish between these modes. As a result, the measure of bus ridership may overstate actual ridership by including some non-bus trips that met the spatial overlap threshold. This binary outcome may also obscure mode-specific effects, as non-bus trips include walking, cycling, and private vehicle trips, which may respond differently to accessibility factors. Future research could enhance accuracy by integrating real-time public transport data with timestamped GPS trajectories or supplementing data with travel diaries, or machine learning models trained on labelled mode data. These approaches would help distinguish between bus and private vehicle trips that share the same corridors and speed profiles, which are difficult to separate using GPS data alone.

Second, although this study advances existing literature by examining accessibility across multiple spatial anchors, it is limited by the absence of explicit trip-purpose data, which constrains the interpretation of behavioural roles associated with each anchor. For example, when trips start or end at home, accessibility measures at home, origin, and destination may coincide. While this overlap reflects the structure of real-world travel, it can make it more difficult to disentangle the distinct effects associated with each spatial anchor. Future research could address this by incorporating trip-purpose data or additional contextual information to better distinguish the behavioural roles of different locations.

Third, this study measured accessibility to bus stops based solely on their spatial proximity, without incorporating service frequency. As a result, the measure does not distinguish between stops with frequent and reliable services and those with infrequent or unreliable ones. While this spatial approach is common, it may oversimplify accessibility in contexts where service frequency strongly influences the attractiveness of a stop. The road network used to generate accessibility metrics also excluded informal pedestrian shortcuts and pedestrian-only paths, potentially underestimating actual pedestrian access. Moreover, because officially reported data often reflect scheduled rather than real-time operations (e.g., GTFS-static feeds), they fail to capture delays, cancellations, and day-to-day variability. Future research should therefore incorporate real-time operational data, such as Automatic Vehicle Location feeds or GTFS-realtime (Braga et al., 2023; Webb et al., 2025), to better represent service frequency and reliability. Combining such service-based measures with comprehensive pedestrian network data would allow more accurate and realistic assessments of accessibility to public transport.

Fourth, the models in this study did not explicitly incorporate individual-level factors known to influence travel behaviour, such as neighbourhood self-selection and psychological constructs (e.g., attitudes toward public transport, perceived service quality, and habitual travel preferences). The absence of these factors represents a limitation, as they may confound or mediate the associations between accessibility and ridership observed here. Future research leveraging high-resolution behavioural data (e.g., GPS and accelerometer data) should explicitly integrate targeted surveys to measure residential-choice motivations and psychological determinants of transport mode choice. Doing so would enhance both the explanatory power and interpretability of findings.

Finally, the findings should be interpreted in light of the study's sample size and the statistical strength of the observed relationships. While several associations were identified, a number of results were non-significant or only marginally significant, introducing uncertainty in the interpretation of the findings. As such, the relationships identified in this study should be considered with caution, taking into account the study context and population. Future research using larger samples and more diverse settings would be valuable for validating these findings, strengthening their statistical robustness, and assessing their generalisability.

Policy implications

The findings of this study suggest that increased proximity to bus stops does not necessarily correspond to higher ridership in this context. While this relationship should be interpreted cautiously given the marginally significant effects and limited sample size, it suggests that the relationship between accessibility and public transport use may be more complex than commonly assumed. From a policy perspective, this points to the potential importance of considering not only the quantity of public transport infrastructure, such as stop density, but also its spatial configuration and interaction with service characteristics. In this regard, transport policy may benefit from moving beyond simple proximity-based measures and incorporating factors such as service reliability, stop spacing, and the practical usability of access networks, including walkable catchments.

The results may also point to the relevance of considering differences in time constraints and travel resources between user groups (e.g., those employed or unemployed) when designing bus services. From a policy perspective, the findings suggest that service design could consider prioritising peak-hour frequency, reduced wait times, and improved reliability in areas with high concentrations of employed populations. By contrast, populations with greater temporal flexibility but fewer mobility resources may benefit from broader spatial coverage and affordable off-peak services. Tailoring service provision in this way may help address differences in mobility needs across population groups, although further evidence from larger and more diverse samples is needed to support such strategies.

In this study, recent movers appeared more likely to use the bus when their destinations were well served by public transport. While the underlying mechanisms remain uncertain, this finding may suggest that accessibility at key destinations, such as employment centres and community services, could play a role in supporting mobility during periods of residential adjustment. From a policy perspective, this points to the potential value of maintaining strong public transport connectivity in areas with higher population turnover. However, further research using larger and more diverse samples is required before drawing firm conclusions about these relationships.

Altogether, these findings suggest that it may be useful to reconsider how accessibility is conceptualised in transport policy. Rather than treating it solely as a static measure of proximity, accessibility may also be viewed as a context-sensitive factor shaped by travel purpose and individual constraints. Future planning approaches could explore combining spatial measures with service performance indicators, such as reliability, and incorporating behavioural data where available. Such approaches may help inform more targeted strategies, although further evidence is needed to assess their applicability beyond the study context.

