The role of accessibility measures in travel behaviour: A focus on conventional and emerging mobility options

Mehdi Barati

A thesis submitted to Auckland University of Technology in fulfilment of the requirements for the degree of Doctor of Philosophy

2026

Faculty of Health and Environmental Sciences

Supervisors:

Associate Professor Tom Stewart

Professor Scott Duncan

Thesis abstract

Promoting active travel is essential for improving public health, reducing environmental impacts, and addressing transport inequities. Walking behaviour is associated with a wide range of personal and environmental factors. Out of these factors, the correlation between urban form and travel behaviour is well established in the literature. The extent to which built environment features are associated with active travel is often expressed through measures of accessibility, reflecting the ease of reaching destinations and activities. Given that public transport and micromobility (e.g., shared e-scooter) services may improve access to destinations and may support walking, many scholars have endeavoured to uncover how accessibility is correlated with these mobility options. Despite this growing body of research, important gaps remain in understanding how accessibility can best inform active and sustainable transport planning. This thesis therefore investigates how different accessibility measures correlate with travel behaviour across conventional and emerging transport modes in a highly car-dependent city, Auckland, New Zealand, drawing on objective mobility data and advanced modelling techniques.

The first study (Chapter 3) examined the relationship between neighbourhood accessibility and objectively measured walking behaviour using GPS and accelerometer data from 2,503 trips. An enhanced two-step floating catchment area (E2SFCA)-based accessibility index was used to quantify access from participants' homes to destinations across eight key domains, such as education, recreation, and public transport. Findings showed positive associations between neighbourhood accessibility and walking behaviour both within and beyond home-neighbourhood boundaries, although these estimates were accompanied by substantial uncertainty. The association for walking beyond the home neighbourhood was estimated more precisely, whereas the estimate for within-neighbourhood walking was less precise. Socio-demographic factors, including age, gender, and work status, were also associated with walking patterns, with older adults and unemployed individuals recording longer walking durations. These findings suggest that neighbourhood accessibility may be more strongly related to walking beyond the immediate neighbourhood than to walking within local areas, although evidence regarding spatial differences in accessibility–walking associations remains uncertain.

The second study (Chapter 4) examined the relationship between accessibility to bus stops, measured from three spatial anchors (home, trip origin, and destination), and actual bus ridership using GPS and accelerometer data from 108 participants (835 trips). Mixed-effects logistic regression models were applied, with work status and neighbourhood residency duration tested as moderators. Results indicated that home-based accessibility was negatively associated with bus use, while origin-based accessibility showed no significant relationship. Destination-based

accessibility interacted significantly with neighbourhood residency, suggesting that the association between destination accessibility and bus use differed according to residency duration. Work status marginally moderated the home-based association, suggesting that the association between home-based accessibility and bus use differed between employed and unemployed participants. These findings underscore the complexity of accessibility–ridership relationships and the importance of individual circumstances, particularly work status and neighbourhood residency duration, in understanding how associations between accessibility and bus use vary across population groups.

The final two studies (Chapters 5 and 6) focused on shared e-scooter use patterns, leveraging more than 470,000 trip records collected between April 2023 and May 2024. The third study applied a gravity-based negative binomial model to examine how domain-specific accessibility measures correlate with trip volumes. Results revealed pronounced distance-decay effects consistent with the short-range nature of e-scooter travel. Higher trip volumes were observed in areas with greater accessibility to public transport and recreational amenities, indicating a spatial alignment between micromobility use and leisure or multimodal transport nodes. Conversely, lower usage was associated with greater accessibility to shopping and education facilities, higher exposure to environmental "bads", elevated car ownership, and increased deprivation. The fourth study employed elastic net regression to investigate how domain-specific accessibility measures were associated with e-scooter trip length. Findings indicated that higher public transport accessibility was associated with shorter trips, consistent with a possible role in first- and last-mile connectivity, whereas greater accessibility to recreation, education, and environmental "bads" corresponded with longer trips. Shopping accessibility showed directional asymmetry, with longer trips originating in retail-rich areas and shorter trips terminating in such destinations. Longer trips were also more common in areas with greater deprivation or higher car-ownership levels, raising equity concerns under distance-based pricing models.

Collectively, these studies indicated that accessibility is an important correlate of active and sustainable travel behaviour. Across walking, public transport, and shared micromobility, the associations between accessibility and travel behaviour varied across population groups according to factors such as age, employment status, neighbourhood residency duration, and local socio-economic conditions. By integrating objective mobility data with multidimensional accessibility metrics, the thesis advances understanding of how accessibility relates to travel behaviour in a highly car-dependent setting. The findings underscore the importance of combining spatial accessibility improvements with policies that acknowledge demographic variation and address socio-economic constraints. Altogether, this thesis provides an evidence base to support more equitable, user-centred transport planning, illustrating that accessibility-focused strategies should be tailored to the circumstances and mobility needs of different groups.

Contents

List of Figures

List of Tables

Attestation of authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor used artificial intelligence tools or generative artificial intelligence tools (unless it is clearly stated and referenced, along with the purpose of use), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

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Mehdi Barati, February 2026

Co-Authorship Contributions

STUDENT AND SUPERVISOR APPROVALS

By signing you are confirming that the co-author contributions stated in the table(s) below are accurate.

Student Name	Mehdi Barati	**Signature**		**Date**	02/02/2026
Supervisor Name	Tom Stewart	**Signature**		**Date**	18/02/2026
Supervisor Name	Scott Duncan	**Signature**		**Date**	18/02/2026

Chapter Number:	3
Manuscript Title:	Does neighbourhood accessibility relate more to local walking or destinations beyond? Evidence from a GPS and accelerometer study Submitted for publication
Publication Status:	Submitted for Publication
AUTHOR SURNAME:	**CONTRIBUTION (CRediT)**
Mehdi Barati	Conceptualisation, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review and editing
Tom Stewart	Conceptualisation, Supervision, Writing – review and editing
Josef Heidler	Software, Writing – review and editing
Daniel Exeter	Writing – review and editing
Jessie Colbert	Writing – review and editing
Milad Mehdizadeh	Writing – review and editing
Scott Duncan	Conceptualisation, Supervision, Writing – review and editing

Chapter Number:	4
Manuscript Title:	Linking multi-anchor bus stop accessibility to bus ridership: Evidence from GPS and accelerometer data
Publication Status:	Submitted for Publication
AUTHOR SURNAME:	**CONTRIBUTION (CRediT)**
Mehdi Barati	Conceptualisation, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review and editing
Tom Stewart	Conceptualisation, Supervision, Writing – review and editing
Melody Smith	Writing – review and editing
Angela Curl	Writing – review and editing
Jonas De Vos	Writing – review and editing
Scott Duncan	Conceptualisation, Supervision, Writing – review and editing

Chapter Number:	5
Manuscript Title:	Is all access equal? Examining how domain-specific accessibility measures correlate with shared e-scooter trip flows
Publication Status:	Submitted for Publication

AUTHOR SURNAME:	CONTRIBUTION (CRediT)
Mehdi Barati	Conceptualisation, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review and editing
Tom Stewart	Conceptualisation, Supervision, Writing – review and editing
Shaya Vosough	Writing – review and editing
Angela Curl	Writing – review and editing
Melody Smith	Writing – review and editing
Scott Duncan	Conceptualisation, Supervision, Writing – review and editing

Chapter Number:	6
Manuscript Title:	How accessibility relates to shared e-scooter trip length: Insights for sustainable micromobility deployment
Publication Status:	Under review

AUTHOR SURNAME:	CONTRIBUTION (CRediT)
Mehdi Barati	Conceptualisation, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review and editing
Tom Stewart	Conceptualisation, Supervision, Writing – review and editing
Mohsen Fallah Zavareh	Writing – review and editing
Angela Curl	Writing – review and editing
Scott Duncan	Conceptualisation, Supervision, Writing – review and editing

Acknowledgements

I would like to express my sincere gratitude to the Ministry of Business, Innovation and Employment, the Health Research Council, and the Te Hotonga Hapori project for their generous financial support throughout my PhD studies.

I am especially grateful to my supervisors, A/Prof Tom Stewart, for his supportive and approachable mentorship and for making this journey a positive experience, and Prof Scott Duncan, for his outstanding supervision and encouragement, and also for making the journey more enjoyable, especially through our many Formula 1 conversations! Their expertise, insightful discussions, and constructive criticism have played a crucial role in shaping both the direction and quality of this thesis.

I am also very thankful to Julia McPhee, Programme Manager of the Te Hotonga Hapori research programme, for her support, positivity, and encouragement from the very beginning of my PhD.

I would also like to thank my co-authors and collaborators, Prof Melody Smith, Prof Daniel Exeter, Prof Jonas De Vos, A/Prof Mohsen Fallah Zavareh, A/Prof Angela Curl, Asst Prof Shaya Vosough, Dr Milad Mehdizadeh, Dr Josef Heidler, and Ms Jessie Colbert, for their contributions, productive cooperation, and the many insightful exchanges that enriched this research. I truly value the opportunity to work alongside them and appreciate the effort and professionalism they brought to our joint work.

Finally, I would like to extend my sincere appreciation to everyone who supported me, directly or indirectly, throughout my PhD journey and contributed to the completion of this thesis. Above all, I dedicate this work to my parents and my siblings, Bardia, Fatemeh, and Azam, whose unwavering love, encouragement, and support have been a constant source of strength. I also dedicate this thesis to my lifelong motto, “Forever Student”, which has inspired my enduring curiosity, commitment to learning, and perseverance throughout this journey.

AI Declaration

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Student Name:	Mehdi Barati	**Signature:**		**Date:**	09/02/2026

Ethical approval

Ethical approval for the research presented in this thesis was granted by the Auckland University of Technology Ethics Committee (AUTEC # 21/361) in May 2022 (Appendix A).

Chapter 1. Introduction

Background

Active travel, principally walking and cycling, has long been recognised as a cornerstone of sustainable urban mobility because it integrates health-enhancing physical activity into everyday routines while also delivering broader environmental, social, and economic benefits (1–6). Regular engagement in transport-related physical activity is associated with reduced risks of chronic disease and improved mental well-being, while at the system level, shifting short trips from private vehicles to active modes can alleviate congestion, lower emissions, and reduce the need for extensive road and parking infrastructure (1,5). From a public-health perspective, active travel is both policy-amenable and equity-relevant: when essential destinations are nearby, safe, and accessible, benefits tend to accrue more rapidly for populations with limited car access (7–9). Nevertheless, many cities have reported declines in walking in recent decades, indicating persistent structural barriers that constrain the realisation of active travel's full potential (10,11).

The behavioural decision-making process related to walking is associated with a set of interacting factors, including individual-level attributes, built environment characteristics, the social environment, and cognitive considerations (12,13). According to Alfonzo's social–ecological model (Figure 1-1), walking needs, namely feasibility, accessibility, safety, comfort, and pleasurability, are organised into a hierarchy of prepotency in which more fundamental needs must be satisfied before higher-order qualities can meaningfully influence behaviour (14). Alfonzo further identifies additional categories of influence, such as individual, social, and cultural factors, which are conceptualised as clusters of potential moderators embedded within a person's life-course circumstances. Within this hierarchy of walking needs, feasibility, the most basic requirement, refers to whether walking is practically possible given an individual's mobility, time constraints, health status, or caregiving and work responsibilities. Once a trip is deemed feasible, individuals evaluate accessibility, commonly defined as the ease with which they can reach desired opportunities, services, or activities within acceptable levels of time, cost, or effort (15,16). If accessibility needs are sufficiently met, individuals then consider additional cognitive factors, including safety (freedom from crime-related threats), comfort (the ease and convenience of walking), and pleasurability (the aesthetic and experiential appeal of the walking environment) (14).

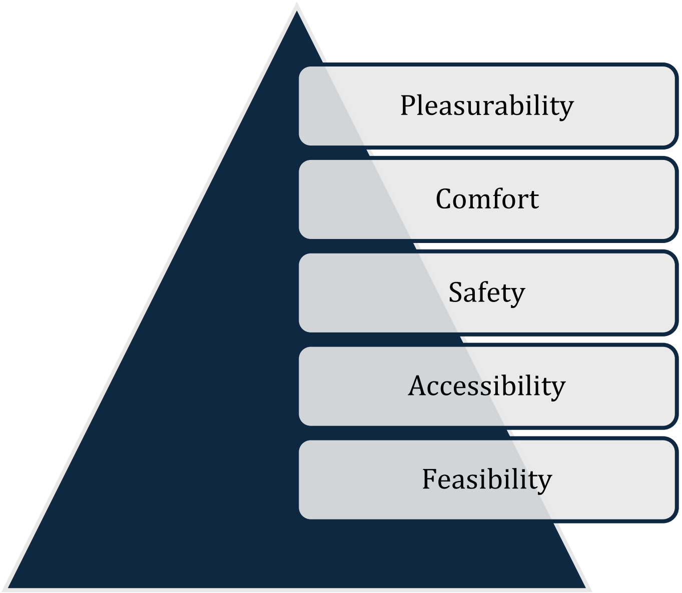


Figure 1-1. Alfonzo's Hierarchy of Walking Needs

Within this landscape, accessibility has emerged as a central organising construct linking land use and transport to travel behaviour. The concept functions both as a lower-order prerequisite for walking and as a highly policy-amenable lever, positioning it as a core instrument in the design of sustainable mobility strategies (15,17). Accessibility encompasses the pattern, quantity, quality, variety, and spatial proximity of available activities, as well as the degree of connectivity among land uses (18). It further reflects the number of destinations located within a reasonable walking distance and the extent of land-use integration within a defined area. In the mode choice literature, accessibility has been operationalised using both subjective and objective approaches. Subjective measures typically rely on self-reported travel time or distance, whereas objective methods employ Geographic Information System (GIS)-based techniques, including network analysis, gravity-based models, and cumulative-opportunity indices that incorporate distance-decay effects (19,20). These approaches can also be distinguished by dimension (i.e., spatial and temporal), with each capturing a different aspect of travel impedance (21). Although methodological complexity varies, these measures are generally based on the expectation that greater accessibility is associated with a greater likelihood of using active or sustainable travel modes. However, existing evidence is not uniformly consistent, suggesting that this relationship may be more context-dependent than is commonly assumed (14,22–25).

Accessibility may also be supported through multimodal transport systems and may therefore indirectly support walking. Public transport, while not typically classified as an active mode, plays an important complementary role in supporting active travel. Most public transport journeys require walking to and from stops or stations, effectively embedding walking within everyday travel routines. Consequently, regular public transport users tend to accumulate more daily physical activity than individuals who rely primarily on private cars (26–28). Transit-oriented developments, which cluster mixed land uses within walking distance of high-quality public transport (29), further support compact urban form and reduce car dependency. Lower reliance on private vehicles creates opportunities to reallocate valuable urban land away from roads and parking facilities toward more socially and economically productive uses, including public open spaces, high-quality active travel infrastructure, affordable housing, and community amenities (30–32).

When appropriately planned and regulated, shared micromobility systems represent a further means of improving access to destinations and services. Micromobility options, such as e-scooters, have emerged as flexible, low-emission alternatives for short trips and have the potential to complement active and sustainable mobility patterns (33,34). By providing convenient first- and last-mile connections to public transport, e-scooters may reduce reliance on private cars for short trips and extend the effective reach of transit networks, thereby indirectly supporting active travel (33,35). Although riding an e-scooter is not physically demanding, users typically walk to and from pickup and drop-off points, incorporating short bouts of walking into their travel routines (36,37). Moreover, micromobility can facilitate car-lite lifestyles by bridging gaps where walking or cycling is impractical due to time constraints, distance, or topography, enabling more trips without a car while still maintaining some degree of active engagement (38,39). Nevertheless, if deployed and regulated inappropriately, micromobility may in some contexts displace walking rather than car use, potentially reducing overall levels of active travel without diminishing car dependency (33,40).

Given the central role of accessibility throughout this thesis, it is important to clarify how the concept is defined and operationalised across the empirical chapters. Accessibility is broadly defined as the ease with which people can reach desired destinations, opportunities, or services. Within the transport and urban-planning literature, accessibility has been conceptualised and measured in multiple ways, including objective measures based on land-use patterns, transport networks, travel time, distance, and destination opportunities, as well as subjective measures that reflect individuals' perceptions of the ease and convenience of reaching destinations (41–44). Accessibility may therefore capture both the opportunities available within an environment and individuals' ability to make use of those opportunities. Accordingly, the thesis distinguishes between neighbourhood walking accessibility, accessibility to public transport infrastructure, and domain-specific accessibility to particular destination types, recognising that each captures a different dimension of access within the broader accessibility framework. In Chapter 3, accessibility refers to neighbourhood accessibility to a range of everyday destinations and activities. In Chapter 4, accessibility refers to accessibility to public transport infrastructure, specifically accessibility to bus stops. In Chapters 5 and 6, accessibility refers to domain-specific accessibility to destinations such as public transport, recreation, shopping, and education. Despite these differences in operationalisation, all accessibility measures examined in this thesis are intended to capture the opportunities available to individuals within their surrounding environment and how these opportunities relate to travel behaviour.

Although numerous studies have explored the relationship between accessibility, mode choice, and travel behaviour, notable gaps persist. Addressing these gaps offers an opportunity to generate robust, evidence-based insights that advance active and sustainable transport for all.

Thesis rationale

Although decision-making processes in mode choice have long been studied in relation to neighbourhood accessibility, important limitations in existing research constrain its practical application. For conventional modes such as walking and public transport, much of the evidence relies on self-reported behaviour and perceived measures, such as survey questionnaires (22,23). However, these self-reports are prone to bias and can systematically mis-estimate trip characteristics, especially for short, routine walking trips (45,46). To obtain estimates that more closely reflect actual walking undertaken in everyday life, the present study uses objectively measured walking behaviour to understand its relationship with neighbourhood walking accessibility. Furthermore, in the public transport literature, accessibility has typically been conceptualised at a single spatial anchor, either home or the workplace (47–52), overlooking the complexity of daily mobility and the role of multiple activity points in the real world. Thus, this study considers accessibility to bus stops at various points (around home, trip origin, and destination) along each trip route. By addressing these methodological limitations, this approach yields more valid insights into how neighbourhood accessibility is associated with real-world walking behaviour and bus ridership across everyday travel patterns.

In parallel, research on emerging mobility options such as shared micromobility has expanded rapidly, reflecting their growing role in sustainable transport systems. Nevertheless, important gaps remain in the empirical evidence base. Origin–destination trip data have long been a cornerstone of transportation research and planning, providing critical insights into travel patterns, demand, and infrastructure needs (53,54); however, the application of origin-destination data in the context of shared micromobility remains limited. Furthermore, to the best of my knowledge, no study to date has examined how specific domains of neighbourhood accessibility are associated with shared e-scooter trip length, a metric that has significant implications for understanding how these services function within broader urban mobility systems. To address these gaps, this study employs a gravity-based origin-destination approach and examines how pedestrian-oriented accessibility is associated with shared e-scooter trip lengths.

Conducting this research in Auckland, New Zealand, offers a distinctive opportunity to address these gaps in a setting where structural and behavioural barriers to sustainable travel are pronounced. Among cities of comparable size, Auckland ranks as one of the most car-dependent metropolitan regions worldwide, with private vehicles accounting for more than 80% of daily trips despite recent investments in public transport and micromobility infrastructure (55–58). The city's dispersed urban form, characterised by substantial suburban sprawl and historically car-oriented planning, limits the effectiveness of conventional strategies for promoting active and shared modes. At the same time, shared e-scooters have seen rapid uptake, with millions of trips recorded annually, yet usage remains concentrated in central areas, raising concerns about spatial equity and integration with other modes (59,60). These conditions make Auckland an ideal context for examining how accessibility interacts with travel behaviour across conventional and emerging options, generating insights that are both locally relevant and transferable to other car-dependent cities seeking to advance sustainable mobility.

Statement of the purpose

The underlying motivation of this thesis is to examine how accessibility measures are associated with travel behaviour across conventional and emerging mobility options in a highly car-dependent urban context, Auckland, New Zealand. Specifically, it aims to:

- Investigate the relationship between neighbourhood accessibility and walking behaviour (Chapter 3).
- Assess how accessibility to public transport relates to bus ridership behaviour (Chapter 4).
- Explore how accessibility to specific destinations is associated with shared e-scooter trip patterns (Chapters 5 and 6).

By integrating objective mobility data with advanced spatial and statistical modelling, this work seeks to generate evidence that is both behaviourally grounded and practically applicable. The findings are intended to inform urban planning and transport policy strategies that promote active and sustainable mobility in Auckland, New Zealand.

Thesis organisation

Context

The first two studies of this thesis (Chapters 3 and 4) have evolved from a larger research project: Te Hotonga Hapori. This programme of research, funded by the Ministry of Business, Innovation, and Employment, aims to enhance community health and wellbeing through optimising urban redevelopment. One component of Te Hotonga Hapori focuses on evaluating people's wellbeing in urban communities where major housing redevelopment is taking place across four Auckland neighbourhoods, namely Aorere, Oranga, Wesley, and Waikōwhai. The socio-demographic characteristics of these neighbourhoods are presented in Appendix C (61). Within these four neighbourhoods, participants were recruited from areas of the neighbourhood undergoing significant redevelopment. A socio-demographically matched comparison group was recruited from an area of the neighbourhood which was largely unaffected by the redevelopment process. By being aligned with Te Hotonga Hapori, this thesis had the opportunity to leverage advanced measurement tools (i.e., accelerometers and GPS receivers) to precisely measure participants' physical activity and mobility behaviours. The PhD candidate was actively involved in this wider study, being in charge of managing these data collection tools, including preparing them for distribution in the field, and extracting and managing the data upon their return.

The next two studies (Chapters 5 and 6) employed micromobility trip data obtained from one of the shared micromobility providers that was active in Auckland at the time of conducting these studies. Auckland is the largest and most populous city in New Zealand, with an estimated population of 1.76 million in 2023. It is characterised by a highly urbanised environment, substantial suburban sprawl, and a reliance on private motor vehicles (62).

Thesis structure

This thesis comprises four sequential studies presented in chapter format (Figure 1-2). Chapter 2 establishes the broader context with a summary of the literature on accessibility, mode choice, and conceptual issues in previous work. Chapters 3 to 6 are empirical studies that are either under review or submitted for publication, and are written as stand-alone articles, which means some repetition of methods and data is unavoidable. Chapter 3 investigates the relationship between neighbourhood accessibility and walking behaviour using objective GPS and accelerometer data. Chapter 4 examines how accessibility to public transport, measured from multiple spatial anchors, relates to bus ridership. Chapter 5 shifts focus to emerging mobility options, analysing how domain-specific accessibility measures correlate with shared e-scooter trip volumes across origin–destination flows. Chapter 6 explores e-scooter trip length as a critical but underexamined dimension of micromobility behaviour, assessing how accessibility interacts with trip distance. Each chapter begins with a preface to explain its role in the overall research progression. Finally, Chapter 7 provides a general discussion, synthesising findings across all studies, addressing limitations, and outlining policy implications and directions for future research.

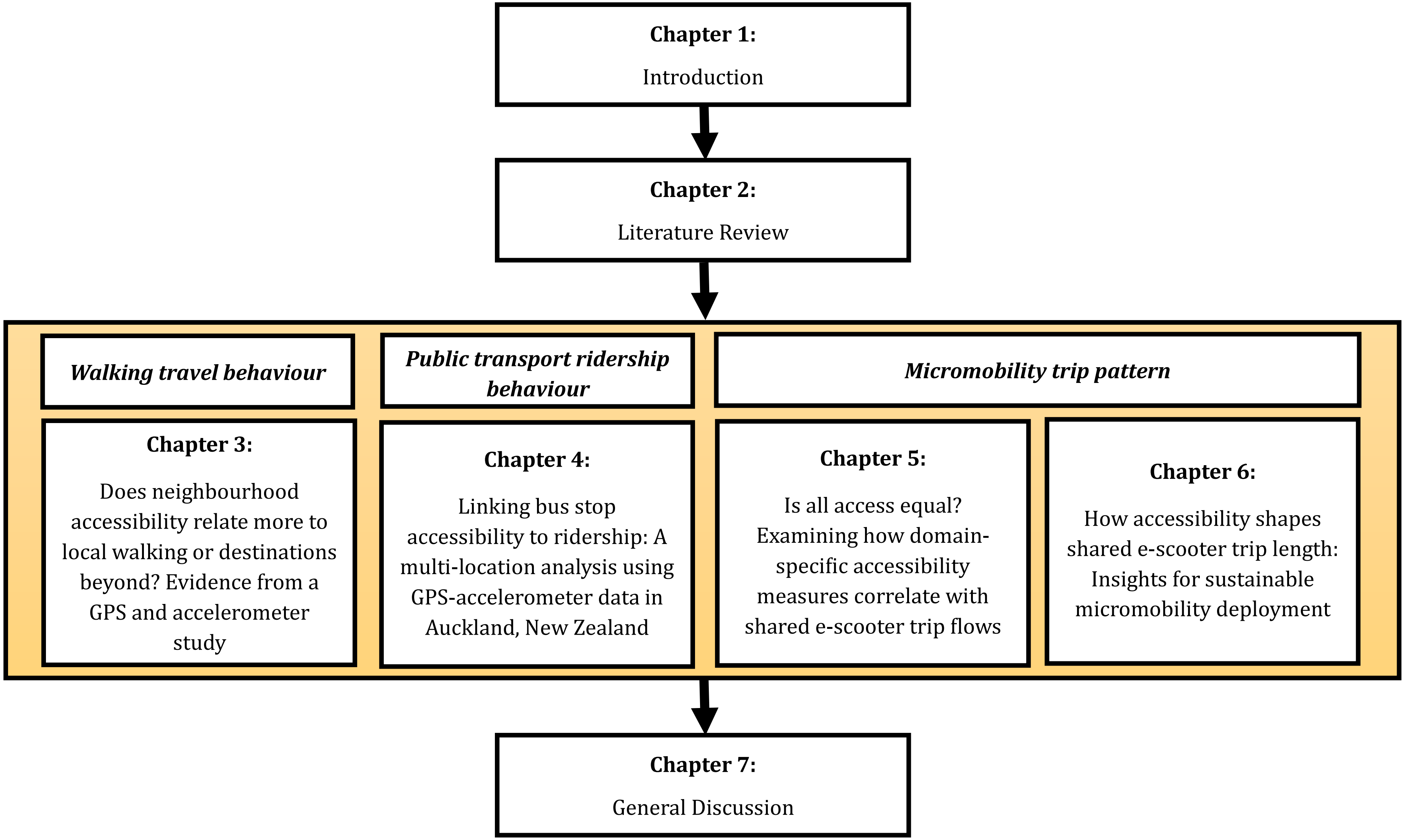


Figure 1-2. Thesis structure and flow

Chapter 2. Literature review

Preface

Promoting active travel is widely recognised as a multifaceted policy lever that enhances population health, mitigates environmental externalities, alleviates traffic pressures, and advances equity within transport systems (63–67). While walking and cycling remain the most visible forms, public transport and emerging micromobility options also contribute meaningfully by embedding short walking segments and supporting car-lite lifestyles where walking or cycling alone may be impractical. These modes share a common foundation of incidental physical activity, yet the factors associated with their use differ substantially (68–72). This chapter reviews the scholarly literature on active and sustainable mobility, with a particular focus on walking, public transport, and shared e-scooter schemes. It begins by outlining the health, environmental, and economic benefits of walking and its role within broader mobility systems. The chapter then examines correlates of walking behaviour across the individual, social, policy, and built environment domains, highlighting accessibility as a central integrative concept. Subsequent sections explore public transport ridership and shared e-scooter trip patterns, synthesising evidence on socio-demographic, attitudinal, policy, and spatial factors. Throughout, the review emphasises how accessibility relates to mode choice and travel behaviour and identifies broad limitations in existing research. These insights provide the conceptual foundation for later chapters, which aim to advance understanding of accessibility-informed strategies for promoting active and multimodal travel.

Background

Walking is widely regarded as an accessible, affordable, and straightforward form of active travel. It is associated with substantial health, environmental, economic, and social benefits and may help mitigate the externalities associated with motorised transport. By integrating physical activity into daily routines, it markedly reduces the prevalence of cardiovascular disease, obesity, diabetes, and mental health disorders, whilst fostering social cohesion and enhancing overall well-being (73–77). Beyond individual health, at a systemic level, replacing short car trips with walking can reduce fuel consumption, alleviate congestion, and improve air quality, thereby lowering greenhouse gas emissions and supporting climate mitigation objectives (65,78–80). Economically, recent WHO projections suggest that health-related global economic losses could reach US $300 billion over the 2020–2030 decade if current inactivity trends continue (81,82). In New Zealand, modelling indicates that switching short car trips to walking and cycling could save between NZ$127 million (with 25% uptake) and NZ$2.1 billion (with full uptake) in lifetime healthcare costs for the current population, highlighting the substantial economic benefits of active transport (83). Beyond these gains, the existing evidence suggests that walking can also strengthen social interaction and community cohesion, which are essential for inclusive, resilient, and sustainable urban development (84,85). In contrast, motorised transport remains a principal source of transport-related air pollution and greenhouse gas emissions, both of which are associated with substantial environmental and public health burdens, including premature mortality, cardiovascular disease, asthma, and lung cancer (86). These health burdens translate into considerable economic costs worldwide, underscoring that prioritising active and shared mobility is not merely a sustainability imperative but a public health.

While walking represents the most fundamental and direct form of active travel, its population-level benefits are often realised through broader mobility systems that either embed walking or depend on walking-supportive infrastructure. Public transport trips, for example, embed walking within access and egress stages, meaning that investments in frequent, reliable services and well-designed networks can substantially increase routine walking even among those who do not primarily identify as pedestrians (87). Likewise, micromobility systems such as shared e-scooters have the potential to extend the spatial reach of walking by providing flexible and short-distance links between dispersed destinations, thereby lowering the generalised cost of non-car travel and supporting car-free daily mobility chains (88). Consequently, understanding the factors that shape not only walking but also public transport and micromobility travel behaviour becomes critical for designing mobility systems that support healthier, more active, and environmentally sustainable futures.

Factors associated with walking behaviour

Factors associated with walking behaviour can broadly be grouped into four main domains, including individual characteristics (e.g., demographics, health status, and attitudes), social environment (e.g., social support and cultural norms), environmental attributes (e.g., land-use mix, street connectivity, and safety), and policy factors (e.g., urban planning regulations, transport policies, and investment in pedestrian infrastructure) (89–92). The following sections discuss these domains and their associations with walking behaviour.

Individual factors associated with walking behaviour

Decisions regarding whether to walk are associated with a range of socio-demographic and psychological characteristics. Among these, employment status emerges as a consistently positive correlate: individuals in employment, particularly those working full-time, tend to engage in more walking and report higher overall walking levels (93–96). In contrast, age demonstrates a robust negative association, with older adults generally less inclined to walk (97,98). Evidence concerning ethnicity, however, remains inconclusive; while some studies identify positive associations, others report no significant relationship (95,99). Similarly, systematic reviews suggest that gender, educational attainment, and income typically exhibit non-significant associations with walking behaviour, indicating that their influence may be marginal or context-dependent (100,101).

Psychological factors have also been associated with walking and active travel behaviour. Individuals who report greater confidence in their ability to use active modes are generally more likely to walk or cycle for transport (102,103). Similarly, favourable attitudes towards active travel, stronger behavioural intentions, and higher levels of motivation have been associated with greater engagement in walking and cycling (104,105). Social influences may also be relevant, as perceived social norms, support, and modelling from family members and peers have been linked to higher levels of active travel participation (102,103). This body of evidence suggests that active travel behaviour is associated not only with the physical environment but also with how individuals evaluate and experience active travel opportunities within their everyday lives (104,105).

Social and interpersonal factors associated with walking behaviour

While personal and psychological attributes are associated with individual choices, these factors often intersect with social dynamics. Social interactions within neighbourhoods not only reflect these personal characteristics but also create supportive environments that may facilitate walking and other forms of active travel (106–108). Social factors have been consistently linked to physical activity and active travel through mechanisms such as social support, social networks, and interpersonal interaction. Evidence from systematic reviews and longitudinal studies indicates that social support from family, friends, and neighbours is among the strongest predictors of physical activity, including walking for transport (109,110). Similarly, larger and more cohesive social networks are associated with higher levels of active travel and reduced sedentary time (111,112). Positive social interactions and participation in community activities also correlate with increased walking and cycling for transport (113,114). Conversely, loneliness and social isolation exhibit negative associations with physical activity, underscoring the importance of social connectedness in sustaining active lifestyles (115,116). While most studies report positive associations between neighbourhood social cohesion and walking (117), some evidence suggests mixed results, particularly for walking and cycling for transport (118).

Built environment factors associated with walking behaviour

The built environment introduces another critical layer of correlates of active travel behaviour. Because these attributes are largely shaped by planning and design regulations, understanding their relationship with travel behaviour can feed back into policy, enabling more effective strategies to promote active and sustainable mobility. This importance has motivated extensive research examining how built-environment characteristics are associated with active travel. Rather than acting independently, supportive built-environment conditions tend to operate by reducing the generalised cost of walking and cycling relative to motorised travel, including travel time, physical effort, and perceived inconvenience. Higher-density and mixed-use environments shorten travel distances and increase the likelihood that daily activities can be undertaken on foot, while well-connected street networks reduce detours and improve route efficiency (119,120). At the street level, infrastructure that prioritises pedestrians and cyclists lowers physical effort and enhances perceived comfort, reinforcing the competitiveness of active modes for routine trips (121,122). In this sense, positive built-environment correlates function not as isolated design features but as interrelated conditions that collectively lower barriers to active travel participation. Conversely, built-environment characteristics that are negatively associated with active travel tend to increase the perceived or actual costs of walking and other environmentally sustainable modes, thereby reinforcing car dependence even in otherwise compact urban settings. High traffic volumes and speeds elevate safety risks and psychological stress, discouraging walking through increased exposure and reduced sense of control (123,124). Similarly, discontinuous pedestrian networks, large block sizes, and car-oriented street hierarchies increase travel effort by forcing longer or indirect routes, further constraining willingness to walk (12,119,125). Together, these findings suggest that walking behaviour emerges from the balance between enabling and constraining spatial conditions that shape how feasible, safe, and convenient walking is experienced in everyday contexts.

While the built-environment literature offers extensive evidence on walking correlates, these relationships are inherently complex, with multiple attributes interacting rather than acting in isolation. Features such as density, land-use mix, street connectivity, and infrastructure quality jointly shape how feasible and attractive walking becomes, often through overlapping mechanisms. Consequently, researchers have increasingly adopted neighbourhood accessibility measures as integrative indicators of walking-supportive environments. In the context of walking behaviour, neighbourhood accessibility reflects the extent to which everyday destinations can be conveniently reached on foot and has become widely used as a summary measure of opportunities for walking within urban environments (126–128).

Research on walking accessibility has examined both objective and perceived dimensions. Objective measures quantify accessibility to destinations using spatial indicators derived from land-use and transport-network characteristics, whereas perceived measures capture individuals' evaluations of how easy and convenient it is to reach destinations on foot (41–44). Evidence consistently suggests that higher levels of perceived walking accessibility are associated with a greater likelihood of walking and using active modes, even after accounting for objective environmental characteristics (44,129). Longitudinal studies further suggest a reciprocal relationship, whereby favourable perceptions of neighbourhood accessibility encourage walking while repeated walking experiences reinforce perceptions of accessibility over time (130). The importance of perceived walking accessibility appears particularly pronounced among populations with limited access to private vehicles, where satisfaction with the proximity of everyday destinations is strongly associated with whether walking is considered a practical travel option (131–133).

Perceived measures of the urban built environment are consistently associated with travel behaviour and mode choice, as they reflect individuals' lived experiences of their surroundings (134). However, because such perceptions are inherently person-specific and not readily generalisable, they are less suited to mapping spatial conditions or modelling policy scenarios at city, regional, or national scales. For these applications, objectively calculated assessments of urban form, typically derived from GIS and other spatial datasets, are indispensable and have therefore attracted substantial empirical attention in multi-neighbourhood and multi-city travel behaviour research. Evidence from systematic reviews focusing on objectively assessed measures indicates that higher accessibility to everyday destinations and public transport nodes is strongly associated with increased walking for utilitarian purposes, although most available studies still rely on self-reported walking outcomes, with comparatively fewer analyses pairing objective accessibility indices with objectively monitored walking (135–138). Empirical studies that incorporate both perceived and objectively measured built-environment attributes further confirm a robust positive relationship between transport-related walking and GIS-based accessibility measures (139). Consistent findings show that neighbourhoods offering a greater number of destinations within short network-based buffers and more highly connected pedestrian networks support higher levels of walking for transport (135,140,141). Infrastructure interventions that reduce travel impedance, such as the provision of sidewalks, safe crossings, and protected cycling facilities, are likewise associated with measurable increases in active travel (142–145). These effects are most pronounced for walking to routine destinations rather than for leisure activities, underscoring the structural role of accessibility in shaping everyday mobility patterns (137).

Policy factors associated with walking behaviour

Policy frameworks represent an upstream determinant of active travel, shaping the conditions under which walking and cycling occur. Evidence from multiple systematic reviews indicates that policies operate across several levels of the socio-ecological framework, including society, city, route, and individual, and influence active travel through both direct and indirect mechanisms (146–150). Policies at the national or regional level shape the overall conditions for active travel by influencing the relative convenience and safety of different modes. Reviews highlight that initiatives, such as reducing speed limits for motor vehicles, increasing the cost of owning and driving a car, and limiting parking availability, can make driving less attractive and thereby encourage walking and cycling (151). Similarly, promoting public transport indirectly supports active travel because transit trips inherently involve walking or cycling to access stops and stations, and to reach final destinations, contributing to higher daily active travel levels (87).

Urban design and land-use policies strongly influence active travel by determining trip distances and network connectivity. Such policies might include encouraging higher residential density, mixed land use, and transit-oriented development, which might consequently increase walking and cycling for transport (152). Existing evidence shows that car-free city centres and zoning regulations that cluster destinations within walking distance further promote active travel, while high traffic volumes and urban highways discourage it (87,148,153). Additionally, initiatives facilitating higher implementation of bike-share programs may also lead to population-level increases in cycling beyond the trips logged by bike-share users (154,155).

