MODELLING THE IMPACT OF MICROMOBILITY ON URBAN TRANSPORT IN NEW ZEALAND CITIES

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ABSTRACT

This study investigates the integration of shared micromobility modes, specifically E-scooters and E-bikes, with public transport (PT) as a solution to the first-mile/last-mile access challenge in three major New Zealand (NZ) cities: Auckland, Christchurch, and Hamilton. The analysis is situated within the context of Central Business District (CBD) redevelopment and sustainable urban transport planning, where improving PT connectivity is critical to enhancing accessibility and reducing reliance on private vehicles. By examining the type and spatial allocation of shared micromobility services, the study seeks to identify strategies that strengthen PT integration and support more efficient CBD access. A review of international literature from cities with established micromobility systems, primarily in Europe, demonstrates the potential of micromobility to complement PT, particularly in dense urban environments with limited space for transport expansion. Such conditions are increasingly relevant in NZ cities, where population growth continues to outpace land availability. Empirical evidence in this area remains limited due to data privacy constraints and the challenges associated with collecting detailed travel behaviour data. These limitations are addressed using stated preference survey data collected between 2020 and 2023 from 1,597 residents, yielding 12,776 choice observations. Multinomial logit (MNL) and mixed logit (MIXL) models are applied to analyse integrated PT–micromobility choices and assess hypothetical policy scenarios. The results indicate that shared micromobility is most effective when integrated with existing PT demand, with impacts varying across cities, socio-economic groups, and trip purposes. The findings provide evidence to inform integrated mobility strategies that support accessible, liveable, and future-ready CBDs.

INTRODUCTION

Micromobility in New Zealand

New Zealand (NZ) CBDs concentrate jobs and activities in compact areas, generating strong peak travel demand and competition for curb space and parking. Auckland's city-centre employment reached about 159,000 in the year to March 2024, indicating the scale of CBD travel flows (Infometrics, 2024). Because first/last-mile segments often drive perceived inconvenience, small access barriers such as long walks, infrequent feeder services, or missing crossings can discourage public transport (PT) use (NZTA, 2024a). With national policy targeting reduced vehicle kilometres travelled and enabling mode shift, improving PT access in CBDs is critical (MfE, 2022; NZTA, 2019). Shared E-scooters and E-bikes can provide low-friction short trips and expand PT catchments when safe, direct routes and suitable parking are available (NZTA, 2024b; Yin et al., 2024). Their contribution to PT access depends on service design, infrastructure, and effective safety and parking controls (Auckland Transport, 2021; Auckland Council, 2024a).

Shared micromobility operations are largely shaped by parking models: docked (station-based) or dockless (free-floating). Docked systems require trips to start and end at stations, which improve control, reduce nuisance, and simplify rebalancing, but can limit spontaneity and point-to-point usefulness if stations are not nearby (ITF, 2020; Shaheen and Cohen, 2019). Dockless systems use GPS and apps to enable flexible pickup and drop-off within a service zone, supporting rapid adoption and wider coverage with lower upfront infrastructure costs, but often create clutter and pedestrian conflicts that drive tighter local regulation (Gössling, 2020; Auckland Council, 2024b). In NZ, dockless E-scooters dominate, mirroring global trends, yet operational issues have led to the adoption of regulated dockless approaches (Ensor et al., 2021). Marked parking areas in Auckland and Christchurch illustrate attempts to balance flexibility with public order by requiring or incentivising parking in designated zones (Christchurch City Council, 2023; Auckland Transport, 2023). These choices affect PT integration: docked systems naturally concentrate demand at nodes that can align with transit stops, while dockless systems rely on stronger digital and regulatory tools to create reliable connections. However, effective integration also requires NZ-specific behavioural evidence, which remains limited. Despite rapid deployment since 2018, local studies on CBD first/last-mile impacts are often descriptive, single-city, or not designed to estimate traveller trade-offs under policy-relevant changes (Ensor et al., 2021; NZTA, 2025). This gap motivates focused research to quantify how NZ travellers choose among integrated mobility options.