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CRediT authorship contribution statement

Angela Curl: Writing – review & editing. **Jonas De Vos:** Writing – review & editing. **Scott Duncan:** Writing – review & editing, Supervision, Conceptualization. **Mehdi Barati:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Tom Stewart:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Melody Smith:** Writing – review & editing.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used OpenAI in order to improve the readability and language of the manuscript. After using this tool, the authors reviewed and edited the content as needed and takes full responsibility for the content of the published article.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Table A. 1
Results of mixed-effects models examining the association between accessibility to bus stops and bus ridership behaviour – Unadjusted for socio-demographics

Parameters	Odds ratio	SE	95% CI	P-value
Home-based accessibility to bus stops	0.79	0.16	[0.57, 1.08]	0.147
Origin-based accessibility to bus stops	1.04	0.05	[0.94, 1.15]	0.480
Destination-based accessibility to bus stops	1.14	0.05	[1.03, 1.27]	0.014
Marginal R^2 = 3.1%; Conditional R^2 = 33.5%				

Table A. 2
Results of mixed-effects models examining the association between accessibility to bus stops and bus ridership behaviour – Adjusted for socio-demographics

Parameters	Odds ratio	SE	95% CI	P-value
Home-based accessibility to bus stops	0.44	0.33	[0.23, 0.84]	0.012
Origin-based accessibility to bus stops	0.83	0.18	[0.58, 1.19]	0.304
Destination-based accessibility to bus stops	0.98	0.10	[0.81, 1.20]	0.870
Age (ref = 18–39 yrs				
40–64 yrs	0.76	0.45	[0.32, 1.84]	0.544
65 yrs and over	1.35	0.77	[0.30, 6.11]	0.701
Gender (ref = female)	1.02	0.43	[0.44, 2.36]	0.967
Household income (ref = high income)	0.54	0.45	[0.22, 1.32]	0.178
Ethnicity (ref = Māori)				
New Zealand European	0.85	0.77	[0.19, 3.86]	0.832
Pacific	1.34	0.88	[0.24, 7.53]	0.741
Other	2.25	0.79	[0.47, 10.70]	0.308
Neighbourhood residency (ref = > 10 yrs)				
3–10 yrs	0.42	1.62	[0.02, 10.18]	0.593
< 3 yrs	0.05	1.77	[0.00, 1.68]	0.096
Work status (ref = employed)	0.17	1.55	[0.01, 3.60]	0.256
Interaction – *Home-based* accessibility to bus stops * work status[a]	1.20	0.38	[0.57, 2.54]	0.629
Interaction – *Home-based* accessibility to bus stops * neighbourhood residency[b] (3–10 yrs)	1.43	0.42	[0.63, 3.29]	0.386
Interaction – *Home-based* accessibility to bus stops * neighbourhood residency[b] (3 yrs >)	1.90	0.41	[0.84, 4.30]	0.121
Interaction – *Origin-based* accessibility to bus stops * work status[a]	1.15	0.13	[0.90, 1.48]	0.272
Interaction – *Origin-based* accessibility to bus stops * neighbourhood residency[b] (3–10 yrs)	1.14	0.19	[0.78, 1.65]	0.509
Interaction – *Origin-based* accessibility to bus stops * neighbourhood residency[b] (3 yrs >)	1.34	0.19	[0.91, 1.95]	0.132
Interaction – *Destination-based* accessibility to bus stops * work status[a]	1.28	0.16	[0.94, 1.73]	0.116
Interaction – *Destination-based* accessibility to bus stops * neighbourhood residency[b] (3–10 yrs)	1.12	0.16	[0.80, 1.54]	0.520
Interaction – *Destination-based* accessibility to bus stops * neighbourhood residency[b] (3 yrs >)	1.23	0.14	[0.93, 1.63]	0.145

Marginal $R^2 = 23.6\%$; Conditional $R^2 = 38.9\%$
[a] Interaction term: effect of accessibility varies by work status.
[b] Interaction term: effect of accessibility varies by neighbourhood residency duration.

References

Besser, L.M., Dannenberg, A.L., 2005. Walking to Public Transit: Steps to Help Meet Physical Activity Recommendations (Nov.). Am. J. Prev. Med. 29 (4), 273–280. https://doi.org/10.1016/j.amepre.2005.06.010.

Rissel, C., Curac, N., Greenaway, M., Bauman, A., 2012. Physical Activity Associated with Public Transport Use—A Review and Modelling of Potential Benefits. Art. no. 7, Jul. Int. J. Environ. Res. Public. Health 9 (7). https://doi.org/10.3390/ijerph9072454.

Roberts, J.D., Rodkey, L., Ray, R., Saelens, B.E., 2018. Do Not Forget About Public Transportation: Analysis of the Association of Active Transportation to School Among Washington, DC Area Children With Parental Perceived Built Environment Measures (Jul.). J. Phys. Act. Health 15 (7), 474–482. https://doi.org/10.1123/jpah.2017-0266.

Saelens, B.E., Vernez Moudon, A., Kang, B., Hurvitz, P.M., Zhou, C., 2014. Relation Between Higher Physical Activity and Public Transit Use (May). Am. J. Public. Health 104 (5), 854–859. https://doi.org/10.2105/AJPH.2013.301696.