Local infrastructure and design standards are among the most direct and effective policy levers for promoting active travel. Reviews consistently report that the development of footpaths, crossings, and pedestrian paths improves convenience and safety for walking (148). For cycling, connected bikeway networks, shorter distances to facilities, and especially physically separated cycle tracks are strongly associated with increased ridership, particularly among less confident cyclists (156,157). End-of-trip facilities such as secure bike parking and showers at workplaces also support bicycle commuting (158). Areas with more walking facilities are also associated with higher rates of active commuting to school, highlighting how such policies may support active travel in different age groups (159).

Policies targeting individuals, such as workplace travel plans, financial incentives, and behaviour-change programs, show mixed evidence when implemented in isolation. Systematic reviews indicate that mass media campaigns and organisational travel plans rarely produce large population-level shifts on their own, whereas targeted interventions like personalised travel marketing have achieved modest but meaningful mode shifts, including reductions in car trips and increases in walking and cycling (160–163). Financial incentives can also support active travel in specific contexts, although evidence remains limited (162). Overall, reviews conclude that these individual-level measures are most effective when combined with structural changes, such as infrastructure improvements and regulatory policies, within comprehensive packages that align personal motivation with enabling environments (148,151,160,161).

Public transport ridership behaviour

Public transport offers another important pathway for promoting active and sustainable mobility, both by embedding walking into everyday trips and by facilitating a shift away from private car use. Empirical evidence consistently shows that public transport users accumulate higher levels of transport-related walking and are more likely to meet physical activity recommendations than non-users, while higher levels of public transport use are associated with reduced car dependence and more transit-oriented patterns of urban development (30). Against this backdrop, and alongside efforts to understand walking behaviour, an expanding body of research has examined factors associated with public transport use, reflecting its dual role as both a contributor to active travel and a cornerstone of sustainable urban mobility (164,165). Analogous to the walking behaviour literature, factors associated with public transport use can be categorised into four broad domains (i.e., individual characteristics, social and interpersonal factors, policy and service attributes, and built environment and accessibility conditions) which are discussed in more detail below (166).

Individual factors associated with public transport ridership

Empirical evidence indicates that socio-demographic factors are among the key correlates of public transport ridership. Age and income emerge as the most frequently cited predictors, with younger individuals (below 30) and older adults (above 50) tend to favour public transport, while middle-aged groups show mixed tendencies (167–169). Gender differences are notable; women generally display a stronger preference for public transport compared to men, particularly in Europe and Asia (170–172). Education level also matters; individuals with higher levels of educational attainment, especially university graduates, are more inclined toward public transport (173). Immigrant status is another influential factor: immigrants, especially those with shorter settlement periods, are more likely to use public transport than long-term residents (174,175). Household characteristics, such as smaller household size, fewer cars, and non-licensed drivers, correlate positively with ridership (176,177). Lower-income populations consistently exhibit higher ridership, whereas higher-income individuals often prefer private vehicles (178,179).

Perceptions of safety, security, and comfort are also strongly correlated with willingness to use public transport, with concerns about harassment and personal security being particularly salient, especially among women and other vulnerable groups (180,181). Cognitive evaluations, such as judgments about reliability, punctuality, and cleanliness, are associated with overall satisfaction and, consequently future travel choices; when service performance falls short of expectations, negative attitudes toward public transport often emerge (182). Attitudinal aspects extend beyond functional considerations like cost and convenience to include symbolic and affective dimensions, where private car ownership is associated with social status and personal success, reinforcing cultural preferences for automobility (183,184). Evidence suggests that addressing these psychological and cognitive concerns through improved service quality, enhanced safety measures, and targeted communication strategies is essential for fostering positive perceptions and encouraging modal shifts toward sustainable transport (185,186).

Social and interpersonal factors associated with public transport ridership

Social factors have been consistently identified as key correlates of public transport ridership, often showing associations comparable to or stronger than those of traditional service quality attributes. Empirical research demonstrates that subjective norms, defined as perceived social pressure from significant others, constitute a critical predictor of behavioural intentions to switch from private vehicles to public transport, with effect sizes frequently surpassing those of attitudinal variables (187–189). Complementing these interpersonal influences, societal norms, reflecting perceptions of public transport's environmental and social utility, emerge as a key driver of loyalty-related behaviours, including willingness to recommend and sustained usage (190,191). Prior studies indicate that these normative constructs function through differentiated mechanisms. Subjective norms primarily affect behavioural intentions by amplifying perceived social expectations, particularly among individuals with less entrenched private vehicle habits (191), whereas societal norms exert an indirect influence by improving overall satisfaction and fostering positive interpersonal communication regarding transit use (190,192).

Built environment factors associated with public transport ridership

The built environment is widely recognised in the scholarly literature as a structural determinant of travel behaviour, principally through its organisation of population distribution, land-use patterns, and service accessibility (193,194). As such, it constitutes a policy-relevant feature associated with mobility outcomes through transport and land-use policy interventions. Empirical research on public transport ridership has consistently demonstrated that higher population and employment densities are positively associated with increased bus use, reflecting the spatial concentration of potential trip origins and destinations within service catchment areas (195–198). Beyond density, land-use mix and functional diversity are also frequently cited as significant correlates of bus ridership, as such environments support a broader array of transit-accessible activities and promote more evenly distributed, bidirectional flows of passengers throughout the day (197,199,200). At the finer-grained scale of the street network, features such as intersection density and connectivity have been linked to greater ridership, as they enhance pedestrian accessibility and reduce the effective distance to transit corridors (196,200). In contrast, the literature consistently associates urban sprawl and suburbanisation with declining transit use, primarily due to their co-evolution with low-density, car-dependent development patterns, conditions widely regarded as antithetical to the competitiveness and operational efficiency of public transport systems (195,196).

While individual aspects of the built environment can influence public transport use, accessibility offers a more holistic framework, widely acknowledged as a key correlate of ridership by attracting new passengers and retaining existing ones (47–49,201–205). In public transport research, accessibility is typically conceptualised in two distinct ways. The first relates to the extent to which individuals can use public transport to reach key destinations, such as jobs, healthcare, or education, commonly referred to as public transport accessibility (206). The second concerns access to the transport system itself, emphasising the spatial availability, density, and proximity of stops or stations, often termed accessibility to public transport (207). Emphasising this latter perspective is crucial, as the benefits of a well-connected or reliable transit network cannot be fully leveraged without convenient access points within walking distance.

Studies examining public transport accessibility to destinations generally define accessibility as the ease with which individuals can reach key opportunities, such as employment, education, healthcare, or retail services, via public transport (208). This concept is most often operationalised using cumulative opportunity measures, which count the number of destinations reachable within a given travel time threshold, or gravity-based measures, which weight opportunities using a distance-decay function to reflect diminishing utility with longer journeys (21,209). Empirical research consistently finds that higher destination accessibility corresponds with greater transit demand. Notably, stop-based models indicate that bus stops enabling faster and wider reach to dense concentrations of nearby opportunities within 30 minutes tend to generate higher boarding volumes, a pattern most clearly observed where job availability is greatest around transit catchments (210). Route-level analyses similarly show that lines traversing corridors with stronger destination pull, particularly those linking major activity centres, tend to attract higher ridership, reflecting demand sensitivities to the kinds of destinations most commonly clustered along employment-rich transit axes (208). These associations extend to larger spatial scales, with census-tract- and city-level studies showing that areas offering stronger transit-based reach to high-intensity destination clusters typically exhibit higher ridership alongside greater residential and economic density, a relationship most pronounced in zones with larger workforce and commuter flows (211–213).

The system access perspective emphasises the spatial distribution and proximity of public transport infrastructure. While public transport accessibility to destinations is important, its benefits cannot be fully realised when individuals are unable to conveniently access the public transport system itself. Consequently, accessibility to public transport has become a major focus of ridership research. This approach recognises that limited access to stops or stations may constrain public transport use regardless of the opportunities available through the wider network. It typically assesses factors such as stop or station density within defined catchment areas, the distance to the nearest transit facility, and the proportion of the population residing within acceptable walking thresholds (52,214,215), Although studies generally report associations between improved access to public transport and higher ridership, the direction and magnitude of these associations appear to vary across transport modes and contexts (71,216,217).

While these studies provide important evidence on the relationship between accessibility to public transport and ridership, accessibility has most commonly been measured from a single spatial anchor, typically the home location and, less frequently, the workplace (201,210). Such approaches implicitly assume that accessibility experienced at fixed locations adequately represents the conditions under which travel decisions are made. However, daily mobility frequently involves movement between multiple activity locations, and accessibility conditions may differ substantially between residential locations, trip origins, and destinations (218). Accessibility at these locations may therefore be associated with travel behaviour through different mechanisms, with origin accessibility reflecting access to the public transport network, destination accessibility reflecting access to opportunities and activities, and residential accessibility relating more closely to longer-term travel routines and preferences. Consequently, reliance on a single spatial anchor may provide only a partial representation of the accessibility conditions associated with public transport use.

Policy factors associated with public transport ridership

Public transport ridership is strongly influenced by policy instruments affecting costs, accessibility, and system performance. The literature consistently associates car-oriented conditions, such as low fuel taxes, abundant free parking, and extensive highway capacity, with reduced transit competitiveness, whereas congestion charging and parking management improve its relative utility (219). Importantly, pricing instruments that increase the cost of driving have been shown to deliver stronger ridership outcomes when supported by transit-oriented land-use and station-area planning policies, which widen viable alternatives and reinforce the price signal (220). Zoning policies further shape ridership by directing development intensity around stations. Higher-density development increases ridership and cost-efficiency, while low-density areas constrain transit use and raise per-passenger costs. Consequently, zoning reform and parking management are regarded as key mechanisms for enhancing the economic and operational performance of transit infrastructure (221,222). Operational frameworks that prioritise reliability and coordination have been shown to influence transit use, as service standards and performance measures can reduce waiting times, crowding, and transfer penalties, thereby improving the system's attractiveness to passengers (223). At the individual level, evidence highlights segment-specific price responsiveness. Adults and children respond elastically to fare reductions; however, seniors and concession card holders remain comparatively inelastic (222).

Micromobility trip patterns

Shared micromobility is often promoted as a way to encourage more active and sustainable mobility by providing flexible, on-demand, lower-emission options for short urban trips, particularly when integrated with supportive urban design to address challenges such as car dependence and transport inequities (39,224–228). Evidence suggests that, in some contexts, e-scooters can substitute a proportion of short car journeys in central urban areas, extend the effective catchment of public transport by bridging first- and last-mile gaps, and incorporate incidental walking to and from devices and parking zones. In doing so, they may complement active and sustainable travel within everyday mobility patterns, although the magnitude and distribution of these benefits vary across cities (229–234). However, such integration is not without risks. If poorly managed, the short-range nature of e-scooter trips may more often displace walking or cycling than private car use, pose safety concerns for pedestrians, and reduce opportunities for physical activity (235–237). In some cases, micromobility may even reinforce car dependency; for example, when limited parking at destinations leads drivers to park farther away and use an e-scooter to complete the final segment of their journey (234). These contrasting effects have prompted substantial scholarly attention to the conditions under which micromobility supports, rather than undermines, sustainable and active travel, an issue explored further in the sections that follow.

Individual factors associated with shared micromobility trip patterns

Owing to their internal consistency and origin from a single respondent, individual-level factors have consistently emerged in the travel behaviour literature as salient predictors of mode choice. Age has consistently emerged as a key correlate of shared micromobility use, with younger individuals significantly more likely to engage with services such as e-scooter sharing. Across academic and non-academic sources, the literature indicates that the average user is typically in their 30s (238–240); although not strictly linear and moderate adoption has been observed among individuals in their 40s in some contexts, such as Singapore and Saudi Arabia (241,242). Intention-based analyses also highlight that younger adults are not only more likely to be current users but also exhibit greater intention to use shared micromobility in the future (243,244). Unlike age, the literature on gender is inconsistent. While many studies find men significantly more likely to use e-scooter sharing than women (40,238), others show the gender effect varies by region, trip purpose, and analytical approach (245,246). Yet intention studies suggest comparable future interest across genders, despite persistent hesitancy among women under current conditions (233,244,247).

The relationship between education and e-scooter use is marked by contextual variability. While higher education is frequently associated with greater usage, particularly in Western urban contexts (238,248,249), some studies report the inverse, with lower adoption or acceptance among university-educated individuals (233,250,251), highlighting the role of local socio-spatial dynamics in shaping how education intersects with micromobility behaviours (245,252). Evidence on the influence of employment remains inconclusive. While some studies find no significant association (250,253), others identify employment as a salient predictor, though in divergent directions (251,254,255). This divergence has also been observed when analysing the impacts of income. While some studies link lower or middle incomes to higher adoption (252,256), a broader body of evidence associates higher income with greater usage intensity (243,245,246,257). Yet, in some contexts, income proves insignificant or operates only through interaction effects (258,259). Digital capability further mediates access. Although most users navigate app-based systems with ease, barriers such as smartphone access, payment systems, and app literacy persist for some (260–263).

Psychological constructs are associated with shared micromobility use not through isolated traits, but through the interplay of values, perceptions, and affective orientations. Environmental concern, while not universally decisive, often distinguishes users from non-users. Many adopters perceive e-scooters as environmentally preferable, aligning their usage with an ecological self-concept and a broader sense of responsible consumption (253,264). However, this instrumental rationale often coexists with experiential motives. The perception of e-scooter travel as easy, novel, and enjoyable, particularly among younger individuals, enhances its affective appeal and contributes to its everyday integration (265,266). Perceived risk, whether related to traffic interactions, personal safety, or vehicle stability, continues to act as a psychological deterrent. However, where trust in the safety of the mode is established, it tends to strengthen both the intention to use and actual engagement with e-scooter sharing (251,255,260,264). Attitudes toward innovation and technology further influence adoption. Individuals who are more comfortable with digital tools and open to new mobility experiences tend to exhibit higher psychological readiness, linking personal disposition with broader digital and experiential capacities (255,267).

Social and interpersonal factors associated with shared micromobility trip patterns

Although empirical studies on social factors remain comparatively limited, existing evidence suggests that social influence plays a subtle yet consequential role in shaping shared micromobility use. Adoption patterns are not merely the product of individual preferences but are mediated by perceived social approval, normative expectations, and culturally embedded understandings of urban mobility. Individuals are more inclined to adopt e-scooters when the behaviour is seen as acceptable or encouraged within their immediate social networks and broader urban environments (247,263,265,267). These dynamics are often captured through the construct of subjective norms, the idea that individuals are guided by what they believe others expect them to do (247,268). Research shows that such norms can significantly shape people's intentions to use e-scooters, especially in places where personal experience with the mode is limited. In these cases, people often rely on social cues, such as peer attitudes, media narratives, or simply seeing others using e-scooters, to form their own perceptions (267). Public visibility of riders, for instance, can reduce hesitation and help make e-scooter use feel more normal and socially acceptable (263). Beyond that, micromobility adoption often connects to broader lifestyle values, such as convenience, innovation, and sustainability, which can be strengthened when they are reflected and supported within one's social environment (247,265).

Built environment factors associated with shared micromobility trip patterns

Building upon foundational insights into the interrelationships between land-use patterns, the built environment, and travel behaviour (119,269–271), recent empirical work has clarified which characteristics are associated with shared e-scooter ridership. Using GIS hotspot analysis on over 886,000 dockless e-scooter trips, Bai and Jiao observed strong spatial clustering in downtown areas and on university campuses (72), a pattern corroborated by Caspi et al., who reported higher use in zones with greater employment density and student populations (259). Consistent with these concentration effects, walk score and bike score have been shown to support higher e-scooter ridership density (259,272). Differentiating trip purposes, Liu et al. employed the ratio of travelled distance to linear origin–destination distance to distinguish recreational from non-recreational use; across urban mixed-use, institutional-oriented mixed-type, and downtown regions, the downtown and institutional-oriented areas produced the highest share of non-recreational trips (273). Street-level attributes have also proven salient. Hawa et al. found that parking metre spaces, as a proxy for the presence of cars, were associated with reduced e-scooter presence, suggesting that e-scooters may be more prevalent in walkable environments (274). Complementing this, Jiao and Bai showed that better street connectivity (i.e., fewer cul-de-sacs and more four-way intersections) aligned with higher ridership, while distance from the city centre was inversely associated with e-scooter trips (249).

A sizable portion of the literature has examined how specific land uses and their spatial composition shape e-scooter trip densities. Geographically Weighted Regression (GWR) analyses have revealed positive local effects for the percentage of commercial land, public and semi-public land, intersection density, walk score, park score, and job proximity index (275). Using a similar approach, Caspi et al. assessed local coefficients of e-scooter ridership and found that residential land use was significant in downtown areas but not around university campuses; their spatial Durbin modelling further indicated positive associations with residential, commercial, educational, and industrial land uses, with commercial and industrial categories exerting the largest associations (259). In Louisville, Kentucky, Generalised Additive Modelling showed that higher percentages of commercial land within a Traffic Analysis Zone (TAZ) were positively related to e-scooter trip density, whereas higher percentages of industrial land use were negatively related. Additionally, TAZs with high walk, transit, and bike scores exhibited greater trip densities than those with uniformly low scores (272). At the trip level, McKenzie found that origins and destinations tended to match by land-use type, with trips between public/recreational areas accounting for the largest share (28.2%) relative to residential and commercial pairings (276). Measures of land-use mix have also mattered. Jiao and Bai reported that a one-unit increase in the land-use entropy index was associated with a doubling of shared e-scooter ridership, and that percentages of mixed-use, educational, open space, commercial, and transit facility areas within hexagons were all positively correlated with usage (249). In line with these results, Bai and Jiao concluded that proximity to the city centre and complex land-use compositions were associated with higher trip counts (72).

Researchers have likewise foregrounded accessibility, long recognised as a key correlate of travel behaviour, as a driver of shared e-scooter usage patterns. In comparative analyses of Austin, TX and Minneapolis, MN, negative binomial models showed that hexagonal units with higher concentrations of bus stops supported greater average daily e-scooter ridership, indicating spatial complementarities between public transit access and micromobility (72). Using the same dataset, ridership was found to decrease by approximately 62 percent for each additional mile from the nearest transit stop (249), pointing to a strong distance-decay effect. Expanding the lens to activity destinations, Hawa et al. treated the average number of e-scooters present per hour within a unit as a proxy for ridership and observed positive associations with museums, restaurants, bars, and national parks, but a negative association with marketplaces (274). Further, Karimpur et al. introduced a gravity-inspired random forest model to estimate e-scooter origin–destination flows, demonstrating that trip volume between TAZs was positively linked to the presence of bars, restaurants, shopping malls, and coffee shops, while parks and museums exerted comparatively limited influence; total trip production and attraction strongly predicted demand, and trip frequency declined sharply with increasing inter-TAZ distance (20).

Factors associated with shared micromobility trip length

Compared with the growing literature on e-scooter adoption and trip density, relatively little attention has been paid to trip length, despite its importance for understanding how shared micromobility functions within broader urban transport systems. Trip distance may provide insight into the role of shared e-scooters relative to other transport modes. Shorter trips are often interpreted as reflecting first- and last-mile connections to public transport or substitution for walking and cycling, whereas longer trips may indicate competition with private motorised modes and potential replacement of short car journeys (39,238).

Studies have shown that trip length varies according to trip purpose and travel context. Recreational trips are often longer than utilitarian trips undertaken for specific destinations, while weekday and weekend travel patterns can differ substantially (39,277). Weather conditions, including rain and temperature, have also been associated with trip distance and usage patterns, with adverse conditions generally linked to shorter trips and lower usage rates (275,278,279). Pricing may also be relevant, as e-scooter services often become relatively more expensive than public transport as trip distance increases, potentially influencing user behaviour (39,280).

Trip length may further provide insight into modal substitution and integration with other transport modes. Shorter trips are frequently discussed in relation to first- and last-mile public transport connections, whereas longer trips may be more consistent with the replacement of motorised journeys, although these relationships appear highly context-dependent (39,241,281).

Despite growing interest in the role of shared e-scooters within urban mobility systems, little evidence exists regarding how multidimensional accessibility to urban opportunities is associated with trip length. Existing studies have primarily focused on trip density, user characteristics, land-use composition, or broad accessibility proxies such as proximity to the city centre or public transport availability (249,259,274). Consequently, limited attention has been paid to how accessibility to specific destination domains, or how accessibility at trip origins and destinations, may be associated with variation in trip distance. This gap limits understanding of how shared micromobility functions within broader transport systems and its implications for sustainability, multimodal integration, and transport equity.

Policy factors associated with shared micromobility trip patterns

The sustainable, safe, and equitable deployment of micromobility sharing schemes depends heavily on regulations and decisions made by policymakers. As a result, a wide range of policies and regulations have been implemented worldwide (282).

In the United Kingdom, e-scooters are treated as motor vehicles and must meet requirements such as tax and licensing. Given that this is mostly failed, their use on public roads and pavements is prohibited, and operation is restricted to private property with penalties for violations (283). France allows e-scooters only on cycle paths or roads with speed limits below 50 km/h. It enforces a maximum speed of 25 km/h and prohibits riding on pavements unless the motor is disengaged. Designated parking is also mandatory (284,285). Germany applies stricter conditions that include traffic authorisation and liability insurance. Speeds are limited to 20 km/h, and use is confined to cycle routes, although helmets remain optional (285,286). In the United States, regulations vary by state. California requires a driving licence, helmet use and a speed limit of 15 mph on cycle paths. Texas permits use on pavements and low-speed streets under bicycle traffic rules. New York prohibits motorised scooters entirely (282).

A limited number of studies have analysed how such policies are associated with e-scooter ridership behaviour. Most research focuses on safety outcomes and parking compliance rather than broader travel behaviour patterns such as trip generation, mode choice, and usage frequency. For example, an agent-based study in Lyon, France, found that enforcing parking mandates reduces daily e-scooter rentals by 37 per cent. This decline occurs mainly because riders must walk further after ending a trip, which increases physical effort and reduces convenience (287). Conversely, the absence of parking regulation has contributed to city-level bans when unregulated parking creates street obstructions, public safety risks and negative social backlash (288). Speed regulations also affect attractiveness. A stated preference study found that lower speed limits substantially reduce appeal. When the assumed operating speed increased from 10 km/h on pavements to 20 km/h on roads, demand for shared e-scooters rose by approximately six percentage points. Most of this increase came from users shifting away from campus shuttle buses (289).

Fleet size and pricing strategies are additional factors associated with ridership and modal substitution patterns. Larger fleets improve spatial and temporal availability, reduce access distances, and increase convenience, which generally promotes adoption. However, this expansion often draws trips away from walking and public transport rather than exclusively replacing private cars (290–292). Pricing plays a similarly influential role. Higher per-minute costs significantly suppress demand, particularly among lower-income users, while subsidies or price reductions have led to substantial ridership growth. Lower prices tend to encourage longer e-scooter trips, which facilitates substitution of car and public transport travel. In contrast, higher prices confine usage to short trips and intensify competition with walking (290,291,293).

Conclusion

The literature converges on a clear message: walking, embedded within broader mobility systems and reinforced by supportive policy and built environments, delivers substantial health, environmental, and economic benefits while mitigating the externalities of automobility. In the broader travel behaviour literature, accessibility is frequently identified as an important concept linking land use, network performance, and perceived convenience to travel behaviour. Yet, despite extensive research, important limitations remain. Walking studies often rely on self-reported measures rather than objective monitoring, limiting the precision of behavioural evidence. Public transport accessibility is typically assessed at a single spatial anchor, overlooking the complexity of daily mobility and the role of multiple activity points in the real world. Micromobility research, while expanding rapidly, continues to rely heavily on coarse or composite accessibility proxies, with comparatively limited attention given to how domain-specific accessibility measures relate to origin–destination travel patterns and trip length. Although several studies have incorporated origins, destinations, and trip flows, less is known about how accessibility to specific destination domains relates to shared micromobility demand and travel distance. These gaps limit the ability to design integrated transport strategies for reducing car dependency and promoting sustainable, health-enhancing mobility. Addressing them is essential for advancing evidence-based planning and policy that aligns infrastructure, service design, and regulatory frameworks to support active and multimodal travel.

Chapter 3. Does neighbourhood accessibility relate more to local walking or destinations beyond? Evidence from a GPS and accelerometer study

Preface

The literature review outlined why understanding associations between neighbourhood accessibility and walking is central to broader efforts to reduce reliance on private vehicles. Previous research has largely relied on self-reported mobility measures and cross-sectional designs, with comparatively few studies using objective mobility data within urban redevelopment settings. As the first empirical chapter of the thesis, this study uses GPS and accelerometer data collected within the context of a broader urban redevelopment programme to examine how neighbourhood accessibility is associated with objectively measured walking behaviour. The analysis considers walking within and beyond home-neighbourhood buffers and separately for walking recorded in redevelopment and control areas. Accessibility is quantified using an enhanced two-step floating catchment area (E2SFCA) index developed in prior research and applied here, and moderating effects of employment status and neighbourhood residency duration are explored as proxies for time constraints and familiarity with local opportunities. This manuscript has been submitted for publication.

Abstract

Despite the well-documented health and transport benefits of increased active travel, including improved cardiovascular fitness, mental wellbeing, reduced traffic congestion, and decreased reliance on private cars, many countries have reported significant and sustained declines in walking over recent decades. Neighbourhood accessibility, representing how easily people can reach everyday destinations from their homes, is a key correlate of active travel, primarily encompassing walking and cycling. This study examined the relationship between objective neighbourhood accessibility and actual walking behaviour. Interaction effects between accessibility and work status, as well as neighbourhood residency duration (used as a proxy for neighbourhood familiarity), were also investigated. Walking behaviour was objectively measured and analysed across different environmental settings, including within and outside home neighbourhoods and within and outside areas undergoing urban redevelopment. An objective multidimensional accessibility index, incorporating socio-cultural facilities and environmental factors, was utilised. A total of 110 participants with 2,503 trips recorded using GPS and accelerometer devices were included in the analyses. Due to repeated measures (trips) for each participant, mixed-effects models were employed. Findings revealed a suggestive positive association between accessibility and walking behaviour after adjusting for sociodemographic covariates, but only for trips outside home neighbourhoods. Age, gender, work status, and household income were also significantly associated with walking duration, depending on the environmental setting. Findings suggested that residential accessibility may be positively associated with walking behaviour, although evidence regarding differences between local and extra-neighbourhood walking was inconclusive.

Introduction

Active travel, encompassing walking and cycling, integrates physical activity into daily transportation and provides substantial health, environmental, and economic benefits for individuals and communities (294,295). Shifting from motorised to active modes has been associated with higher physical activity levels and consequent reductions in cardiovascular disease (296), bone health issues (75), metabolic syndrome (297), obesity (298), and mental health disorders (299),(300), while also contributing to improved air quality (301). A growing body of research shows that active travel behaviour is correlated with a range of factors, including sociodemographic characteristics (e.g., age, household income, employment status), social and built environment attributes (e.g., neighbourhood connectivity, pedestrian infrastructure), and cognitive factors (e.g., safety perceptions) (108,137,302–306). Among these, built environment attributes, such as street network connectivity (307,308), and the provision of cycling and pedestrian infrastructure (151,309), are widely recognised as one of the critical correlates of active mobility. The extent to which these environmental features support walking and cycling is often expressed through measures of neighbourhood accessibility, a key construct linking urban form to active travel behaviour (310).

Proximity to key neighbourhood destinations (e.g., healthcare services and recreational facilities) has consistently been associated with increased pedestrian activity (22–25,80). This relationship is typically examined within administrative or neighbourhood boundaries, commonly defined as areas extending approximately 400 to 1,200 metres from one's home, measured either in a straight line or along the street network (311). While this spatial definition has traditionally guided accessibility analyses, recent urban paradigms, such as the 15-minute city model, have shifted attention toward time-based and experiential dimensions of accessibility (312). In this context, neighbourhood accessibility is conceptualised through the lens of chrono-urbanism, which emphasises that essential services should be reachable within a 15-minute walk or bike ride from home, which may support active travel (312).

To operationalise these evolving understandings of accessibility, researchers have increasingly sought to refine its measurement in order to more accurately capture the multiplicity of human experiences in urban environments. Broadly, two main methodological approaches have been used to evaluate accessibility and related walking behaviours: subjective and objective measures (313). Subjective measures capture valuable insights into individual perceptions and experiences, and given their internal consistency, they can strongly explain travel behaviour (130,314,315). For example, research on urban greenspace indicates that perceptions of safety and aesthetic quality are substantially associated with park visitation, even when objective characteristics such as proximity or size are favourable (316,317). In essence, subjective evaluations reflect how people interpret and emotionally respond to their surroundings, and these interpretations often directly relate to behavioural outcomes (318). Nevertheless, self-reported measures are vulnerable to various sources of bias, including recall bias (319), misreporting (320), and social desirability effects (45,46). In contrast, objective approaches provide more standardised, transparent, and replicable means of quantifying accessibility and thus offer a more stable evidence base for informing urban planning decisions and promoting environments that support active mobility.

While accessibility research has advanced conceptually and methodologically, empirical evidence on how these relationships manifest in contexts of major urban redevelopment remains limited. In Auckland, New Zealand, the Te Hotonga Hapori research programme provides a unique opportunity to examine mobility patterns within neighbourhoods undergoing urban redevelopment and comparison areas, offering a useful context for investigating accessibility and travel behaviour. The development areas are currently undergoing substantial transformations to the built environment, including new housing, roads, public spaces, and greenspaces, whereas control areas experience no planned interventions (61). Although urban redevelopment may promise long-term benefits, short-term disruptions, such as street closures, diversions, changes in public transport services, and modifications to pedestrian networks, can temporarily reshape travel behaviour, particularly walking, during the redevelopment period. These disruptions may also alter walking patterns both within and beyond home neighbourhoods, as individuals seek alternative routes or shift their walking activities outside their immediate residential area. In contrast, walking behaviour in areas not undergoing redevelopment is likely to remain more stable, though still associated with broader accessibility conditions and neighbourhood characteristics. Therefore, analysing walking behaviour separately within and beyond areas undergoing major built environment changes, as well as across locations inside and beyond home neighbourhood buffers, is essential to deepen understanding of the relationship between accessibility and mobility behaviour (321,322). These insights can inform planning strategies related to minimising disruption and understanding walking behaviour during periods of urban transformation.

To advance knowledge in this field, this study undertakes a cross-sectional observational analysis using data collected within the context of the broader Te Hotonga Hapori natural experiment programme, combining objectively measured walking behaviour (via GPS and accelerometer data) with an objectively constructed neighbourhood accessibility index derived from participants' residential locations and surrounding urban features. Building on the discussion of neighbourhood accessibility and spatial variations in walking, this research aims to: (1) examine the relationship between neighbourhood accessibility and objectively measured walking behaviour, both within and beyond home neighbourhood buffers, while controlling for sociodemographic attributes; and (2) explore the relationship between neighbourhood accessibility and actual walking behaviour in development and control areas, accounting for sociodemographic variations. Recognising that individuals' engagement with their local environments can vary depending on contextual factors such as time availability and familiarity with neighbourhood surroundings (323–325), this study also considers work status and neighbourhood residency duration as moderating variables to provide a more contextualised understanding of the accessibility–walking relationship. Collectively, these insights offer valuable implications for urban planners and policymakers seeking to promote active mobility in evolving urban environments. It is important to note that the data capture walking behaviour during the redevelopment period; thus, the study does not assess pre- or post-intervention differences.

Methods and materials

Study design

This study was conducted within a natural-experiment context arising from planned urban redevelopment but employed a cross-sectional observational design. The designation of redevelopment and control areas was determined by the broader Te Hotonga Hapori programme rather than by random allocation; therefore, systematic differences between areas cannot be ruled out. Accordingly, the present analysis should be interpreted as a quasi-experimental, cross-sectional assessment of walking behaviour within a naturally occurring redevelopment setting, rather than a full natural experiment involving randomisation or pre–post comparison.

Participants

Participants in this study were part of the Te Hotonga Hapori research programme. The Te Hotonga Hapori study design and recruitment processes are described in detail elsewhere (61). Briefly, participants were drawn from one of four regions across Auckland: Aorere, Oranga, Wesley, and Waikōwhai. In each region, the area expected to be immediately impacted by urban redevelopment (i.e., in the vicinity of construction) was defined as the 'development area', while a separate part of the region, sharing similar socioeconomic characteristics but unaffected by redevelopment, was defined as the 'control area'. Wesley was treated as a control area in its entirety, as no redevelopment activity was underway there at the time of data collection. Figure 3-1 presents the areas scheduled for redevelopment, along with the designated control areas, within each region.

To recruit participants, household interviews were conducted in the selected regions. Households with at least one adult (aged 18 years or above) willing to participate were included in this study. Data were collected across two time points in the Te Hotonga Hapori research programme: May 2023 to April 2024, and June 2024 to May 2025. However, as the second round of data collection was ongoing when this study began, only the baseline phase (May 2023 to April 2024) was utilised. At the time data collection began, approximately 75%–80% of each development area was undergoing urban redevelopment (excluding the development area scheduled in Wesley). In total, 485 participants were initially approached and interviewed during this period. Ethics approval for this study was obtained from the Auckland University of Technology Ethics Committee, and informed written consent was secured from all participants (AUTEC # 21/361).

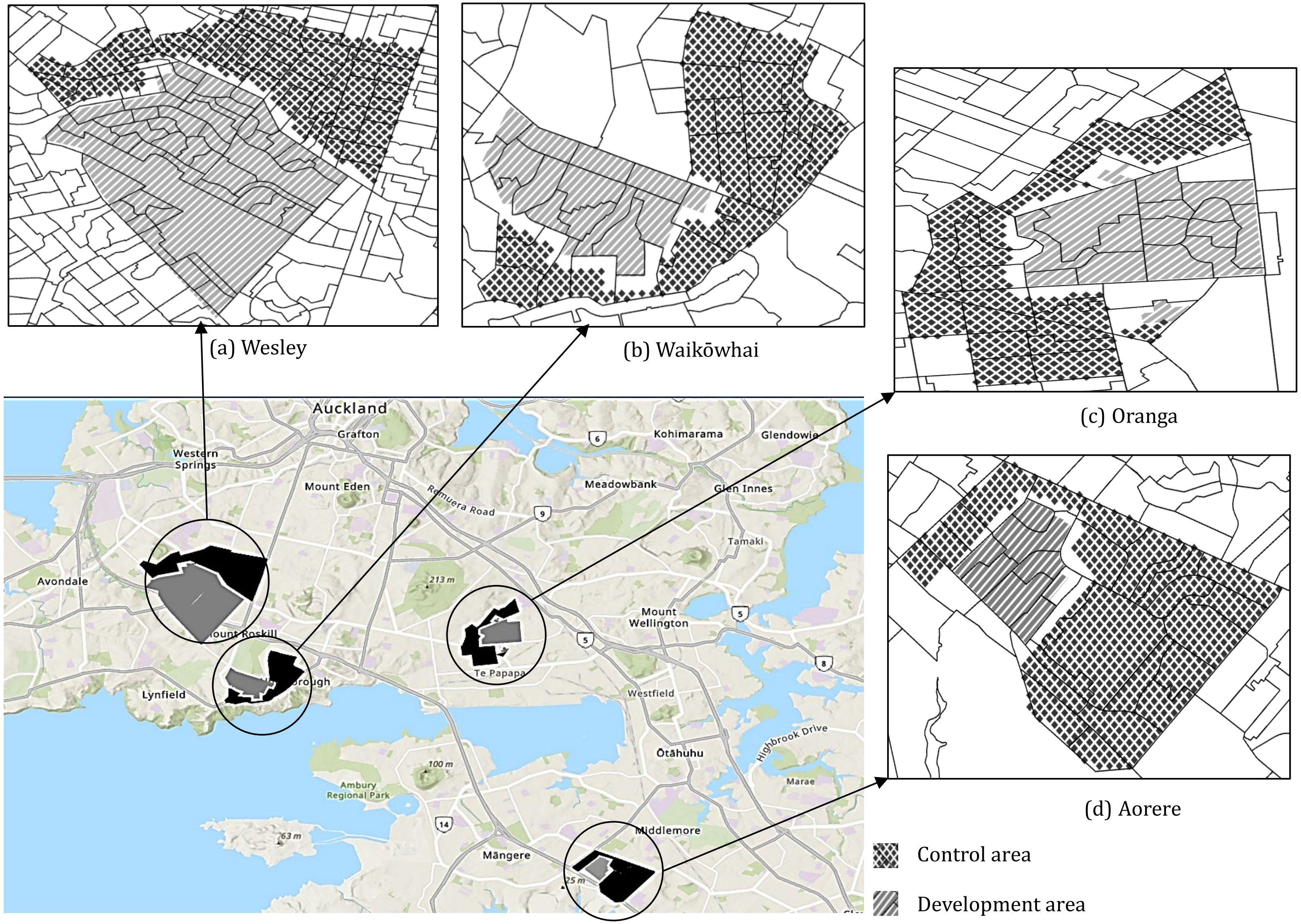


Figure 3-1. Study area

Equipment

To collect data on physical activity and travel behaviour, GPS receivers (QStarz BT-Q1000XT) and accelerometer devices (Axivity AX3) were utilised (Figure 3-2). The QStarz BT-Q1000XT, a GPS data logger validated in previous studies (326,327), provides real-time positional information. Using the QTravel software (QStarz International, Taipei, Taiwan), the QStarz BT-Q1000XT was configured to log latitude and longitude coordinates every 20 seconds. Additional recorded parameters included UTC date/time, GPS fixed mode (VALID), and satellite information, including signal-to-noise ratio (SNR) of viewed satellites. The Axivity AX3, a device known for its high accuracy in detecting physical activity intensity, was used to measure physical activity behaviour (328). Using the Open Movement software (OMGUI, Newcastle University, Newcastle upon Tyne, UK), the AX3 devices were initialised to record data at 100 Hz with ±8 g bandwidth.