Integrating Public Transport and Micromobility

A consistent theme in public transport (PT) guidance is that access and egress shape perceived journey quality: small "first/last mile" frictions can reduce ridership even when trunk services perform well. NZ guidance explicitly prioritises stronger first/last-mile connections and pedestrian access to stops to support mode shift, emphasising wayfinding, directness, safety, and crossing quality (NZTA, 2024a; NZTA, 2019). Within this framework, micromobility is positioned not only as a standalone mode but to strengthen the end-to-end PT journey. Micromobility includes small, lightweight devices, most notably shared E-scooters and E-bikes, that operate at urban speeds and often use cycling facilities. International bodies define micromobility using mass/speed thresholds and a Safe-System framing, while NZ councils set operator definitions and parking/operational controls for rental schemes (ITF, 2020; Auckland Council, 2024a, 2024b). Evidence from reviews and meta-analyses points to common determinants of use: service availability (fleet density and rebalancing), generalised costs (time and price), built form (density and land-use mix), weather, and infrastructure quality. Protected lanes and well-managed parking (e.g., lock-to or designated areas) consistently support uptake and safer, more acceptable routing, while perceived safety and pedestrian interactions are especially important in busy CBD footpaths (Ghaffar et al., 2023; Badia and Jenelius, 2023; Dias et al., 2024). Socio-demographic patterns are present but vary by context, with younger users more prevalent, and gender and income differences differ by region, suggesting that coverage, affordability, and safe facilities remain central to policy design (Badia and Jenelius, 2023; Dias et al., 2024). Together, these determinants provide a foundation for examining how micromobility can be deliberately integrated into the PT network.

On PT integration, the literature shows both complementarity (e.g., improved station access) and substitution (especially of walking and some bus trips). By reducing door-to-door time for short trips, E-scooters can substitute for PT when access is weak and complement rapid transit when they bridge to it (Aarhaug and Skollerud, 2023; Wang, Zudina and Akkaya, 2023; Yin et al., 2024). Environmental outcomes depend on which trips are displaced and on lifecycle impacts. Early LCAs suggested manufacturing and servicing logistics can dominate impacts relative to active modes and high-load PT; more recent work highlights device longevity, charging logistics, and the extent of car-trip displacement as key drivers of net benefits (Hollingsworth et al., 2019; Badia and Jenelius, 2023). International guidance emphasises a Safe-System approach, focusing on speed management, appropriate separation, and parking management (ITF, 2020). In NZ, Auckland evidence highlights incident patterns (including footpath conflicts) and reinforces the role of protected space and clear parking rules. NZ councils regulate shared-mobility operators through bylaws and codes of practice covering deployment, parking, slow zones, and data sharing, reflecting local concerns around footpath conflicts and public order. International studies also show demand concentrates in dense, mixed-use cores and university precincts, settings comparable to parts of NZ CBDs, and that infrastructure continuity, parking order, and PT integration strongly influence public acceptance. Overall, NZ CBD strategies likely need to pair service design (supply, pricing, operations) with street-management measures to enable connectivity with PT while minimising conflicts (Badia and Jenelius, 2023; Dias et al., 2024). However, despite practical guidance and incident monitoring, NZ still lacks multi-city, behaviourally grounded evidence on how travellers trade off time, cost, infrastructure, and parking controls under CBD conditions. Prior national work scoped mode-shift potential but did not estimate preference parameters suitable for policy simulation across different urban contexts.

'How-To' Promoting Public Transport Integrating with Micromobility

Public transport (PT) benefits most from micromobility when pricing and onboarding make the first/last mile feel "included" in the PT cost. Across regions, agencies and operators execute this through fare-linked incentives (e.g., free minutes), discounted memberships for transit passholders, and institutional integration via smartcards or joint passes (concessions), often supported by operator promotions and time-limited discounts.

International cases illustrate how these mechanisms work in practice. Several German networks link bike-share minutes directly to active transit subscriptions, reducing the marginal cost of PT access trips. Elsewhere, agencies achieve similar effects through tight operational integration. In the Netherlands, OV-fiets is operated by the national rail operator (NS) and can be rented with the OV-chipkaart at rail stations under a simple day price (€4.65/24h), effectively packaging bike-share as the "last mile of rail" (NS, 2025). Belgium's Blue-bike links memberships to the MoBIB smartcard across many locations, keeping annual fees low and per-ride pricing straightforward (Blue-bike, 2025). Pricing also matters for habit formation: LA Metro Bike Share offers reduced-fare passes ($5/month or $50/year), including 30-minute trips and free E-bike unlocks for passholders, and runs time-limited promotions (e.g., $1 monthly passes during Bike Month) to stimulate trial (LA Metro, 2025). Platform-based integration can amplify these measures: Berlin's BVG Jelbi unifies PT and shared-mobility booking/payment and regularly features partner promotions, signalling that shared modes are part of the PT ecosystem (BVG, 2025a; BVG, 2025b). Finally, "pricing shocks" can shift demand at scale: when Taipei reinstated a free first 30 minutes on YouBike, the city reported ~50% higher daily use alongside improved availability and satisfaction (Taipei DOT, 2025).