Lachapelle, U., Frank, L., Saelens, B.E., Sallis, J.F., Conway, T.L., 2011. Commuting by Public Transit and Physical Activity: Where You Live, Where You Work, and How You Get There. J. Phys. Act. Health 8 (. 1), S72–S82. https://doi.org/10.1123/jpah.8.s1.s72.

Frank, L.D., Andresen, M.A., Schmid, T.L., 2004. Obesity relationships with community design, physical activity, and time spent in cars (Aug.). Am. J. Prev. Med. 27 (2), 87–96. https://doi.org/10.1016/j.amepre.2004.04.011.

Hamilton, M.T., Hamilton, D.G., Zderic, T.W., 2007. Role of Low Energy Expenditure and Sitting in Obesity, Metabolic Syndrome, Type 2 Diabetes, and Cardiovascular Disease (Nov.). Diabetes 56 (11), 2655–2667. https://doi.org/10.2337/db07-0882.

Hamilton, M.T., Healy, G.N., Dunstan, D.W., Zderic, T.W., Owen, N., 2008. Too little exercise and too much sitting: Inactivity physiology and the need for new recommendations on sedentary behavior (Jul.). Curr. Cardiovasc. Risk Rep. 2 (4), 292–298. https://doi.org/10.1007/s12170-008-0054-8.

Litman, T., 2012. Evaluating Public Transportation Health Benefits. Victoria Transport Policy Institute, Victoria, BC, Canada.

Litman, T., 2024. Better Speed Valuation for Transportation Planning. Victoria Transport Policy Institute.

Shoaib, A., 2025. Addressing women's mobility challenges in the public transportation system of Lahore, Pakistan (May). J. Transp. Geogr. 125, 104187. https://doi.org/10.1016/j.jtrangeo.2025.104187.

Wahab, S.N., Hamzah, M.I., Suki, N.M., Chong, Y.S., Kua, C.P., 2025. Unveiling passenger satisfaction in rail transit through a consumption values perspective (Mar.). Multimodal Transp. 4 (1), 100196. https://doi.org/10.1016/j.multra.2025.100196.

Aston, L., Currie, G., Delbosc, A., Kamruzzaman, Md, Teller, D., 2021. Exploring built environment impacts on transit use – an updated meta-analysis (Jan.). Transp. Rev. 41 (1), 73–96. https://doi.org/10.1080/01441647.2020.1806941.

Wang, X., Shao, C., Yin, C., Dong, C., 2021. Exploring the effects of the built environment on commuting mode choice in neighborhoods near public transit stations: evidence from China (Jan.). Transp. Plan. Technol. 44 (1), 111–127. https://doi.org/10.1080/03081060.2020.1851453.

Pan, M. (Melrose), Ryan, A., 2025. Promoting Sustainable Transportation Modes: A Systematic Review of Behavior-Change Strategies (Feb.). ' Transp. Res. Rec. 2679 (2), 1993–2012. https://doi.org/10.1177/03611981241274641.

Bree, S., Fuller, D., Diab, E., 2020. Access to transit? Validating local transit accessibility measures using transit ridership (Nov.). ' Transp. Res. Part. Policy Pract. 141, 430–442. https://doi.org/10.1016/j.tra.2020.09.019.

Chakraborty, A., Mishra, S., 2013. Land use and transit ridership connections: Implications for state-level planning agencies (Jan.). Land. Use Policy 30 (1), 458–469. https://doi.org/10.1016/j.landusepol.2012.04.017.

Currie, G., 2004. Gap Analysis of Public Transport Needs:Measuring Spatial Distribution of Public Transport Needs and Identifying Gaps in the Quality of Public Transport Provision (Jan.). Transp. Res. Rec. J. Transp. Res. Board. 1895 (1), 137–146. https://doi.org/10.3141/1895-18.

Jacques, C., El-Geneidy, A.M., 2014. Does travel behavior matter in defining urban form? A quantitative analysis characterizing distinct areas within a region. J. Transp. Land. Use 7 (1), 1–14.

Lindsey, M., Schofer, J.L., Durango-Cohen, P., Gray, K.A., 2010. Relationship between proximity to transit and ridership for journey-to-work trips in Chicago (Nov.). ' Transp. Res. Part. Policy Pract. 44 (9), 697–709. https://doi.org/10.1016/j.tra.2010.07.003.

Rahman, F., Rabby, F., 2024. Predict. Anal. Bus. Serv. Qual. Dhaka City Choice Model. 12 (3).

Taylor, B.D., Fink, C.N.Y., 2013. Explaining transit ridership: What has the evidence shown? (Jan.). Transp. Lett. 5 (1), 15–26. https://doi.org/10.1179/1942786712Z.0000000003.

Tsai, Y.-H., 2009. Impacts of self-selection and transit proximity on commute mode choice: evidence from Taipei rapid transit system (Dec.). Ann. Reg. Sci. 43 (4), 1073–1094. https://doi.org/10.1007/s00168-008-0233-z.

Murray, A.T., Davis, R., Stimson, R.J., Ferreira, L., 1998. Public Transportation Access (Sep.). ' Transp. Res. Part. Transp. Environ. 3 (5), 319–328. https://doi.org/10.1016/S1361-9209(98)00010-8.