(a) (b)

Figure 3-2. Equipment; (a): AX3 accelerometer, (b): QStarz BT-Q1000XT GPS

Procedures

On a weekly basis, GPS receivers and accelerometers were initialised using QTravel and OMGUI, respectively, and sent to the market research company via courier. Their door-to-door interviewers met participants in person to conduct interviews and distribute the devices. The interview primarily focussed on wellbeing outcomes along with individual- and household-related characteristics (e.g., age, gender, work status, and income). A full copy of the interview schedule is available at (61). Each participant received one GPS receiver (worn on their waist) and one Axivity AX3 (worn on their non-dominant wrist), both of which were continuously used for one week. Prior to the interview, participants received a briefing on the Te Hotonga Hapori study, including its purpose and objectives. They were also instructed to wear the accelerometer at all times, including during sleep, and to charge the GPS receiver each night using the provided charging cable. The GPS device was required to be worn during waking hours. After one week, the interviewers retrieved the equipment from the participants and returned it for data processing. Upon completion, each participant received an NZ$50 voucher as a token of appreciation.

Data processing – 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 steps 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 = 110). Similar inclusion criteria have been applied in previous studies (329,330). Although a sample size of approximately 200 individuals or more is generally recommended for parametric statistical models (331), the analytic unit in this study was individual trips (n = 2,503), which provides a substantially larger number of observations for estimating fixed effects in mixed-effects models. Simulation studies indicate that fixed-effect estimates in mixed-effects models can remain largely unbiased with modest samples, though precision and power, particularly for random effects and subgroup interactions, are constrained by the number of clusters (participants), warranting cautious interpretation (332,333).

The Python package LABDA (version 0.0.12) was used to preprocess GPS and accelerometer data (334). GPS data were downsampled to 30-second intervals, and the appropriate time zone (NZST, UTC+12, or NZDT, UTC+13) was applied automatically based on the date. The coordinate reference system (CRS) was transformed from EPSG:4326 (WGS 84) to EPSG:32760 (UTM Zone 60S) for spatial analysis. Additionally, home location data were projected to EPSG:2193 (New Zealand Transverse Mercator 2000) for national-scale mapping. GPS points with a sum of viewed SNRs greater than 260 were identified as indoor points, indicating the participant was likely inside a building (335). Previous studies demonstrated that an SNR threshold of 250 provide strong discrimination between indoor and outdoor environments (79.4% sensitivity, 84.1% specificity, and AUC = 0.927) (335). We therefore adopted a slightly more conservative threshold (260) to minimise false outdoor classifications. Accelerometer data were downsampled to 30-second intervals, and counts were derived (336). Non-wear time for the accelerometer was defined as periods where the device recorded zero counts continuously for a minimum of 60 minutes (337). The GPS and accelerometer data were combined based on the nearest date and time.

The LABDA package was also used to analyse travel patterns and identify travel modes. A trip was defined as a series of GPS points not interrupted by a stationary period longer than three minutes within a 25-metre radius. A trip starting point (trip origin) was identified when a participant began moving beyond a 25-meter radius after remaining stationary for at least three minutes. Conversely, a trip ending point (trip destination) was identified when a participant remained within a 25-meter radius for at least three minutes. Similar cut points have been utilised and validated in previous studies (329,338). Trips for which 60% or more of the GPS points were classified as "indoor" were discarded, as these were more likely to indicate GPS signal fluctuation (jitter) while the person was stationary inside a building with poor GPS reception rather than actual travel (339).

Trips could be multimodal, meaning they might involve multiple modes of transportation. Therefore, each trip was broken down into shorter segments based on the occurrence of pauses, defined as brief stops within a 25-meter radius for two minutes. Each segment was then classified by transport mode. Segments with an average speed of up to 10 km/h were considered walking trips, while those exceeding this threshold were classified as non-walking trips (340,341). However, if most of the accelerometer data points (more than 50%) within a segment indicated sedentary behaviour, the segment, even if initially classified as a walking trip, was classified as non-walking. The rationale was that slow movement recorded from GPS during sedentary behaviour likely represents slow-moving vehicular travel, rather than walking (339). Sedentary behaviour was defined as 2860 counts per minute (CPM) for wrist-based devices (342). The processing script is available in Appendix D.

The PALMSplusR package was utilised in RStudio (Version: 2024.12.0+467) to summarise travel information across days of the week and locations where trips were undertaken (i.e., within or outside the home neighbourhood buffer, and in development or control areas). Based on the trip locations, four walking outcomes were analysed separately: 1) walking duration within the home-neighbourhood buffer; 2) walking duration outside the home-neighbourhood buffer; 3) walking duration in development areas; and 4) walking duration in control areas. For each outcome, the analysis was conditioned on walking having occurred in the relevant setting. Consequently, only trips containing a walking segment within the corresponding location category were included in the respective model. Although development or control areas can spatially overlap with home-neighbourhood buffers, each walking outcome was analysed separately in distinct models, and no aggregation across categories was performed. Consequently, overlapping locations did not result in double counting within any single analysis.

Figure 3-3 illustrates a trip comprising both walking and non-walking travel modes, with the respective walking parts undertaken within and outside a home neighbourhood buffer. The orange segment represents the walking part recorded inside the home neighbourhood buffer (grey-shaded region), while the blue segment represents the walking part recorded outside the home neighbourhood buffer. The green segment denotes the non-walking part of an entire trip. The same approach was used for trips recorded in development and control areas.

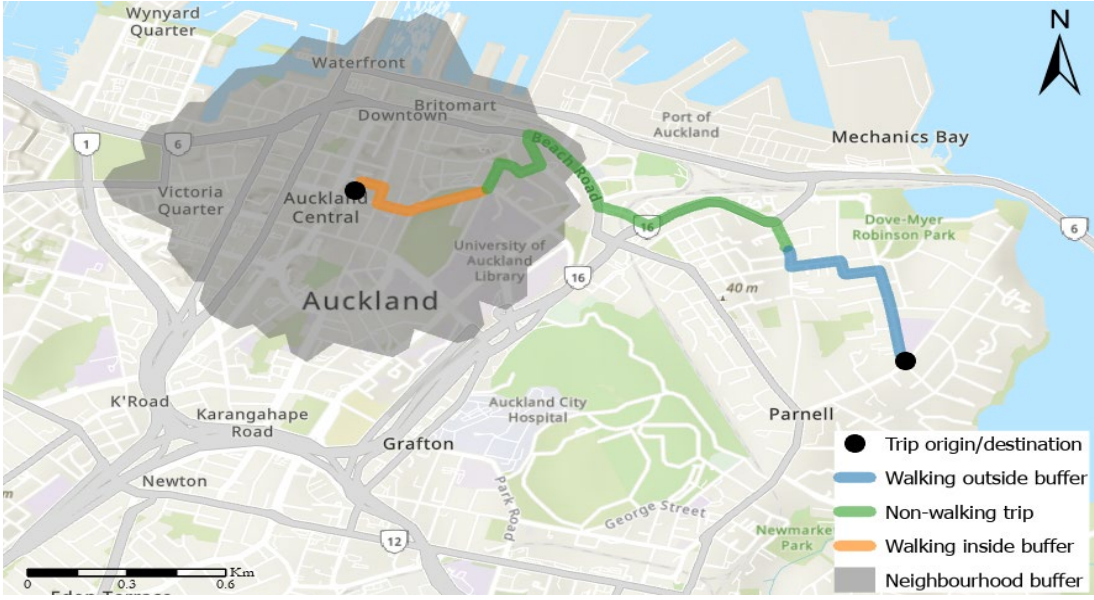


Figure 3-3. Location-based travel modes

ArcGIS Pro (version 3.4.0) was utilised to create spatial data layers. Participants' home addresses, obtained from the interviews, were geocoded. Neighbourhood buffers were defined as one-kilometre road network buffers originating from the participants' homes and following the street network, as depicted in Figure 3-3. This distance was selected based on prior research and guidance identifying walkable catchments of approximately 10–12 minutes (around 1 km) for local access and on evidence that short proximity strongly predicts walking trips (343–345). It also reflects the principles of the 15-minute city concept, in which daily needs are reachable within a 15-minute walk or bike ride (346,347). Road network data was obtained from Land Information New Zealand (LINZ) data service (348). The development and control areas included in this study were also geocoded according to the Te Hotonga Hapori programme records.

Data processing – accessibility

This study employed an existing enhanced two-step floating catchment area (E2SFCA)-based accessibility index that was previously developed for urban areas across New Zealand (349). The E2SFCA represents a well-established gravity-based approach for quantifying accessibility and forms part of the broader floating catchment area (FCA) family of methods (350–352). In essence, these methods consider both the supply of destinations and the demand from surrounding populations, applying distance-decay weighting to reflect the declining likelihood of access with increasing travel distance.

The New Zealand E2SFCA index quantifies the relative ease with which residents can walk to a wide range of everyday destinations within a 30-minute walking threshold. It captures accessibility across eight domains: education, environmental “bads” (e.g., alcohol outlets and takeaway food shops), health, Māori culture, public transport, recreation, social and cultural amenities, and shopping. An overall accessibility score, ranging from 1 (lowest) to 21,508 (highest), is calculated by combining these eight domains and assigned to each Statistical Area 1 (SA1). To improve interpretability and model estimation, the original accessibility index was rescaled by dividing it by 10,000 before being entered into the regression models. SA1s are the smallest geographic units used in the New Zealand census, typically comprising 100–200 residents, providing a fine-grained spatial resolution while maintaining privacy (353). This index was adopted because it represents the most recent and comprehensive national dataset of walkability-based accessibility available for New Zealand, ensuring consistency and comparability across study regions. Detailed methods for its construction are available elsewhere (349).

Statistical analysis

Descriptive statistics were used to summarise the sociodemographic characteristics of participants, accessibility scores of the study area, and trip information. To investigate the relationship between the accessibility index and actual walking behaviour within and outside home neighbourhood buffers (Aim 1), linear mixed-effects models were employed. The dependent variable was the total duration of the walking component of each trip (in minutes) that was recorded within or outside the home neighbourhood buffer (separately). Each participant’s accessibility score was treated as a fixed effect, and participant ID was included as the random effect to account for repeated measures (i.e., multiple trips per participant).

These models were then adjusted for the following sociodemographic attributes as fixed effects: age (18–39 years, 40–64 years, 65 years and over), gender (male, female), household income (low to middle income, high income), ethnicity (Māori, New Zealand European, Pacific, Other), neighbourhood residency (less than 3 years, 3 to 10 years, more than 10 years), and work status (employed, unemployed). Ethnicity was self-reported and classified using prioritised ethnicity. Māori, New Zealand European, and Pacific were retained as separate categories, while participants belonging to other ethnic groups were combined into an “Other” category because of small sample sizes. Interaction terms between accessibility index and work status, as well as accessibility index and neighbourhood residency, were included as fixed effects in the models. The reference categories for the covariates were individuals aged 18–39 years, female participants, high-income households, Māori participants, and residents who had lived in the neighbourhood for more than 10 years.

Linear mixed-effects models were also applied to examine the association between the accessibility index and objective walking behaviour in development and control areas (Aim 2), following the same analytical approach used for Aim 1. All models were fitted using the *lmer* function from the *lme4* package in RStudio (Version: 2024.12.0+467). Model assumptions were assessed using the *check_model()* function, while model fit, marginal and conditional R^2 values were calculated using the *model_performance()* function in the performance package.

Results

Descriptive analysis

Table 3-1 summarises the sociodemographic attributes of the study participants. The highest proportion of participants resided in Waikōwhai (32.7%), were aged 18–39 years (43.6%), were female (62.7%), and identified as New Zealand European (35.5%). The majority of participants were classified as low- to middle-income (54.5%). Most had lived in their neighbourhoods for three to ten years (36.4%) and were employed (61.8%).

Table 3-1. Participant demographic descriptives

Parameters	**n (%)**
Number of participants in each region	
Aorere	22 (20.0)
Oranga	27 (24.5)
Waikōwhai	36 (32.7)
Wesley	24 (21.8)
Age	
18 – 39	48 (43.6)
40 – 64	47 (42.7)
65 and over	9 (8.2)
Gender	
Male	35 (31.8)
Female	69 (62.7)
Ethnicity	
Māori	10 (9.0)
New Zealand European	39 (35.5)
Pacific	22 (20.0)
Other	33 (30.0)
Household income (NZD)	
Low to middle income (0–100,000)	60 (54.5)
High income (Over 100,000)	44 (40.0)
Neighbourhood Residency	
< 3 years	30 (27.3)
3–10 years	40 (36.4)
> 10 years	34 (30.9)
Work status	
Employed	68 (61.8)
Unemployed	36 (32.7)

Table 3-2 presents descriptive statistics for travel behaviour and accessibility scores across the study areas. Region-level accessibility indices ranged from 0.446 (SD = 0.167) in Waikōwhai to 1.230 (SD = 0.184) in Oranga. Development and control areas exhibited similar accessibility scores (mean = 0.791, SD = 0.323 and mean = 0.878, SD = 0.463, respectively). On average, participants recorded 22.8 trips (SD = 14.7), with a mean trip duration of 12.5 minutes (SD = 11.4) and a mean trip distance of 4.8 km (SD = 5.7). Across all trips, the mean walking duration was around 8 minutes (SD = 10.6), while the mean non-walking duration was 13.5 minutes (SD = 10.7). Walking trips within home neighbourhoods were longer (mean = 11.5 minutes, SD = 9.4) than those outside the neighbourhood buffer (mean = 6.7 minutes, SD = 7.6). In contrast, non-walking trips were longer outside the home neighbourhood (mean = 12.0 minutes, SD = 10.5). Both walking and non-walking trips tended to be slightly longer in control areas compared to development areas. Across all regions, average walking duration ranged from 6.7 minutes (SD = 7.6) in Waikōwhai to 10.1 minutes (SD = 14.3) in Oranga.

Table 3-2. Trip- and environment-related descriptives

Parameters	**Mean (SD)**
Region-based accessibility index ($*10,000^{-1}$)	
Aorere	0.652 (0.229)
Oranga	1.230 (0.184)
Waikōwhai	0.446 (0.167)
Wesley	1.150 (0.290)
Area-based accessibility index ($*10,000^{-1}$)	
Control	0.878 (0.463)
Development	0.791 (0.323)
Trips per person	22.8 (14.7)
Trip duration (min)	12.5 (11.4)
Trip distance (km)	4.8 (5.7)
Walking/non-walking duration (min)	
Walking	8.1 (10.6)
Non-walking	13.5 (10.7)
Neighbourhood-based walking/non-walking duration (min)	
Walking within home neighbourhood	11.5 (9.4)
Non-walking within home neighbourhood	2.7 (1.5)
Walking outside home neighbourhood	6.7 (7.6)
Non-walking outside home neighbourhood	12.0 (10.5)
Area-based walking/non-walking duration (min)	
Walking in control area	8.4 (11.1)
Walking in development area	7.6 (9.5)
Non-walking in control area	13.7 (10.9)
Non-walking in development area	13.3 (10.3)
Region-based walking/non-walking duration (min)	
Walking - Aorere	7.3 (8.6)
Non-walking - Aorere	14.2 (9.6)
Walking - Oranga	10.1 (14.3)
Non-walking - Oranga	13.8 (11.6)
Walking - Waikōwhai	6.7 (7.6)
Non-walking - Waikōwhai	13.3 (9.9)
Walking - Wesley	8.6 (10.2)
Non-walking - Wesley	13.4 (11.7)
Note: SD = Standard deviation	

Accessibility and walking behaviour – neighbourhood buffers (Aim 1)

Table 3-3 presents the results of unadjusted and adjusted linear mixed-effects models examining the correlation between the home-based accessibility score, defined based on participants' home locations, and walking behaviour (i.e., the total walking duration per trip, in minutes, recorded within the home neighbourhood buffer). In the unadjusted model, no significant association was found between improved accessibility and increased walking duration ($\beta = 1.6$; 95% CI = -4.04, 7.32; $p = 0.569$). The conditional R^2 value, representing the proportion of variance explained by both fixed and random effects, showed that the model accounted for 36.3% of the variance in walking duration, whereas the marginal R^2 value, reflecting the variance explained by fixed effects alone, was only 0.4%. These results suggest that accessibility was only minimally associated with walking behaviour, while most of the explained variation was attributable to between-participant differences rather than the measured fixed effects.

The adjusted model explained approximately 40% of the variance in walking behaviour, with nearly 17% attributed to fixed effects alone. The findings showed no statistically significant relationship between accessibility and walking within home neighbourhood buffers (β = 5.7; 95% CI = -5.96, 17.41; p = 0.334). Among covariates, only age was significantly associated with walking behaviour. Participants aged 65 and over had an average walking duration per trip that was 12 minutes longer than younger participants (β = 12.4; 95% CI = 2.80, 22.04; p = 0.012).

Table 3-3. Factors associated with walking duration (min) within home neighbourhood buffers

Parameters	**Coeff.**	**SE**	**95% CI**	**P-value**
Unadjusted model				
Accessibility index	1.6	2.87	[-4.04, 7.32]	0.569
Adjusted model				
Accessibility index	5.7	5.91	[-5.96, 17.41]	0.334
Age (ref. = 18–39)				
40–64	3.4	2.63	[-1.81, 8.60]	0.199
65 and over	12.4	4.87	[2.80, 22.04]	0.012
Gender (ref. = female)	4.3	2.34	[-0.35, 8.88]	0.070
Household income (ref. = high income)				
Low to middle income	-0.7	2.70	[-6.02, 4.67]	0.802
Ethnicity (ref. = Māori)				
New Zealand European	2.7	5.17	[-7.55, 12.91]	0.606
Pacific	-3.3	6.49	[-16.15, 9.50]	0.609
Other	1.1	5.01	[-8.79, 11.04]	0.823
Neighbourhood residency (ref. = > 10 yrs)				
3–10 yrs	3.1	9.10	[-14.92, 21.05]	0.737
< 3 yrs	4.4	8.44	[-12.31, 21.06]	0.605
Work status (ref. = employed)	6.9	6.32	[-5.57, 19.41]	0.275
Accessibility index * work status	-3.9	6.11	[-15.97, 8.20]	0.526
Accessibility index * neighbourhood residency (3–10 yrs)	-2.0	8.10	[-18.01, 14.00]	0.804
Accessibility index * neighbourhood residency (3 yrs >)	-0.8	7.77	[-16.21, 14.53]	0.914
Participants: 110; trips: 1339				
Unadjusted model: Marginal R^2 = 0.4 %; Conditional R^2 = 36.3 %				
Note: Coeff. = Coefficient; SE = Standard error; CI = Confidence interval				

Table 3-4 presents the results of unadjusted and adjusted linear mixed-effects models examining the correlation between the home-based accessibility index and walking behaviour (i.e., the total walking duration per trip, in minutes, recorded outside the home neighbourhood buffer). In the unadjusted model, no significant association was observed between accessibility and walking duration for trips outside the buffer (β = 0.71; 95% CI = -1.13, 2.55; p = 0.447). The conditional

R^2 value indicated that the model explained 9.2% of the variance in walking for trips outside the home neighbourhood. However, the marginal R^2 value was only 0.2%, suggesting that the fixed effect (accessibility score) explained very little of the variance.

After adjusting for sociodemographic covariates, the model's conditional R^2 increased to 11.7%, with fixed effects accounting for 4.6%. The association between accessibility and walking duration approached conventional levels of statistical significance, with each unit increase in home-based accessibility associated with nearly 4 minutes more walking per trip outside the home neighbourhood buffer (β = 3.9; 95% CI = -0.04, 7.79; p = 0.052). Among all covariates, only age was significantly associated with walking duration, as participants aged 65 and over walked, on average, approximately 4 minutes more per trip than younger groups (β = 4.1; 95% CI = 0.64, 7.64; p = 0.020).

Table 3-4. Factors associated with walking duration (min) outside home neighbourhood buffers

Parameters	**Coeff.**	**SE**	**95% CI**	**P-value**
Unadjusted model				
Accessibility index	0.71	0.94	[-1.13, 2.55]	0.447
Adjusted model				
Accessibility index	3.9	1.99	[-0.04, 7.79]	0.052
Age (ref. = 18–39)				
40–64	-0.5	0.99	[-2.46, 1.44]	0.608
65 and over	4.1	1.78	[0.64, 7.64]	0.020
Gender (ref. = female)	-0.2	0.91	[-2.00, 1.56]	0.806
Household income (ref. = high income)				
Low to middle income	1.3	1.05	[-0.78, 3.36]	0.220
Ethnicity (ref. = Māori)				
New Zealand European	2.3	1.71	[-1.08, 5.64]	0.183
Pacific	0.1	1.96	[-3.79, 3.90]	0.979
Other	2.3	1.65	[-0.92, 5.56]	0.161
Neighbourhood residency (ref. = > 10 yrs)				
3–10 yrs	1.7	2.43	[-3.04, 6.51]	0.476
< 3 yrs	3.2	2.67	[-2.07, 8.41]	0.235
Work status (ref. = employed)	1.6	2.07	[-2.42, 5.69]	0.429
Accessibility index * work status	-3.6	2.25	[-8.04, 0.79]	0.108
Accessibility index * neighbourhood residency (3–10 yrs)	-2.9	2.44	[-7.70, 1.89]	0.235
Accessibility index * neighbourhood residency (3 yrs >)	-3.2	2.80	[-8.67, 2.32]	0.257
Participants: 109; trips: 2359				
Unadjusted model: Marginal R^2 = 0.2 %; Conditional R^2 = 9.2 %				
Note: Coeff. = Coefficient; SE = Standard error; CI = Confidence interval				

Accessibility and walking behaviour – development and control areas (Aim 2)

Table 3-5 presents the results of unadjusted and adjusted linear mixed-effects models examining the correlation between the home-based accessibility index, measured based on participants' home locations, and walking behaviour (i.e., the total walking duration per trip, in minutes, recorded in development areas). In the unadjusted model, no statistically significant association was observed between accessibility and walking duration (β = 1.2; 95% CI = -2.73, 5.13; p = 0.543). The conditional R^2 value indicated that the model explained nearly 21% of the variance in walking behaviour, whereas the marginal R^2 value was very low, accounting for only 0.7%. These results suggest that, in development areas, accessibility is minimally associated with walking duration, and individual-level factors may play a more substantial role.

After adjusting for sociodemographic covariates, the model explained nearly 31% of the variance in walking behaviour, with about 27% attributed to fixed effects. Among all covariates, only age was significantly associated with walking duration. Participants aged 40–64 years walked, on average, 4 minutes more per trip than those aged 18–39 years (β = 4.0; 95% CI = 0.06, 7.99; p = 0.047). No significant association was found between the accessibility index and walking duration in areas undergoing redevelopment (β = 0.0; 95% CI = -9.30, 9.35; p = 0.996).

Table 3-5. Factors associated with walking duration (min) within development areas

Parameters	**Coeff.**	**SE**	**95% CI**	**P-value**
Unadjusted model				
Accessibility index	1.2	1.97	[-2.73, 5.13]	0.543
Adjusted model				
Accessibility index	0.0	4.65	[-9.30, 9.35]	0.996
Age (ref. = 18–39)				
40–64	4.0	1.97	[0.06, 7.99]	0.047
65 and over	5.0	3.15	[-1.32, 11.33]	0.118
Gender (ref. = female)	-0.8	2.03	[-4.92, 3.25]	0.683
Household income (ref. = high income)				
Low to middle income	0.9	1.88	[-2.85, 4.71]	0.624
Ethnicity (ref. = Māori)				
New Zealand European	-1.6	5.32	[-12.27, 9.04]	0.762
Pacific	-5.8	5.80	[-17.46, 5.80]	0.319
Other	-2.9	5.46	[-13.90, 8.03]	0.593
Neighbourhood residency (ref. = > 10 yrs)				
3–10 yrs	-1.3	5.45	[-12.19, 9.69]	0.819
< 3 yrs	3.5	5.85	[-8.20, 15.26]	0.549
Work status (ref. = employed)	2.9	4.39	[-5.86, 11.75]	0.505
Accessibility index * work status	0.5	4.56	[-8.68, 9.60]	0.920
Accessibility index * neighbourhood residency (3–10 yrs)	0.8	5.26	[-9.79, 11.33]	0.885
Accessibility index * neighbourhood residency (3 yrs >)	-1.7	7.10	[-15.97, 12.54]	0.810
Participants: 94; trips: 703				
Unadjusted model: Marginal R^2 = 0.7 %; Conditional R^2 = 20.6 %				
Note: Coeff. = Coefficient; SE = Standard error; CI = Confidence interval				

Table 3-6 presents the results of unadjusted and adjusted linear mixed-effects models assessing the association between the home-based accessibility index and walking behaviour (i.e., total walking duration per trip, in minutes, recorded in control areas). In the unadjusted model, no statistically significant association was observed between accessibility and walking duration (β = 0.8; 95% CI = -5.38, 6.99; p = 0.796). The conditional R^2 value indicated that the model explained 45.7% of the variance in walking behaviour for trips in control areas, while the marginal R^2 was only 0.1%, indicating that fixed effects explained very little of the variance in walking duration.

After adjusting for sociodemographic covariates, the model explained approximately 49% of the variance in walking behaviour, with fixed effects accounting for about 40%, as reflected in the R^2 values. The association between the home-based accessibility index and walking duration remained non-significant (β = 4.6; 95% CI = -3.67, 12.82; p = 0.274). However, age emerged as a significant factor, with individuals aged 65 and over walking, on average, 11 minutes more per trip than the younger group (β = 11; 95% CI = 3.20, 18.81; p = 0.006). Males also appeared to walk nearly 5 minutes more per trip than females (β = 4.8; 95% CI = 1.25, 8.36; p = 0.009). Participants from low- to middle-income households, regardless of whether they resided in development or control areas, walked an average of 5 minutes less per trip than those from high-income households (β = -5.0; 95% CI = -9.20, -0.71; p = 0.023). A significant interaction was observed between accessibility and work status (β = -16.3; 95% CI = -26.90, -5.62; p = 0.003), indicating that the association between accessibility and walking duration differed between employed and unemployed participants. Specifically, walking duration decreased more sharply with increasing accessibility among unemployed participants than among employed participants (Figure 3-4).

Table 3-6. Factors associated with walking duration (min) within control areas

Parameters	Coeff.	SE	95% CI	P-value
Unadjusted model				
Accessibility index	0.8	3.13	[-5.38, 6.99]	0.796
Adjusted model				
Accessibility index	4.6	4.16	[-3.67, 12.82]	0.274
Age (ref. = 18–39)				
40–64	2.6	2.27	[-1.94, 7.08]	0.261
65 and over	11.0	3.93	[3.20, 18.81]	0.006
Gender (ref. = female)	4.8	1.79	[1.25, 8.36]	0.009
Household income (ref. = high income)				
Low to middle income	-5.0	2.14	[-9.20, -0.71]	0.023
Ethnicity (ref. = Māori)				
New Zealand European	0.6	4.29	[-7.95, 9.06]	0.897
Pacific	-4.7	5.74	[-16.08, 6.67]	0.414
Other	-0.5	3.99	[-8.42, 7.42]	0.900
Neighbourhood residency (ref. = > 10 yrs)				
3–10 yrs	-11.3	7.27	[-25.68, 3.15]	0.124
< 3 yrs	2.2	6.72	[-11.10, 15.53]	0.742
Work status (ref. = employed)	22.4	5.88	[10.72, 34.02]	0.001
Accessibility index * work status	-16.3	5.37	[-26.90, -5.62]	0.003
Accessibility index * neighbourhood residency (3–10 yrs)	9.7	6.24	[-2.73, 22.03]	0.125

Table 3-6. Factors associated with walking duration (min) within control areas

Parameters	**Coeff.**	**SE**	**95% CI**	**P-value**
Accessibility index * neighbourhood residency (3 yrs >)	0.7	5.76	[-10.71, 12.15]	0.901
Participants: 109; trips: 1055				
Unadjusted model: Marginal R^2 = 0.1 %; Conditional R^2 = 45.7 %				
Note: Coeff. = Coefficient; SE = Standard error; CI = Confidence interval				

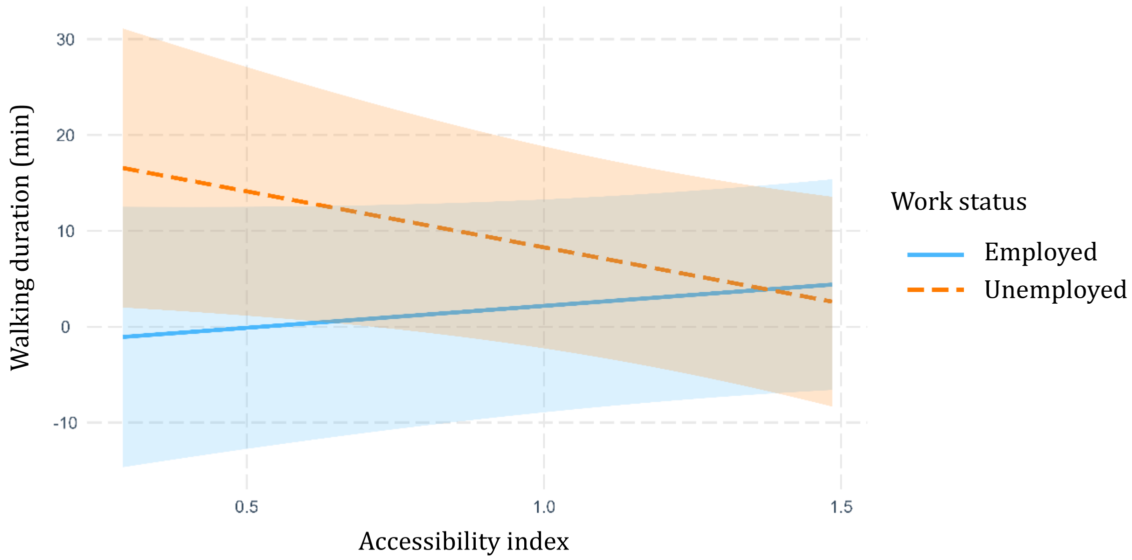


Figure 3-4. Accessibility–work status interaction

Discussion and conclusion

This study examined the association between neighbourhood accessibility and walking behaviour across distinct spatial contexts, utilising GPS and accelerometer data to capture objective measures of walking. Accessibility was measured objectively and assigned based on the SA1s (small geographic areas) within which participants' homes were located, whereas walking behaviour was categorised based on the actual locations where walking trips occurred, irrespective of residential address. By analysing accessibility and walking behaviour separately within and outside home neighbourhood buffers, as well as in development and control areas, the findings revealed that the nexus between neighbourhood accessibility and walking patterns varies according to spatial context, with evidence suggesting that this relationship is context-sensitive and spatially dependent.

Across the models, the associations between neighbourhood accessibility and walking duration were weak or non-significant. One likely explanation is the spatial mismatch between where accessibility was measured (based on participants' home locations) and where walking was measured (based on the actual locations where participants walked). Because walking trips in these areas may involve both residents and non-residents, the built environment characteristics of the walking location may not align with the accessibility index assigned to each participant's home, potentially weakening observable associations. For example, a person living in a control area may walk there frequently, even if their assigned accessibility index is low, while someone from a development area may only walk in a control area occasionally, regardless of their home-based accessibility score. In such cases, the location where walking is recorded does not necessarily reflect the built environment associated with the participant's measured accessibility, which may further attenuate the relationship.

Another possible explanation is that unmeasured individual and perceptual factors, such as travel habits, familiarity with the area, and personal attitudes toward walking, may account for some of the variation (354,355). This outcome is plausible, as individual-level factors are typically more internally consistent, being derived from the same respondent, and may therefore show stronger associations with walking behaviour than objectively measured environmental attributes. However, this does not negate the importance of built environment characteristics, which may be underrepresented when measured solely through objective indicators (356). For instance, an area may exhibit high objective accessibility, yet individuals who prefer driving or perceive safety risks may still avoid walking; conversely, those with strong pro-walking attitudes may walk frequently even in less accessible environments (357,358).

In addition, such perceptual factors may differ systematically between residents and non-residents. Residents are generally more familiar with and comfortable in their local surroundings, which may support more frequent walking, whereas non-residents may experience less familiarity or greater perceived risk when walking in unfamiliar environments (124,359,360). These perceptual differences may jointly relate to walking patterns and further contribute to the weak or context-dependent associations observed. Consequently, variations in accessibility alone may explain only a modest proportion of the observed variability in walking behaviour, as reflected in the relatively low marginal R^2 values across models.

Although the overall associations between accessibility and walking were weak and accompanied by substantial uncertainty, accessibility coefficients were positive for both walking within and outside home-neighbourhood buffers. While the estimate for walking outside the home-neighbourhood buffer was more precisely estimated and approached conventional levels of statistical significance, the findings do not provide clear evidence that accessibility was more strongly associated with one setting than the other. Accordingly, the results should be interpreted as suggestive rather than conclusive regarding spatial differences in accessibility-walking associations. Nevertheless, previous research has suggested that macro-scale characteristics of the built environment, accessibility in particular, are often more strongly associated with destination-oriented active travel beyond the immediate neighbourhood (12,361,362). Such trips are typically destination-oriented, and a richer mix of reachable amenities may correspond with longer walking bouts. By contrast, walking within the home-neighbourhood buffer is often undertaken for leisure, where macro-scale features of the built environment, such as accessibility, may be less pertinent (322). Instead, micro-scale attributes, such as aesthetics, safety, and building characteristics, may have stronger associations with walking behaviour (321,322).

The interaction between work status and neighbourhood accessibility suggests potential differences in how population subgroups engage with the built environment. Among employed individuals, walking behaviour appeared less responsive to variations in accessibility to local amenities. This may reflect the nature of their walking patterns, which are often structured around fixed commuting routines, particularly between home and public transport nodes, making them more dependent on transit access than on local amenities (363,364). Additionally, habitual commuting patterns may render this group less responsive to changes in local accessibility, as established travel routines often persist despite environmental changes (365,366). In contrast, unemployed individuals appeared to exhibit higher levels of walking in low-accessibility areas, with a sharper decline in walking as accessibility improved. One plausible explanation is that unemployed individuals, who may face fewer time constraints, undertake longer walking trips to reach distant destinations when local accessibility is limited. At higher accessibility levels, shorter walking durations could reflect shorter required travel distances; however, this mechanism was not measured. While these interpretations remain speculative, they underscore the likelihood that walking behaviour is associated not only with the built environment but also with other factors such as trip purpose and time constraints. Differentiating between types of accessibility (e.g., amenity-based versus transit-based) and considering diverse socio-economic contexts in planning initiatives, rather than assuming uniform behavioural responses to accessibility, may be essential for achieving equitable increases in pedestrian activity.

This study found no statistically significant interaction between neighbourhood residency duration and accessibility in relation to walking behaviour, despite prior research suggesting that longer residency can enhance familiarity with local areas and amenities, thereby supporting active travel (367,368). One possible explanation for this finding is that participants in the examined neighbourhoods may have become familiar with key destinations and accessibility features relatively quickly. If amenities are easily identifiable and centrally located, prolonged residency may be less critical for developing functional knowledge of the area. It is therefore plausible that, within the residency durations assessed in this study, participants had already achieved sufficient familiarity with their surroundings, limiting any further association between extended time living in the area and walking behaviour in relation to accessibility. These insights imply that the relationship between residency duration and walking in the context of neighbourhood accessibility may be highly contingent upon local conditions, highlighting the need for future research across diverse spatial and social environments.

Findings indicated that younger participants (ages 18–39) were less likely to walk than older participants (aged 65 and over) in all settings, which may relate to time constraints from work or family obligations and could help explain a preference for faster modes of transport (369). Conversely, older adults, who may have greater time flexibility, appeared to walk more frequently across various environments, a pattern that might reflect engagement in leisure activities, social interactions, or daily errands (370). They may also prefer residing in highly walkable settings, such as retirement villages, which can accommodate mobility limitations and may support walking (371). Consistent with previous studies (372–377), this study also observed that males tended to walk more than females, which might be associated with the trip-chaining behaviours often reported among women (378). Women are more likely to incorporate errands, such as household tasks, school drop-offs, or visits to friends and family, into their daily trips, which may act as barriers to walking, cycling, or using public transport (379–381). Additionally, in line with the literature (382,383), this study also found that participants from low- to middle-income households recorded lower walking durations in control areas than those from high-income households. The reasons for this association cannot be determined from the current dataset. Further research is needed to better understand the mechanisms underlying income-related differences in walking behaviour.

Limitations and future research

While this study adds to the knowledge base about the relationship between accessibility and walking behaviour, certain limitations should be acknowledged. This study was not designed to maximise heterogeneity in accessibility levels, as participants were clustered within four relatively small areas. Consequently, individuals living in the same area had nearly identical accessibility scores, limiting variability in these measures. The areas were further selected based on urban redevelopment rather than differences in accessibility, meaning that overall accessibility conditions across the study locations may have been very similar. This could reduce the ability to detect associations between accessibility and walking behaviour, particularly if the range of accessibility values was too narrow to capture meaningful variation in its associations. Future research could address this by including study areas with a wider range of accessibility levels. A more diverse selection of urban environments, ranging from high-accessibility city centres to lower-accessibility suburban areas, would enable a more comprehensive examination of how accessibility is correlated with walking behaviour.

Another limitation relates to the geographic scale at which the accessibility score was calculated (i.e., the SA1-level accessibility based on participants' home locations). The SA1 unit may not accurately reflect the environments to which participants have access or those they perceive as their neighbourhood, particularly for individuals residing near the boundaries of their SA1. This spatial constraint could introduce discrepancies between measured and experienced accessibility. Although finer spatial units may offer a more accurate representation than administrative boundaries, such approaches were not feasible in this study because accessibility scores were only available at the SA1 level from existing datasets. Future research could address this limitation by using more granular spatial units or by simultaneously integrating perceived accessibility indices to provide deeper insights into the accessibility–walking relationship.