While shared bikes are commonly integrated through passholder discounts or fare-linked minutes, e-scooter integration more often occurs through agency-run mobility platforms that unify discovery, booking and payment across PT and private scooter fleets. In Berlin, the Jelbi app aggregates multiple scooter operators (e.g., Voi, Lime, Bolt, Dott) and tends to deliver time-limited promotions rather than a standing concession (BVG, 2025a; BVG, 2025b). Brussels follows a similar model via Floya, offering integrated planning/booking for scooters alongside transit, again, integration-by-platform rather than permanent scooter discounts (STIB-MIVB, 2024; Floya, 2025). A second approach is pilot-based bundling of scooter credits with transit: Sydney's Opal+ micromobility trial tested weekly bundles combining PT with Lime/Neuron E-scooter credits to influence first/last-mile choices (Mobility Payments, 2022; CCAM, 2022; Bicycle Network, 2021). Equity pilots show a more targeted model: Pittsburgh's Universal/Guaranteed Basic Mobility program combined unlimited Spin scooter rides with free PT for low-income users, illustrating how subsidy design can address access and first/last-mile connectivity simultaneously (City of Pittsburgh, 2023; Spin, 2022; NUMO, 2023).

Evidence from Europe suggests substantial benefits when shared bicycles are deliberately coupled with rail/bus services and station access (NS, 2025; BiTiBi, 2019). In Belgium, evaluation within the EU BiTiBi programme reported more new train users among shared-bike participants and shifts from car to bike for station access, indicating that bike–PT integration can stimulate PT use even where network-wide uplift is difficult to isolate (BiTiBi, 2019). For shared E-scooters, the evidence base points more to platform integration and targeted bundling rather than to consistent ridership uplift from scooters alone. This "menu" of approaches highlights the task for NZ policymakers: identifying which mechanisms, or combinations, best fit local preferences and urban form. In NZ comparators (Auckland, Christchurch, Hamilton), operator programmes offer discounts (e.g., Lime Access; Flamingo Student Concession Pass), but PT-linked scooter concessions and published evaluations demonstrating PT ridership uplift attributable to scooters appear limited. Christchurch monitoring suggests only a small minority of scooter trips connect to or replace PT, implying weak feeder effects. Where participant-level PT increases are observed, they typically occur when free or bundled PT is included in the intervention (e.g., Pittsburgh's pilots pairing free PT with shared micromobility) (Lime, 2025; Metroinfo, 2025; City of Pittsburgh, 2023). Overall, the weight of evidence most strongly supports bike–rail integration and targeted PT + micromobility bundles, rather than scooters alone, as credible levers to increase PT ridership.

METHODOLOGY

Logistic Regression: Multinomial Logit (MNL) and Mixed Logit (MIXL) Model

Under the multinomial logit (MNL) specification, the error terms are assumed to be independently and identically distributed extreme value. Preferences are homogeneous across individuals. The probability that individual n chooses alternative j is given by:

$$P_{nj} = \frac{exp^{(V_{nj})}}{\sum_k exp^{(V_{nk})}}$$

Model parameters are estimated by maximising the log-likelihood function:

$$\mathcal{L} = \sum_n \sum_j y_{nj} \ln\,(P_{nj})$$

where $y_{nj} = 1$ if alternative j is chosen and 0 otherwise. The MNL model serves as a transparent baseline and provides a benchmark for more flexible specifications.

To relax the restrictive assumptions of the MNL, a mixed logit (MIXL) model is estimated. In this framework, selected coefficients are allowed to vary across individuals:

$$\beta_{nk} = \bar{\beta}_k + \eta_{nk}$$

where $\bar{\beta}_k$ represents the population mean and η_{nk} captures unobserved individual-specific deviations. The unconditional choice probability is obtained by integrating over the distribution of random parameters:

$$P_{nj} = \int \frac{\exp\left(V_{nj}(\beta_n)\right)}{\sum_k \exp\left(V_{nk}(\beta_n)\right)} f(\beta_n)\, d\beta_n$$

Because this integral has no closed-form solution, estimation is conducted using simulated maximum likelihood with quasi-random draws. Panel estimation accounts for repeated choices made by each respondent. Model performance is evaluated using log-likelihood values, McFadden's pseudo-R^2, likelihood ratio tests and information criteria.