Chen, C., Gong, H., Paaswell, R., 2008. Role of the built environment on mode choice decisions: additional evidence on the impact of density (May). Transportation 35 (3), 285–299. https://doi.org/10.1007/s11116-007-9153-5.

Fang, J., 2017. THE IMPACT OF THE BUILT ENVIRONMENT AT TRIP ORIGIN AND DESTINATION ON INDIVIDUAL MODE CHOICE: AN EMPIRICAL STUDY OF PORTLAND. OREGON.

Givoni, M., Rietveld, P., 2007. The access journey to the railway station and its role in passengers' satisfaction with rail travel (Sep.). Transp. Policy 14 (5), 357–365. https://doi.org/10.1016/j.tranpol.2007.04.004.
Azimi, G., Rahimi, A., Lee, M., Jin, X., 2021. Mode choice behavior for access and egress connection to transit services (Jun.). Int. J. Transp. Sci. Technol. 10 (2), 136–155. https://doi.org/10.1016/j.ijtst.2020.11.004.
Abdul Sukor, N.S., Jarani, N., Muhammad Fisal, S.F., 2017. ANALYSIS OF PASSENGERS' ACCESS AND EGRESS CHARACTERISTICS TO THE TRAIN STATION (Nov.). Eng. Herit. J. 1 (2), 01–04. https://doi.org/10.26480/gwk.02.2017.01.04.
Gao, J., Ettema, D., Helbich, M., Kamphuis, C.B.M., 2019. Travel mode attitudes, urban context, and demographics: do they interact differently for bicycle commuting and cycling for other purposes? (Dec.). Transportation 46 (6), 2441–2463. https://doi.org/10.1007/s11116-019-10005-x.
Handy, S., Cao, X., Mokhtarian, P.L., 2006a. Self-Selection in the Relationship between the Built Environment and Walking: Empirical Evidence from Northern California (Mar.). J. Am. Plann. Assoc. 72 (1), 55–74. https://doi.org/10.1080/01944360608976724.
Olayode, I.O., Chau, H.-W., Jamei, E., 2025. Barriers Affecting Promotion of Active Transportation: A Study on Pedestrian and Bicycle Network Connectivity in Melbourne's West. Art. no. 1, Jan. Land 14 (1). https://doi.org/10.3390/land14010047.
Van Cauwenberg, J., Nathan, A., Barnett, A., Barnett, D.W., Cerin, E., the Council on Environment and Physical Activity (CEPA)-Older Adults Working Group, Jul. 2018. Relationships Between Neighbourhood Physical Environmental Attributes and Older Adults' Leisure-Time Physical Activity: A Systematic Review and Meta-Analysis. Sports Med. 48 (7), 1635–1660. https://doi.org/10.1007/s40279-018-0917-1.
Yeboah, G., Cottrill, C.D., Nelson, J.D., Corsar, D., Markovic, M., Edwards, P., Jun. 2019. Understanding factors influencing public transport passengers' pre-travel information-seeking behaviour. Public. Transp. 11 (1), 135–158. https://doi.org/10.1007/s12469-019-00198-w.
WorldStats. (2026). Auckland, New Zealand - Population & Statistics. Retrieved May 22, 2026, from https://worldstats.io/city/auckland-nz.
Shi, Y., Blainey, S., Sun, C., Jing, P., Jul. 2020. A literature review on accessibility using bibliometric analysis techniques. J. Transp. Geogr. 87, 102810. https://doi.org/10.1016/j.jtrangeo.2020.102810.
Environmental Health Intelligence NZ, "Household travel time by mode of transport," Massey University, Wellington, New Zealand, 2023. [Online]. Available: https://www.ehinz.ac.nz/assets/Surveillance-reports/Released_2023/Household-travel-time-by-mode-2023.pdf?utm_source=chatgpt.com. Accessed: Jul. 24, 2025.
T.J. Kimpel, K.J. Dueker, and A.M. El-Geneidy, 'Using GIS to Measure the Effect of Overlapping Service Areas on Passenger Boardings at Bus Stops', vol. 19, no. 1, 2007.
A. Prajapati, N. Bhattarai, and T.R. Bajracharya, 'Spatio-Temporal Analysis Of Public Transportation System Using Static Transit Accessibility Methodological Framework', vol. 9, no. 10, 2020.
S.P. Nemer, 'Assessing and Improving Accessibility to Public Transport in Montevideo, Uruguay', M.S. thesis, Facultad de Ingeniería, Universidad de la República, Montevideo, Uruguay, Dec. 2024.
García-Palomares, J.C., Gutiérrez, J., Cardozo, O.D., 2013. 'Walking accessibility to public transport: an analysis based on microdata and GIS'. Environ. Plan. B Plan. Des. 40 (6), 1087–1102.
Chakour, V., Eluru, N., 2016. Examining the influence of stop level infrastructure and built environment on bus ridership in Montreal (Feb.). J. Transp. Geogr. 51, 205–217. https://doi.org/10.1016/j.jtrangeo.2016.01.007.