This study may also be subject to spatial mismatches between the locations where accessibility was measured and where walking occurred, particularly in the analysis of development and control areas (Aim 2). Although walking trips in both Aim 1 and Aim 2 were classified based on where the trips occurred, Aim 1 remained spatially anchored to each participant's home by analysing walking within and outside the home neighbourhood buffer while using the same home-based accessibility index throughout. However, Aim 2 examined walking behaviour in development and control areas regardless of whether participants resided in those areas. This means that some participants' walking activity may have occurred in locations with built environment characteristics that differed substantially from those of their home SA1, yet their walking behaviour was still interpreted based on home-based accessibility scores. This spatial misalignment may have diluted the observed associations. Future studies could address this limitation by restricting analyses to walking within participants' own residential areas or by assigning accessibility scores based on the actual locations where walking occurred.

The relatively small sample size in this study may have limited the precision of estimates and the statistical power of the analyses, particularly for interaction and subgroup effects such as those involving work status. Although mixed-effects models, as commonly used in natural-experiment research, can yield approximately unbiased fixed-effect estimates with modest samples when model assumptions are met, reduced precision can increase the likelihood of Type II errors (332,333). Several non-significant results in this study were accompanied by confidence intervals that encompassed potentially meaningful effects, suggesting that limited power may have influenced these findings. In addition to sample size constraints, the exclusion of perceptual and attitudinal factors, such as familiarity with the area, perceived safety, and personal preferences for walking, may also have contributed to the limited or inconsistent associations observed. These factors, which often exert strong influences on walking behaviour, were not available in the dataset and could not be directly incorporated into the models. Future studies with larger and more diverse samples that integrate both objective and perceptual measures of accessibility would improve statistical power, enhance explanatory depth, and strengthen the generalisability of results.

An additional limitation relates to the timing of data collection. Participants wore the GPS and accelerometer devices at different times between May 2023 and April 2024 as part of an ongoing rolling recruitment process. Device allocation was not targeted towards specific participants, neighbourhoods, accessibility levels, or travel behaviours, reducing the likelihood of systematic bias related to the timing of measurement. However, walking behaviour may vary according to seasonal conditions, weather, or holiday periods. Although data collection was distributed across the study period and relatively few participants were monitored during major public holiday periods, the potential influence of temporal variation on walking behaviour was not completely excluded. Future studies could address this limitation by collecting data within comparable seasons or periods of the year, thereby reducing temporal variability, or by explicitly adjusting for seasonal and weather-related factors within the analytical models.

Although participants were clustered within four neighbourhoods, a neighbourhood-level random effect was not included because only four higher-level geographic units were available, which is insufficient for reliable estimation of area-level variance components in multilevel models. Consequently, any residual area-level clustering or spatial dependence could not be explicitly modelled and may have influenced the estimated associations. Future studies including a larger number of neighbourhoods would be better positioned to account for geographic clustering and spatial dependence directly.

Policy implications

Urban mobility initiatives often prioritise neighbourhood accessibility improvements based on the assumption that they encourage local walking behaviours. In the present study, positive accessibility coefficients were observed for both within- and beyond-neighbourhood walking, although the estimates were accompanied by substantial uncertainty. The association for walking beyond home-neighbourhood boundaries was estimated more precisely, but the findings did not provide clear evidence that accessibility was more strongly associated with walking in one spatial context than another. Nevertheless, the results are broadly consistent with previous research suggesting that accessibility may be particularly relevant for destination-oriented travel. Future research is needed to determine whether such patterns are replicated in larger and more diverse populations.

This study also observed differing walking patterns between employed and unemployed individuals in relation to neighbourhood accessibility, particularly in control areas. However, these subgroup findings should be interpreted cautiously because they were derived from interaction analyses within a relatively small sample. While the observed patterns may indicate that the relationship between accessibility and walking differs across population groups, further research is needed to establish whether these differences are consistent across other settings and populations. Consequently, these findings are best viewed as generating hypotheses for future investigation rather than providing a direct basis for targeted policy interventions.

Chapter 4. Linking multi-anchor bus stop accessibility to bus ridership: Evidence from GPS and accelerometer data

Preface

The previous chapter focused on walking as a direct pathway for reducing car dependency. This chapter extends the analysis to public transport, recognising its close link to walking through access and egress trips and its potential role in supporting sustainable mobility. Existing research on public transport accessibility has largely relied on static home-based measures and overlooked the complexity of daily mobility across multiple anchors. Addressing this gap, the study uses GPS and accelerometer data from Auckland to examine how accessibility to bus stops, measured separately from home, trip origin, and trip destination, relates to actual bus ridership. Mixed-effects logistic regression models are applied to assess these associations and explore whether employment status and neighbourhood residency duration moderate the accessibility–ridership relationship. This manuscript has been submitted for publication.

Abstract

Public transport contributes to health and sustainability by reducing emissions, encouraging active travel, and supporting efficient land use. However, accessibility analyses often rely on static home-based proximity measures that fail to capture the complexity of daily mobility. This study examines how accessibility to bus stops, measured from three locations (home, trip origin, and destination), relates to actual bus use 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 home-based accessibility was negatively associated with bus use, suggesting that areas with dense stop networks may also offer walkable environments or experience operational inefficiencies that nay discourage bus travel. Destination-based accessibility showed a positive association with ridership, but only among newer residents, indicating that the association between destination-based accessibility and ridership differed by residency duration. Employed participants were more sensitive to residential-level accessibility than unemployed individuals, likely reflecting possible differences in time constraints. These findings indicate that spatial accessibility alone may not adequately account for variation in ridership behaviour. Policies that combine spatial accessibility with service quality and behavioural factors may better support equitable and effective public transport use.

Introduction

The numerous health, environmental, and economic benefits of public transport have been extensively documented across diverse urban contexts. Many public transport users, such as bus passengers, routinely attain recommended levels of physical activity simply by walking to and from stops, thereby fostering healthier and more active lifestyles (87,384). In contrast, private car use is linked to prolonged sitting, which is now recognised as an additional health risk over and above the risks associated with limited physical activity (26,384–389). Beyond individual wellbeing, the widespread adoption of public transport contributes significantly to reducing car dependency, easing urban traffic congestion, and mitigating associated externalities such as air and noise pollution, greenhouse gas emissions, and road traffic injuries (390). Moreover, reduced reliance on private vehicles enables the reallocation of valuable urban land away from roads and car parks towards more socially and economically productive uses, including public open spaces, active travel infrastructure, affordable housing, and community amenities (30). In sum, transitioning toward greater reliance on public transport supports more compact, sustainable, and equitable land use patterns, while also enhancing public health and wellbeing.

Travel behaviour related to public transport use is associated with a constellation of factors, including sociodemographic characteristics (e.g., age, gender, car ownership, and employment), user perceptions of service attributes (e.g., perceived reliability, safety, and comfort), psychological constructs (e.g., self-efficacy, attitudes, and habits), and built environment features (e.g., land-use diversity, population density, and street connectivity) (391–395). Within this multifactorial framework, improved accessibility to public transport is widely regarded as one of the critical associates of increased ridership, attracting new passengers and retaining existing ones (47–49,201–205). In the context of public transport, accessibility is often discussed in two ways: first, as the ability to reach opportunities such as employment, healthcare, or education using public transport, commonly termed public transport accessibility (206); and second, as accessibility to the public transport system itself, which refers to the proximity, density, and availability of stops or stations, often called accessibility to public transport (207). Focusing on the latter approach is important because without nearby access points, the broader benefits of network connectivity and even service reliability cannot be realised.

Although proximity to public transport is generally associated with higher ridership, individual responses to accessibility vary substantially depending on personal circumstances. Two behavioural factors that are particularly relevant to how people engage with accessible services are work status and neighbourhood residency duration, which together shape daily routines and familiarity with local environments (396–400). The temporal structure of travel varies according to work status: full-time workers with rigid schedules may be less inclined to rely on nearby services if they do not meet time-specific commuting demands, whereas those with regular schedules and a single workplace often benefit from predictable routines that make public transport a viable option when stops are conveniently located (401,402). Conversely, unemployed individuals or part-time workers, who might have flexible routines, lower income, or fewer private transport options (e.g., household vehicles), may use public transport even when accessibility is relatively limited (403–407).

Neighbourhood familiarity operates in a similar way, shaping how people make use of accessible services (400,408). Longer-term residents tend to be more knowledgeable about available routes and how to navigate them effectively, whereas recent movers may not take full advantage of accessible options despite favourable local service provision (400,409). While other sociodemographic characteristics, such as income or car ownership, also contribute to ridership, work status and neighbourhood familiarity are especially relevant because they directly interact with how individuals perceive and respond to transit accessibility (397,410,411). Although both factors have been examined in travel behaviour research, their role as moderators of the relationship between accessibility and actual public transport use has been understudied. Together, these behavioural dimensions indicate that accessibility cannot be fully understood through spatial indicators alone and should be examined in relation to the contexts in which people make travel decisions.

Capturing these behavioural nuances requires accessibility to be evaluated across the actual activity spaces individuals use. Existing research, however, predominantly examines public transport access in relation to the home location (47,47–52). While this approach is common, it provides only a partial view of travel behaviour because daily mobility is rarely confined to a single anchor. Commuters often begin or end trips at non-home anchors, such as schools, cafés, retail stores, or park-and-ride lots, where accessibility conditions may differ substantially from the residential environment. These differences matter because the built environment associates with mode choice differently at trip origins compared to destinations: origins might typically be associated with time pressure and reliability concerns, while destinations may allow greater flexibility, making walking or transfers more acceptable (412–414). Ignoring these behavioural asymmetries, which refer to variations in decision-making between trip start and end, risks misrepresenting real-world constraints on public transport use (415–417).

Given the gaps identified above, more comprehensive analyses are needed to consider accessibility from multiple points (i.e., home, trip origin, and destination) to more accurately capture how public transport accessibility relates to ridership. While accessibility reflects the potential to reach destinations, understanding how individuals engage with this potential in practice requires behavioural data (418). High-resolution data collection methods, such as GPS tracking and accelerometers, are particularly valuable for examining *origin*- and *destination-based* accessibility with fine spatial and temporal granularity (419). These tools enable the identification of actual trip start and end points, which are often generalised or aggregated in conventional datasets such as census surveys (420). Although census data provide broad population coverage and include origin–destination and mode-of-travel information, they are typically limited to work-related trips and coarse spatial units, which can obscure nuanced travel patterns. In contrast, GPS and accelerometer data provide continuous, real-time monitoring of movement across all trip purposes and contexts, offering a dynamic account of travel behaviour (421). This level of detail allows researchers to examine how accessibility is experienced and acted upon in daily life. Despite their potential, only a limited number of studies have integrated these technologies to examine objective public transport accessibility and ridership behaviour (419,422).

Understanding these dynamics is particularly important in the New Zealand context, where empirical evidence on public transport accessibility remains limited compared to the extensive body of research from Europe and North America (423). New Zealand ranks among the highest globally for private vehicle ownership while exhibiting comparatively low levels of public transport use (55). This imbalance underscores the need for regionally focused investigations that incorporate multi-anchor accessibility to capture behavioural realities more accurately. Thus, using GPS- and accelerometer-derived travel data, this study aims to: 1) assess the relationship between objectively measured accessibility to bus stops and actual bus ridership, and 2) examine whether work status and duration of neighbourhood residency moderate the relationship between accessibility to bus stops and ridership. These objectives will be explored by calculating accessibility to public transport from three distinct points: home residence, trip origin, and trip destination, separately.

Methods and materials

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 (424), which provide specific recommendations for studies using GPS, accelerometers, and other location-based data.

Participants and setting

Participants in this study were drawn from four regions across Auckland: Aorere, Oranga, Wesley, and Waikōwhai (Figure 4-1), all of whom were part of the *Te Hotonga Hapori* research programme, a study focusing on the link between urban redevelopment and community wellbeing. The *Te Hotonga Hapori* study design and recruitment processes are described in detail elsewhere (61). Briefly, as part of this programme, trained interviewers visited households in the four aforementioned regions, explained the study, and invited residents to take part. Eligibility required households to have at least one adult (18 years or older) who consented to participate. Residents who agreed were then interviewed face-to-face in their homes (one participant per household was included). Data were collected at two distinct time points in the Te Hotonga Hapori research programme: from May 2023 to April 2024, and from June 2024 to May 2025. However, as data collection for the second phase was still ongoing when this study began, only the first time point (May 2023 to April 2024) was utilised in this analysis. In total, 485 participants were initially approached and interviewed, of which 108 were included in the study, contributing 835 trips with valid data (described further on). Ethical approval for the study was granted by the Auckland University of Technology Ethics Committee, and informed written consent was obtained from all participants (AUTEC # 21/361).

Figure 4-1. Study area

Spatial data

To collect spatial data, GPS trackers (QStarz BT-Q1000XT) and accelerometers (Axivity AX3) were utilised over seven consecutive days (Figure 4-2). The QStarz BT-Q1000XT, a GPS data logger validated in previous studies (326,327), provides real-time positional information. Using the QTravel software (QStarz International Taipei, Taiwan), the QStarz BT-Q1000XT receivers 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 (328), was used to measure physical activity behaviour. Using the Open Movement software (OMGUI, Newcastle University, Newcastle upon Tyne, UK), the AX3 devices were initialised to record data at 100 Hz with ±8 g bandwidth.

(a) (b)

Figure 4-2. Equipment; (a): AX3 accelerometer, (b): QStarz BT-Q1000XT GPS

Procedures

Between May 2023 and April 2024, several GPS receivers and accelerometers were configured weekly using QTravel and OMGUI software, respectively, and deployed to participants to collect spatial and temporal data. Subsequently, the door-to-door interviewers met participants in person to conduct interviews and distribute the devices. The interview primarily focused on wellbeing outcomes, along with individual- and household-related characteristics (e.g., age, gender, work status, and income). A full copy of the interview schedule is available elsewhere (61). Each participant was provided with one GPS receiver (worn on their waist using a supplied belt) and one Axivity AX3 (worn on their non-dominant wrist using a supplied wristband), both of which were to be worn continuously for one week. Prior to the interview, participants were briefed on the Te Hotonga Hapori study, including its purpose and objectives. They were also instructed to wear the accelerometer at all times, including during sleep, and to charge the GPS receiver each night using the provided charging cable. The GPS device was required to be worn during waking hours. After one week, the interviewers retrieved the equipment from the participants and returned it for data processing. Upon completion, each participant received an NZD 50 (≈USD 30) voucher as a token of appreciation.

Spatial methods – 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 (329,330).

The Python package LABDA (version 0.0.12) was employed to preprocess the GPS and accelerometer data. GPS data were downsampled to 30-second intervals, and the appropriate time zone (NZST, UTC+12, or NZDT, UTC+13) was applied automatically based on the date. The coordinate reference system (CRS) was transformed from EPSG:4326 (WGS 84) to EPSG:32760 (UTM Zone 60S) for spatial analysis. Additionally, home location data were projected to EPSG:2193 (New Zealand Transverse Mercator 2000) for national-scale mapping. GPS points with a sum of viewed SNRs greater than 260 were identified as indoor points, indicating that the participant was likely inside a building. Accelerometer data were downsampled to 30-second intervals, and counts were derived (336). Non-wear time for the accelerometer was defined as periods where the device recorded zero counts continuously for a minimum of 60 minutes (337). 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-meter radius. The starting point of a trip segment (trip origin) was identified when a participant began moving beyond a 25-meter 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-meter radius for at least three minutes. Similar cut points have been utilised and validated in previous studies (329,338). 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 (339).

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 ≤ 10 km/h) and non-walking (> 10 km/h) (340,341). 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 (339). Then, consecutive trip segments that occurred within a temporal gap of less than two hours and within a 50-metre 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 (425). 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.

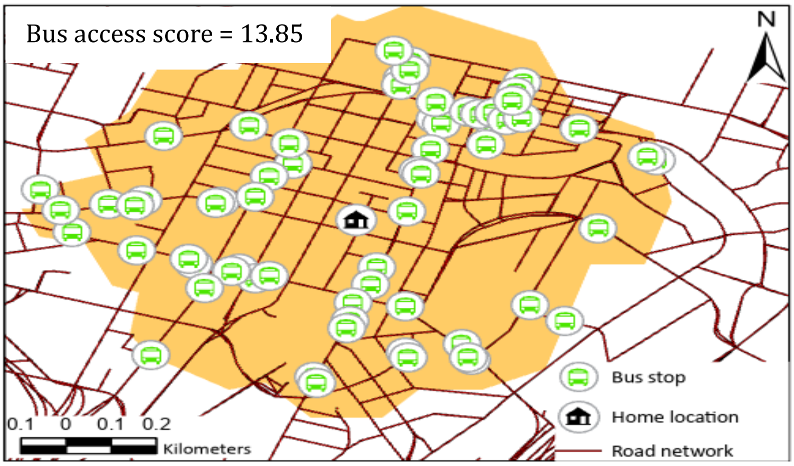
For the purposes of this study, all non-bus modes (walking, cycling, and private motor vehicle trips) were grouped together and contrasted against bus trips. This binary classification reflects the study's primary focus on identifying the factors associated with bus use rather than modelling every travel mode. Accurately distinguishing between non-bus modes (e.g., walking and cycling) 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 (≥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.

Spatial methods – Accessibility to bus stops

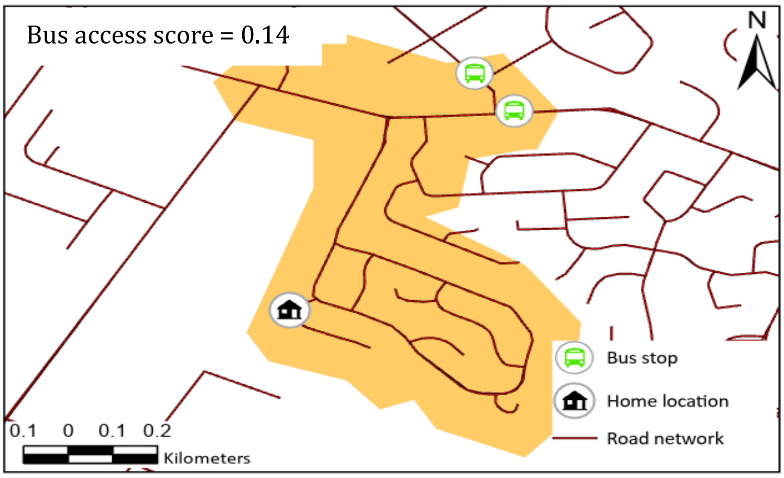
To assess accessibility to bus stops at various key locations (i.e., home, trip origin, and trip destination), participants' residential addresses, trip origins, and destinations were geocoded using ArcGIS Pro (version 3.4.3). Based on road network data from the Land Information New Zealand (LINZ) data service (348), an 800-metre road network buffer was created around each location for every participant. The number of bus stops located within these buffers was then counted. A distance-decay weighting was applied to each identified bus stop. The total weighted accessibility score was calculated by summing the weights of all bus stops within each buffer. This process was repeated to generate *home-based* accessibility to bus stops scores per participant, and *origin-* and *destination-based* accessibility scores per trip.

To calculate the weightings for each identified bus stop, a negative exponential distance decay function (Eq. 4-1) was employed, where d is the distance to the bus stop (in kilometres), and β = 0.4 km is the decay parameter. This value reflects the steep decline in walking propensity over short distances, particularly within dense urban contexts where accessibility is highly sensitive to distance, especially for accessibility to bus stops (426,427). The negative exponential form is theoretically grounded and widely applied in spatial interaction and transport accessibility modelling, owing to its ability to represent distance deterrence effects (21,418,428). Figure 4-3 illustrates a location with high *home-based* accessibility (Figure 4-3a) and another with low *home-based* accessibility to bus stops (Figure 4-3b). The same methodology was applied to both *origin-* and *destination-based* accessibility to bus stops.

$$W(d)=\exp(-d/\beta) \qquad \textbf{(Eq. 4-1)}$$



(a)



(b)

Figure 4-3. *Home-based* bus stop accessibility; (a): High access, (b): Low access

Statistical methods

Descriptive statistics were used to summarise participants' sociodemographic characteristics, the study area's built environment attributes, and trip information. Mixed-effects logistic regression models were employed to investigate the relationship between accessibility to bus stops and bus ridership. This analytical approach accounted for repeated trips within participants, as each participant could have multiple trips. In the unadjusted models, the dependent variable was dichotomised as 0 for non-bus trips and 1 for bus trips. The accessibility to bus stops score in each trip was treated as the fixed effect (independent variable), and participant ID was included as the random effect.

These models were then adjusted for the following sociodemographic covariates as fixed effects: age (18–39 years, 40–64 years, 65 years and over), gender (male, female), household income (low to middle income, high income), ethnicity (Māori, New Zealand European, Pacific, Other), neighbourhood residency duration (less than 3 years, 3 to 10 years, more than 10 years), and work status (employed, unemployed). Ethnicity was self-reported and classified using prioritised ethnicity. Māori, New Zealand European, and Pacific were retained as separate categories, while participants belonging to other ethnic groups were combined into an "Other" category because of small sample sizes. Interaction terms between accessibility to bus stops and work status, as well as accessibility to bus stops and neighbourhood residency duration, were included as fixed effects to test whether these characteristics moderate the relationship between accessibility and ridership. These two factors were selected because they have strong theoretical links with travel behaviour and have been comparatively less examined as moderators, despite evidence that work constraints and familiarity with local facilities can alter how individuals respond to accessibility to public transport (397,429,430). The reference categories for the covariates were individuals aged 18–39 years, female participants, high-income households, Māori participants, and residents who had lived in the neighbourhood for more than 10 years.

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.

All mixed-effects logistic regression models were fitted using the *glmer* function from the *lme4* package in R. Multicollinearity was assessed using variance inflation factors (VIF) (431). Model diagnostics were conducted with the *DHARMa* package. Model fit, as well as marginal and conditional R^2 values were obtained using the *model_performance()* function from the *performance* package.

Results

Descriptive statistics

Table 4-1 provides an overview of the sociodemographic 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 to 10 years (36.11%) and were employed (62.04%).

The mean accessibility to bus stops scores for home locations, trip origins, and destinations were 4.01 (SD = 1.31), 2.11 (SD = 2.48), and 4.32 (SD = 2.28), respectively. The *home-based* accessibility scores ranged from 0.93 to 7.13, *origin-based* scores ranged from 0.14 to 16.70, and *destination-based* scores ranged 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, cycling, and private cars). Non-bus trips had an average duration of 32.50 minutes (SD = 26.40). Bus trips had a shorter average duration of 22.40 minutes (SD = 15.60).

Table 4-1. Descriptives of sociodemographic, 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		
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)	
Accessibility to bus stops		
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)	

Table 4-1. Descriptives of sociodemographic, trip, and built environment characteristics

Parameters	n (%)	Mean (SD)
Trip duration (min)		
Bus trips		22.40 (15.60)
Non-bus trips		32.50 (26.40)

Home-based accessibility to bus stops and bus ridership

Table 4-2 presents the results of unadjusted and adjusted logistic mixed-effects models analysing how objective *home-based* accessibility to bus stops (independent variable) is associated with actual bus ridership (dependent variable). In the unadjusted model, no significant association was found between accessibility to bus stops and ridership behaviour (log-odds = -0.10; 95% CI = -0.38, 0.18; p = 0.490). The conditional R^2 value, which reflects the proportion of variance explained by both fixed and random effects combined, indicated that the model accounted for 33% of the variance in ridership behaviour. In contrast, the marginal R^2 value, representing the variance explained by fixed effects alone, was 0.30%. The intraclass correlation coefficient (ICC = 0.33) indicated that approximately 33% of the total variance in ridership behaviour was attributable to differences between participants (random effects). These findings suggest that *home-based* accessibility to bus stops explained little variation in bus use. This likely reflects that social and individual-level factors are measured more reliably, while objective environmental measures may not capture what matters most to riders.

After individual-level covariates were added to the models, the model explained approximately 40% of the variance in ridership behaviour, with 15% attributable to fixed effects alone and 26% to differences between participants (ICC = 0.26). The results indicated a significant negative association between *home-based* accessibility to bus stops and bus use (log-odds = -0.88; 95% CI = -1.50, -0.25; p = 0.006). No other covariates (e.g., age, gender, ethnicity) showed statistically significant associations with bus use. A borderline significant interaction was observed between accessibility to bus stops and work status (log-odds = 0.59; 95% CI = -0.02, 1.20; p = 0.058), suggesting that the negative effect of accessibility to bus stops on bus use is weakened for unemployed individuals compared to employed individuals, as depicted in Figure 4-4.

Table 4-2. *Home-based* accessibility–bus ridership association - mixed-effects models

Parameters	Log-Odds	SE	95% CI	P-value
Unadjusted model				
Accessibility index	-0.10	0.14	[-0.38, 0.18]	0.490
Adjusted model				
Accessibility index	-0.88	0.32	[-1.50, -0.25]	0.006
Age (ref = 18–39)				
40–64	-0.26	0.43	[-1.11, 0.59]	0.555
65 and over	-0.03	0.78	[-1.55, 1.49]	0.971
Gender (ref = female)	-0.31	0.42	[-1.13, 0.51]	0.454

Table 4-2. *Home-based* accessibility–bus ridership association - mixed-effects models

Parameters	Log-Odds	SE	95% CI	P-value
Household income (ref = high income)	-0.62	0.45	[-1.51, 0.27]	0.169
Ethnicity (ref = Māori)				
New Zealand European	0.27	0.79	[-1.27, 1.81]	0.732
Pacific	0.39	0.88	[-1.33, 2.11]	0.655
Other	0.80	0.80	[-0.77, 2.37]	0.317
Neighbourhood residency (ref = > 10 yrs)				
3–10 yrs	-1.07	1.44	[-3.89, 1.75]	0.457
< 3 yrs	-1.91	1.66	[-5.16, 1.34]	0.250
Work status (ref = employed)	-1.70	1.35	[-4.35, 0.94]	0.207
Accessibility*work status (ref = employed)				
Unemployed	0.59	0.31	[-0.02, 1.20]	0.058
Accessibility*neighbourhood residency (ref =>10 yrs)				
3–10 yrs	0.50	0.37	[-0.22, 1.23]	0.175
3 yrs >	0.72	0.40	[-0.07, 1.51]	0.073
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				

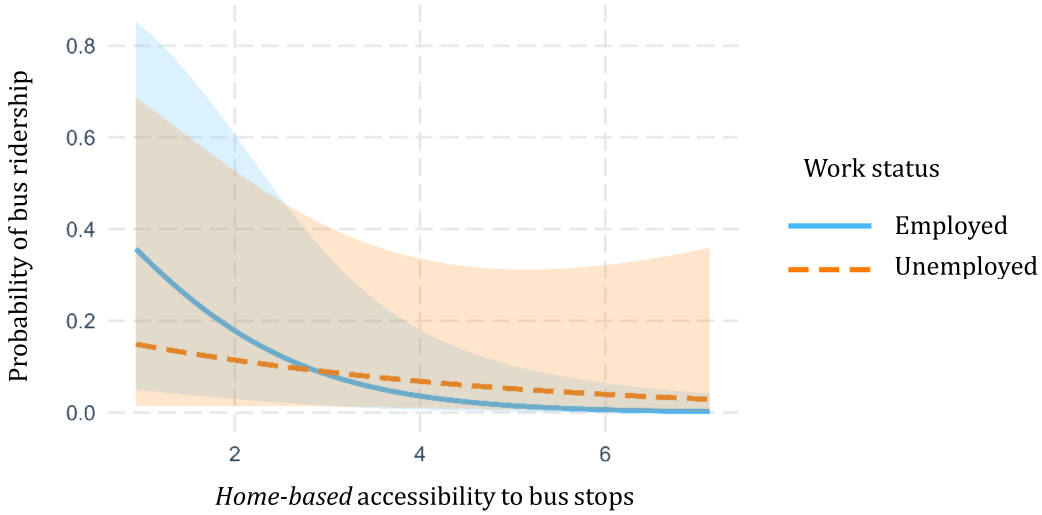


Figure 4-4. *Home-based* accessibility–work status interaction

Origin-based accessibility to bus stops and bus ridership

Table 4-3 presents the results of adjusted and unadjusted logistic mixed-effects models examining the relationship between objective *origin-based* accessibility to bus stops (independent variable) and actual bus ridership behaviour (dependent variable). In the unadjusted model, no statistically significant association was found between accessibility to bus stops and bus use (log-odds = 0.03; 95% CI = -0.06, 0.13; p = 0.502). The conditional R^2 value indicated that the model explained 34% of the variance in ridership behaviour. However, the marginal R^2 value was nearly 0.10%, while the intraclass correlation coefficient (ICC = 0.34) suggested that the majority of the explained variance was attributable to differences between participants. This indicates that the fixed effects contributed minimally to explaining variation in bus use behaviour.

When adjusting for sociodemographic covariates, the total explanatory power of the model, based on the conditional and marginal R^2 values, was approximately 37%, with nearly 9% attributed to the fixed effects and roughly 31% to differences between participants. Similarly, no significant relationship was found between the *origin-based* accessibility to bus stops and ridership behaviour (log-odds = -0.24; 95% CI = -0.63, 0.15; p = 0.230). Furthermore, none of the covariates showed statistically significant associations with bus use.

Table 4-3. *Origin-based* accessibility–bus ridership - mixed-effects models

Parameters	Log-Odds	SE	95% CI	P-value
Unadjusted model				
Accessibility index	0.03	0.05	[-0.06, 0.13]	0.502
Adjusted model				
Accessibility index	-0.24	0.20	[-0.63, 0.15]	0.230
Age (ref = 18–39)				
40–64	-0.39	0.49	[-1.36, 0.58]	0.431
65 and over	0.02	0.82	[-1.59, 1.62]	0.985
Gender (ref = female)	-0.06	0.45	[-0.94, 0.82]	0.892
Household income (ref = high income)	-0.56	0.50	[-1.53, 0.42]	0.261
Ethnicity (ref = Māori)				
New Zealand European	0.01	0.84	[-1.63, 1.65]	0.994
Pacific	0.19	0.92	[-1.61, 2.00]	0.833
Other	0.66	0.82	[-0.95, 2.27]	0.420
Neighbourhood residency (ref = > 10 yrs)				
3–10 yrs	0.36	0.63	[-0.87, 1.59]	0.569
< 3 yrs	-0.02	0.72	[-1.44, 1.39]	0.973
Work status (ref = employed)	0.35	0.61	[-0.84, 1.54]	0.566
Accessibility*work status (ref = employed)				
Unemployed	0.15	0.13	[-0.11, 0.41]	0.264
Accessibility*neighbourhood residency (ref = > 10 yrs)				
3–10 yrs	0.15	0.20	[-0.25, 0.55]	0.467
3 yrs >	0.36	0.21	[-0.05, 0.77]	0.087
Unadjusted model: Marginal R^2 = 0.10 %; Conditional R^2 = 34 %; ICC = 0.34				

Destination-based accessibility to bus stops and bus ridership

Table 4-4 presents the results of adjusted and unadjusted logistic mixed-effects models examining the relationship between objective *destination-based* accessibility to bus stops (independent variable) and actual bus ridership behaviour (dependent variable). In the unadjusted model, the correlation between *destination-based* accessibility and bus use behaviour was found to be statistically significant (log-odds = 0.12; 95% CI = 0.02, 0.22; p = 0.017). The conditional R^2 indicated that the model explained nearly 31% of the variance in ridership behaviour, while the marginal R^2 was approximately 2%, suggesting that fixed effects explained only a small portion of the variability. The ICC (0.30) further indicated that a substantial proportion of the total variance was attributable to differences between participants, underscoring the importance of accounting for individual-level variability in the model.

When adjusting for individual-level attributes, the model explained approximately 32% of the variance in bus usage, with 8.50% attributable to fixed effects and about 26% to between-participant differences (ICC = 0.26). No statistically significant association was found between the *destination-based* accessibility to bus stops and ridership behaviour (log-odds = -0.05; 95% CI = -0.25, 0.15; p = 0.623). However, the positive association between *destination-based* accessibility and bus use was stronger among residents who had lived in the neighbourhood for less than three years (log-odds = 0.29; 95% CI = 0.01, 0.57; p = 0.045), which is depicted in Figure 4-5.

Table 4-4. *Destination-based* accessibility–bus ridership - mixed-effects models

Parameters	**Log-Odds**	**SE**	**95% CI**	**P-value**
Unadjusted model				
Accessibility index	0.12	0.05	[0.02, 0.22]	0.017
Adjusted model				
Accessibility index	-0.05	0.10	[-0.25, 0.15]	0.623
Age (ref = 18–39)				
40–64	-0.08	0.43	[-0.91, 0.76]	0.856
65 and over	0.25	0.76	[-1.23, 1.73]	0.741
Gender (ref = female)	-0.25	0.39	[-1.02, 0.52]	0.520
Household income (ref. = high income)	-0.53	0.44	[-1.40, 0.34]	0.230
Ethnicity (ref = Māori)				
New Zealand European	0.22	0.75	[-1.26, 1.70]	0.769
Pacific	0.22	0.84	[-1.43, 1.88]	0.794
Other	0.55	0.75	[-0.92, 2.03]	0.461
Neighbourhood residency (ref = > 10 yrs)				
3–10 yrs	0.12	0.78	[-1.40, 1.64]	0.876
< 3 yrs	-0.51	0.86	[-2.20, 1.19]	0.559
Work status (ref = employed)	-0.20	0.76	[-1.68, 1.29]	0.794
Accessibility*work status (ref = employed)				
Unemployed	0.16	0.13	[-0.10, 0.42]	0.220
Accessibility*neighbourhood residency (ref = > 10 yrs)				
3–10 yrs	0.12	0.15	[-0.16, 0.41]	0.394
3 yrs >	0.29	0.14	[0.01, 0.57]	0.045
Unadjusted model: Marginal R^2 = 1.60 %; Conditional R^2 = 31%; ICC = 0.30				

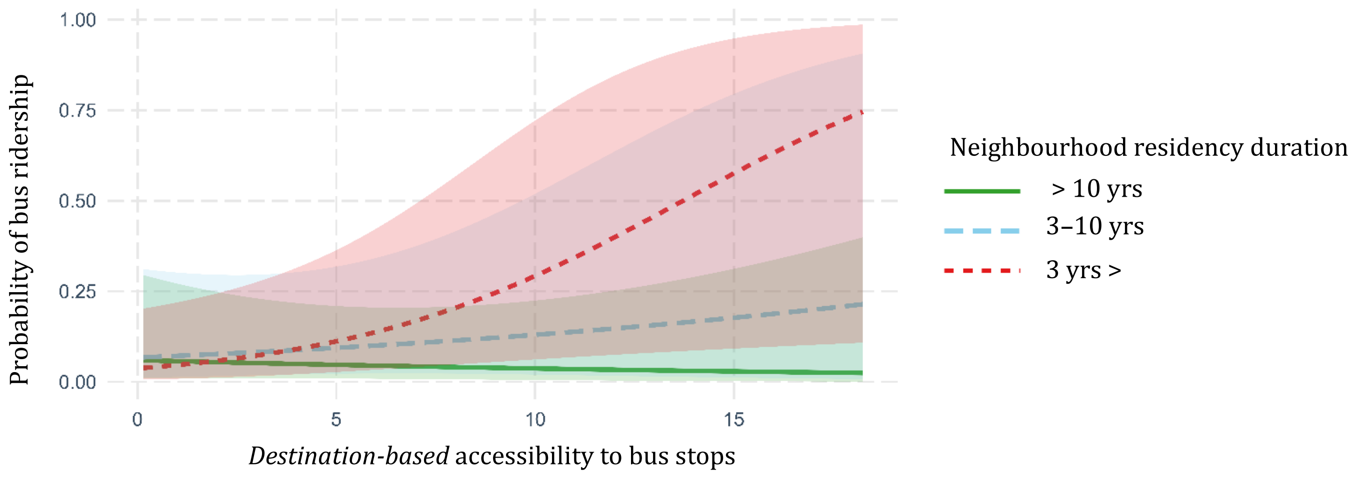


Figure 4-5. *Destination-based* accessibility–residency duration interaction

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 (Appendix C). Including all three spatial anchors simultaneously allows for the assessment of distinct accessibility contexts encountered during a single trip, providing a comprehensive representation of real-world travel patterns. This model showed that *home-based* accessibility remained negatively associated with actual ridership behaviour (log-odds = -0.82; 95% CI = -1.45, -0.18; p = 0.012).

Discussion and conclusion

This study investigated how accessibility to bus stops, measured from multiple spatial anchors—home, trip origin, and destination—relates to actual bus use. By incorporating all three anchors, the analysis moved beyond traditional home-based approaches to reflect the complex, multi-sited nature of everyday mobility. Using GPS and accelerometer data to capture real-world travel behaviour, the study also examined how individual factors, such as work status and neighbourhood residency duration, moderate the association between accessibility and ridership. The results challenge the common assumption that greater proximity to public transport often translates into higher ridership (119,432), revealing instead a more nuanced and context-dependent relationship that varied according to individual circumstances.

Across the models, the associations between accessibility to bus stops and bus ridership appeared to be mainly correlated with unmeasured individual-level characteristics, such as travel habits, personal attitudes, or lifestyle preferences (355,433). This outcome is plausible, as individual-level factors are typically more internally consistent, being collected from the same respondent, and may therefore exert a stronger association with 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 (434). 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 (357,358,433). Residential self-selection may further contribute, as housing decisions often reflect broader lifestyle preferences, including school access, housing features, and neighbourhood amenities. As a result, proximity to bus stops does not necessarily translate into frequent or intensive public transport use (433,435). Together, these behavioural and structural factors plausibly explain why accessibility measures alone accounted for only a small proportion (low marginal R^2 values and high ICCs) of the observed variability in bus ridership in this study.

An additional feature of the results was the notable difference between the unadjusted and adjusted models for home-based accessibility to bus stops. While the unadjusted model showed little evidence of an association with ridership behaviour, the association became considerably stronger after adjusting for socio-demographic covariates and interaction terms. This pattern suggests that the relationship between accessibility and bus ridership may have been obscured by participant characteristics associated with both accessibility and travel behaviour. In particular, work status, neighbourhood residency duration, and their interactions with accessibility appeared to alter the estimated association, indicating that accessibility–ridership relationships may differ across population subgroups. Although the present analysis was not designed to formally distinguish between confounding and suppression effects, this result highlights the importance of accounting for individual circumstances when examining associations between accessibility and public transport use.