The modelling approach adopted in this study aligns with a growing body of research examining the integration of public transport (PT) and micromobility using discrete choice methods. Several studies have applied MNL and MIXL models to capture first/last-mile access behaviour and unobserved preference heterogeneity in urban contexts. In European cities, MIXL models have been widely used to analyse the integration of shared bicycles and E-scooters with PT. For example, Campbell et al. (2016) and Kroesen (2017) demonstrate that access distance and service availability are critical determinants of integrated mode choice, while taste heterogeneity plays a significant role in explaining variation in willingness to adopt micromobility. Similarly, Cai et al. (2022) apply MIXL models to examine first/last-mile access to rail stations, finding substantial heterogeneity in sensitivity to costs and access effort. Studies in dense urban environments, such as those by Shaheen et al. (2020) and Zhao et al. (2023), emphasise the importance of modelling unobserved heterogeneity when analysing shared micromobility adoption, particularly where alternatives share unobserved attributes such as perceived safety or convenience. These studies commonly employ staged modelling strategies, beginning with MNL specifications and progressing to MIXL models to improve behavioural realism. The present study contributes to this literature by applying a comparable modelling framework to the New Zealand (NZ) context, where empirical evidence on PT–micromobility integration remains limited. By combining longitudinal survey data with both pooled and city-specific MNL and MIXL models, the methodology follows established international practice while accounting for the distinct urban structure and transport conditions of NZ cities.

Data Collection and Survey Sample

The analysis is based on a combined revealed preference (RP) and stated preference (SP) survey conducted in the Central Business Districts (CBDs) of Auckland, Christchurch, and Hamilton between 2020 and 2023. The survey was designed to capture current travel behaviour as well as potential responses to integrated public transport (PT) + micromobility options, with particular emphasis on first/last-mile access to PT.

The RP component collected information on respondents' most recent CBD trip, including primary travel mode, trip purpose, and basic socio-demographic characteristics. This information provides contextual grounding for the SP experiment and allows observed travel patterns to be compared with hypothetical choice outcomes. Trip purposes include work, education, shopping, and leisure activities, reflecting the diverse functions of CBDs across the three cities. The SP component employed a discrete choice experiment in which respondents evaluated hypothetical access alternatives to the CBD. Each choice task presented three options: PT with walking access (status quo), PT with E-bike access, and PT with E-scooter access. The attributes varied across choice scenarios include access cost, travel time, walking distance to the micromobility device, and service availability. These attributes were selected based on prior literature on micromobility and first-/last-mile access and were framed to reflect realistic conditions in NZ cities. Each respondent completed eight choice tasks, generating panel data suitable for both MNL and MIXL estimation. The final sample comprises 1,597 respondents and 12,776 stated-choice observations across the three cities.

Sampling quotas were applied to ensure reasonable representation across age groups, gender, and employment status within each city. Summary statistics describing the sample composition by city, socio-demographic characteristics, and travel behaviour are reported in Table 1. The combined RP/SP design enables the analysis to capture both observed behaviour and potential responses to integrated PT and micromobility services, providing a robust empirical foundation for the discrete choice modelling undertaken in this study.

The SP experiment varies four attributes that capture key first/last-mile conditions for integrating PT and micromobility. Service cost (COST) is measured in New Zealand dollars (NZD) per trip and represents the total monetary cost of using PT and shared E-bikes or E-scooters compared to PT with walking. Travel time (TIME) is expressed in minutes and reflects the duration of the access leg, including walking or riding time, depending on the alternative. Accessibility (ACC) measures the walking distance, in metres, from the PT stop to the nearest available micromobility device or parking location, capturing the physical effort required to access. Availability (AVA) is expressed as a percentage and represents the likelihood of finding a usable micromobility device at the time of travel, capturing perceived service reliability. Alternative specific constants (ASCs) are included for the PT plus E-bike and PT plus E-scooter options to account for systematic preferences not explained by observed attributes, such as familiarity, comfort, or perceived safety. Together, these attributes provide a parsimonious representation of the main trade-offs travellers face when considering micromobility as a complement to PT for CBD access.