Cui, B., DeWeese, J., Wu, H., King, D.A., Levinson, D., El-Geneidy, A., Feb. 2022. All ridership is local: Accessibility, competition, and stop-level determinants of daily bus boardings in Portland, Oregon. J. Transp. Geogr. 99, 103294. https://doi.org/10.1016/j.jtrangeo.2022.103294.
J. Dill, 'Predicting transit ridership at the stop level: the role of service and urban form', 2013.
Chu, X. (2004). Ridership models at the stop level.
Miller, E., 2023. The current state of activity-based travel demand modelling and some possible next steps (Jul.). Transp. Rev. 43 (4), 565–570. https://doi.org/10.1080/01441647.2023.2198458.
Levinson, D.M., 1998. Accessibility and the journey to work (Mar.). J. Transp. Geogr. 6 (1), 11–21. https://doi.org/10.1016/S0966-6923(97)00036-7.
Cui, B., Boisjoly, G., El-Geneidy, A., Levinson, D., 2019. Accessibility and the journey to work through the lens of equity (Jan.). J. Transp. Geogr. 74, 269–277. https://doi.org/10.1016/j.jtrangeo.2018.12.003.
Tilahun, N., Thakuriah, P. (Vonu), Li, M., Keita, Y., 2016. Transit use and the work commute: Analyzing the role of last mile issues (Jun.). J. Transp. Geogr. 54, 359–368. https://doi.org/10.1016/j.jtrangeo.2016.06.021.
Handy, S., Cao, X., Mokhtarian, P., 2005. Correlation or causality between the built environment and travel behavior? Evidence from Northern California (Nov.). ' Transp. Res. Part. Transp. Environ. 10 (6), 427–444. https://doi.org/10.1016/j.trd.2005.05.002.
K. Manaugh and A.M. El-Geneidy, (n.d.)'Who Benefits from New Transportation Infrastructure? Using Accessibility Measures to Evaluate Social Equity in Transit Provision'.
Barbosa, H., et al., 2018. Human mobility: Models and applications (Mar.). Phys. Rep. 734, 1–74. https://doi.org/10.1016/j.physrep.2018.01.001.
Mohammed, M., Oke, J., 2023. Origin-destination inference in public transportation systems: A comprehensive review (Mar.). Int. J. Transp. Sci. Technol. 12 (1), 315–328. https://doi.org/10.1016/j.ijtst.2022.03.002.
Stopher, P., FitzGerald, C., Xu, M., 2007. Assessing the accuracy of the Sydney Household Travel Survey with GPS (Nov.). Transportation 34 (6), 723–741. https://doi.org/10.1007/s11116-007-9126-8.
Chen, C., Ma, J., Susilo, Y., Liu, Y., Wang, M., 2016. The promises of big data and small data for travel behavior (aka human mobility) analysis (Jul.). Transp. Res. Part. C. Emerg. Technol. 68, 285–299. https://doi.org/10.1016/j.trc.2016.04.005.
Carrel, A., Lau, P.S.C., Mishalani, R.G., Sengupta, R., Walker, J.L., 2015. Quantifying transit travel experiences from the users' perspective with high-resolution smartphone and vehicle location data: Methodologies, validation, and example analyses (Sep.). Transp. Res. Part. C. Emerg. Technol. 58, 224–239. https://doi.org/10.1016/j.trc.2015.03.021.
Joyce, M., Dunn, R., 2009. A proposed methodology for Measuring Public Transport Accessibility to Employment Sites in the Auckland CBD'. Proc. 32nd Australas. Transp. Res. Forum.
Zubair, H., Susilawati, S., Talei, A., Pu, Z., 2024. Investigating the role of flex-time working arrangements in optimising morning peak-hour travel demand: A survival analysis approach (Dec.). ' Transp. Res. Part. Policy Pract. 190, 104229. https://doi.org/10.1016/j.tra.2024.104229.
Beimborn, E.A., Greenwald, M.J., Jin, X., 2003. Accessibility, Connectivity, and Captivity: Impacts on Transit Choice (Jan.). ' Transp. Res. Rec. 1835 (1), 1–9. https://doi.org/10.3141/1835-01.
Garrett, M., Taylor, B., 1999. Reconsidering Social Equity in Public Transit. Berkeley Plan. J. 13 (1). https://doi.org/10.5070/BP313113028.
Jacques, C., Manaugh, K., El-Geneidy, A.M., 2013. Rescuing the captive [mode] user: an alternative approach to transport market segmentation (May). Transportation 40 (3), 625–645. https://doi.org/10.1007/s11116-012-9437-2.
Krizek, K.J., El-Geneidy, A., 2007. Segmenting Preferences and Habits of Transit Users and Non-Users (Jul.). J. Public. Transp. 10 (3), 71–94. https://doi.org/10.5038/2375-0901.10.3.5.