Contrary to established findings in the literature (208,436,437), a negative association emerged between *home-based* accessibility to bus stops and ridership, suggesting that higher local stop density may sometimes be associated with lower use. This pattern may reflect the complex interplay between built environment characteristics and travel behaviour. Areas with dense bus stop coverage are often centrally located and highly walkable, where short distances and pedestrian-friendly infrastructure make walking or cycling more attractive alternatives to public transport. At the same time, high stop density does not necessarily equate to efficient or reliable service. Closely spaced stops can contribute to slower travel times and reduced schedule adherence, particularly in cities with mixed-traffic operations or limited bus prioritisation (438). Recent evidence from Auckland's bus network illustrates this point. Despite abundant stops and frequent services, Auckland's buses often experience delays exceeding 30 minutes and frequent cancellations (439,440). Furthermore, official performance metrics, measuring punctuality only at initial stops and excluding missed services, often obscure commuters' real-world experiences, ultimately undermining trust (441). Thus, high stop density does not ensure attractive services if operational performance remains poor, potentially prompting continued reliance on private transport.

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. The findings suggest that the association between home-based accessibility to bus stops and bus ridership differed between employed and unemployed participants. This may reflect the greater temporal flexibility afforded to those outside the workforce, allowing them to adapt more easily to longer travel times or less reliable services (442). It is also possible that unemployed individuals, due to lower incomes or limited access to private vehicles, are effectively captive users of public transport, regardless of its quality or availability (443). In both cases, these patterns may reflect greater adaptability to service conditions or fewer viable transport alternatives. One possible explanation is that employed individuals, who often face rigid schedules and time constraints, may experience accessibility and service conditions differently from unemployed participants. However, the mechanisms underlying these differences cannot be determined from the present study.

Destination-based accessibility showed a distinct pattern of association with bus use, moderated by how long individuals had lived in their neighbourhood. Specifically, its association with bus ridership was significant only among newer residents, with no comparable effects for home- or origin-based measures. This asymmetry may reflect the fact that home and trip origin environments are typically more familiar and habitually navigated, which limits the behavioural influence of accessibility in those spaces, regardless of how long someone has lived there (358,435,444). In contrast, destination environments, such as workplaces, service centres, or recreational facilities, are often more varied and purpose-driven, making accessibility at these locations more behaviourally salient, particularly for newer residents. While such variability exists for all individuals, long-term residents are more likely to rely on established travel routines, reducing their sensitivity to contextual differences. Relocation, by contrast, disrupts these habits and creates a period of behavioural flexibility, during which destination accessibility can more strongly relate to travel choices (357,445,446). Newer residents may also be more likely to be employed and still forming commute patterns, making accessibility at destinations especially salient during this period of adjustment (445).

Taken together, these findings highlight the limitations of relying on static, home-based accessibility measures as proxies for public transport use. More broadly, they suggest that accessibility alone may be insufficient to explain ridership behaviour. Engagement with public transport depends not only on spatial proximity, but also on behavioural context, flexibility of routines, service quality, and the purpose and variability of destinations.

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 merged when the temporal gap was less than two hours and the spatial separation was less than 50 metres, 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 use may overstate actual ridership by including some non-bus trips that met the spatial overlap threshold. This binary outcome may also obscure mode-specific associations, 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 capturing a broader spectrum of real-world trip destinations and evaluating accessibility across multiple spatial anchors, it is limited by the absence of explicit trip-purpose data and conceptual ambiguity regarding anchor roles. For instance, when trips start at home, *home-based* and *origin-based* accessibility measures coincide; similarly, when returning home, *destination-based* and *home-based* accessibility overlap. These cases complicate efforts to differentiate distinct behavioural associations. While this research extends beyond the conventional focus on commuting to workplaces, future studies could enhance interpretability by explicitly collecting trip-purpose data, or by incorporating additional context related to activity type, directionality, and trip purpose segmentation.

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 is an important characteristic associated with stop attractiveness. 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 (AVL) feeds or GTFS Realtime (447,448), 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.

Another limitation is that the analysis focused specifically on accessibility to bus stops and did not explicitly account for accessibility by competing travel modes, such as walking, cycling, or private vehicles. Although accessibility to bus stops was calculated using the pedestrian road network and therefore incorporated the ability to walk to transit infrastructure, broader accessibility conditions associated with other travel modes were not examined. Because travel modes often compete with one another, accessibility associated with one mode may influence the use of others. Future studies could simultaneously examine accessibility across multiple travel modes to better understand their relative associations with public transport ridership.

Finally, 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 associates of transport mode choice. Doing so would enhance both the explanatory power and interpretability of findings.

Policy implications

The findings of this study suggest that simply increasing proximity to bus stops does not necessarily translate into higher ridership. Instead, other factors may also be important correlates of travel behaviour, highlighting the need to consider service quality and individual-level characteristics alongside spatial accessibility. In the Auckland context, higher *home-based* bus stop density was associated with lower bus use. Although this study did not account for key factors such as travel time, service quality, or operational efficiency, one plausible explanation is that an overly dense stop network may coincide with slower or less reliable services, particularly for individuals with rigid time constraints. These interpretations are necessarily speculative and underscore the need for further empirical investigation. Nonetheless, the findings suggest that transport policy could benefit from considering not only the quantity but also the spatial configuration of public transport infrastructure, including the acceptable walking distances for accessing services, when seeking to improve public transport use.

The results underscore the importance of aligning bus service design with the differing time constraints and travel resources of user groups. Employed individuals in this study were more sensitive to *home-based* accessibility, which may reflect their need for predictable and time-efficient travel. For employment-dense residential areas, this suggests that services could prioritise peak-hour frequency, reduced wait times, and reliable schedules. By contrast, unemployed or part-time populations, who may have greater temporal flexibility but also face lower incomes and limited access to private vehicles, might benefit more from broad spatial coverage and affordable off-peak services. Tailoring service provision to these differentiated needs could help mitigate transport disadvantage among vulnerable groups.

Although the association between *destination-based* accessibility and bus use in relation to residency duration warrants further investigation, it may have implications for transport planning in areas experiencing high residential turnover. Recent movers, who may be younger, more likely to be employed, or living in public housing managed by Kāinga Ora (the New Zealand government agency responsible for public housing and urban development), appeared more likely to use the bus when their destinations were well served by public transport. While the underlying mechanisms remain uncertain, this pattern suggests that ensuring strong public transport connectivity around key destinations such as employment hubs and community services may be particularly important for supporting mobility during periods of residential adjustment. Policies aimed at improving accessibility in such contexts may help facilitate public transport use among populations undergoing transition.

Altogether, these findings highlight the complexity of accessibility-ridership relationships and suggest that accessibility alone may not be sufficient to explain variation in public transport use. Given the observational nature of the study and the potential influence of unmeasured confounding factors, the findings should be interpreted cautiously. Future research would benefit from study designs that more explicitly account for competing explanations, including service quality, residential self-selection, and accessibility associated with other travel modes. Such work would help clarify the extent to which accessibility is associated with public transport use and inform the development of more comprehensive measures of accessibility.

Chapter 5. Is all access equal? Examining how domain-specific accessibility measures correlate with shared e-scooter trip flows

Preface

The previous chapters examined walking and public transport as two established pathways for reducing car dependency. The following two studies shift focus to micromobility, investigating how emerging modes can be more effectively integrated into sustainable urban mobility systems. Despite rapidly expanding literature on shared micromobility services, empirical evidence remains limited regarding how specific built environment characteristics at trip origins and destinations are associated with usage patterns for shared e-scooters. Employing a gravity-based origin–destination framework, this study provides nuanced insights into how domain-specific accessibility measures at both ends of a trip are associated with trip generation within a predominantly car-dependent urban context. This manuscript has been submitted for publication. The data-sharing agreement under which the data were received from a service provider in Auckland is presented in Appendix B.

Abstract

Shared e-scooters are increasingly integral to sustainable urban mobility networks, yet the spatial factors underlying their demand remain context-specific and insufficiently understood. Existing research often relies on aggregate land-use proxies or predictive models, limiting interpretability for policy and planning. This study addresses these gaps by examining associations between domain-specific accessibility and shared e-scooter usage in Auckland, New Zealand. Drawing on 57,842 origin–destination trip pairs recorded over a 14-month period, we applied a gravity-based negative binomial model to assess trip volumes in relation to accessibility to public transport, recreational areas, shopping centres, education facilities, and environmental "bads" (e.g., alcohol and fast-food outlets), along with network-based trip length, socio-economic indicators, and weather attributes. Results reveal pronounced distance-decay effects consistent with the short-range nature of e-scooter travel. Higher trip volumes were observed in areas with greater accessibility to public transport and recreational amenities, indicating a spatial alignment between micromobility use and leisure or multimodal transport nodes. In contrast, lower usage was associated with greater accessibility to shopping and education facilities, higher exposure to environmental "bads," elevated car ownership, and increased deprivation. These spatial disparities underscore the associations of urban form and local context with shared micromobility patterns and highlight the need for equity-oriented planning in sustainable transport systems.

Introduction

Shared electric scooters (e-scooters) have rapidly emerged as a defining feature of contemporary urban transport systems, offering flexible, on-demand, and low-emission mobility solutions for short-distance travel. Their compact design, electric propulsion, and relatively high travel speed make them a time-efficient and less physically demanding options for short trips. These attributes have contributed to a sharp increase in global ridership (39,224–228). In New Zealand, approximately 28.6 million micromobility trips have been recorded since their introduction in late 2018, with nearly 28 million trips undertaken on shared e-scooters, underscoring their dominance in a small, car-dependent transport market (449). Similar patterns are evident in North America, where systems in the United States and Canada collectively logged 157 million trips in 2023, with shared e-scooters accounting for nearly half (449,450). In Europe, the sector has expanded even more dramatically, with over 268 million shared micromobility trips recorded across 515 cities in 24 countries in 2022, 240 million of which were made on shared e-scooters (451). This surge in adoption, particularly in dense urban centres, highlights the growing role of shared micromobility in global efforts to promote more sustainable and equitable transport systems. In this context, understanding the factors associated with e-scooter use has become increasingly important.

A growing body of research on shared e-scooters has examined travel behaviour, safety concerns, and environmental impacts (72,276,452–459). Studies of travel behaviour suggest that shared e-scooters can meet short-trip mobility demands in central urban areas, facilitating access to destinations such as university campuses, shopping centres, restaurants, and parks in dense, mixed-use settings (20,72,460). Evidence from transatlantic contexts often associates e-scooter use with leisure and tourism, particularly during warmer seasons, while others highlight more utilitarian purposes, including errands and social visits (20,276,277,279,455,461,462). In contrast, early survey data from New Zealand reveal a stronger emphasis on commuting-oriented trips (234). Overall, the literature indicates that shared e-scooter use is associated not only with individual travel needs but also by the surrounding built-environment context, with higher usage frequencies observed in central areas where infrastructure and activity density support short-distance travel (256,259,274,463). This spatial concentration, while consistent with the short-trip nature of e-scooter travel, may also reflect uneven service provision, raising concerns that shared e-scooter systems could perpetuate rather than mitigate existing transport inequities.

Advancing equitable micromobility infrastructure and policy requires analytical tools that reveal the spatial mechanics of demand, enabling planners to identify both high-demand zones and systematically underserved areas (464). Gravity-based origin–destination (OD) approaches, long established in transport research and planning, capture flows between origins and destinations and elucidate how land use and urban form are associated with usage patterns (20,53,54,465–469). These models typically represent flows as increasing with the "mass" of origins and destinations, often proxied by population, land use, or service opportunities, and decreasing with the impedance of separation, such as distance, cost, or time (470,471). This balance between attraction and friction gives rise to the well-documented distance-decay pattern in travel behaviour. Yet despite their potential, OD models have rarely been applied to shared e-scooter systems. A notable exception is the work of Karimpour and colleagues (20), who employed a gravity-inspired random forest model to analyse e-scooter trip flows. Their findings revealed a strong distance-decay effect and showed that trip volumes were highest in areas with strong production and attraction capacities, particularly in retail and entertainment districts. However, the absence of coefficient estimates in machine learning methods, commonly employed in prior studies, limited the interpretability of their findings (460). These insights highlight the importance of OD approaches that combine advanced spatial modelling with interpretable frameworks to inform equitable service allocation and support sustainable micromobility planning.

Accessibility, conceived as the ease of reaching nearby services and amenities, is a fundamental correlate of OD flows and thus central to the explanatory capacity of gravity-based models (21,310). Notwithstanding its central role, micromobility research often relies on coarse proxies of accessibility, such as relative location within the urban hierarchy (e.g., distance from the city centre) or aggregate measures of land-use diversity (e.g., see (72,274)). While such measures capture macro-level spatial structure, they provide limited insight into how access to specific destinations aligns with observed travel patterns. Collapsing different forms of accessibility into a composite index, for example, combining access to public transport, employment, recreation, and nightlife, can obscure their distinct associations. The positive effect of one domain may be diluted or masked by the contrasting effect of another, reducing the clarity and validity of the results. Recent work has begun to consider accessibility to particular amenities, such as restaurants or museums, and has shown differentiated effects on e-scooter use patterns (20). However, such studies remain scarce, particularly for shared e-scooter systems, highlighting the importance of investigating how usage patterns are shaped by disaggregated, domain-specific dimensions of accessibility.

Auckland, New Zealand, offers a compelling context to address these gaps. As one of the most automobile-dependent metropolitan regions globally among cities of comparable size, it is marked by the predominance of private vehicle travel and persistently low uptake of alternative modes (56,57). In an effort to confront these systemic mobility challenges, Auckland Council and Auckland Transport launched a pilot e-scooter scheme in late 2018 to test the potential of shared micromobility for reducing car dependence and facilitating modal shift (472,473). The programme observed rapid uptake, with more than 40,000 trips recorded in the first week alone and annual ridership increasing to approximately two million trips (59,60). Despite this growth, more than 80% of Aucklanders continue to rely on private vehicles for their daily travel (58). This paradox of high initial adoption amidst enduring car dependence raises critical questions about how shared e-scooter systems are being used, by whom, and in which parts of the city. Understanding the spatial distribution of demand, and the extent to which it aligns with or diverges from existing accessibility and socio-economic patterns, is vital for evaluating the potential of shared micromobility to support a meaningful modal shift in cities such as Auckland. Without such insight, there is a risk that shared e-scooter systems remain concentrated in already well-served, high-amenity areas, thereby constraining their contribution to broader goals of transport equity and sustainability.

Accordingly, the primary motivation of this study is to contribute to the knowledge base on the sustainable and inclusive deployment of shared e-scooters in an Asia–Pacific context by:

- Incorporating fine-grained, domain-specific accessibility measures, allowing policymakers to assess how different urban amenities are associated with shared micromobility use beyond what aggregate proxies can capture.
- Applying a gravity-inspired negative binomial model to OD patterns of shared e-scooter trips, providing a transferable analytical tool for evaluating spatial demand and informing deployment strategies.

Altogether, these contributions generate empirical evidence on distance-decay patterns, land-use relationships, and equity-related disparities in a highly car-dependent city, while introducing a transferable, data-driven framework to support equitable micromobility planning.

Methods and materials

This section outlines the methodological framework for analysing spatial patterns of shared e-scooter demand in Auckland, New Zealand. It describes the study area, data, and analytical procedures employed to construct OD trip matrices. A gravity-inspired generalised linear model (GLM) with a negative binomial specification is then introduced to assess how domain-specific accessibility measures, socio-economic context, and weather conditions are associated with trip volumes. Figure 5-1 summarises the workflow, showing data inputs, processing steps, and the estimation of the gravity-based negative binomial model.

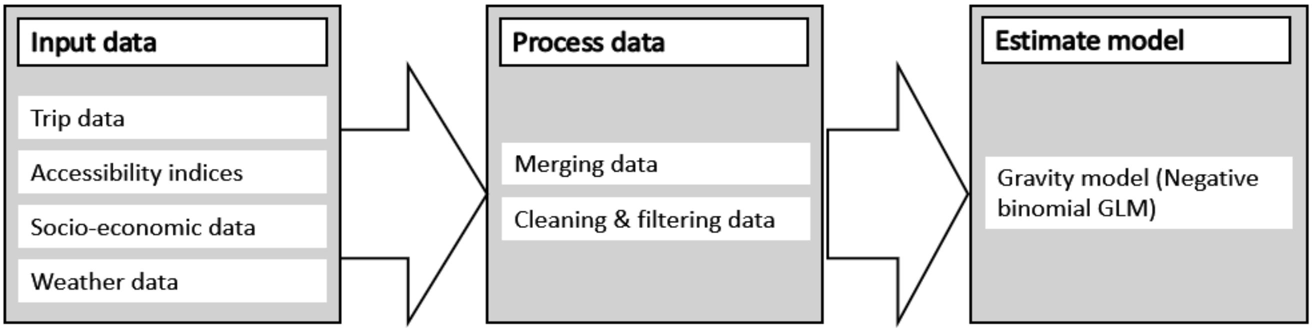


Figure 5-1. Methodological workflow of this study

Study area

This study was conducted in Auckland (Figure 5-2), the largest and most populous city in New Zealand, with an estimated population of 1.76 million in 2023 (62). As shown in Figure 5-2, the population is predominantly concentrated in the central parts of Auckland, where administrative areas are smaller in size, reflecting higher population density. Auckland is characterised by a highly urbanised environment, substantial suburban sprawl, and a reliance on private motor vehicles, alongside recent investments in micromobility infrastructure such as cycleways and e-scooter sharing schemes (474). The city's varied urban form and transport network make it a relevant context for examining relationships between urban form, socio-economic conditions, and shared micromobility use.

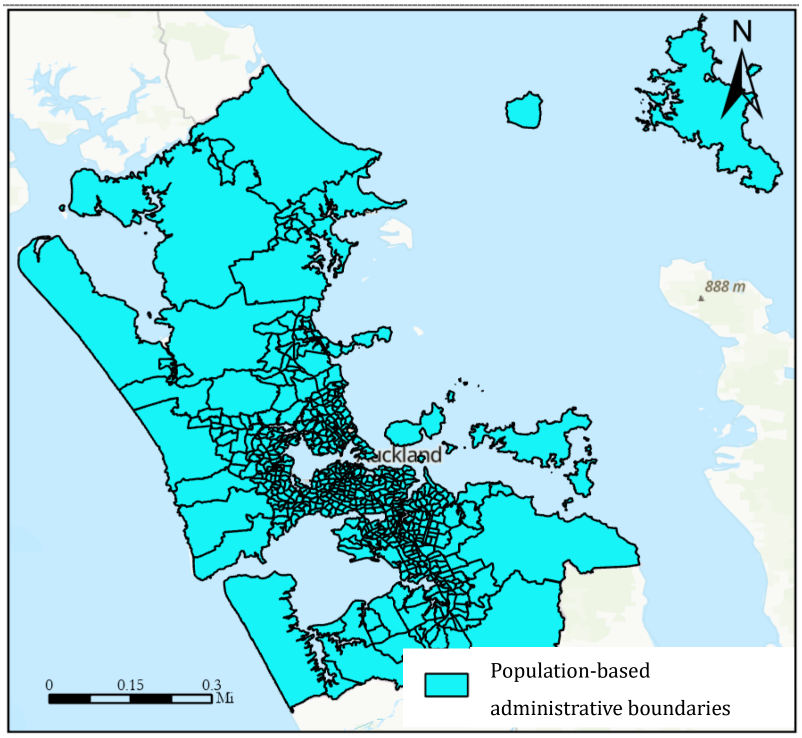


Figure 5-2. Study area – Auckland, New Zealand

Study data

For this study, e-scooter trip records were obtained from a shared micromobility operator, covering trips undertaken in Auckland, New Zealand, between 1 April 2023 and 31 May 2024. The dataset includes origin and destination coordinates, as well as timestamp information for each e-scooter trip. The micromobility operator provided access to the trip data but had no role in the study design, data analysis, interpretation of findings, or preparation of the thesis. Although the data-sharing agreement permitted the operator to review outputs prior to publication, it had no influence over the analyses, results, or conclusions presented in this thesis.

The walkability-based accessibility index used in this study was originally developed for urban areas in New Zealand. It captures accessibility to a range of destinations, including education, public transport, recreational amenities, shopping facilities, and facilities such as fast-food and alcohol outlets that are labelled as environmental "bads". The original index ranks domain-specific accessibility in urban areas at the SA1 level, from 1 (highest accessibility) to 21,508 (lowest accessibility). SA1s are New Zealand's smallest statistical geography (approximately 100–200 residents), offering fine spatial granularity while preserving individual privacy (475). Detailed information on the construction of the index is available elsewhere (349).

To capture the socio-economic context, we incorporated NZDep2023, developed by the University of Otago, and car ownership data (mean number of vehicles per household at the SA1 level) from the 2023 New Zealand Census (476). NZDep2023 is the New Zealand Index of Socioeconomic

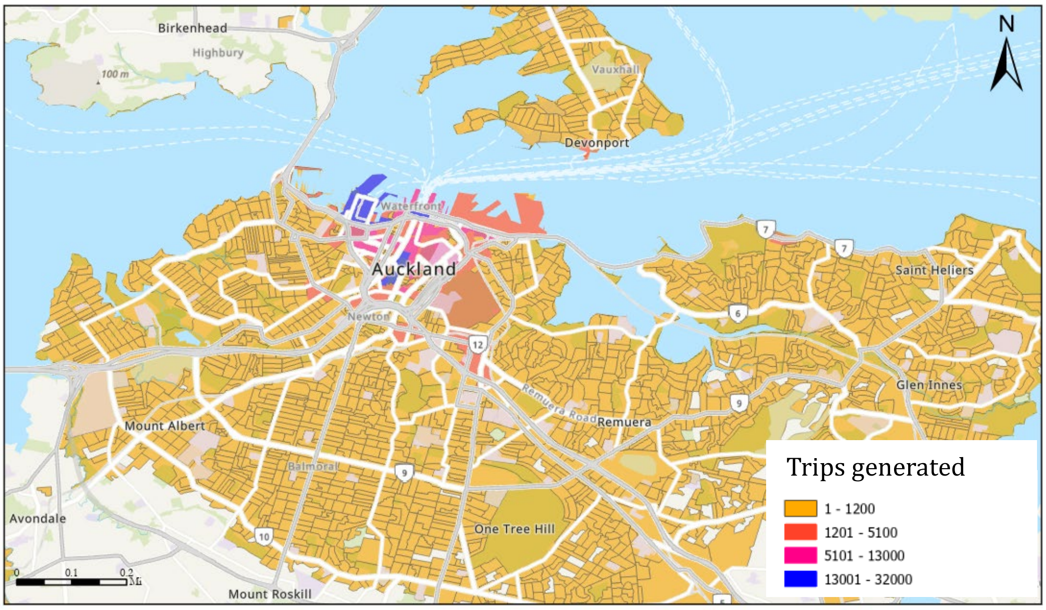
Deprivation, a small-area measure constructed using 2023 Census data. It combines eight dimensions of deprivation, including communication, income, employment, education, home ownership, access to support, living space, and housing condition, to assign a deprivation score to each SA1. These scores are ranked into deciles, with decile 1 representing the least deprived areas and decile 10 the most deprived. The index measures area-level deprivation rather than individual or household circumstances and is widely used in public health and urban planning to identify and address social inequalities (477).

Weather conditions were also incorporated into the analysis using temperature data from the Auckland Airport meteorological station, sourced via Meteostat (478). Although temperatures in Auckland are generally mild, this variable was retained to facilitate comparability with the international literature. Precipitation data were obtained from NIWA, based on records from the Raoul Island meteorological station (479). Humidity data contained substantial missing values and were therefore excluded from the analysis.

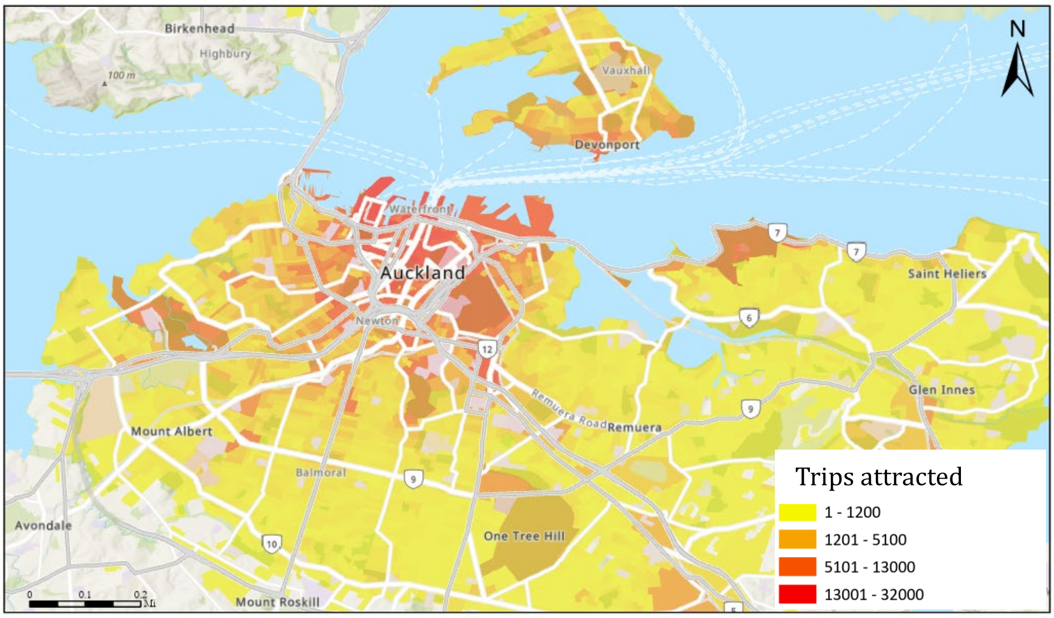
Data processing

Trip origin and destination coordinates were first spatially matched to SA1 polygons using ArcGIS Pro (version 3.5.2). Then, to estimate travel distances between trip origins and destinations, a Python-based geospatial analysis pipeline was developed (Appendix D), leveraging OpenStreetMap (OSM) road network data. The bikeable road network for Auckland, New Zealand, was retrieved and projected using the *osmnx* library, forming the basis for network-based trip distance calculations. Origin and destination coordinates were geospatially matched to the nearest nodes on the OSM network using a Haversine-based nearest-neighbour search, which estimates great-circle distances between points on the Earth's surface based on latitude and longitude (480). Shortest-path distances between these nodes were computed via *networkx*, with edge weights corresponding to the physical lengths of road segments. To reduce noise arising from GPS error and implausible routing, trips were filtered to include only those with network-based lengths between 200 metres and 5,000 metres, following established best practices (481,482).

Area-level accessibility indices (i.e., accessibility to education, recreation areas, shopping facilities, public transport, environmental "bads"), socio-economic covariates (i.e., NZDep2023 and vehicle ownership), and weather attributes (i.e., temperature and precipitation) were linked to both trip origins and destinations via SA1 codes. Trips were aggregated into a directional OD matrix at the SA1 level, with each OD pair representing trips from a specific origin SA1 to a specific destination SA1. For each directional OD pair, the total number of trips was calculated, along with the mean values of trip-level attributes, including network-based trip distance, temperature, and precipitation, across all trips between that origin and destination. To provide a clearer visualisation of e-scooter trip activity across SA1s, Figure 5-3 presents total trip generation (Figure 5-3a) and trip attraction (Figure 5-3b). As shown, most trips originated and ended in central SA1s.



(a)



(b)

Figure 5-3. Travel demand patterns; (a): Trip origins, (b): Trip destinations

To reduce skewness, the accessibility indices were reversed and log-transformed, such that a value of $\ln(1) = 0$ represented the lowest accessibility and $\ln(21{,}508) = 9.97$ represented the highest accessibility to neighbourhood facilities. The network-based trip distance was also log-transformed for analysis. To enhance interpretability, all variables were standardised, including trip length, accessibility indices, weather attributes, and socio-economic characteristics.

Statistical modelling

All analyses were conducted using RStudio (version 2025.5.0.496). Given that machine learning models (e.g., random forest) are primarily predictive and do not provide interpretable coefficient estimates, we employed a negative binomial generalised linear model (GLM) within a gravity modelling framework to examine the association between walking accessibility and shared e-scooter trip volumes (Eq. 5-1). The negative binomial specification was selected both for its ability to produce interpretable coefficients and to appropriately account for overdispersion in trip count data (20). Within this framework, total trip demand (trip count) is modelled as a function of the attractiveness (e.g., accessibility) of both the origin and the destination, as well as the distance (or cost) between them. The expectation is that the attractiveness of an origin and destination is positively associated with trip count, whereas cost is negatively associated. The model was estimated using only OD pairs with at least one observed trip, thereby focusing on variation in trip volume conditional on trip presence. Estimation was undertaken via maximum likelihood, with initial values generated from a Poisson GLM and final estimates obtained using the *glm.nb* function in the MASS package.

Formally, let y_{ij} denote the number of trips from origin i to destination j. We assume

$$\boldsymbol{y_{ij} \sim NegBin\left(\mu_{ij}, \alpha\right), \qquad log\, \mu_{ij} = \beta_0 + \beta_1\, x_{1,ij} + \beta_2 x_{2,ij} + \cdots + \beta_p x_{p,ij}} \qquad \textbf{(Eq. 5-1)}$$

where $\mu_{ij} = \mathbb{E}[y_{ij}]$, α is the overdispersion parameter, and $x_{k,ij}$ denotes explanatory variables.

The dependent variable was the number of trips per OD pair at the SA1 level. The independent variables included in the analysis were the accessibility scores for education facilities, recreation zones, shopping centres, public transport services, and environmental "bads" (each measured separately for the origin and destination SA1s). The number of vehicles per household and the NZDep2023 deprivation index were also included for both the origin and destination zones. In addition, the mean network-based trip distance, mean trip-level temperature, and mean trip-level precipitation for each OD pair were specified as independent variables.

To assess the impact of influential observations, Cook's distance was calculated for all OD pairs in the z-standardised negative binomial model. A conservative threshold of 4/n (where n is the number of OD pairs) was applied, corresponding to a cutoff of 5.77×10^{-5} in this study (483). OD pairs exceeding this threshold were excluded from the analyses to improve model fit. As a sensitivity analysis, the results based on the full sample, prior to the exclusion of influential OD pairs, are reported in Appendix C, whereas the trimmed-sample model formed the basis of the main analyses. To examine whether origin and destination characteristics differed meaningfully, Pearson correlation coefficients between origin and destination values were also calculated. Model estimates are presented as incidence rate ratios (IRRs) with 95% confidence intervals (CIs), obtained by exponentiating the estimated coefficients.

Results

Descriptive statistics

Out of 478,028 trips, 60,014 valid OD pairs were retained after data cleaning and filtering. After excluding OD pairs exceeding the Cook's distance threshold, 57,842 OD pairs remained for the analysis. Figure 5-4 illustrates how shared e-scooter usage fluctuates throughout the day. Distinct morning and evening peaks are evident on weekdays, whereas weekend patterns are characterised by later starts and higher evening activity.

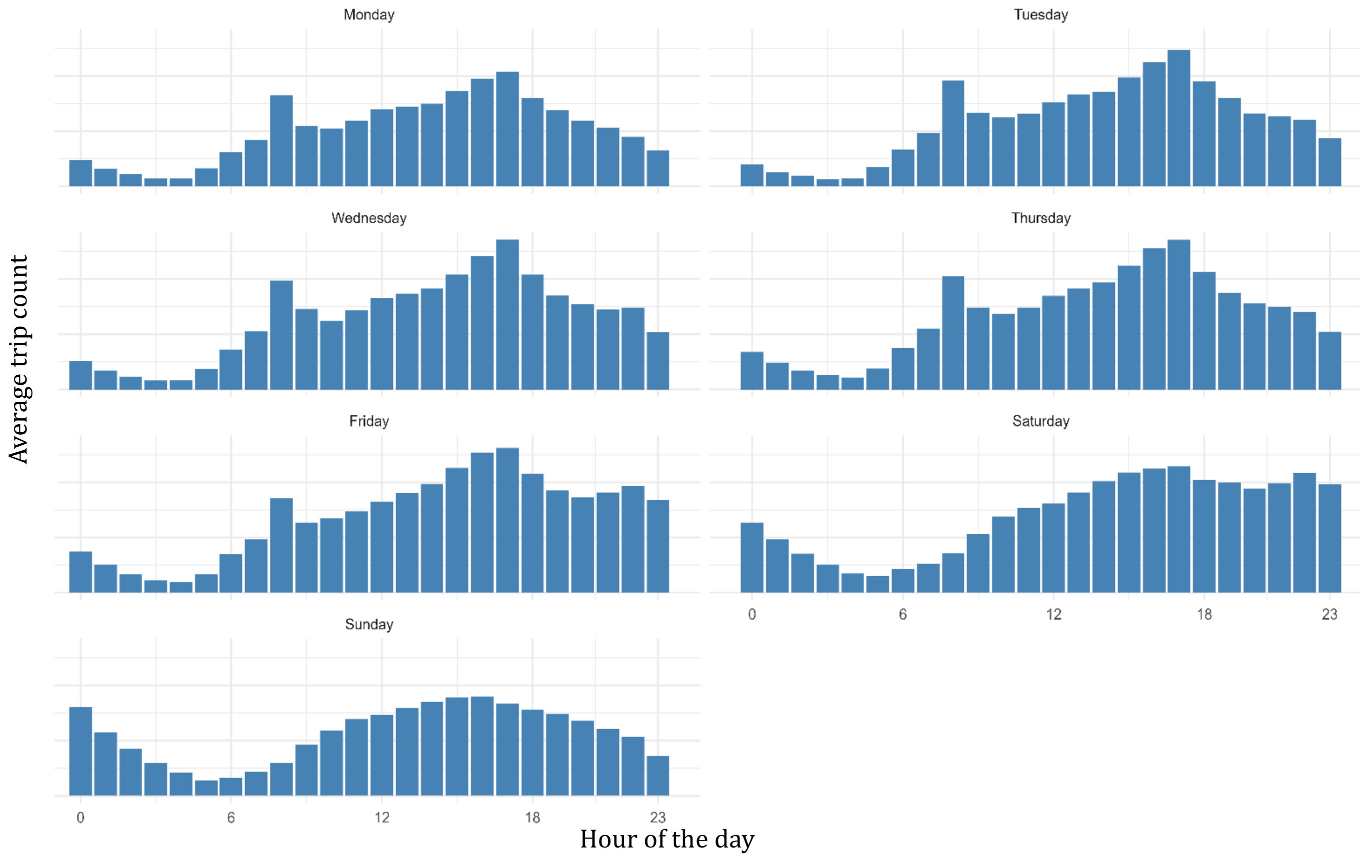


Figure 5-4. Average hourly distribution of e-scooter trips

Table 5-1 provides descriptive statistics for key variables used in the analysis of OD pairs. The average number of trips per OD pair was 6.90 (SD = 61.02), reflecting substantial variability in trip frequencies across OD pairs, consistent with the high dispersion addressed in the subsequent modelling. The mean inter-SA1 network-based trip distance was 1.67 km (SD = 1.05), consistent with typical shared e-scooter trip lengths.

Accessibility scores were generally balanced between origins and destinations, with higher scores (maximum = 9.97) indicating greater access and lower scores (minimum = 0) indicating poorer access. Among the five domains, the highest average accessibility was observed for recreation, with a mean of 9.66 (SD = 0.41) at origins and 9.64 (SD = 0.42) at destinations. Accessibility to shopping, education, and environmental "bads" was also relatively high, while public transport accessibility showed the lowest average scores, with a mean of 5.79 (SD = 4.21) at origins and 5.63 (SD = 4.24) at destinations. Notably, Pearson correlation coefficients between origin and destination scores were generally low to moderate, suggesting that each end of a trip captures distinct contextual conditions rather than mirrored characteristics.

Socio-economic characteristics also showed minimal divergence across trip ends. Vehicle ownership per household averaged 1.39 (SD = 0.59) at origins and 1.42 (SD = 0.59) at destinations. The NZDep2023 had mean values of 5.26 (SD = 2.60) and 5.20 (SD = 2.61), respectively (i.e., mid-range deprivation). Lastly, the average temperature across OD pairs was 17.26 °C (SD = 3.56), while mean precipitation was 3.12 mm/day (SD = 8.29).

Table 5-1. Descriptive statistics for the study data

Variables	**Mean (SD)**
Trip count per OD pair	6.9 (61.02)
Trip distance (km) per OD pair	1.67 (1.05)
Education accessibility (log rank)	
Origin	9.58 (0.51)
Destination	9.57 (0.51)
Recreation accessibility (log rank)	
Origin	9.66 (0.41)
Destination	9.64 (0.42)
Shopping accessibility (log rank)	
Origin	9.60 (0.45)
Destination	9.59 (0.46)
Public transport accessibility (log rank)	
Origin	5.79 (4.21)
Destination	5.63 (4.24)
Environmental bads accessibility (log rank)	
Origin	8.30 (0.94)
Destination	8.34 (0.92)
Vehicles per household	
Origin	1.39 (0.59)
Destination	1.42 (0.59)
NZDep2023	

Table 5-1. Descriptive statistics for the study data

Variables	Mean (SD)
Origin	5.26 (2.60)
Destination	5.20 (2.61)
Temperature (°C) per OD pair	17.26 (3.56)
Precipitation (mm) per OD pair	3.12 (8.29)

Negative binomial model results

Table 5-2 reports the estimated associations between the predictors and e-scooter trip volumes, derived from the negative binomial regression model. Trip volumes were significantly lower for OD pairs with longer network distance. A one-standard-deviation (SD) increase in log-transformed distance, approximately equivalent to 0.8 km, was associated with a 32% decrease in expected trip count (IRR = 0.676; 95% CI: 0.671–0.682), representing the strongest association in the model.