Table 1: Sample composition: Comparison with Auckland, Christchurch and Hamilton (%)

Variable	Categories	Auckland	Christchurch	Hamilton
Gender	Male	52.4	54.5	54.9
	Female	47.2	44.7	45.1
	N/A	0.4	0.9	0
Age	Under 18	10.4	5.4	9.4
	19–29	39	43.6	32
	30–39	20.5	19.6	21.1
	40–49	15	12.4	15
	50–59	9.4	11.1	10.2
	60–69	3.6	5	9.4
	70+	2	2.8	2.9
	N/A	10.4	5.4	9.4
Education	No degree	9.4	9.4	10.2
	High school/diploma	26.3	25.1	28.6
	Some college/associate	24.5	13.5	17.9
	Bachelor's or higher	26.3	50.5	42.8
	N/A	13.4	1.5	0.5
Income	< $12k	23.2	25.9	25.2
	$12k–$24k	9.6	13.1	11.2
	$25k–$39k	21.8	13.7	14.8
	$40k–$74k	25.4	28.1	31.5
	$75k+	16.5	17.6	14.8
	N/A	3.4	1.5	2.4
Marital status	Married, no child	18.5	24.8	35.8
	Married, with child	25.6	12.6	18.9

Variable	Categories	Auckland	Christchurch	Hamilton
	Never married	26.1	12.6	22.8
	N/A	29.8	49.9	22.5
Survey Sample collected (Year)	2020	210	181	160
	2022	90	151	218
	2023	210	225	152
Total Samples		551	459	587

MODELLING RESULTS AND ANALYSIS

Pooled Multinomial logit (MNL) and mixed logit (MIXL) models

The empirical analysis follows a structured modelling sequence that increases behavioural realism while preserving parsimony and interpretability. Estimation moves (i) from pooled to city-specific models and (ii) from multinomial logit (MNL) to mixed logit (MIXL) specifications. This progression first establishes average behavioural responses, then addresses spatial heterogeneity across Auckland, Hamilton, and Christchurch, and finally captures unobserved preference heterogeneity across individuals. All specifications model choice among three alternatives: the status quo (PT with walking access), PT with E-bike access, and PT with E-scooter access. Utilities include service cost (fare, NZD per trip), travel time (minutes), access distance to a vehicle (metres), vehicle availability (percentage), and alternative specific constants (ASCs). Socio-demographic influences enter via interactions with ASCs, capturing systematic differences in baseline preferences without proliferating attribute interactions. Estimation begins with pooled MNL using the full sample (n = 1,597) across all cities. Pooling provides a transparent benchmark and improves statistical efficiency, yielding average responses to the key attributes. This specification assumes homogeneous preferences and imposes the independence of irrelevant alternatives (IIA) property. The pooled MNL estimates are behaviourally plausible, with statistically significant coefficients for all core attributes (Table 2).

Table 2. Pooled MNL and MIXL Modelling Results

	Multinomial Logit Model (MNL)		Mixed Logit Model (MIXL)	
Attributes	Coeff.	S.E	Coeff.	S.E
Random parameters in utility functions				
SERVICE AVAILABILITY (AVA)	0.013***	0.002	0.006**	0.002
TRAVEL TIME (TIME)	-0.007	0.018	-0.033	0.021
Nonrandom parameters in utility functions				
SERVICE COST (COST)	-1.387***	0.086	-1.604***	0.096
SERVICE ACCESSIBILITY (ACC)	-0.006***	0.001	-0.006***	0.001
ASC_BIKE	-0.104***	0.021	-0.146***	0.031
ASC_SCO	-0.233***	0.022	-0.280***	0.032
ASC_SQ x MARRIAGE	-0.268***	0.082	-0.409***	0.090
COST x INCOME	0.026***	0.005	0.034***	0.008
TIME x AGE	-0.022***	0.004	-0.012***	0.005
AVA x MARRIAGE	-0.003***	0.001	-0.004***	0.001
Derived standard deviations of random parameter distributions				
SERVICE AVAILABILITY			0.019***	0.001
TRAVEL TIME			0.090***	0.006

Model Statistics		
Log-Likelihood	-7731.96	-7008.84
Pseudo- R^2	0.0448	0.2389
AIC/N	1.847	1.675
Observations	12776	