Pasha, M., Rifaat, S.M., Tay, R., De Barros, A., 2016. Effects of street pattern, traffic, road infrastructure, socioeconomic and demographic characteristics on public transit ridership (Apr.). KSCE J. Civ. Eng. 20 (3), 1017–1022. https://doi.org/10.1007/s12205-016-0693-6.
Anburuvel, A., Perera, W.U.L.D.P., Randeniya, R.D.S.S., 2022. A demand responsive public transport for a spatially scattered population in a developing country (Mar.). Case Stud. Transp. Policy 10 (1), 187–197. https://doi.org/10.1016/j.cstp.2021.12.001.
Bastiaanssen, J., Johnson, D., Lucas, K., 2020. Does transport help people to gain employment? A systematic review and meta-analysis of the empirical evidence (Sep.). Transp. Rev. 40 (5), 607–628. https://doi.org/10.1080/01441647.2020.1747569.
Handy, S., Cao, X., Mokhtarian, P.L., 2006b. Self-Selection in the Relationship between the Built Environment and Walking: Empirical Evidence from Northern California (Mar.). J. Am. Plann. Assoc. 72 (1), 55–74. https://doi.org/10.1080/01944360608976724.
Jamei, E., Chan, M., Chau, H.W., Gaisie, E., Lättman, K., 2022. Perceived Accessibility and Key Influencing Factors in Transportation (Jan.). Sustainability 14 (17), 10806. https://doi.org/10.3390/su141710806.
Jia, P., et al., 2020. Spatial Lifecourse Epidemiology Reporting Standards (ISLE-ReSt) statement (Jan.). Health Place. 61, 102243. https://doi.org/10.1016/j.healthplace.2019.102243.
Besen, P., et al., 2026. Contrasts within New Zealand cities: perceived liveability across five neighbourhoods in Tāmaki Makaurau Auckland (Mar.). Urban. Sustain. Soc. 3 (4), 1–26. https://doi.org/10.1108/USS-12-2024-0090.
Radio New Zealand. (2026). Auckland more dependent on cars, less density than its peers, report finds. Retrieved May 18, 2026, from https://www.rnz.co.nz/news/business/566892/auckland-more-dependent-on-cars-less-density-than-its-peers-report-finds.
Mavoa, S., Witten, K., McCreanor, T., O'Sullivan, D., 2012. GIS based destination accessibility via public transit and walking in Auckland, New Zealand (Jan.). J. Transp. Geogr. 20 (1), 15–22. https://doi.org/10.1016/j.jtrangeo.2011.10.001.
Te Hotonga Hapori, 'Te Hotonga Hapori – Connecting Communities', 2025. [Online]. Available: https://tehotongahapori.ac.nz/. Accessed: Aug. 4, 2024.
Oliver, M., Badland, H., Mavoa, S., Duncan, M.J., Duncan, S., 2010. Combining GPS, GIS, and Accelerometry: Methodological Issues in the Assessment of Location and Intensity of Travel Behaviors (Jan.). J. Phys. Act. Health 7 (1), 102–108. https://doi.org/10.1123/jpah.7.1.102.
Duncan, S., et al., 2013. Portable Global Positioning System Receivers: Static Validity and Environmental Conditions' (Feb.). Am. J. Prev. Med. 44 (2), e19–e29. https://doi.org/10.1016/j.amepre.2012.10.013.
Vorlíček, M., Stewart, T., Dygrýn, J., Rubín, L., Mitáš, J., Schipperijn, J., 2019. The comparison of Holux and Qstarz GPS receivers in free living conditions: Dynamic accuracy in different active transport modes (Sep.). Acta Gymnica 49 (3), 109–114. https://doi.org/10.5507/ag.2019.009.
L. Hedayatrad, T. Stewart, and S. Duncan, 'Concurrent Validity of ActiGraph GT3X+ and Axivity AX3 Accelerometers for Estimating Physical Activity and Sedentary Behavior', Dec. 2020, doi: 10.1123/jmpb.2019-0075.
Almanza, E., Jerrett, M., Dunton, G., Seto, E., Pentz, M.A., 2012. A study of community design, greenness, and physical activity in children using satellite, GPS and accelerometer data (Jan.). Health Place. 18 (1), 46–54. https://doi.org/10.1016/j.healthplace.2011.09.003.
Stewart, T., Duncan, S., Schipperijn, J., 2017a. Adolescents who engage in active school transport are also more active in other contexts: A space-time investigation (Jan.). Health Place. 43, 25–32. https://doi.org/10.1016/j.healthplace.2016.11.009.
Kang, M., Moudon, A.V., Hurvitz, P.M., Saelens, B.E., 2018. Capturing fine-scale travel behaviors: a comparative analysis between personal activity location measurement