Domain-specific accessibility measures at both trip ends were significantly associated with e-scooter use. Accessibility to recreation facilities and public transport showed consistent positive associations across both origins and destinations. For instance, a one-SD increase in log-transformed public transport accessibility, approximately equivalent to 69 ranks on the original 1–21,508 accessibility scale, at the destination was associated with a 6% increase in trip volume (IRR = 1.060; 95% CI: 1.050–1.070). Recreation accessibility at the origin showed an association of comparable magnitude, where a one-SD increase, roughly one rank on the original scale, was associated with a 5% increase in trip volume (IRR = 1.050; 95% CI: 1.040–1.070).

Conversely, accessibility to environmental “bads” was negatively associated with trip volumes. At the destination, a one-SD increase in log-transformed accessibility, equivalent to roughly three ranks on the original scale, was associated with a 23% reduction in trip count (IRR = 0.773; 95% CI: 0.763–0.784). Negative associations were also observed for education and shopping accessibility. For education, a one-SD increase, approximately two ranks on the original scale, was associated with a 6.5% reduction in trip volumes at the origin (IRR = 0.935; 95% CI: 0.924–0.947) and a 4.2% reduction at the destination (IRR = 0.958; 95% CI: 0.946–0.971). For shopping accessibility, the corresponding decreases were 4% at the origin (IRR = 0.960; 95% CI: 0.946–0.975) and 7.6% at the destination (IRR = 0.924; 95% CI: 0.910–0.938).

Among socio-economic indicators, both vehicle ownership and area-level deprivation were inversely associated with e-scooter use. For example, higher vehicle ownership at the origin was associated with a 23% decrease in the expected e-scooter trip count (IRR = 0.770; 95% CI: 0.760–0.780). Similarly, a one-SD increase in deprivation at the origin (approximately 2.6 ranks on the

1–10 NZDep2023 index scale) corresponded to a 9% reduction in trip volume (IRR = 0.911; 95% CI: 0.901–0.920).

Finally, temperature was not significantly associated with e-scooter trip use (IRR = 0.996; 95% CI: 0.987–1.000; p = 0.292), suggesting limited sensitivity to temperature fluctuations within the study context. However, precipitation showed a small but significant negative association: a one-SD increase in rainfall (≈8.3 mm) was linked to a 3% decrease in trip volume (IRR = 0.973; 95% CI: 0.965–0.981).

Table 5-2. Estimated associations between accessibility and e-scooter OD trips

Variable	IRR (95% CI)	Std. Error	Z-value	P-value
Log distance z-score	0.676 (0.671-0.682)	0.004	-97.8	< 0.001
Log education accessibility z-score				
Origin	0.935 (0.924–0.947)	0.006	-10.2	< 0.001
Destination	0.958 (0.946–0.971)	0.006	-6.3	< 0.001
Log recreation accessibility z-score				
Origin	1.050 (1.040–1.070)	0.008	6.1	< 0.001
Destination	1.040 (1.030–1.060)	0.008	5.1	< 0.001
Log shopping accessibility z-score				
Origin	0.960 (0.946–0.975)	0.007	-5.2	< 0.001
Destination	0.924 (0.910–0.938)	0.007	-10.0	< 0.001
Log public transport accessibility z-score				
Origin	1.050 (1.040–1.060)	0.004	10.5	< 0.001
Destination	1.060 (1.050–1.070)	0.004	11.7	< 0.001
Log environmental bads accessibility z-score				
Origin	0.786 (0.776–0.796)	0.006	-36.5	< 0.001
Destination	0.773 (0.763–0.784)	0.006	-38.7	< 0.001
Vehicles per household z-score				
Origin	0.770 (0.760–0.780)	0.006	-39.3	< 0.001
Destination	0.788 (0.778–0.799)	0.006	-35.9	< 0.001
Deprivation index z-score				
Origin	0.911 (0.901–0.920)	0.005	-17.7	< 0.001
Destination	0.919 (0.909–0.928)	0.005	-16.2	< 0.001
Temperature z-score	0.996 (0.987–1.000)	0.004	-1.0	0.292
Precipitation z-score	0.973 (0.965–0.981)	0.004	-6.5	< 0.001
AIC = 224,602.9				

Discussion and conclusion

This study investigated spatial patterns of shared e-scooter use in Auckland through the lens of OD flows and their association with domain-specific neighbourhood accessibility indices. Employing a directional gravity-based negative binomial model applied to a large set of trip pairs, the analysis provides a nuanced account of how different urban contexts generate and attract shared micromobility demand. The results reveal marked asymmetries: shared e-scooter flows were consistently and positively associated with access to destinations linked to discretionary and multimodal travel; however, accessibility to more utilitarian destinations showed inverse, and in some cases weaker, associations with trip generation and attraction. These spatial patterns were most strongly associated with trip length, which exhibited a pronounced distance-decay effect, and to a lesser extent, by socio-economic context, which provided important background but did not fully explain the spatial distribution of demand.

Trip volumes were markedly lower for OD pairs with greater spatial separation, demonstrating a strong distance-decay relationship that aligns with findings from international studies showing that shared e-scooters are predominantly used for short-range travel (276,484). In this study, the average network-based trip distance between origin and destination areas was 1.67 km, which is near the upper limit of what is generally considered walkable in urban planning contexts (12,485). This finding suggests that shared e-scooters are most intensively used within spatial ranges that overlap with pedestrian travel, reinforcing their role as a mode suited for short-distance mobility. While this analysis does not directly assess modal substitution, previous literature suggests that substitution patterns may depend on trip purpose and urban form. For instance, in leisure-oriented areas such as parks or entertainment districts, e-scooters may be used over distances typically associated with walking (240). In contrast, in employment-dense districts with higher levels of time-sensitive travel, they may substitute for short car trips, particularly in contexts with limited parking or roadway congestion (240,486). Although these interpretations remain speculative in the absence of user-level mode choice data, they underscore the importance of contextualising micromobility demand within the broader geography of urban land use and travel purpose.

E-scooter trip volumes were significantly higher between areas with greater access to public transport infrastructure, consistent with previous research highlighting the important role of transport-oriented opportunities in shared micromobility use (39,259,276). Notably, each 690-rank increase in public transport accessibility (on the original 1–21,508 scale) was associated with a 60% increase in e-scooter trip volumes. This association likely reflects the complementary role of e-scooters within multimodal travel systems, where they are used opportunistically as first- and last-mile connectors rather than as substitutes for transit (35,39,259). This interpretation is tentatively supported by recent survey data from New Zealand, where 42% of users with mobility impairments reported using e-scooters to connect to public transport, compared to 21% of non-impaired users, a disparity that could point to their enabling role for groups facing greater access barriers (487). At the same time, the proximity of trip clusters to transit services may also imply a degree of modal substitution for walking, particularly for short access or egress segments (33). While such substitution may enhance convenience and system efficiency, it might also raise potential concerns regarding reduced incidental physical activity, with implications for transport-related health outcomes.

The analysis also revealed a positive association with discretionary travel, particularly toward recreational destinations. While this aligns with findings from studies conducted in other urban settings (39,256,276), it diverges from earlier survey-based research in New Zealand, which identified commuting as the dominant trip purpose among shared e-scooter users, with approximately 55% of trips reported as being for work or study (234,487). This apparent shift may reflect the evolving maturity of micromobility systems, alongside increased user familiarity, broader trip purposes, and expanded service coverage. As shared e-scooters become more embedded in urban mobility networks, usage patterns may diversify beyond commuting to encompass more flexible, leisure-oriented behaviours (488). These findings underscore the dynamic and context-sensitive nature of micromobility uptake, reinforcing the need for longitudinal, behavioural, and spatially resolved analyses to better understand how system roles and user preferences change over time.

In contrast to the above, higher accessibility to education and shopping facilities, as well as proximity to environmental "bads" such as alcohol outlets and fast-food chains, was associated with lower shared e-scooter trip volumes. These amenity types, often embedded within car-oriented urban forms characterised by ample parking and road capacity, may be less conducive to micromobility use and may coincide with greater car dependence. The particularly strong negative association with environmental "bads" may also reflect behavioural and regulatory dynamics: although such amenities are concentrated in central locations like Queen Street and the Viaduct precinct, these areas are frequently subject to operational restrictions, including low-speed limits or geofencing, which may reduce the functional appeal of shared e-scooters and, in turn, suppress trip activity (489,490). In addition, temporary disruptions caused by large-scale infrastructure projects, most notably Auckland's City Rail Link, may also have contributed to the observed pattern. Survey data suggest that 54% of city-centre residents reported impeded walking due to construction, and nearly one-third (31%) noted disruptions to cycling or e-scooter use (491). These spatial and temporal constraints may partially account for the reduced trip volumes in otherwise accessible areas, indicating that infrastructure context, behavioural deterrents, and operational limitations can moderate or even override accessibility-driven demand.

Patterns of shared e-scooter use also varied according to socio-economic context, albeit likely through different mechanisms. Areas with higher car ownership were associated with lower trip volumes, which may reflect a greater reliance on private vehicles, particularly in Auckland's outer suburbs where lower density and car-oriented infrastructure could reduce the attractiveness or necessity of micromobility options. This pattern is broadly consistent with findings from other urban settings, where higher car access has been linked to reduced adoption of shared micromobility services (234,492). In contrast, lower levels of shared e-scooter use were observed in more deprived areas. While this pattern may be consistent with barriers to micromobility uptake reported in previous research, including financial constraints and digital exclusion (493,494), differences in service availability and deployment practices may also contribute to the observed associations. While dockless systems are often seen as offering broader geographic coverage, they may still fall short of serving disadvantaged communities if deployment strategies are guided primarily by demand potential rather than social need. Consequently, the lower usage observed in more deprived areas should be interpreted cautiously, as it may reflect differences in demand, service provision, or a combination of both.

Interestingly, though not unexpectedly, temperature was not a significant correlate of e-scooter trip volumes in the Auckland context. Despite the dataset spanning more than one year, most trips occurred within a relatively narrow thermal band centred around 17 °C (IQR: 15–19 °C), suggesting minimal exposure to temperature extremes. This constrained variation likely limited the detectability of temperature associations, reinforcing the notion that, under consistently mild conditions, small thermal fluctuations may have limited association with micromobility usage. In contrast, precipitation exhibited a modest but statistically significant negative association with trip volumes, indicating some reduction in demand during wetter periods. This aligns with findings from other urban contexts where rainfall tends to suppress micromobility uptake by reducing perceived comfort and safety (278,495). However, the smaller effect observed in Auckland may reflect the city's light rainfall and users' potential adaptation to mild wet conditions. These patterns highlight the context-dependent nature of weather associations with micromobility, though further behavioural data would be needed to confirm these interpretations.

Altogether, the findings suggest that shared e-scooter demand in Auckland is more strongly associated with neighbourhood features that enable discretionary travel and multimodal access than with those that support routine utilitarian trips. This usage pattern implies that e-scooters currently serve more as opportunistic connectors, linking users to nearby leisure destinations or transit infrastructure, than as widespread alternatives to private vehicle use. While such associations may reflect the present stage of system maturity and integration within the urban fabric, they also highlight structural constraints, such as dispersed land use and car-oriented planning, that may limit the extent to which shared micromobility can drive a broader modal shift. Without more supportive built environments and equitable spatial coverage, these services may continue to cluster in already well-resourced areas, potentially reinforcing rather than alleviating transport inequities. Their long-term contribution to sustainable and inclusive mobility, therefore, is likely to depend on how they are integrated into the evolving geography of urban accessibility.

Limitations and future directions

These findings should be interpreted in light of several limitations. While the study employed fine-grained accessibility indicators, these reflect potential access rather than realised accessibility during the study period. The indices do not account for temporary constraints such as construction works, road closures, or service disruptions that may have limited users' actual ability to reach destinations. As a result, the accessibility measures capture opportunity structures in principle but may diverge from the conditions experienced in practice. Future research could address this by integrating static indicators with dynamic data, such as construction timelines, service interruptions, or temporary restrictions, to better capture real-world accessibility.

The analysis relied on aggregated origin–destination trip data to enhance statistical robustness and focus on spatial associates of e-scooter flows. While this approach supports stable inferences at the neighbourhood level, it necessarily abstracts from temporal variability. Seasonal shifts, institutional calendars, and event-specific fluctuations were outside the scope of analysis. Future work using temporally disaggregated trip records could explore these dimensions in greater detail and assess how short-term changes, including policy interventions or major events, influence micromobility demand.

Another limitation relates to the potential dependence among origin–destination observations. Although the analysis was conducted at the OD-pair level, many observations shared the same origin or destination SA1s, resulting in repeated use of the same accessibility, deprivation, and vehicle-ownership values across multiple origin–destination pairs. Consequently, the assumption of fully independent observations may not have been completely satisfied. In addition, potential spatial autocorrelation between neighbouring areas was not explicitly modelled. While the large number of origin–destination pairs provided substantial statistical power, unmodelled dependence may have affected standard errors and the apparent precision of some estimates. Future research could explore hierarchical, network-based, or spatial modelling approaches that explicitly account for shared origins, destinations, and spatial dependence.

A further limitation relates to the use of trip data from a single shared micromobility operator. The observed trip volumes reflect realised trips rather than underlying demand and may therefore be influenced not only by user behaviour but also by operational factors such as scooter availability, fleet rebalancing practices, operating boundaries, parking restrictions, and geofencing policies. Because detailed fleet deployment and availability data were not available, these factors could not be explicitly incorporated into the analysis. Consequently, observed spatial differences in trip volumes may reflect both demand-side and supply-side influences. Future research incorporating detailed operational and fleet availability data would help disentangle these effects.

Although the study revealed strong spatial associations between trip volumes and neighbourhood characteristics, the mechanisms driving these relationships remain speculative. In particular, the absence of user-level or mode-choice data precludes direct inference regarding substitution effects or trip purposes. Future studies that combine spatial modelling with behavioural surveys or trip-level data would be better positioned to examine the motivations and contexts behind shared e-scooter use, thereby strengthening interpretations.

Policy implications

Shared e-scooters appear to function most effectively as short-range connectors to leisure destinations and public transport, particularly within urban corridors just beyond comfortable walking distance. For operators, this highlights the need for spatially adaptive strategies, such as prioritised fleet rebalancing and maintenance near high-demand recreational areas and transport nodes, aligned with predictable temporal and spatial patterns of use. For policymakers, maximising the value of shared micromobility requires integrated planning approaches, including dedicated parking infrastructure at key interchanges (e.g., bus or train stations), protected micromobility corridors, and digital platforms that embed e-scooter availability into multimodal trip-planning tools, such as an expanded Auckland Transport mobile app. However, this convenience may risk displacing active modes, particularly walking, rather than private car use. One potential mitigation strategy could involve using these digital tools to encourage balanced usage, for example through voluntary or incentivised weekly ride limits that discourage unnecessary substitution of walking trips. More broadly, complementary policies are needed to uphold the primacy of walking and cycling for short-distance travel, such as maintaining pedestrian-priority streets, improving footpath quality, and ensuring that active modes remain the most attractive and accessible option, while also investing in safe, connected micromobility infrastructure.

While shared e-scooters were associated with discretionary and multimodal travel, the findings also point to notable gaps in their role in necessity-based mobility. Although this study did not directly evaluate the structural barriers contributing to these patterns, several policy interventions may help address them. These include enhancing micromobility infrastructure around key retail and educational destinations, maintaining continuity of safe travel routes during large-scale construction projects, and embedding shared e-scooters more fully within broader multimodal transport strategies. By addressing such contextual constraints, shared e-scooter systems could extend their utility beyond leisure and first-/last-mile connections, positioning them as a more viable option for routine, utilitarian travel. In doing so, they may play a greater role in advancing a more resilient, inclusive, and functionally diverse urban mobility system.

The lower usage observed in high-deprivation and car-dominant neighbourhoods may reflect deeper structural barriers, such as poor street connectivity, limited infrastructure, and the legacy of car-oriented planning, that constrain micromobility adoption. To address these disparities, regulators should consider implementing inclusive service obligations, including minimum coverage requirements for underserved areas, equity-adjusted pricing schemes, and sustained investment in safe, accessible infrastructure that supports micromobility use beyond the urban core. Where operators receive public subsidies or exclusive operating rights, such privileges should be conditional on demonstrable contributions to spatial equity and inclusive access.

Chapter 6. How accessibility relates to shared e-scooter trip length: Insights for sustainable micromobility deployment

Preface

The previous chapter examined how domain-specific accessibility relates to e-scooter trip flows, highlighting spatial factors associated with where micromobility trips occur. Continuing the third pathway toward reducing car dependency, this chapter shifts attention from trip counts to trip length, an underexplored dimension of e-scooter behaviour with important implications for sustainability and equity, particularly under distance-based pricing and multimodal integration. Addressing this gap, the next study applies an interpretable machine-learning framework (elastic net regression) to analyse associations between e-scooter trip length and domain-specific accessibility measures. This manuscript is under review at Transportation Research Part D: Transport and Environment. The data-sharing agreement under which the data were received from a service provider in Auckland is presented in Appendix B.

Abstract

Shared micromobility research has expanded rapidly, yet little is known about how accessibility to different destination types correlates with the spatial extent of e-scooter trips, limiting efforts to deploy these services sustainably. This study examines associations between domain-specific accessibility and shared e-scooter trip length in Auckland, New Zealand. Using 473,096 trips, elastic net regression assessed how accessibility to education, recreation, shopping, public transport, and environmental "bads" such as alcohol outlets relates to trip distance, controlling for socio-economic, temporal, and weather conditions. Higher public transport accessibility at both trip ends is associated with shorter trips, while greater accessibility to recreation, education, and environmental "bads" corresponds to longer journeys. Shopping accessibility shows directional asymmetry: longer trips originate in retail-rich areas, whereas shorter trips end in them. Longer trips are also more common in more deprived areas with higher car-ownership levels, raising potential equity concerns. These findings offer insights for sustainable micromobility deployment.

Introduction

As cities pursue sustainability objectives and adopt transit-oriented development strategies, shared electric scooter (e-scooter) programmes, one strand of shared micromobility, have rapidly become integral components of urban transport systems (496). Their compact form and electric propulsion offer the potential to mitigate urban transport externalities, such as congestion and greenhouse gas emissions arising from increased motor vehicle use, particularly during peak periods, if they replace short car trips at a meaningful rate. However, evidence suggests that substitution is highly context-dependent (33,497,498). With their predominantly dockless design, e-scooters offer the potential to support public transport, particularly in low-density cities with sparse transit services, such as those in New Zealand. They enable door-to-door travel and help bridge first- and last-mile gaps, improving accessibility and overall network efficiency for individuals with limited access to public transport (229–233). By requiring users to walk to and from vehicles at the beginning and end of trips, these services may also encourage short walking segments, complementing active travel modes (234). Although there is evidence indicating that e-scooters themselves do not qualify as active travel, raising concerns about reduced opportunities for health-enhancing movement, they can still play a valuable role in sustainable transport planning. When e-scooters replace short car journeys or complement public transport, they contribute to lower emissions and support car-free or car-lite lifestyles (228).

However, emerging evidence highlights potential drawbacks: e-scooters may substitute for walking and cycling and complement car travel; for example, by enabling drivers to park farther from their destinations and complete the remainder of their journey by e-scooter, potentially reinforcing car dependency and reducing active travel (234). Their relatively high speeds, combined with the use of constrained pedestrian infrastructure, can disrupt walking environments and negatively affect pedestrians' perceptions of safety when both modes share the pavement (235–237). Moreover, micromobility services may generate other adverse subjective well-being outcomes, including reduced autonomy when embedded within public transport trip chains (less control over timing and route), unpleasant social interactions (conflicts or discomfort in shared spaces), and stress associated with crowded pedestrian environments (overcrowding and competition for space) (235). These evolving dynamics, both beneficial and adverse, underscore the importance of examining less-studied dimensions of travel patterns, including factors associated with trip length.

In micromobility schemes, trip distance emerges as a critical yet comparatively underexamined dimension of travel behaviour, with direct implications for how these services function within broader urban mobility systems. Short-distance trips may indicate substitution for walking or cycling, for example as connectors to public transport. Whereas, longer trips may suggest competition with private motorised modes and partial replacement of short car journeys (39,499). Beyond sustainability, understanding the factors associated with trip length might also have equity implications. Since most e-scooter pricing models charge by time or distance, longer trips can become disproportionately expensive compared to flat-fare public transport, potentially disadvantaging users in areas where longer journeys are unavoidable. Prior research has provided insights on how meteorological conditions, temporal patterns, and broader economic dynamics are associated with shared e-scooter trip length (278,279,500). However, to inform urban planning and deployment strategies aimed at sustainable and equitable provision of micromobility services, it is vital to explore how availability of opportunities and accessibility to these activities (e.g., recreation, education, health) might interact with trip length.

Neighbourhood accessibility, conceived as the ease of reaching nearby services and amenities from a given location (501), is consistently associated with both general travel behaviour and shared e-scooter usage (119,502–504). Despite its significance, research on micromobility often depends on broad indicators of accessibility, such as the proximity to key urban areas (e.g., distance from the city centre) or general land-use diversity (e.g., (72,274)). While these measures help outline larger spatial patterns, they offer limited insight into how access to particular destinations correlates with travel behaviour. Moreover, combining different accessibility factors into a single index, such as public transport, health-related facilities, and recreational spaces, can obscure the unique impact of each factor (502). This blending may dilute the positive effect of one area or amplify the negative influence of another, compromising the clarity and reliability of the findings. Thus, more refined approaches are needed to capture the nuanced relationships between access to specific destinations and travel behaviour. By disaggregating accessibility into distinct domains and considering how these relate to the physical and social context, we can better understand the associates of micromobility use and its integration into the broader transport network. This more granular perspective has the potential to inform policies that align micromobility deployment with the accessibility needs of diverse urban populations, ensuring more equitable and efficient outcomes for users.

Auckland, which ranks among the most car-oriented urban regions globally (505), presents a distinctive context for investigating the spatial and behavioural dynamics of shared micromobility use. Since the launch of a pilot e-scooter programme in 2018, adoption has grown to nearly two million trips annually, by the time of writing this study (59,60). Although this represents meaningful uptake given the novelty of the mode and its concentration in central areas, it remains modest relative to other transport modes. Aucklanders made roughly 89 million public transport boardings in 2024, and car travel accounts for more than 80% of trips (506,507). The per-capita rate of e-scooter use is slightly above one trip per person per year. This limited use highlights the need for a more detailed understanding of micromobility patterns. Accordingly, this study endeavours to examine: (1) how accessibility to specific activity domains and amenities at trip origins and destinations, along with weather, deprivation, and temporal attributes, are associated with variation in e-scooter trip length in the Auckland context; and (2) the extent to which domain-specific accessibility measures at both trip ends, along with other covariates, predict shared e-scooter trip length, using an interpretable machine-learning framework. By focusing on Auckland, New Zealand, where empirical evidence on micromobility remains limited, this study provides contextual and methodological insights relevant to the local study context.

Methods and materials

Study area

This study was conducted in Auckland (Figure 6-1), the largest and most populous city in New Zealand, with an estimated population of 1.76 million in 2023 (62). As shown in Figure 6-1, the population is predominantly concentrated in the central parts of Auckland, where administrative areas are smaller in size, reflecting higher population density. Auckland is characterised by a highly urbanised environment, substantial suburban sprawl, and a reliance on private motor vehicles, alongside recent investments in micromobility infrastructure such as cycleways and e-scooter sharing schemes (474). The city's varied urban form and transport network make it a relevant context for examining relationships between urban form, socio-economic conditions, and shared micromobility use.

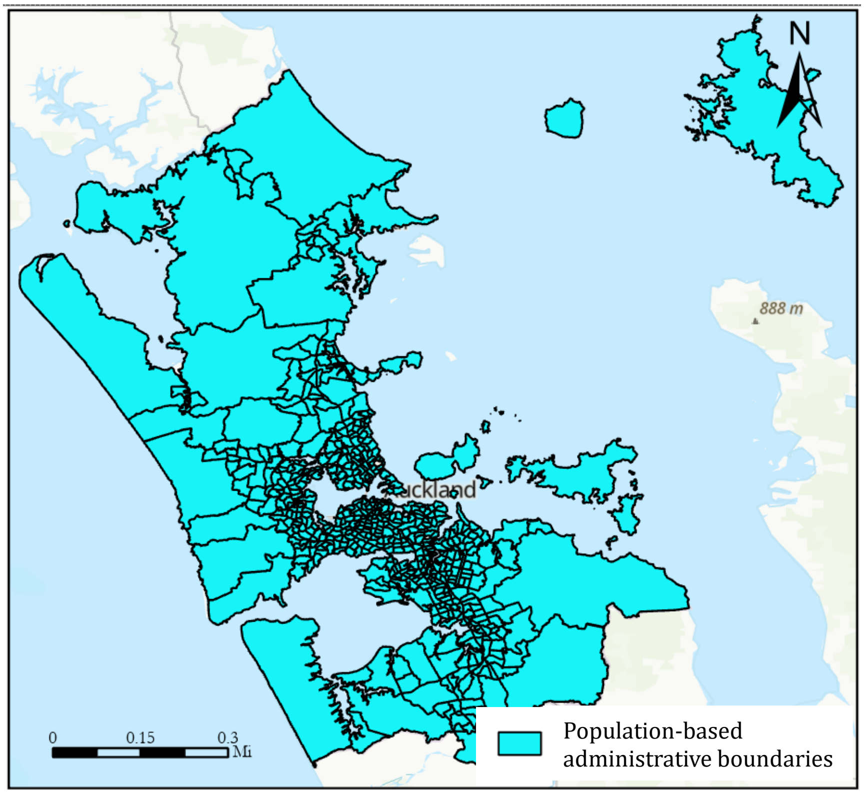


Figure 6-1. Study area – Auckland, New Zealand

Study data

For this study, anonymised e-scooter trip records were sourced from a shared micromobility provider, covering trips undertaken in Auckland, New Zealand, between 1 April 2023 and 31 May 2024. The dataset includes origin and destination coordinates, as well as timestamp information for each e-scooter trip. The micromobility operator provided access to the trip data but had no role in the study design, data analysis, interpretation of findings, or preparation of the thesis. Although the data-sharing agreement permitted the operator to review outputs prior to publication, it had no influence over the analyses, results, or conclusions presented in this thesis.

This study employed an existing enhanced two-step floating catchment area (E2SFCA)-based accessibility index that was previously developed for urban areas across New Zealand (349). The E2SFCA represents a well-established gravity-based approach for quantifying accessibility and forms part of the broader floating catchment area (FCA) family of methods (350–352). In essence, these methods consider both the supply of destinations and the demand from surrounding populations, applying distance-decay weighting to reflect the declining likelihood of access with increasing travel distance.

The New Zealand E2SFCA index quantifies the relative ease with which residents can walk to a wide range of everyday destinations within a 30-minute walking threshold. It captures accessibility to a range of destinations, including education, public transport, recreational amenities, shopping facilities, and facilities such as fast-food and alcohol outlets that are labelled as environmental "bads". The original index ranks domain-specific accessibility in urban areas at the Statistical Area 1 (SA1) level, from 1 (highest accessibility) to 21,508 (lowest accessibility). SA1s are New Zealand's smallest statistical geography (approximately 100–200 residents), offering fine spatial granularity while preserving individual privacy (475). This index was adopted because it represents the most recent and comprehensive national dataset of accessibility available for New Zealand, ensuring consistency and comparability across study regions. Detailed methods for its construction are available elsewhere (349).

To capture the socio-economic context, we incorporated NZDep2023, developed by the University of Otago, and car ownership data at the SA1 level from the 2023 New Zealand Census (476,477). NZDep2023 is the New Zealand Index of Socioeconomic Deprivation, a small-area measure constructed using 2023 Census data. It combines eight dimensions of deprivation, including communication, income, employment, education, home ownership, access to support, living space, and housing condition, to assign a deprivation score to each SA1. These scores are ranked into deciles, with decile 1 representing the least deprived areas and decile 10 the most deprived. The index measures area-level deprivation rather than individual or household circumstances and is widely used in public health and urban planning to identify and address social inequalities (477).

Weather conditions were also incorporated into the analysis using temperature data from the Auckland Airport meteorological station, sourced via Meteostat (478). Although temperatures in Auckland are generally mild, this variable was retained to facilitate comparability with the international literature. Precipitation data were also obtained from NIWA, based on records from the Raoul Island meteorological station (479).

Data processing

Trip origin and destination coordinates were first spatially matched to SA1 polygons using ArcGIS Pro (version 3.5.2). Then, to estimate travel distances (in metres), a Python-based geospatial analysis pipeline was developed (Appendix D), leveraging OpenStreetMap (OSM) road network data. The bikeable road network for Auckland, New Zealand, was retrieved and projected using the *osmnx* library, forming the basis for network-based trip distance calculations. Origin and destination coordinates were geospatially matched to the nearest nodes on the OSM network using a Haversine-based nearest-neighbour search, which estimates great-circle distances between points on the Earth's surface based on latitude and longitude (480). Shortest-path distances between these nodes were computed via *networkx*, with edge weights corresponding to the physical lengths of road segments. To reduce noise arising from GPS error and implausible routing, trips were filtered to include only those with network-based lengths between 200 metres and 5,000 metres, following established best practices for e-scooter trips (482).

SA1-level accessibility indices (education, recreation, shopping, public transport, and environmental "bads") and socio-economic attributes (NZDep2023 and vehicle ownership) were assigned to both the origin and destination of each trip based on the SA1 in which each location was situated.

For interpretability, the accessibility indices were reversed so that a value of 1 represented the lowest accessibility and 21,508 represented the highest accessibility to neighbourhood facilities. To reduce skewness, the reversed values were then log-transformed, such that $\ln(1) = 0$ represented the lowest accessibility and $\ln(21{,}508) = 9.97$ represented the highest accessibility to neighbourhood facilities. Similarly, network-based trip distances were log-transformed to reduce skewness and improve model fit. Figure 6-2 summarises the methodological workflow, illustrating the data inputs, processing steps, and modelling approach used in this study.

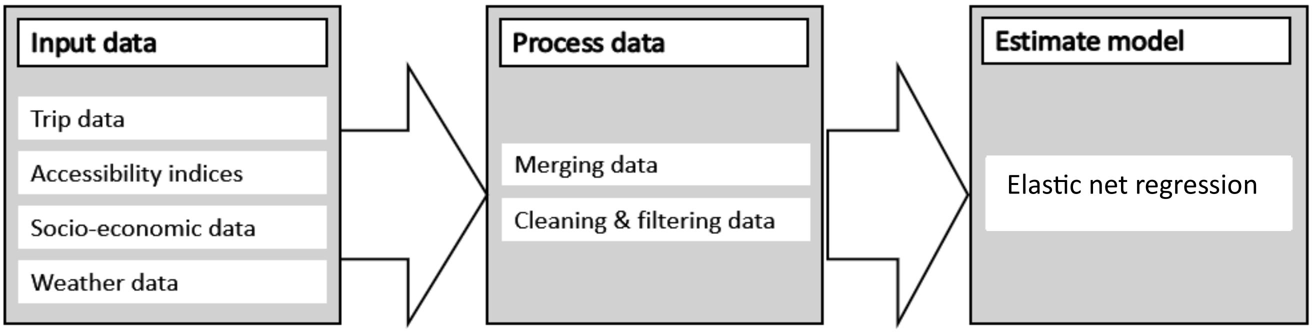


Figure 6-2. Methodological workflow of this study

Statistical modelling

To model variation in trip length and examine associations with accessibility, we employed Elastic Net regularised linear regression (via *glmnet*), which combines L1 (Lasso) and L2 (Ridge) penalties (508). This approach offers advantages over both traditional regression and more complex machine learning models. Compared to ordinary least squares regression, Elastic Net improves model robustness and predictive performance by applying regularisation, which mitigates overfitting and stabilises coefficient estimates when predictors vary in scale or exhibit modest correlations (509). In contrast to machine learning algorithms such as random forests or gradient boosting, which prioritise prediction at the expense of interpretability, Elastic Net retains transparent, easily interpretable coefficients that quantify the direction and magnitude of associations. This balance between predictive accuracy and interpretability makes Elastic Net particularly well suited for modelling e-scooter trip behaviour in relation to multidimensional accessibility and contextual factors.

Following this modelling framework, the dependent variable was the log-transformed network-based distance travelled by shared e-scooters. Independent variables comprised accessibility scores for education facilities, recreation zones, shopping centres, public transport services, and environmental “bads” such as alcohol and fast-food outlets (each measured separately for the origin and destination SA1s). These domains represent both beneficial and adverse urban features, which may be associated differently with trip length due to their spatial distribution, density, and the distinct types of travel demand they typically generate (e.g., discretionary vs. convenience-based trips).

Socio-economic, temporal, and weather attributes were included as covariates. Socio-economic indicators included the NZDep2023 index of deprivation (scaled from 1 = least deprived to 10 = most deprived) and the number of vehicles per household. Temporal variables were represented using categorical indicators for time of day (morning peak, evening peak, off-peak [reference]), season (warm [reference] vs cool), and day of week (weekday [reference] vs weekend). Ambient temperature (°C) and precipitation (mm) were entered as continuous predictors.

The full dataset (n = 473,096 trips) was randomly partitioned into training (80%) and test (20%) subsets. The regularisation hyperparameter λ (lambda) was tuned via 10-fold cross-validation, with model performance evaluated across a sequence of α (alpha) values ∈ {0.00, 0.25, 0.50, 0.75, 1.00}. Optimal hyperparameters were selected based on the minimum cross-validated mean squared error (MSE).

To generate unbiased predictions on the original (metre) scale, Duan’s smearing estimator was applied to back-transform the log-transformed predictions (510). The smearing factor was computed as the mean of the exponentiated residuals from the training set and subsequently multiplied by the exponentiated model predictions to obtain corrected trip distance estimates. Model coefficients were then estimated from the training data using the optimal parameter combination. These coefficients were used to assess associations between accessibility, socio-economic, temporal, and weather predictors and trip length (Aim 1). Model predictive performance (Aim 2) was evaluated on the test set using root mean square error (RMSE) and mean absolute error (MAE). All analyses were conducted in RStudio (version 2025.09.1).

Results

Descriptive statistics

Table 6-1 provides a summary of key socio-economic, temporal, and weather attributes in the dataset. Of the 473,096 trips recorded from 1 April 2023 to 31 May 2024, most occurred during off-peak hours (76.93%), with morning and evening peak periods accounting for 7.74% and 15.33% of trips, respectively. E-scooter activity was higher during the warm season (October–April), comprising 69.03% of all trips, compared to 30.97% during the cooler months (May–September) in Auckland. Weekdays accounted for 71.07% of trips, while weekends represented 28.93%. The average temperature at the time of travel was 17.12 °C (SD = 4.16), and precipitation averaged 3.21 mm (SD = 8.40), with a median of 0.20 mm and an interquartile range (IQR) of 2.00 mm, indicating that most trips occurred under mild and relatively dry conditions. Socio-economic indicators, ranging from 1 to 10, showed moderate deprivation at trip origins and destinations, with mean NZDep2023 scores of 5.85 (SD = 2.43) and 5.87 (SD = 2.45), respectively. The average number of vehicles per household was similar across origin (0.89, SD = 0.52) and destination (0.90, SD = 0.54) areas, providing context for interpreting travel behaviour in relation to the built environment.

To examine whether trip origins and destinations differed in their contextual characteristics, paired t-tests were conducted for all SA1-level variables used in the model, including accessibility, deprivation, and car ownership. While several comparisons were statistically significant due to the large sample size (n = 473,096 trips), the corresponding effect sizes were negligible (Cohen's d < 0.03). These results indicate that origins and destinations are statistically comparable in practical terms, supporting their joint inclusion as predictors in the modelling framework and confirming that observed associations are not driven by contextual imbalances between origin and destination areas.

Table 6-1. Descriptive statistics of temporal, socio-economic, and weather attributes

Variables	**n (%)**	**Mean (SD)**
Time of day		
Off-peak	363,930 (76.93)	
Morning peak	36,640 (7.74)	
Evening peak	72,526 (15.33)	
Day of week		
Weekday	336,218 (71.07)	
Weekend	136,878 (28.93)	
Season (trip per month)		
Warm		99,295 (8,576)
Cool		81,548 (3,926)
NZDep2023		
Origin		5.85 (2.43)
Destination		5.87 (2.45)
Vehicles per household		
Origin		0.89 (0.52)
Destination		0.90 (0.54)
Temperature (°C)		17.12 (4.16)
Precipitation (mm)		3.21 (8.40)

Building on the trip characteristics summarised in Table 6-1, Figure 6-3 shows the distribution of e-scooter trip lengths. The log-transformed data indicate that most trips cluster around one kilometre (exp (7)), reflecting the short-range functionality typical of shared micromobility services.

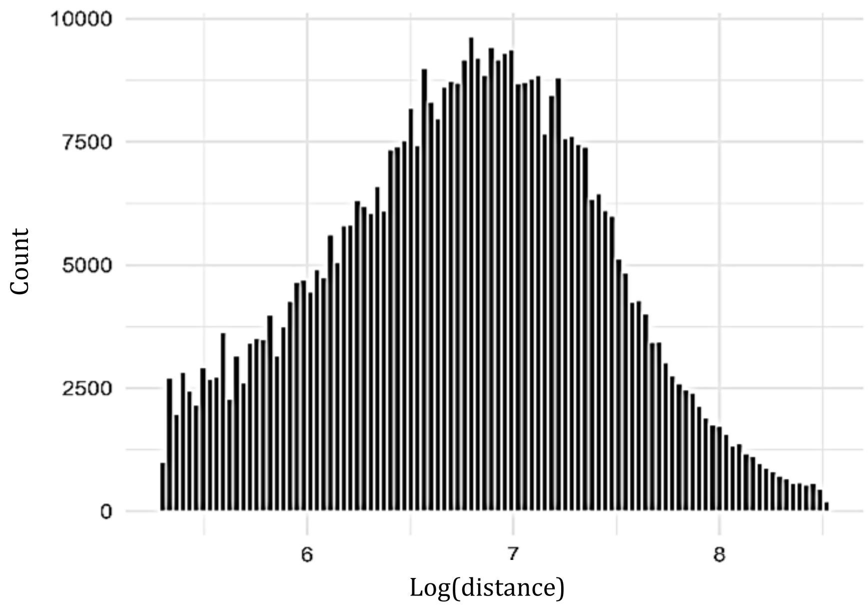


Figure 6-3. E-scooter trip length distribution

To contextualise these behavioural patterns spatially, Figure 6-4 maps the distribution of e-scooter trips across Auckland during the study period (April 2023–May 2024). Trip density is highest in the central business district, gradually tapering through the surrounding inner suburbs.

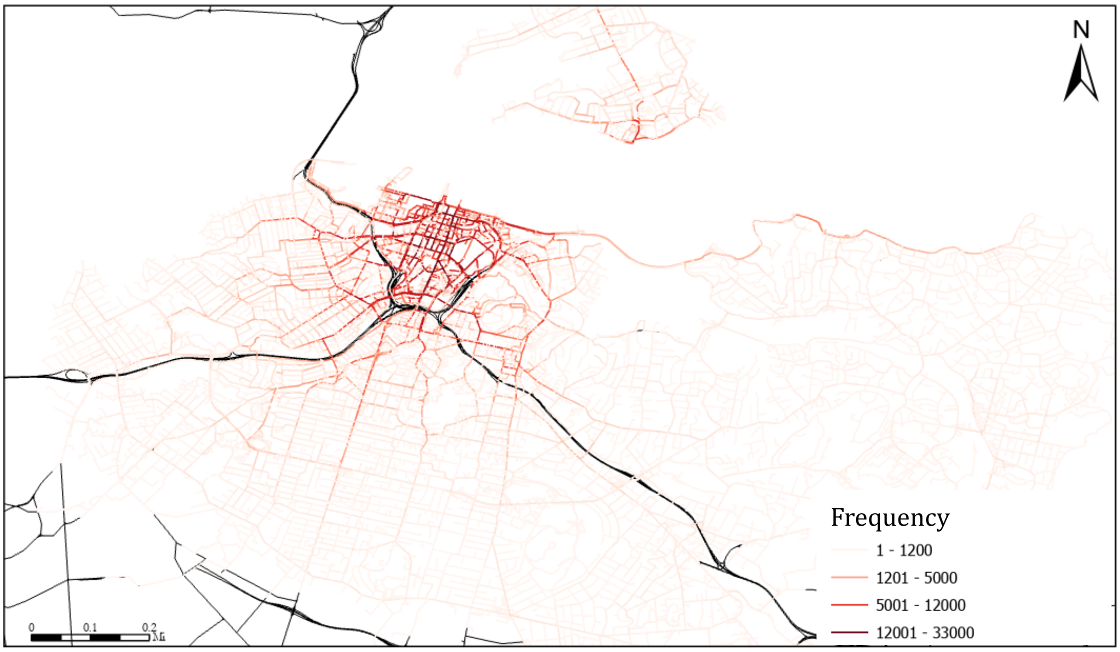


Figure 6-4. Spatial distribution of e-scooter trips

In addition to overall trip and spatial characteristics, Table 6-2 summarises trip characteristics and log-transformed accessibility measures at both origins and destinations. The mean network-based distance travelled by e-scooters was 1,076 m (SD = 745.46), consistent with the short-range nature of shared micromobility services. Education accessibility averaged 9.68 (SD = 0.43) at trip origins and 9.69 (SD = 0.41) at destinations. Recreation and shopping accessibility showed similarly close alignment, with mean values of 9.83 (SD = 0.23) versus 9.83 (SD = 0.24), and 9.80 (SD = 0.27) versus 9.79 (SD = 0.28), respectively. Public transport accessibility was comparatively lower, averaging 7.72 (SD = 3.41) at origins and 7.69 (SD = 3.43) at destinations. Accessibility to environmental "bads" was lowest overall, with mean values of 7.41 (SD = 0.88) and 7.43 (SD = 0.89) at origins and destinations, respectively. Although mean values were nearly identical across trip ends, both origin and destination measures were retained in the modelling to maintain spatial specificity and account for potential origin-destination asymmetries in associations between the built environment and trip patterns. Given that accessibility indices were ranked and log-transformed across SA1s in Auckland, the high mean values for most domains primarily reflect the compression of the transformed scale rather than uniformly high accessibility citywide, indicating that e-scooter trips occurred within generally well-connected urban areas.

Table 6-2. Descriptive statistics for accessibility measures and trip characteristics

Variables	Mean (SD)
Overall trip distance (m)	1,076.05 (745.46)
Education accessibility (log rank)	
Origin	9.68 (0.43)
Destination	9.69 (0.41)
Recreation accessibility (log rank)	
Origin	9.83 (0.23)
Destination	9.83 (0.24)
Shopping accessibility (log rank)	
Origin	9.80 (0.27)
Destination	9.79 (0.28)
Public transport accessibility (log rank)	
Origin	7.72 (3.41)
Destination	7.69 (3.43)
Environmental “bads” accessibility (log rank)	
Origin	7.41 (0.88)
Destination	7.43(0.89)

Elastic net regression results

The Elastic Net model selected α = 0.75, with λ determined at λ.min = 0.000238. On the independent test set, predictive accuracy corresponded to a root mean squared error (RMSE) of approximately 715 m and a mean absolute error (MAE) of 527 m after back-transformation using Duan’s smearing estimator. Performance at the more conservative λ.1se penalty was nearly identical, indicating stability across penalisation thresholds and supporting the robustness of the final estimates.

Table 6-3 presents the results of an elastic net regression examining predictors of e-scooter trip distance. Several accessibility domains showed significant associations with trip length. Higher public transport accessibility at both trip origins and destinations was associated with shorter e-scooter trips (origin: β = −0.006, 95% CI [−0.007, −0.005]; Δ = −5.2 m; destination: β = −0.007, 95% CI [−0.008, −0.006]; Δ = −6.5 m), such that each one-unit increase in the log-transformed accessibility index (ranging from 0 to 9.97) corresponded to an estimated reduction of approximately 5–7 metres in trip distance.

Recreation accessibility showed positive associations with trip distance at both trip ends, with the larger coefficient observed for origins (β = 0.082, 95% CI [0.064, 0.097]; Δ = +76.6 m), indicating that each unit increase in the log-transformed accessibility rank was associated with trips nearly 80 metres longer. The corresponding destination-side association was smaller but remained positive (β = 0.017, 95% CI [0.002, 0.032]; Δ = +15.6 m).

Similarly, education accessibility was positively related to trip distances at origins and destinations (origin: β = 0.033, 95% CI [0.025, 0.039]; Δ = +30.0 m; destination: β = 0.038, 95%

CI [0.030, 0.048]; $\Delta = +34.5$ m). Accessibility to environmental "bads" (e.g., alcohol outlets) was also positively associated with trip distance, with a notably larger coefficient at destinations (origin: $\beta = 0.035$, 95% CI [0.029, 0.040]; $\Delta = +31.5$ m; destination: $\beta = 0.053$, 95% CI [0.048, 0.058]; $\Delta = +48.4$ m), indicating that each unit increase in the log-transformed accessibility rank corresponded to approximately 31–48 metres of additional travel.

Patterns for shopping accessibility were asymmetric across trip ends. At origins, higher shopping accessibility was associated with longer trips ($\beta = 0.037$, 95% CI [0.025, 0.050]; $\Delta = +34.0$ m), whereas at destinations, higher shopping accessibility was associated with shorter trips ($\beta = -0.031$, 95% CI [−0.042, −0.021]; $\Delta = -27.6$ m). Interpreted on the 0–9.97 log-transformed scale, these estimates indicate that for each one-unit increase in log-transformed shopping accessibility, trips are approximately 34 metres longer when departing from shopping-rich areas, and about 28 metres shorter when arriving in such areas.

Temporal covariates showed consistent associations. Relative to off-peak periods, morning peak periods were associated with longer e-scooter trips ($\beta = 0.082$, 95% CI [0.075, 0.088]; $\Delta = +76.0$ m), as were evening peak periods ($\beta = 0.027$, 95% CI [0.022, 0.033]; $\Delta = +24.8$ m). In contrast, weekend trips were shorter than weekday trips ($\beta = -0.009$, 95% CI [−0.014, −0.005]; $\Delta = -8.3$ m).

Socio-economic and contextual variables also contributed, with NZDep2023 showing small positive associations at both ends (origin: $\beta = 0.002$, 95% CI [0.001, 0.003]; $\Delta = +1.5$ m; destination: $\beta = 0.005$, 95% CI [0.004, 0.006]; $\Delta = +4.7$ m) per unit increase in the NZDep2023 index. Vehicles per household exhibited relatively large positive associations with trip distance (origin: $\beta = 0.081$, 95% CI [0.073, 0.089]; $\Delta = +75.7$ m; destination: $\beta = 0.133$, 95% CI [0.124, 0.141]; $\Delta = +127.0$ m), suggesting that more auto-oriented residential contexts are linked to longer scooter trips.

Seasonal and meteorological covariates showed modest effects. Compared to the warm season, the cool season was associated with shorter trips ($\beta = -0.029$, 95% CI [−0.035, −0.026]; $\Delta = -25.8$ m). Higher temperatures were also associated with slightly shorter trips ($\beta = -0.002$, 95% CI [−0.003, −0.002]; $\Delta \approx -1.9$ m per 1 °C increase). Precipitation, however, showed no discernible association with trip distance in this study context ($\beta \approx 0.000$, 95% CI [−0.000, 0.000]; $\Delta \approx 0$ m).

Table 6-3. Elastic net regression results for predictors of e-scooter trip distance

Variables	Coeff. (β)	95% CI	Δ distance (m)
Public transport accessibility			
Origin	-0.006	[-0.007, -0.005]	-5.2
Destination	-0.007	[-0.008, -0.006]	-6.5
Recreation accessibility			
Origin	0.082	[0.064, 0.097]	76.6
Destination	0.017	[0.002, 0.032]	15.6
Shopping accessibility			
Origin	0.037	[0.025, 0.050]	34.0
Destination	-0.031	[-0.042, -0.021]	-27.6
Environmental “bads” accessibility			
Origin	0.035	[0.029, 0.040]	31.5
Destination	0.053	[0.048, 0.058]	48.4
Education accessibility			
Origin	0.033	[0.025, 0.039]	30.0
Destination	0.038	[0.030, 0.048]	34.5
Time of day (ref. = off-peak)			
Morning peak	0.082	[0.075, 0.088]	76.0
Evening peak	0.027	[0.022, 0.033]	24.8
Day of week (ref. = weekday)			
Weekend	-0.009	[-0.014, -0.005]	-8.3
NZDep2023			
Origin	0.002	[0.001, 0.003]	1.5
Destination	0.005	[0.004, 0.006]	4.7
Vehicles per household			
Origin	0.081	[0.073, 0.089]	75.7
Destination	0.133	[0.124, 0.141]	127.0
Season (ref. = warm)			
Cool	-0.029	[-0.035, -0.026]	-25.8
Temperature (°C)	-0.002	[-0.003, -0.002]	-1.9
Precipitation (mm)	0.000	[-0.000, 0.000]	0.0

Note: β = regression coefficient for log-transformed trip distance, Δ distance (m) = back-transformed using Duan’s smearing estimator

Figure 6-5 visualises the modelled relationships between predicted e-scooter trip length and log(accessibility) scores across the five domains. Consistent with Table 6-3, greater accessibility to recreation (with less variation at destinations) and education facilities was associated with longer trips, with notably steeper gradients for recreation at trip origins. In contrast, higher accessibility to public transport and shopping destinations corresponded to shorter predicted trip lengths. Accessibility to environmental “bads” showed positive relationships with trip distance at both trip ends, particularly for destinations. Overall, these patterns highlight distinct spatial associations between accessibility and e-scooter travel behaviour, with origin- and destination-specific patterns.

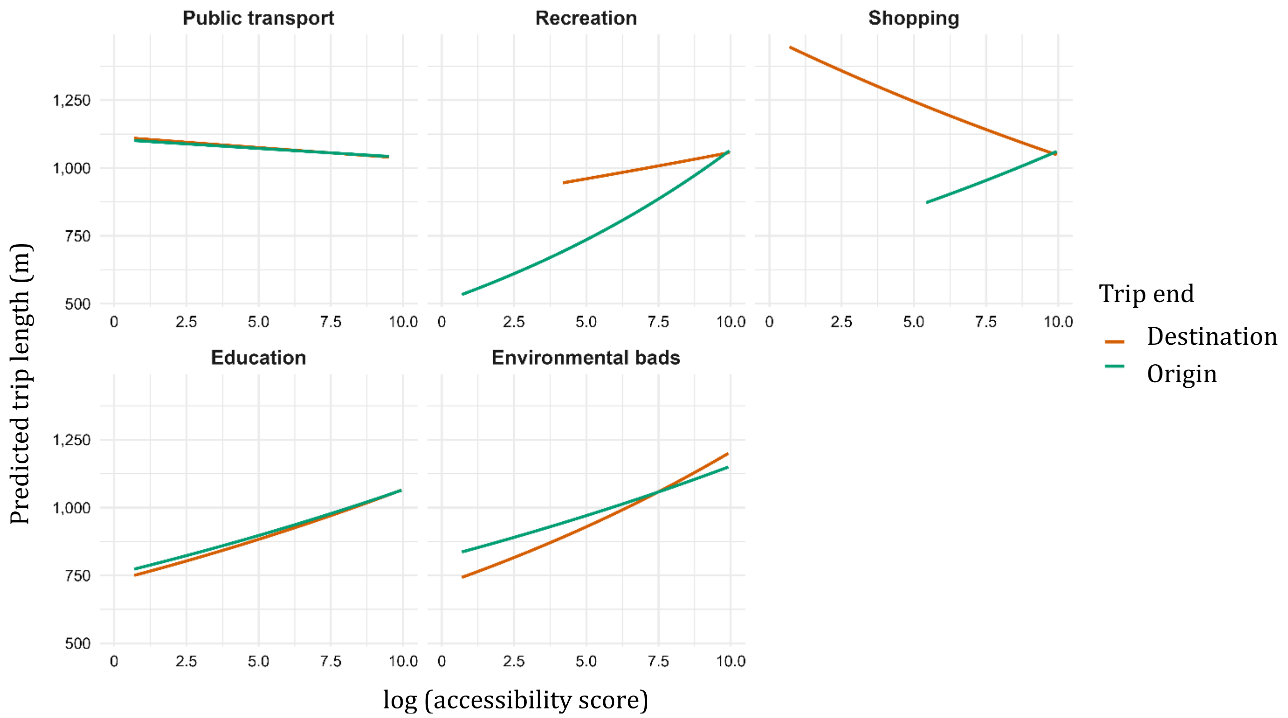


Figure 6-5. Predicted e-scooter trip length by accessibility domain

Discussion and policy implications

This study explored how the spatial length of shared e-scooter trips is correlated with domain-specific accessibility measures and contextual conditions in Auckland, a highly car-dependent city. While analyses of trip counts and usage volume have yielded valuable insights into where and when e-scooters are used, understanding the factors associated with travel distance offers an additional behavioural perspective, particularly for advancing sustainability goals and equity principles in micromobility deployment. By linking a large dataset of e-scooter trips to domain-specific accessibility indicators at both trip origins and destinations, the study moves beyond aggregate usage analyses to consider how local urban context may be associated with the spatial extent of travel. An interpretable machine learning framework (Elastic Net) was used to model associations between accessibility and trip length, while controlling for temporal, weather, and socio-economic variation. Although predictive accuracy was modest, the results revealed consistent spatial patterns, suggesting that even in a discretionary, short-range mode like shared micromobility, travel distance is systematically correlated with built environment conditions.

While the analysis enabled interpretable estimation, its predictive performance was limited. Error values (RMSE ≈ 715 m; MAE ≈ 527 m) were relatively large compared to the mean trip length (approximately 1,076 m), suggesting that much of the variation remains unexplained. This may reflect unmeasured individual-level factors, such as trip purpose, attitudes, or lifestyle preferences. Findings from broader travel behaviour research support this interpretation, indicating that personal attributes are often more strongly associated with travel behaviour than environmental indicators (12,355,433,511,512). However, these individual-level preferences themselves are significantly correlated, to some extent, with the surrounding built environment (512,513). Despite the model's limited predictive power, the consistent associations observed between accessibility characteristics and trip length highlight that built environment conditions remain systematically associated with micromobility behaviour.

A negative association emerged between public transport accessibility and e-scooter trip length, with shorter journeys more frequently occurring in transit-rich areas. Although the association is small (5 to 7 m reduction in trip length for each unit increase in log-transformed accessibility to public transport), it reflects the limited variability in public transport access across the study area, with most origins and destinations concentrated at the upper end of the accessibility scale, creating a saturation effect. The sensitivity check confirmed this pattern, while adding public transport accessibility to a controls-only model increased the out-of-sample R^2 by just 0.0014 (from 0.0549 to 0.0563), indicating that the weak but stable association is due to constrained variability rather than model instability.

Despite its modest magnitude, the negative relationship suggests an important behavioural distinction. In areas with higher accessibility to public transport, shared e-scooters are likely to support short-distance connectivity, potentially serving as access or egress links within broader multimodal journeys. Conversely, in areas with poor accessibility to public transport, users may rely on e-scooters for longer, standalone trips to reach their destinations. Although prior studies have not explicitly examined how trip length varies with transit accessibility, several have documented strong spatial clustering of e-scooter activity around public transport stops and central districts, where transit availability is a key correlate of demand (240,259,514).

From an urban planning perspective, these results indicate that higher transit accessibility may be associated with shorter e-scooter trips, reinforcing their role as connectors and supporting the efficiency of public transport networks. For micromobility providers, this pattern highlights the potential value of prioritising short-trip pricing models or locating stations near transit hubs. However, given that the average e-scooter trip distance in this study context (approximately 1,076 m) falls within typical walking thresholds, planners should also consider the health implications of reduced walking and ensure that strategies maintain opportunities for active travel.

Shopping accessibility demonstrated a pronounced directional asymmetry between trip origins and destinations. Higher accessibility at origins was associated with longer e-scooter journeys, which may reflect trip chaining and outbound movement. Shared e-scooter users starting a trip in commercial zones may combine shopping with other activities, leading to longer trips (515). These areas may also be characterised by well-connected hubs from which micromobility users might disperse into more distant residential or recreational destinations. In contrast, greater accessibility at destinations corresponded to shorter trips, suggesting that arrivals into shopping-dense areas typically involve compact commercial clusters where high accessibility is likely to reduce the need for extended travel and enable short, targeted errands.

These patterns highlight differentiated implications for urban design and micromobility management. Shopping-rich origins may require infrastructure that supports longer, multi-purpose trips (e.g., improved connectivity, parking, and safety features), whereas shopping-rich destinations may benefit from facilities that accommodate high turnover and short-trip activity (e.g., quick-drop zones, dynamic pricing). For operators, these findings suggest longer outbound trips from commercial hubs and shorter inbound trips to retail clusters, providing useful guidance for fleet distribution and rebalancing strategies.

Recreation accessibility was positively associated with e-scooter trip length at both origins and destinations, with origin-side accessibility showing a stronger relationship. This pattern aligns with evidence that leisure-oriented trips often involve greater flexibility, including the selection of indirect or elongated routes and slower travel speeds, which can contribute to longer spatial and temporal distances (39,516–518). These findings suggest that recreational contexts are associated with a higher tolerance for distance compared to utilitarian purposes such as shopping or commuting (519,520). The larger association at origins indicates that the characteristics of areas where trips begin may play a stronger role in travel extent than those at destinations.

Building on these observations, planning and operational strategies could be tailored to reflect this demand pattern. Urban planning approaches might consider enhancing recreational infrastructure not only at destination leisure amenities such as parks but also within neighbourhoods, as greater origin-side accessibility appears linked to longer leisure-oriented trips. Such investments could support equitable opportunities for discretionary travel while informing micromobility deployment in areas where longer trips are more likely. For operators, these patterns point to the potential for higher demand and extended trip durations in recreation-rich areas, suggesting adjustments to pricing structures, battery range, and fleet allocation to accommodate these behaviours.

The analysis identified a consistent relationship between longer shared e-scooter journeys and areas characterised by higher concentrations of environmental “bads”, such as fast-food and alcohol outlets. This suggests that such destinations may exert a spatial draw on users, potentially reflecting travel motivated by leisure, convenience, or social engagement (521–523). The more pronounced association at trip destinations indicates that these locations may function as attractors, encouraging longer journeys towards them. However, the origin association may reflect that neighbourhoods with greater exposure to these outlets are situated within urban contexts, such as commercial corridors or mixed-use zones, that may inherently support longer travel distances (524,525).

The above finding carries implications for urban planning and micromobility infrastructure, particularly in areas where environmental “bads” are spatially concentrated. Furthermore, the observed association prompts reflection on how micromobility systems interact with urban environments that may pose public health risks, highlighting the potential for integrated interventions, such as zoning regulations or targeted awareness initiatives, that align mobility access with health-promoting urban design.

The positive association between education accessibility and e-scooter trip length may reflect spatial and behavioural patterns linked to educational activities. At both trip ends, as accessibility to educational facilities increases users tend to travel farther by e-scooter. These patterns may reflect student and staff travel behaviour, where e-scooters are used for medium-distance commutes to and from campuses (526–528). The slightly larger effect at destinations implies that users may be travelling toward educational hubs, such as universities, colleges, or schools, located farther from their starting points. This might also hold true for people departing from areas with more accessible educational facilities, possibly due to better infrastructure or broader activity options nearby. This interpretation is tentatively supported by the observation of longer trips during weekday morning and afternoon periods, which coincide with typical education-related travel times.

Building on these patterns, urban master plans might benefit from embedding educational zones within well-connected, mixed-use environments that support diverse travel needs. Such integration may help foster longer shared micromobility trips, substituting car trips and complementing sustainable transport goals. Additionally, prioritising high-quality micromobility infrastructure around educational institutions, particularly in areas with limited public transport, may enhance accessibility for students and staff, reduce reliance on private vehicles, and promote equitable, low-carbon mobility options (529,530).

In addition to accessibility measures, socio-economic attributes demonstrated nuanced associations with e-scooter trip length. Longer trips were more common in areas with greater area-level deprivation (NZDep2023) and in highly auto-oriented zones, which are typically located farther from central areas and key transit connections (531). The stronger association at destinations with greater area-level deprivation, compared to origins, suggests that users may be travelling longer distances into more deprived areas. Similarly, the stronger effect at highly auto-oriented destinations, compared to origins, indicates that users often travel farther into car-dependent zones, perhaps to visit friends, family, or services located in less walkable suburbs and lower-density environments with fewer nearby destinations (487,532).

From an equity perspective, these patterns raise important concerns. Most shared e-scooter pricing models are distance- or time-based, meaning users in deprived or peripheral areas may incur higher costs simply because of structural land-use and accessibility gaps. This could exacerbate transport inequities by making micromobility less affordable for those who might benefit most, particularly where public transport options are limited, and essential destinations are farther away (533). Addressing these disparities may require targeted interventions, such as fare caps or subsidies for trips starting or ending in high-deprivation zones and land-use strategies that bring key services closer to underserved communities. These measures could help ensure that micromobility systems support equitable access rather than reinforcing existing spatial and socio-economic inequalities.

Seasonal and weather conditions showed only weak associations with e-scooter trip length. Journeys tended to be marginally shorter at higher temperatures and during the cooler months (May–September). Precipitation showed no meaningful association, which may be related to Auckland's frequent but generally light rainfall. The limited sensitivity observed could also be consistent with Auckland's mild oceanic climate, where seasonal contrasts are moderate and extreme conditions uncommon (534). Collectively, these patterns suggest that environmental factors are only weakly associated with variations in trip length, with built-environment, temporal, and socio-economic characteristics appearing to account for a greater share of observed differences.

Limitations and future directions

Although this study provided insights into how domain-specific accessibility and contextual factors are associated with e-scooter trip length in a highly car-dependent city, these findings should be interpreted with caution due to several limitations that warrant further consideration. One limitation concerns the routing method, which relied on shortest-path calculations derived from the OpenStreetMap bikeable road network. While this approach provides a reasonable approximation, it may not fully capture actual rider behaviour, such as the use of pedestrian links, shared paths, or informal shortcuts not represented in the network. Consequently, estimated trip distances may differ from actual travel distances, potentially introducing bias into the analysis of trip length patterns. Future research could address this by incorporating micromobility-specific infrastructure into routing networks and, where feasible, leveraging anonymised GPS-based path data from operators to develop behaviourally representative routing models. These enhancements would improve accuracy and strengthen the validity of associations between accessibility and trip length.

A second limitation relates to the absence of user-level attributes. Because individual characteristics such as trip purpose, demographics, and attitudes were not available, the analysis relied exclusively on area-level variables. This means that some of the variation in trip length attributed to spatial and temporal factors may actually reflect underlying individual behaviours, which could not be examined in this study. Future research could address this gap by integrating survey or profile data with trip records, enabling explicit analysis of user heterogeneity and motivations.

Finally, weather variables were derived from a single-station dataset, which likely reduced sensitivity to local variation in rainfall and temperature across Auckland. This aggregation may partly explain the minimal weather associations observed. Future research could address this by using spatially disaggregated or sensor-based climate data to capture microclimatic differences.

Chapter 7. General discussion

Active travel is widely recognised as a cornerstone of sustainable urban mobility, delivering substantial health, environmental, and social benefits. By embedding physical activity into daily routines, it reduces the risk of chronic disease, enhances mental well-being, and contributes to lower emissions and congestion, while fostering more liveable and equitable cities (1,4,5,535,536). These benefits can be realised through direct engagement in active modes, such as walking and cycling, and indirectly through transport options that incorporate active segments within multimodal journeys. Public transport exemplifies this indirect pathway: although not classified as an active mode, it typically requires walking to and from stops, thereby integrating physical activity into everyday travel (537). Similarly, emerging micromobility services such as shared e-scooters, despite being motorised, involve short walking segments and can complement active travel by bridging first- and last-mile gaps (234). Together, these modes form an interconnected system that has the potential to reduce car dependency and support healthier, more sustainable urban lifestyles.

The built environment is consistently associated with travel behaviour because it substantially structures the opportunities available for movement and is uniquely amenable to policy intervention. By adjusting land-use mix, street connectivity, and destination density, policy decisions can modify spatial conditions that may be associated with how people travel. At the centre of this association lies accessibility, the ease of reaching desired activities within acceptable time and effort, which serves as the mechanism linking spatial opportunity to mode choice (15,17). Yet persistent analytical gaps across modes limit the practical application of this relationship. More broadly, persistent reliance on self-reported walking measures, narrow operationalisation of public transport accessibility at a single spatial anchor, and coarse or aggregate approaches to micromobility analysis, often coupled with limited use of objective mobility data and interpretable modelling, continue to impede translation of accessibility research into practice. Collectively, these limitations constrain the development of evidence-based planning and policy, weakening the translation of accessibility concepts into practical strategies for promoting sustainable and active mobility.

Research summary

The first study (Chapter 3) investigated whether neighbourhood accessibility was more strongly associated with local walking or walking to destinations beyond the immediate neighbourhood, using objective measures of mobility captured through GPS and accelerometers. Employing a multidimensional accessibility index and mixed-effects modelling of 2,503 trips, the analysis showed positive accessibility coefficients for walking both within and beyond home-neighbourhood buffers, although these estimates were accompanied by substantial uncertainty. The association for walking beyond home-neighbourhood boundaries was estimated more precisely, but the findings did not provide clear evidence that accessibility was more strongly associated with one setting than the other. Sociodemographic factors, particularly age, exerted stronger associations with walking behaviour than accessibility, with older adults walking more frequently across all contexts. These findings underscored the spatial sensitivity of accessibility–walking relationships and highlighted the importance of considering trip purpose and broader urban contexts when designing interventions. Rather than focusing solely on neighbourhood-level improvements, planners may need to adopt strategies that enhance pedestrian environments around key destinations such as transit hubs and central business areas to support walking across wider spatial scales.

The second study (Chapter 4) examined how accessibility to bus stops, measured from multiple spatial anchors (i.e., home, trip origin, and destination), related to actual bus use, using GPS and accelerometer data from 108 participants who recorded 835 trips. Mixed-effects logistic models revealed that home-based accessibility was negatively associated with bus ridership, suggesting that areas with dense stop networks may also offer walkable environments or experience operational inefficiencies that might discourage bus travel. Destination-based accessibility showed a positive association with bus use only among newer residents, who may also have been younger and in transitional life stages, indicating that accessibility at destinations became a stronger associate during periods of residential adjustment. Work status moderated the home-based relationship, with employed individuals more sensitive to local accessibility than unemployed participants, likely reflecting time constraints. These findings challenged the assumption that greater proximity to bus stops uniformly increased ridership and underscored the need for initiatives that incorporate demographic and behavioural context. Improving operational reliability and tailoring service provision to diverse user needs may be more effective than simply increasing stop density.

The third study (Chapter 5) explored spatial associates of e-scooter trip volumes using a gravity-based negative binomial model applied to 57,842 origin–destination trip pairs. The analysis revealed a pronounced distance-decay effect, confirming that e-scooters were predominantly used for short-range travel, with average trip distances near 1.7 km. Accessibility to public transport and recreational amenities was positively associated with trip volumes, highlighting the complementary role of e-scooters in multimodal travel and leisure contexts. Conversely, higher accessibility to shopping and education facilities, as well as exposure to environmental "bads" such as alcohol outlets, was linked to lower usage. Socio-economic factors also mattered. Trip volumes were lower in high-deprivation and high car-ownership areas, likely pointing to structural inequities in service uptake. These findings underscored the need for equity-oriented deployment strategies and integrated planning that prioritised micromobility infrastructure near transit hubs and recreational destinations while addressing barriers in underserved communities. At the same time, policies should ensure that these improvements complement rather than replace walking, preserving opportunities for active travel through pedestrian-friendly design and balanced mode choices.

The fourth study (Chapter 6) extended the analysis by examining how domain-specific accessibility and contextual factors are associated with the spatial extent of e-scooter trips. Using elastic net regression on nearly half a million trips, the study found systematic associations between trip length and built environment conditions, even for a discretionary, short-range mode like shared micromobility. Higher public transport accessibility was linked to shorter trips, consistent with a possible first- and last-mile connector role, while greater accessibility to recreation and education facilities corresponded to longer journeys, likely reflecting leisure and campus-related travel patterns. Shopping accessibility exhibited directional asymmetry: trips originating in retail-rich areas tended to be longer, whereas those terminating in such areas were shorter, suggesting complex trip-chaining behaviours. Longer trips were also associated with auto-oriented and more deprived areas, raising equity concerns, particularly under distance-based pricing models. These findings highlighted the need for policies that integrate micromobility with public transport and address spatial inequities, while ensuring that these services complement rather than displace walking. Maintaining pedestrian-friendly environments and balanced mode choices remained essential to preserve health benefits associated with active travel.

Significance of findings

This research advances understanding of how accessibility relates to mode choice and informs strategies to promote active and sustainable travel. By introducing context-sensitive measures and integrating emerging mobility options, it moves beyond traditional static approaches to reveal spatial, behavioural, and equity dimensions across walking, public transport, and shared micromobility. These contributions provide actionable insights for healthier, more sustainable urban mobility, as discussed below.

Accessibility as a context-sensitive measure

A central insight emerging from this thesis is that associations between accessibility and travel behaviour are not uniform; rather, its behavioural relevance depends on how it is conceptualised and the context in which it is applied. Therefore, accessibility measures should be calibrated to the mode, spatial anchor, and population context.

In Chapter 3 (walking behaviour study), accessibility measures showed positive associations with both local and extra-neighbourhood walking, although these estimates were accompanied by considerable uncertainty. While associations for walking beyond local areas were estimated more precisely, the findings did not provide clear evidence that accessibility was more strongly associated with one setting than the other. This is broadly consistent with previous research suggesting that walking for transport and utilitarian purposes, which often occurs outside home-neighbourhood buffers (e.g., work-related trips), may be more strongly associated with macro-scale built environment characteristics such as accessibility (12,361,362). From a policy perspective, when the goal is to alleviate traffic externalities while improving the health and environmental benefits of walking, policymakers and urban planners might need to prioritise investments that strengthen pedestrian access to major destinations beyond local neighbourhoods, such as employment centres, transit hubs, and mixed-use activity zones. However, the findings of Chapter 4 (bus ridership behaviour) introduce a critical nuance: increasing accessibility to public transport, specifically bus stops, was associated with lower bus ridership. This might imply that indiscriminate accessibility improvements may not uniformly advance sustainable mobility goals. If bus-stop proximity is correlated with lower public transport use and its consequent walking, then accessibility strategies must be carefully calibrated. Rather than blanket enhancements, planners should adopt domain-specific approaches that optimise investment across modes, ensuring that improvements for walking and transit complement rather than compete with each other.

More broadly, accessibility should not be considered in isolation for any single transport mode. Accessibility associated with one mode may influence the attractiveness and use of competing modes. The findings from Chapter 4 highlight this possibility, as bus ridership may be associated not only with accessibility to bus stops but also with the accessibility and convenience of alternative travel options. For example, accessibility favouring private vehicle use may reduce the relative attractiveness of public transport or walking, whereas improved accessibility to public transport may support both transit use and associated walking. Future research should therefore consider accessibility across multiple modes simultaneously rather than examining each mode independently.

The moderating role of individual-level factors

Consistent with prior research (355,433), the findings from the walking and public transport analyses (Chapters 3 and 4) indicated that individual-level and socio-behavioural factors were important correlates of travel behaviour, reflected in the modest explanatory power of accessibility measures when considered in isolation. However, this research extends beyond established findings by suggesting that the accessibility–ridership association may differ by employment status, with substantive policy implications for how accessibility interventions are designed and targeted.

Walking behaviour among employed residents appeared only modestly responsive to variations in overall neighbourhood accessibility compared with unemployed participants. However, their response to changes in accessibility to bus stops was markedly different. As proposed in Chapter 3, this limited sensitivity to neighbourhood amenity accessibility may reflect structured walking patterns tied to fixed commuting routines, such as walking between home and public transport nodes, which makes employed residents more dependent on transit access than on local amenities (363,364). The moderation analysis in Chapter 4 reinforced this interpretation. Relative to unemployed individuals, employed residents showed greater variation in bus use behaviour across levels of accessibility to bus stops within their residential environment. From a policy perspective, this suggests that the type of accessibility being enhanced, whether transit-focused or amenity-focused, should be strategically aligned with the employment composition and mobility patterns of residents, and that investment priorities should be directed toward the accessibility improvements most likely to support eco-friendly travel behaviour in the targeted area given its specific resident characteristics.

Spatial selectivity of e-scooter flows

Although prior research has predominantly established that e-scooter activity tends to be concentrated within central urban districts (20,72,240,460), broader evidence about how specific dimensions of spatial accessibility relate to this demand, and how these accessibility domains interact across origin–destination (OD) flows, has remained limited. Chapter 5 advanced this understanding by demonstrating that e-scooter flows did not simply rise in all highly accessible areas; rather, they followed a selective spatial logic. Flows intensified around major mobility hubs and leisure-oriented destinations, aligning with patterns of movement that reflect multimodal connectivity and recreational appeal (35,39,259). In contrast, flows were markedly weaker in zones dominated by retail, educational, and health-risk amenities (e.g., fast-food and alcohol outlets), suggesting that the built environment typically surrounding these land uses may be less conducive to shared e-scooter use within the context of this study. Crucially, the spatial inequalities revealed in Chapter 5 provide only one dimension of the story. Chapter 6 extended this analysis by showing how the very same accessibility conditions were associated with how far people travelled by e-scooter, offering a complementary and integrated account of how accessibility is associated with both where e-scooters are used and the spatial extent of those trips, an aspect of micromobility behaviour that has received considerably less attention in prior research.

Considering trip frequency and trip length together provides a more nuanced understanding of how the role of shared e-scooters varies across different built-environment contexts. The findings indicated that higher accessibility to educational, shopping, and health-risk facilities correspond with lower shared e-scooter use overall. This may be because these land-use clusters, often situated in central parts of the city, are embedded within urban forms characterised by extensive car-parking provision, arterial road frontages, and, in the case of Auckland, ongoing construction activities, all of which may suppress micromobility uptake and reinforce automobile primacy (72,259,272,274). Yet, Chapter 6 showed that these same central, amenity-rich areas, despite weaker e-scooter demand, were associated with longer e-scooter trips. Considered together in the Auckland setting, these findings indicate that e-scooters in such areas appear less likely to function as local connectors within central districts and may instead serve as a medium-distance option linking surrounding residential neighbourhoods to central activity hubs. While the data do not allow direct identification of the modes these trips might otherwise have replaced, the pattern of longer trips in amenity-rich central areas is consistent with the possibility that some e-scooter journeys substituted for short car trips rather than for very short walking trips.

The origin–destination analyses revealed a significant positive association between e-scooter activity and accessibility to public transport, suggesting that e-scooters often serve as connectors within the broader mobility network. This interpretation was further supported by findings in Chapter 6, which showed that higher levels of public transport accessibility corresponded to shorter e-scooter trip lengths, reinforcing their role as a first- and last-mile solution (35,39,259). These findings indicate that, rather than uniform deployment, service planning could benefit from strategies that respond to spatial variations in accessibility. In areas with strong public transport accessibility, initiatives such as increasing device availability and improving parking management near transit nodes may help accommodate frequent short transfers. However, to avoid excessive substitution of walking for very short trips, policymakers and operators might consider complementary measures, such as pricing adjustments or usage limits, to encourage active travel. Conversely, in areas with lower accessibility, where trips are likely to be longer, ensuring that vehicles are well maintained and adequately charged remains important, alongside pricing strategies that balance affordability with operational sustainability for extended journeys. Such nuanced approaches can enhance operational efficiency while encouraging healthier travel behaviours within an integrated and sustainable transport system.

Study limitations and future directions

In addition to the chapter-level limitations and directions already noted, several overarching issues warrant careful consideration.

A key cross-cutting limitation is the absence of individual-level behavioural data across all four studies. Although spatial and transport measures were rich, the datasets did not capture person-level factors such as trip purpose, attitudes, perceived accessibility, or time constraints. Consequently, interpretations of mode choice remained partly inferential, as the analyses could not determine why trips occurred, what alternatives they may have replaced, or how individual motivations were associated with behaviour. This constrains the ability to disentangle behavioural mechanisms from spatial patterns. Future work combining GPS-derived mobility data with trip-purpose information, attitudinal surveys, or linked behavioural datasets would enable stronger inference and a more precise understanding of how individuals respond to accessibility in different contexts.