system (PALMS) and travel diary (Dec.). Int. J. Health Geogr. 17 (1), 40. https://doi.org/10.1186/s12942-018-0161-9.

Stewart, T., Duncan, S., Schipperijn, J., 2017b. Adolescents who engage in active school transport are also more active in other contexts: A space-time investigation (Jan.). Health Place. 43, 25–32. https://doi.org/10.1016/j.healthplace.2016.11.009.

J. Heidler, M. Marchioriand J. Schipperijn, 'LET's DO IT AGAIN: A NEW TOOL FOR ADDING SPATIOTEMPORAL CONTEXT TO HUMAN MOVEMENT BEHAVIOUR DATA', presented at the 9th International Conference on Ambulatory Monitoring of Physical Activity and Movement (ICAMPAM), Rennes, France, Jun. 18, 2024. doi: 10.5281/zenodo.14698687.

Krenn, P.J., Titze, S., Oja, P., Jones, A., Ogilvie, D., 2011. Use of Global Positioning Systems to Study Physical Activity and the Environment: A Systematic Review' (Nov.). Am. J. Prev. Med. 41 (5), 508–515. https://doi.org/10.1016/j.amepre.2011.06.046.

Kerr, J., Duncan, S., Schipperjin, J., 2011. Using Global Positioning Systems in Health Research: A Practical Approach to Data Collection and Processing' (Nov.). Am. J. Prev. Med. 41 (5), 532–540. https://doi.org/10.1016/j.amepre.2011.07.017.

Auckland Transport, 'Auckland Transport Open GIS Data,' 2025. [Online]. Available: https://data-atgis.opendata.arcgis.com/. Accessed: Apr. 16, 2025.

Talpur, M.A.H., Khahro, S.H., Abro, S., Shaikh, H., 2024. Measuring GIS-based pedestrian accessibility to bus stops: a sustainable approach to ease urban traffic problems at Hyderabad, Pakistan (Nov.). Discov. Cities 1 (1), 28. https://doi.org/10.1007/s44327-024-00031-5.

Taylor, M.A.P., Somenahalli, S., 2024. Distributions of walking access to public transport in Melbourne, Australia – Evidence on acceptable and tolerable walking distances (Jul.). Int. J. Sustain. Transp. 18 (7), 576–588. https://doi.org/10.1080/15568318.2024.2385641.

NZ Transport Agency Waka Kotahi. (n.d.). Bus stop spacing. Retrieved May 13, 2026, from https://nzta.govt.nz/walking-cycling-and-public-transport/public-transport/public-transport-framework/integrated-planning-and-design/public-transport-design-guidance/bus-stop/bus-stop-location-planning/location-fundamentals/bus-stop-spacing.

Zhao, F., Chow, L., Li, M., Ubaka, I., Gan, A., 2003. Forecasting transit walk accessibility: Regression model alternative to buffer method. ' Transp. Res. Rec. 1835 (1), 34–41. https://doi.org/10.3141/1835-05.

Alshalalfah, B.W., Shalaby, A.S., 2007. Case Study: Relationship of Walk Access Distance to Transit with Service, Travel, and Personal Characteristics (Jun.). J. Urban. Plan. Dev. 133 (2), 114–118. https://doi.org/10.1061/(ASCE)0733-9488(2007)133:2(114).

Handy, S.L., Niemeier, D.A., 1997. Measuring Accessibility: An Exploration of Issues and Alternatives (Jul.). ' Environ. Plan. Econ. Space 29 (7), 1175–1194. https://doi.org/10.1068/a291175.

Geurs, K.T., Van Wee, B., 2004. Accessibility evaluation of land-use and transport strategies: review and research directions (Jun.). J. Transp. Geogr. 12 (2), 127–140. https://doi.org/10.1016/j.jtrangeo.2003.10.005.

Koenig, J.G., 1980. Indicators of urban accessibility: Theory and application (Jun.). Transportation 9 (2), 145–172. https://doi.org/10.1007/BF00167128.

Te Whata. (n.d.). Usual residence. Retrieved May 15, 2026, from https://tewhata.io/social/people/usual-residence/.

Gim, T.-H.T., 2022. How does the length of residence in a neighborhood vary the effects of neighborhood land use on commuting trip time and mode choice? Ann. Reg. Sci. 68 (1), 95–123.

Shin, E.J., 2019. Self-employment and travel behavior: A case study of workers in central Puget Sound (Jan.). Transp. Policy 73, 101–112. https://doi.org/10.1016/j.tranpol.2018.11.002.

Persoskie, A., Ferrer, R.A., 2017. A Most Odd Ratio: Interpreting and Describing Odds Ratios' (Feb.). Am. J. Prev. Med. 52 (2), 224–228. https://doi.org/10.1016/j.amepre.2016.07.030.

Wilms, R., Mäthner, E., Winnen, L., Lanwehr, R., 2021. Omitted variable bias: A threat to estimating causal relationships (Dec.). Methods Psychol. 5, 100075. https://doi.org/10.1016/j.metip.2021.100075.

Cao, X. (Jason), Mokhtarian, P.L., Handy, S.L., 2009. Examining the Impacts of Residential Self-Selection on Travel Behaviour: A Focus on Empirical Findings (May). Transp. Rev. 29 (3), 359–395. https://doi.org/10.1080/01441640802539195.

van der Vlugt, A.-L., Curl, A., Wittowsky, D., 2019. What about the people? Developing measures of perceived accessibility from case studies in Germany and the UK (May). Appl. Mobilities 4 (2), 142–162. https://doi.org/10.1080/23800127.2019.1573450.

Bamberg, S., Ajzen, I., Schmidt, P., 2003. Choice of Travel Mode in the Theory of Planned Behavior: The Roles of Past Behavior, Habit, and Reasoned Action (Sep.). Basic. Appl. Soc. Psychol. 25 (3), 175–187. https://doi.org/10.1207/S15324834BASP2503_01.