In addition to the absence of individual-level behavioural data, several broader methodological considerations apply across the empirical studies. All analyses were observational and predominantly cross-sectional, meaning residual confounding, self-selection, and other sources of bias cannot be fully ruled out. Accessibility measures were also operationalised at different spatial scales and reference locations, which may have introduced exposure misclassification where measured accessibility did not fully correspond to the environments in which behaviour occurred. Some analyses, particularly the origin–destination and trip-level models, may additionally be affected by spatial dependence or non-independence among observations. Furthermore, deprivation measures were analysed at the area level and therefore should not be interpreted as direct measures of individual socio-economic circumstances. Finally, the shared e-scooter analyses relied on data from a single operator and did not incorporate detailed information on fleet availability or deployment practices, meaning that observed usage patterns may reflect both demand-side and supply-side influences.

All four studies were conducted in Auckland, a city characterised by high car dependency, a dispersed urban form, and relatively modest public transport provision. These structural conditions are correlated with both accessibility patterns and behavioural responses, meaning that the observed associations may not readily generalise to cities with denser land-use configurations, higher transit service levels, or different micromobility regulatory environments. For instance, the behavioural salience of accessibility to public transport or recreational amenities may be stronger in contexts with higher service quality or where micromobility systems operate under alternative pricing, coverage, or governance models (281). Similarly, the interaction between accessibility and socio-economic factors may differ in cities with more comprehensive equity-oriented transport policies or more inclusive infrastructure provision.

To strengthen external validity, future research might pursue comparative analyses across cities with diverse urban forms and policy regimes. Multi-city studies employing harmonised accessibility metrics and behavioural measures would enable clearer identification of which associations are broadly transferable and which are context contingent. Incorporating contextual descriptors, such as transit intensity, micromobility governance frameworks, and land-use mix, into comparative or meta-analytic approaches could further clarify how structural conditions moderate accessibility–behaviour relationships.

Conclusion

This thesis examined how accessibility relates to travel behaviour across conventional and emerging transport modes in Auckland, with the aim of informing healthier, more sustainable, and more equitable mobility in a car-dependent urban context. Drawing on four empirical studies, it employed objective mobility traces, multi-anchor and domain-specific accessibility measures, and interpretable models to characterise context-specific associations between accessibility, mode choice, and travel patterns.

Overall, the findings indicate that accessibility is differentially associated with travel behaviour across modes and spatial reference points. Accessibility showed positive associations with walking behaviour, although evidence regarding differences between local and destination-oriented walking remained inconclusive. For public transport, accessibility associations differed across home, origin, and destination anchors and were moderated by user characteristics, revealing behavioural asymmetries obscured by single-anchor approaches. In the micromobility context, domain-specific accessibility was central to both trip volume and trip length: multimodal and leisure-oriented environments were associated with higher activity and shorter trips, while more utilitarian and auto-oriented settings were associated with longer journeys and equity concerns.

Methodologically, the thesis advances accessibility research by moving beyond static residential indices toward activity-space, multi-anchor measures grounded in observed behaviour. Collectively, the findings support planning approaches that prioritise pedestrian access at key destinations, adopt anchor-aware public transport strategies, and integrate micromobility as a short-range connector within multimodal systems, with explicit attention to equity. Overall, the thesis contributes a more nuanced understanding of how accessibility may support sustainable urban mobility in car-dependent cities.

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Appendices

Appendix A – Ethical Approval

Auckland University of Technology Ethics Committee (AUTEC)

Auckland University of Technology
D-88, Private Bag 92006, Auckland 1142, NZ
T: +64 9 921 9999 ext. 8316
E: ethics@aut.ac.nz
www.aut.ac.nz/researchethics

3 May 2022

Scott Duncan
Faculty of Health and Environmental Sciences

Dear Scott

Re Ethics Application: **21/361 Optimising urban redevelopment planning and delivery to enhance neighbourhood liveability and community wellbeing.**

Thank you for providing evidence as requested, which satisfies the points raised by the Auckland University of Technology Ethics Committee (AUTEC).

Your ethics application has been approved for three years until 3 May 2025.

Non-Standard Conditions of Approval

1. Please send through the updated Information Sheet and translations once finalised.

Non-standard conditions must be completed before commencing your study. Non-standard conditions do not need to be reviewed by AUTEC before commencing your study.

Standard Conditions of Approval

1. The research is to be undertaken in accordance with the Auckland University of Technology Code of Conduct for Research and as approved by AUTEC in this application.
2. A progress report is due annually on the anniversary of the approval date, using the EA2 form.
3. A final report is due at the expiration of the approval period, or, upon completion of project, using the EA3 form.
4. Any amendments to the project must be approved by AUTEC prior to being implemented. Amendments can be requested using the EA2 form.
5. Any serious or unexpected adverse events must be reported to AUTEC Secretariat as a matter of priority.
6. Any unforeseen events that might affect continued ethical acceptability of the project should also be reported to the AUTEC Secretariat as a matter of priority.
7. It is your responsibility to ensure that the spelling and grammar of documents being provided to participants or external organisations is of a high standard and that all the dates on the documents are updated.
8. AUTEC grants ethical approval only. You are responsible for obtaining management approval for access for your research from any institution or organisation at which your research is being conducted and you need to meet all ethical, legal, public health, and locality obligations or requirements for the jurisdictions in which the research is being undertaken.

Please quote the application number and title on all future correspondence related to this project.

For any enquiries please contact ethics@aut.ac.nz. The forms mentioned above are available online through http://www.aut.ac.nz/research/researchethics

(This is a computer-generated letter for which no signature is required)

The AUTEC Secretariat
Auckland University of Technology Ethics Committee

Cc: jmcphee@aut.ac.nz; Erica Hinkson; lisa.mackay@aut.ac.nz; tom.stewart@aut.ac.nz; moushumi.chaudhury@aut.ac.nz; Albert Refiti; tkaai@aut.ac.nz

Appendix B – Data Sharing Agreement

Data-Sharing and Usage Agreement

Agreement Details

[redacted]	[redacted]
AUT	**Auckland University of Technology** a tertiary education institute pursuant to the provisions of the Education and Training Act 2020, located at Auckland, New Zealand (hereinafter referred to as the "University") (NZBN 9429041901069) Address: 55 Wellesley Street East, Auckland Central
Commencement Date	The date of signature hereof by the last party in time to do so
Term	Until the Permitted Purpose has been achieved, which is envisaged to be 1 Feb 2026
Permitted Purpose	AUT is conducting the Te Hotonga Hapori – connecting communities – research programme, and, as part thereof, a PhD study project is being conducted to (a) investigate the correlation between access to micro-mobility facilities and mode choice behaviour; and (b) examine how access to micro-mobility is associated with mode choice for the access and egress legs of trips among public transport users (e.g., before and after catching a bus) ("**the Study**"). The Study is focussed on the Aorere, Oranga, Wesley, and Waikowhai neighbourhoods of Auckland ("**Study Areas**") over the period from May 2023 until 31 December 2024 ("**Study Period**") in respect of which AUT has collected the travel behaviour data (assessed via GPS receiver and a survey) for approximately 500 people. [redacted] 'Data' (as defined below) would facilitate the creation of a measure of people's accessibility to micro-mobility services during the Study Period in relation to the Study Areas. AUT will prepare a written report/thesis ("**Report**") setting out the Study parameters, methodology, assumptions and results which Report may contain aggregated anonymous data sets, but no personally identifiable information. The Report will also not mention the participating micromobility service operators by name or link any of the data to any particular such operator (instead referring to them as 'Company A' and 'Company B' for example). The Report may be published in peer-reviewed academic journal articles and presented at academic conferences, provided that [redacted] have the opportunity to review AUT's Study outcomes/analysis and Report, related to this data, prior to such publication.

Operative Provisions

1. Ownership and rights to use Data

All rights, title and interest in the Data and Derivatives (including all Intellectual Property Rights subsisting in them) remain with [redacted] and this Agreement does not transfer any such rights to AUT other than as expressly set out in this Agreement.

2. Permitted Purpose and Use of Data

2.1. Data transferred pursuant to the terms of this Agreement shall be used by AUT solely for the Permitted Purpose.

2.2. AUT agrees that it will not, without the prior written consent of [redacted] in its absolute discretion:

- (a) provide or transfer any Data to a third party;
- (b) collect, use or disclose the Data or Derivatives for any purpose other than the Permitted Purpose;
- (c) use or store the Data or Derivatives in any location other than at the Location; and
- (d) provide any of its employees, contactors or any other individual with access to the Data except for the Permitted Users.

2.3. AUT agrees that it will, to the extent necessary to allow [redacted] to comply with applicable PI Protection Laws:

- (a) assist [redacted] with any requests it may receive from Individual's requesting access to their Personal Information;
- (b) carry out any reasonable request from [redacted] to amend, transfer or delete Personal Information of any Individual;
- (c) notify [redacted] of any enquiries it receives directly from Individuals regarding their Personal Information;
- (d) notify [redacted] within 5 Business Days about any enquiries from any relevant regulatory body in relation to the Data and cooperate promptly and thoroughly with such data protection authority; and
- (e) notify [redacted] within 5 Business Days about any legally binding request for disclosure of Data by a law enforcement authority unless otherwise prohibited.

2.4. AUT shall take all reasonable steps (including providing adequate training and maintaining a training record) to ensure the reliability of any of its personnel who have access to Personal Information.

3. Sensitive Information

3.1. If applicable to the Data subject to this Agreement, AUT acknowledges and agrees that a failure to protect Sensitive Information is particularly likely to cause harm to Individuals.

3.2. AUT must have in place the Additional Precautions (if any) in relation to Sensitive Information.

4. Privacy Officer

Where the Data includes Personal Information and/or Sensitive Information:

4.1. AUT must maintain a person with the responsibility for monitoring and ensuring AUT's compliance with this Agreement (Privacy Officer).

4.2. AUT will ensure that the Privacy Officer provides reasonable co-operation to Individuals and [redacted] for the purposes of clauses 11 and 12.

5. Disclosure to third party

5.1. In accordance with clause 2 and subject to [redacted] written consent, AUT may disclose Data to a third party, provided that the third party:

- (a) enters into a binding and enforceable agreement with AUT, imposing on the third party at least the same obligations in respect of that Data as are imposed on AUT under this Agreement; and
- (b) the AUT remains responsible for the third party's acts and omissions in relation to the Data as if they were the acts or omissions of AUT.

6. Record Keeping

6.1. AUT must record adequate details of access to, use, storage, disclosure and disposal of Data.

6.2. Upon request by [redacted], AUT must promptly provide [redacted] with a report detailing access, use, storage, disclosure and disposal of Data.

7. Intellectual Property

7.1. All Data and Intellectual Property Rights subsisting in or in relation to the Data remain the sole property of [redacted].

7.2. [redacted] grants AUT a non-exclusive, non-transferrable, royalty-free licence to use [redacted] Intellectual Property Rights in or in relation to the Data solely for the Permitted Purpose.

7.3. All Intellectual Property Rights created by or on behalf of AUT as a result of using the Data other than in accordance with this Agreement will vest in and, by this Agreement, is assigned to [redacted] upon its creation.

7.4. AUT must:

(a) sign all documents and do all things necessary to perfect and record [redacted] ownership rights under this clause; and

(b) not directly or indirectly engage in any conduct that might impair or prevent the protection of Intellectual Property Rights in Data.

7.5. If AUT wishes to commercialise the Data or any Derivatives, it must first enter into an appropriate licence agreement with [redacted] (to be negotiated and entered into in good faith).

7.6. Neither party is under any obligation to enter into a licence agreement.]

8. PI Protection Laws

8.1. Without limiting any other provision of this Agreement, in respect of any Personal Information it receives or has access to in connection with this Agreement:

(a) each party agrees to comply at all times with PI Protection Laws;

(b) AUT agrees to collect, use and disclose Personal Information only for the Permitted Purpose;

(c) each party agrees to provide reasonable cooperation to the other party:

(i) to resolve any complaint alleging a breach of PI Protection Laws; or

(ii) in relation to a third party seeking access to Personal Information in accordance with PI Protection Laws; and

(d) AUT agrees to comply with any reasonable directions, guidelines, determinations or recommendations of [redacted] in relation to privacy issues, to the extent that they are not inconsistent with the requirements of PI Protection Laws.

8.2. At the time of sending to AUT, [redacted] undertakes that the Personal Information has been collected, processed and sent to AUT in compliance with all laws applying to [redacted].

8.3. Where a requirement of the Local Privacy Law is less protective than the other requirements of this Agreement, to the extent permitted by law AUT will comply with the requirement that is most protective of Personal Information and the interests of the relevant Individuals.

8.4. AUT must notify [redacted] as soon as reasonably practicable after any new applicable law that is a PI Protection Law is enacted in the jurisdiction of AUT.

9. Personal Information Safeguards

9.1. AUT must protect the Personal Information by implementing and maintaining Best Practice safeguards against any loss of the Personal Information, and any unauthorised access, use, modification or disclosure of the Data.

9.2. AUT must take reasonable steps to ensure that the Personal Information is accurate, up to date, complete, relevant and not misleading before using it.

9.3. AUT must:

(a) promptly and securely destroy or delete the Personal Information once it is no longer reasonably required by AUT for any Permitted Purpose;

(b) promptly and securely destroy or delete the Personal Information upon request from [redacted]; and

(c) promptly notify [redacted] when it has destroyed or deleted the Personal Information in accordance with subclause 9.3(a) or 9.3(b).

10. Data breach and notification

10.1. AUT must have a data breach response plan in place prior to the Commencement Date, which:

(a) details the appropriate remedial action to a data breach based upon the type of Data it receives or has access to under this Agreement; and

(b) includes a mechanism for notifying [redacted] (in accordance with clause 10.2(a)).

10.2. Where AUT suspects on reasonable grounds or becomes aware of, any unauthorised access, use, storage, copying, disclosure or breach of security in relation to, any Data provided to AUT by [redacted], AUT must:

(a) promptly notify [redacted] in writing and specify the details of the incident;

(b) reasonably co-operate and comply with all reasonable directions of [redacted] relating to the incident;

(c) where possible, take all reasonable steps to rectify or remedy the incident; and

(d) ensure compliance with all mandatory data breach reporting obligations arising out of the breach or suspected breach under any PI Protection Laws.

10.3. If a data incident occurs and AUT chooses to, or is required under applicable law to, communicate with or notify a relevant regulatory body or impacted Individuals, AUT must:

(a) consult with [redacted] in relation to the form of correspondence or notification; and

(b) comply with any applicable PI Protection Laws.

11. Confidential Information

11.1. AUT must:

(a) keep [redacted] Confidential Information confidential, and not deal with it in any way that might prejudice its confidentiality, except as permitted under this Agreement or with prior written consent of [redacted];

(b) only use Confidential Information for the Permitted Purpose;

(c) not perform any analysis or reverse engineering of any Confidential Information without the prior written consent of [redacted];

(d) ensure that each of its Permitted Users with access to any Confidential Information agree and are bound to hold all Confidential Information in confidence to the standard required under this Agreement; and

(e) promptly notify [redacted] if AUT suspects, or becomes aware of, any unauthorised use, storage, access, copying or disclosure of Confidential Information.

11.2. This clause shall not apply to any information which:

(a) is or subsequently becomes generally available in the public domain, other than as a result of breach of this clause; or

(b) was known by AUT prior to [redacted] disclosing the information to AUT.

11.3. At the termination of this Agreement, or at any time when directed by [redacted], AUT must immediately return to [redacted], or destroy and erase as [redacted] directs, all original documents that are or contain Confidential Information and copies, extracts or summaries of Confidential Information.

11.4. AUT may disclose Confidential Information where required to do so by law or any competent regulatory authority or securities exchange. In this scenario, AUT must provide [redacted] with prior written notice of the disclosure (where lawful to do so).

11.5. AUT indemnifies [redacted] fully against all liabilities, cost and expenses which [redacted] may incur as a result of any breach of this clause by AUT.

12. Restrictions on release of Data and Publications

12.1. AUT will not use the name or logo of [redacted] in any publication without [redacted] consent.

12.2. AUT will not share, publish or otherwise release any Data or Derivatives (including any findings or conclusions from carrying out the Permitted Purpose) without prior approval from [redacted].

13. Warranties

Except where expressly provided in this Agreement, no representation or warranty is made as to the accuracy, completeness or fitness for purpose of the Data or otherwise is given by [redacted] and all such representations and warranties are excluded to the extent their exclusion is not prohibited by law.

14. Insurance

AUT warrants that at the Commencement Date it has, and will maintain at its cost, appropriate insurance coverage in respect of potential loss or damage of the Data.

15. Indemnity

15.1. AUT indemnifies [redacted] against any loss suffered or incurred by [redacted] due to AUT's use, storage, handling and disposal of Data and Derivatives or a breach of this Agreement by AUT.

15.2. AUT's liability under this clause is reduced proportionately to the extent that any negligent act or omission of [redacted] contributed to the loss suffered.

16. Term

16.1. The Agreement commences on the Commencement Date and continues for the Term (as specified in the Agreement Details), unless terminated earlier in accordance with its terms.

16.2. If the Commencement Date is earlier than the date of signing, this Agreement will apply as if it had been signed on the Commencement Date.

17. Termination and Suspension

17.1. Either party may terminate this Agreement at any time by providing the other party with 30 days' written notice of intention to terminate.

17.2. Either party may terminate this agreement by written notice to the other if the party notified fails to observe any term of this Agreement and fails to rectify this breach, to the satisfaction of the notifying party, following the expiration of 7 days' notice of the breach being given in writing by the notifying party to the other party.

17.3. If AUT is in breach of this Agreement, [redacted] may suspend any further disclosure of, or access to, Data to AUT until AUT has corrected the breach.

17.4. [redacted] may terminate this Agreement upon giving notice to AUT if:

(a) [redacted] reasonably considers that AUT is subject to one or more laws that have a material adverse effect on the protections intended under this Agreement;

(b) compliance by AUT with its obligations under this Agreement would put it in breach of one or more laws that apply to AUT;

(c) AUT undergoes an Insolvency Event; or

(d) a suspension under clause 17.3 has continued for more than 30 days.

17.5. Clauses 7 (Intellectual Property), 8 (PI Protection Laws), 10 (Data breach & notification), 11 (Confidential Information), 12 (Restrictions of release of Data and publications), 14 (Insurance) and 15 (Indemnity), survive expiry or termination of this Agreement.

17.6. All clauses of this Agreement continue to apply to Personal Information that [redacted] sent to AUT during the Term. The clauses will stop applying once AUT has securely and permanently deleted or destroyed all of the Personal Information.

17.7. At any time on demand in writing by [redacted] and in any event on termination of this Agreement, AUT will, within twenty Business Days:

(a) destroy or return to [redacted] any documents containing the Data; and

(b) use all reasonable endeavours to expunge all Data provided to it from any computer, word processor or other device containing Data except any automatically generated backup files.

18. General

18.1. Any notices to be provided under this Agreement must be in writing and delivered to the party address in the Agreement Details.

18.2. Neither party may assign, delegate, subcontract, mortgage, charge or otherwise transfer any or all of its rights and obligations under this Agreement without the prior consent of the other party.

18.3. Where a clause in this Agreement is prohibited by law, void or unenforceable, the provision will, to the extent required, be severed without affecting the enforceability of the remaining provisions of this Agreement.

18.4. This Agreement is governed by and construed in accordance with the law of New Zealand and the parties submit to the exclusive jurisdiction of competent courts in New Zealand.

18.5. This Agreement takes priority over all other agreements between [redacted] and AUT, except as agreed to in writing between the parties.

18.6. Each party undertakes that it has full power, capacity and authority to execute, deliver and perform its obligations under this Agreement.

18.7. Each party undertakes that it has, and will continue to have, all the necessary consents, permissions, licences and rights to enter into and perform its obligations under this Agreement.

18.8. Each party undertakes that its obligations as set out in this Agreement are legal, valid, binding, and enforceable in accordance with their terms.

18.9. No amendment to this Agreement will be effective unless in writing and signed by [redacted] and AUT.

18.10. If a party fails to exercise, or delays or holds off exercising, a power or right under this agreement, that is not a waiver of the power or right. A single or partial exercise of such a power or right does not preclude further exercises of that power or right or any other.

19. Definitions

In the Agreement:

Agreement means this agreement and any amendments entered into in accordance with its terms.

Best Practice means at least the standard of practice generally expected globally in the same or similar circumstances, from a reasonable and prudent processor of Personal Information that is the same or of a similar nature to the Data.

Business Day means a day (other than a Saturday, Sunday or public holiday) on which banks are generally open in New Zealand for normal business.

Confidential Information means information of [redacted], including:

(a) any information marked, or AUT has been told is, confidential;

(b) any information received or developed by AUT during the term of the Agreement that is not publicly available and relates to processes, systems of work, equipment, techniques used by [redacted] in the course of its business, including all information, drawings, specifications, documentation, source or object code, designs, construction, workings, functions, features and performance notes, techniques, concepts not reduced to material form, agreements with third parties, schematics and proposals and intentions, technical data and marketing information such as customer lists, financial information and business plans;

(c) Data (defined in the Agreement Details); and

(d) trade secrets.

Local Privacy Law as defined in the Agreement Details.

PI Protection Laws means any applicable legislation that [redacted] and/or AUT are subject to which affects privacy or any personal information (including the collection, storage, use or processing of such information) including, to the Australian Privacy Act 1998 (Cth) and the New Zealand Privacy Act 2020.

Derivatives means anything derived by AUT from or using the Data, including but not limited to, any improvements or modifications to the Data.

Individual means an individual to whom the Data relates.

Insolvency Event means AUT: ceases, or threatens to cease, all or substantially all of its business; is insolvent or bankrupt, or has a receiver, liquidator, administrator, bankruptcy trustee, statutory manager or similar officer appointed; and/or makes an assignment for the benefit of its creditors, or makes any arrangement or composition with its creditors.

Intellectual Property Rights means all intellectual property rights, including all copyright, patents, trade marks, design rights, trade secrets, domain names, know how and other rights of a similar nature, whether registrable or not and whether registered or not, and any applications for registration or rights to make such an application.

Personal Information means:

(a) any information relating to an identified or identifiable natural person, which is provided by or on behalf of [redacted] or which is collected by AUT as part of its use of the Data. An identifiable natural person is one who can be identified directly or indirectly, in particular by reference to an identifier such as a name, identification number, location data, online identifier or to one or more factors specific to the physical, psychological, genetic, mental, economic, cultural or social identity of that natural person;

(b) any other information of a similar nature that is regulated by, or under any other PI Protection Laws; and

(c) includes Sensitive Information.

Appendix C – Supplementary Tables

Appendix C. 1. Descriptive statistics of the neighbourhoods included in this study

Neighbourhoods variables	**Aorere n (%)**	**Oranga n (%)**	**Wesley n (%)**	**Waikōwhai n (%)**
Age				
Under 15 years	1263 (23.92)	1251 (21.25)	2712 (19.33)	1065 (18.36)
15-29 years	1344 (25.45)	1347 (22.88)	3225 (22.98)	1443 (24.88)
30-64 years	2205 (41.76)	2775 (47.14)	6570 (46.82)	2703 (46.61)
65 years and over	468 (8.86)	513 (8.71)	1524 (10.86)	588 (10.14)
Gender				
Male	2670 (50.48)	2871 (48.55)	7041 (50.11)	3021 (51.91)
Female	2619 (49.52)	3042 (51.44)	7011 (49.89)	2799 (48.09)
Ethnicity				
New Zealand European	663 (10.72)	2604 (37.16)	5064 (31.62)	1386 (21.65)
Māori	867 (14.01)	888 (12.67)	1233 (7.70)	432 (6.75)
Pacific	3228 (52.18)	1980 (28.25)	3297 (20.58)	1158 (18.09)
Other	1428 (23.08)	1536 (21.92)	6423 (40.10)	3426 (53.51)
Household income				
Less than 70,000	282 (32.15)	570 (31.40)	1503 (35.36)	420 (26.17)
70,001 – 100,000	162 (18.47)	183 (10.08)	540 (12.70)	234 (14.58)
100,001 – 200,000	411 (46.86)	657 (36.20)	1425 (33.52)	603 (37.57)
More than 200,000	222 (25.31)	405 (22.31)	783 (18.42)	348 (21.64)
No of vehicle				
None	45 (4.67)	144 (8.74)	387 (9.66)	63 (4.27)
One	216 (22.43)	525 (31.88)	1434 (35.80)	375 (25.41)
Two or more	702 (72.90)	978 (59.38)	2184 (54.53)	1038 (70.32)

Appendix C. 2. Results of mixed-effects models examining the association between accessibility to bus stops and bus use behaviour – Unadjusted for socio-demographics

Parameters	**Log-Odds**	**SE**	**95% CI**	**P-value**
Home-based bus access	-0.24	0.16	[-0.56, 0.08]	0.147
Origin-based bus access	0.04	0.05	[-0.06, 0.14]	0.480
Destination-based bus access	0.13	0.05	[0.03, 0.24]	0.014
Marginal R^2 = 3.1 %; Conditional R^2 = 33.5 %				

Appendix C. 3. Results of mixed-effects models examining the association between accessibility to bus stops and bus use behaviour – Adjusted for socio-demographics

Parameters	**Log-Odds**	**SE**	**95% CI**	**P-value**
Home-based bus access	-0.82	0.33	[-1.45, -0.18]	0.012
Origin-based bus access	-0.19	0.18	[-0.54, 0.17]	0.304
Destination-based bus access	-0.02	0.10	[-0.21, 0.18]	0.870
Age (ref. = 18–39)				
40–64	-0.27	0.45	[-1.15, 0.61]	0.544
65 and over	0.30	0.77	[-1.21, 1.81]	0.701
Gender (ref. = female)	0.02	0.43	[-0.82, 0.86]	0.967
Household income (ref. = high income)	-0.61	0.45	[-1.50, 0.28]	0.178
Ethnicity (ref. = Māori)				
New Zealand European	-0.16	0.77	[-1.68, 1.35]	0.832
Pacific	0.29	0.88	[-1.43, 2.02]	0.741
Other	0.81	0.79	[-0.75, 2.37]	0.308
Neighbourhood residency (ref. = > 10 yrs)				
3–10 yrs	-0.87	1.62	[-4.05, 2.32]	0.593
< 3 yrs	-2.95	1.77	[-6.42, 0.52]	0.096
Work status (ref. = employed)	-1.76	1.55	[-4.81, 1.28]	0.256
Home-based bus accessibility*work status	0.18	0.38	[-0.56, 0.93]	0.629
Home-based bus accessibility* residency (3–10 yrs)	0.36	0.42	[-0.46, 1.19]	0.386
Home-based bus accessibility * residency (3 yrs >)	0.64	0.41	[-0.17, 1.46]	0.121
Origin-based bus accessibility*work status	0.14	0.13	[-0.11, 0.39]	0.272
Origin-based bus accessibility*residency (3–10 yrs)	0.13	0.19	[-0.25, 0.50]	0.509
Origin-based bus accessibility*residency (3 yrs >)	0.29	0.19	[-0.09, 0.67]	0.132
Destination-based bus accessibility*work status	0.25	0.16	[-0.06, 0.55]	0.116
Destination-based bus accessibility*residency (3–10 yrs)	0.11	0.16	[-0.22, 0.43]	0.520
Destination-based bus accessibility*residency (3 yrs >)	0.21	0.14	[-0.07, 0.49]	0.145
Marginal R^2 = 23.6 %; Conditional R^2 = 38.9 %				

Appendix C. 4. Estimated associations between accessibility and e-scooter OD trips – Pre-exclusion

Variable	IRR (95% CI)	Std. Error	Z-value	P-value
Log distance z-score	0.601 (0.595–0.607)	0.004	-106.00	< 0.001
Log education accessibility z-score				
Origin	0.855 (0.843–0.867)	0.007	-22.20	< 0.001
Destination	0.870 (0.858–0.882)	0.007	-19.40	< 0.001
Log recreation accessibility z-score				
Origin	1.070 (1.050–1.090)	0.008	7.89	< 0.001
Destination	1.070 (1.050–1.090)	0.008	7.51	< 0.001
Log shopping accessibility z-score				
Origin	0.980 (0.964–0.996)	0.008	-2.39	< 0.001
Destination	0.935 (0.920–0.951)	0.008	-7.92	< 0.001
Log public transport accessibility z-score				
Origin	1.060 (1.040–1.070)	0.005	9.59	< 0.001
Destination	1.060 (1.050–1.080)	0.005	10.80	< 0.001
Log environmental bads accessibility z-score				
Origin	0.725 (0.714–0.737)	0.007	-42.50	< 0.001
Destination	0.716 (0.705–0.728)	0.007	-43.80	< 0.001
Vehicles per household z-score				
Origin	0.715 (0.703–0.726)	0.007	-43.30	< 0.001
Destination	0.743 (0.731–0.755)	0.007	-38.40	< 0.001
Deprivation index z-score				
Origin	0.864 (0.854–0.874)	0.006	-23.70	< 0.001
Destination	0.896 (0.886–0.907)	0.006	-17.90	< 0.001
Temperature z-score	1.020 (1.000–1.030)	0.005	3.23	< 0.001
Precipitation z-score	0.986 (0.977–0.996)	0.004	-2.85	< 0.001
AIC = 278,235.6				

Appendix D – Analysis Code

Analysis codes - Chapter 1:

1. Parse GPS data

```python
# 1) Parse GPS data
from datetime import timedelta
from pathlib import Path

from labda.parsers import Qstarz, bulk_parser

path = Path("GPS")

gps = bulk_parser(path, Qstarz.from_csv)
gps.set_crs()
gps.set_timezone()
gps.resample(timedelta(seconds=30))
check, errors = gps.consistency()

if check:
    gps.to_folder(path / "gps_parquets", overwrite=True)

```

2. Parse accelerometer data

```python
# 2) Parse accelerometer data
from datetime import timedelta
from pathlib import Path

from labda.parsers import Axivity

path = Path("ACC")
files = path.glob("*.cwa")

for file in files:
    acc = Axivity.from_cwa(file, resample=30)
    acc.detect_counts_from_raw(timedelta(seconds=30))
    acc.to_parquet(f"ACC/acc_parquets/{acc.id}.parquet", overwrite=True)

```

3. Merge parsed data

```python
# 3) Merge parsed data
from labda import Collection

gps = Collection.from_folder("GPS/gps_parquets")

acc = Collection.from_folder("ACC/acc_parquets")
acc.set_timezone(gps.subjects[0].metadata.timezone)

gps.merge(acc)
gps.to_folder("merged_parquets", overwrite=True)

```

4. Define cut-points

```python
# 4) Define cut-points
from labda.cut_points import TRANSPORTATION_CUT_POINTS

# Add custom cut points
TRANSPORTATION_CUT_POINTS["mehdi_cut_points"] = {
    "name": "Mehdi Custom Cut Points",
    "reference": None,
    "required_data": "speed",
    "units": "kph",
    "cut_points": [
        {"name": "pedestrian", "max": 10},
        {"name": "bicycle", "max": 25},
        {"name": "vehicle", "max": float("inf")},
    ],
}

from labda.cut_points import COUNTS_CUT_POINTS
# from labda.utils import SampleRate

COUNTS_CUT_POINTS["mehdi_count_cut_points"] = {
    "name": "Mehdi",
    "reference": None,
    "sample_rate": {"value": 15, "unit": "s"},  # Use the enum directly
    "category": None,
    "placement": None,
    "required_data": "counts_vm",
    "cut_points": [
        {"name": "sedentary", "max": 2860},
        {"name": "light", "max": 3940},
        {"name": "moderate_vigorous", "max": float("inf")},
    ],
}

```

5. Detect travel modes, wear times, and count vector measures

```python
# 5) Detect travel modes, wear times, and count vector measures
from datetime import timedelta
from pathlib import Path
import geopandas as gpd
from labda import Subject
from labda.cut_points import (
    COUNTS_CUT_POINTS,
    TRANSPORTATION_CUT_POINTS,
    WEAR_CUT_POINTS,
)

trip_params = {
    "gap_duration": timedelta(minutes=1),
    "stop_radius": 25,
    "stop_duration": timedelta(minutes=3),
    "pause_radius": None,
    "pause_duration": timedelta(minutes=2),
    "min_duration": timedelta(minutes=2),
    "min_length": None,
    "min_distance": None,
    "indoor_limit": 60,
}

path = Path("merged_parquets")
files = path.glob("*.parquet")

for file in files:
    sbj = Subject.from_parquet(file)
    sbj.add_counts_vector_magnitude(overwrite=True)
    sbj.detect_activity_intensity_from_counts(
        COUNTS_CUT_POINTS["mehdi_count_cut_points"], overwrite=True
    )
    sbj.detect_wear(WEAR_CUT_POINTS["choi_2011"], overwrite=True)

    sbj.detect_trips(**trip_params, overwrite=True)
    sbj.detect_transportation(
        TRANSPORTATION_CUT_POINTS["mehdi_cut_points"],
        activity=True,
        overwrite=True
    )

    sbj.df.to_csv(f"output/{sbj.id}_df.csv")
    sbj.get_timeline().to_csv(f"output/{sbj.id}_timeline.csv")

```

Analysis codes - Chapter 5 and 6

1. Install packages

```
# Install required packages (run in a notebook cell if needed)
%pip install osmnx networkx pandas numpy tqdm geopandas shapely pyproj rtree

# Import libraries
import os
import osmnx as ox
import networkx as nx
import pandas as pd
import numpy as np
import geopandas as gpd
from shapely.geometry import LineString
from tqdm import tqdm
```

2. Setting

```
# Settings
INPUT_CSV = "input_trip_data.csv"
OUTPUT_CSV = "output_trips_with_network_distance.csv"
BATCH_SIZE = 100_000
CITY_NAME = "Auckland, New Zealand"
NETWORK_TYPE = "bike"  # 'bike', 'drive', 'walk'
```

3. Load and clean trip data

```
# Load trip data
print("Loading trip data…")
df = pd.read_csv(INPUT_CSV)
print(f"✓ Loaded {len(df):,} trips")

# Validate required columns
required_cols = {"start_trip_lat", "start_trip_long", "end_trip_lat", "end_trip_long"}
if not required_cols.issubset(df.columns):
    raise ValueError(f"Missing required columns: {required_cols - set(df.columns)}")

# Remove trips with missing or zero coordinates
df = df[
    df["start_trip_lat"].notna() & df["start_trip_long"].notna() &
    df["end_trip_lat"].notna() & df["end_trip_long"].notna() &
    (df["start_trip_lat"] != 0) & (df["start_trip_long"] != 0) &
    (df["end_trip_lat"] != 0) & (df["end_trip_long"] != 0)
].copy()
print(f"✓ After removing missing/zero coordinates: {len(df):,} trips")
```

`

4. Load and clean spatial data

```
# Load study area boundary and filter trips
BOUNDARY_SHAPEFILE = "boundaries_countries.shp"
STUDY_COUNTRY = "New Zealand"

boundary_data = gpd.read_file(BOUNDARY_SHAPEFILE)
if "NAME" in boundary_data.columns:
    study_area = boundary_data[boundary_data["NAME"] == STUDY_COUNTRY]
else:
    study_area = boundary_data[boundary_data["name"] == STUDY_COUNTRY]

gdf_orig = gpd.GeoDataFrame(
    df,
    geometry=gpd.points_from_xy(df["start_trip_long"], df["start_trip_lat"]),
    crs="EPSG:4326",
)
gdf_dest = gpd.GeoDataFrame(
    df,
    geometry=gpd.points_from_xy(df["end_trip_long"], df["end_trip_lat"]),
    crs="EPSG:4326",
)

orig_in_area = gdf_orig.geometry.within(study_area.unary_union)
dest_in_area = gdf_dest.geometry.within(study_area.unary_union)
df = df[orig_in_area & dest_in_area].copy()
print(f"✓ After filtering to study area: {len(df):,} trips")

# Download OSM road network
print("Downloading OSM road network…")
G = ox.graph_from_place(CITY_NAME, network_type=NETWORK_TYPE)
G_proj = ox.project_graph(G)
print("✓ Road network ready")
```

5. Snap origins and destinations to road nodes and clean OD nodes

```
# Snap origins and destinations to nearest road nodes
print("Snapping origins and destinations to nearest road nodes…")
df["orig_node"] = ox.distance.nearest_nodes(G, X=df["start_trip_long"], Y=df["start_trip_lat"])
df["dest_node"] = ox.distance.nearest_nodes(G, X=df["end_trip_long"], Y=df["end_trip_lat"])
print("✓ Snapping complete")

# Check identical snapped nodes
same_nodes = (df["orig_node"] == df["dest_node"]).sum()
print(f"{same_nodes} out of {len(df)} trips have identical snapped nodes.")
```

6. Calculate trip distance and filter outliers

```
# Calculate shortest path distances
def shortest_distance(u, v):
    try:
        return nx.shortest_path_length(G_proj, u, v, weight="length")
    except Exception:
        return np.nan

print("Calculating network distances…")
distances = np.empty(len(df), dtype=float)

for start_idx in range(0, len(df), BATCH_SIZE):
    end_idx = min(start_idx + BATCH_SIZE, len(df))
    print(f"  Processing {start_idx:,} – {end_idx-1:,}")
    batch = df.iloc[start_idx:end_idx]
    distances[start_idx:end_idx] = [
        shortest_distance(o, d)
        for o, d in zip(batch["orig_node"], batch["dest_node"])
    ]

df["network_distance_m"] = distances
print("✓ Distance calculations complete")

# Filter trips by distance range
MIN_DISTANCE = 200
MAX_DISTANCE = 5000
df = df[
    (df["network_distance_m"] >= MIN_DISTANCE) &
    (df["network_distance_m"] <= MAX_DISTANCE)
].copy()
print(f"✓ After filtering to {MIN_DISTANCE}–{MAX_DISTANCE} m: {len(df):,} trips remain")
```