Verplanken, B., Aarts, H., Van Knippenberg, A., 1997. Habit, information acquisition, and the process of making travel mode choices'. Eur. J. Soc. Psychol. 27 (5), 539–560. https://doi.org/10.1002/(SICI)1099-0992(199709/10)27:5%3C539::AID-EJSP831%3E3.0.CO;2-A.

Krizek, K.J., 2003. Residential Relocation and Changes in Urban Travel: Does Neighborhood-Scale Urban Form Matter? (Sep.). J. Am. Plann. Assoc. 69 (3), 265–281. https://doi.org/10.1080/01944360308978019.

Salon, D., 2009. Neighborhoods, cars, and commuting in New York City: A discrete choice approach (Feb.). ' Transp. Res. Part. Policy Pract. 43 (2), 180–196. https://doi.org/10.1016/j.tra.2008.10.002.

Van Acker, V., Witlox, F., 2010. Car ownership as a mediating variable in car travel behaviour research using a structural equation modelling approach to identify its dual relationship (Jan.). J. Transp. Geogr. 18 (1), 65–74. https://doi.org/10.1016/j.jtrangeo.2009.05.006.

Lucas Albuquerque-Oliveira, J., Moraes Oliveira-Neto, F., Pereira, R.H.M., 2024. A novel route-based accessibility measure and its association with transit ridership (Jan.). ' Transp. Res. Part. Policy Pract. 179, 103916. https://doi.org/10.1016/j.tra.2023.103916.

Welch, T.F., Mishra, S., 2013. A measure of equity for public transit connectivity (Dec.). J. Transp. Geogr. 33, 29–41. https://doi.org/10.1016/j.jtrangeo.2013.09.007.

El-Geneidy, A., Grimsrud, M., Wasfi, R., Tétreault, P., Surprenant-Legault, J., 2014. New evidence on walking distances to transit stops: identifying redundancies and gaps using variable service areas (Jan.). Transportation 41 (1), 193–210. https://doi.org/10.1007/s11116-013-9508-z.

1News, 'A joke'': Delays plague Auckland bus line after route changes,' May 9, 2025. [Online]. Available: https://www.1news.co.nz/2025/05/09/a-joke-delays-plague-auckland-bus-line-after-route-changes/. Accessed: Jul. 28, 2025.

F. Hancock and D. journalist, 'The big problem with Auckland Transport's bus reliability measures', RNZ. Accessed: Jul. 28, 2025. [Online]. Available: https://www.rnz.co.nz/news/in-depth/487537/the-big-problem-with-auckland-transport-s-bus-reliability-measures.

F. H. of RNZ, 'Auckland's least reliable bus routes revealed', Stuff. Accessed: Jul. 28, 2025. [Online]. Available: https://www.stuff.co.nz/auckland/300846430/aucklands-least-reliable-bus-routes-revealed.

Rasouli, S., Timmermans, H., Van Der Waerden, P., 2015. Employment status transitions and shifts in daily activity-travel behavior with special focus on shopping duration (Nov.). Transportation 42 (6), 919–931. https://doi.org/10.1007/s11116-015-9655-5.

J. Mengedoth, 'Transportation Access as a Barrier to Work,' Econ Focus, Federal Reserve Bank of Richmond, Fourth Quarter 2023. [Online]. Available: https://www.richmondfed.org/publications/research/econ_focus/2023/q4_district_digest. Accessed: Dec. 1, 2025.

Wang, S., 2025. The Workplace Dilemma: Examining the Effects of Work-Related Constraints on Travel Decision-Making. Art. no. 2, Jun. Tour. Hosp. 6 (2). https://doi.org/10.3390/tourhosp6020065.

Lu, Z., Wang, S., Olsen, W., 2023. Revisiting the "flexibility paradox": degree of work schedule flexibility and time use patterns across gender and occupational groups (Nov.). Humanit. Soc. Sci. Commun. 10 (1), 1–10. https://doi.org/10.1057/s41599-023-02205-9.

Ewing, R., Cervero, R., 2010. Travel and the Built Environment: A Meta-Analysis (Jun.). J. Am. Plann. Assoc. 76 (3), 265–294. https://doi.org/10.1080/01944361003766766.

Clark, B., Chatterjee, K., Melia, S., 2016. Changes to commute mode: The role of life events, spatial context and environmental attitude (Jul.). ' Transp. Res. Part. Policy Pract. 89, 89–105. https://doi.org/10.1016/j.tra.2016.05.005.

D. Kim, J. Park, and A. Hong, (n.d.) 'The role of destination built environment on nonmotorized travel behavior: A case of Long Beach, California'.

Braga, C.K.V., Loureiro, C.F.G., Pereira, R.H.M., 2023. Evaluating the impact of public transport travel time inaccuracy and variability on socio-spatial inequalities in accessibility (May). J. Transp. Geogr. 109, 103590. https://doi.org/10.1016/j.jtrangeo.2023.103590.

Webb, L., Higgs, G., Langford, M., Berry, R., 2025. Evaluating Real-Time and Scheduled Public Transport Data: Challenges and Opportunities (Jul.). ISPRS Int. J. Geo-Inf. 14 (7), 243. https://doi.org/10.3390/ijgi14070243.