*** p<0.01, ** p<0.05, *p<0.1

Service cost has a strong negative effect, confirming substantial price sensitivity. In the pooled MNL, the travel time coefficient is not statistically significant; however, this is more consistent with unobserved heterogeneity than with a genuine absence of time effects. The MIXL results show significant dispersion in time sensitivity across individuals, indicating that mean estimates can mask meaningful variation in how travel time shapes micromobility choice (Train, 2009; Hensher and Greene, 2003). Accessibility also reduces utility: greater access distance lowers the attractiveness of micromobility options, whereas higher availability increases utility, highlighting the value of reliable access. ASCs for the E-bike and E-scooter alternatives are generally negative relative to the status quo, suggesting baseline resistance to switching once observable attributes are held constant. The inclusion of socio-demographic interaction terms allows for the capture of preference heterogeneity without over-parameterising the core utility structure. The results indicate that baseline mode preferences and sensitivities vary systematically across population groups, with income moderating cost sensitivity, age affecting travel time disutility, and marital status influencing both status quo preference and responsiveness to service availability. These patterns are behaviourally intuitive and stable across model specifications, supporting the robustness of the estimated effects and the appropriateness of the modelling approach. Overall, the model fit aligns with expectations for mode choice applications, though the pooled MNL necessarily abstracts from individual-level and spatial variation.

To relax the restrictive assumptions of the MNL, pooled MIXL models are estimated. MIXL allows selected coefficients to vary randomly across individuals, capturing unobserved taste heterogeneity while relaxing the IIA property. In this specification, travel time and availability are treated as random parameters, while cost and access distance remain fixed. Treating travel time as random is motivated by both theory and evidence. Travel time sensitivity commonly differs by scheduling constraints, trip purpose, and tolerance for effort, and discrete choice theory recognises that observable characteristics do not fully explain such variation; MIXL therefore often models time as random to improve behavioural realism and fit (Train, 2009; Hensher and Greene, 2003). Empirical work likewise documents substantial heterogeneity in the valuation of travel time (Hensher, 2001). Availability is also specified as random to reflect differences in perceived reliability: tolerance for uncertainty varies with experience, risk attitudes, and available substitutes. Statistically significant standard deviations for both parameters confirm the presence of meaningful unobserved heterogeneity. Relative to the pooled MNL, the pooled MIXL produces clear improvements in log-likelihood and pseudo-R^2. Notably, the MIXL also removes the sign instability observed in simpler specifications, suggesting that earlier anomalies were driven by unmodelled heterogeneity rather than counterintuitive behaviour.

Pooled models identify general behavioural drivers, but they impose a common structure across cities. Spatial heterogeneity is therefore examined through separate MNL models estimated for Auckland, Hamilton, and Christchurch. Estimating city-specific models allows baseline preferences and attribute sensitivities to vary by context without relying on extensive city–attribute interaction terms. Across cities, coefficient signs remain behaviourally consistent for cost, time, accessibility, and availability. Coefficient magnitudes and ASCs, however, differ, suggesting systematic variation in baseline preferences plausibly linked to local conditions such as urban form, infrastructure quality, and micromobility market maturity. Compared with the pooled MNL, city-specific MNL models provide a clearer picture of spatial variation while retaining transparency.

City-specific Multinomial logit (MNL) and mixed logit (MIXL) models

To capture spatial heterogeneity, separate MNL and MIXL models are estimated for Auckland, Christchurch, and Hamilton. This allows baseline preferences and attribute sensitivities to vary by context without relying on extensive pooled interaction structures. City-specific MNL results are summarised in Table 3.

In every city, service cost enters with a negative and statistically significant coefficient, reinforcing price as a primary driver of micromobility choice. Access distance is likewise negative and significant throughout, showing that longer walks to reach a vehicle reduce the appeal of micromobility. Consistently higher availability increases utility, indicating that denser, more reliable fleets encourage uptake. By contrast, travel time is not statistically significant in any of the city-level MNL models. Once cost, access distance, and availability are accounted for, average time differences across alternatives appear less influential in the aggregate city models, an outcome that aligns with the short-trip context of micromobility, where perceived convenience and flexibility may dominate marginal in-vehicle time differences.

Table 3 City-specific Multinomial Logit (MNL) Modelling Results

	Auckland		Christchurch		Hamilton	
Attributes	Coeff.	S.E	Coeff.	S.E	Coeff.	S.E
SERVICE COST	-1.538***	0.166	-1.003***	0.179	-1.477***	0.138
TRAVEL TIME	0.016	0.030	-0.044	0.039	-0.009	0.028
ACCESSIBILITY	-0.006***	0.002	-0.004**	0.002	-0.006***	0.001
AVAILABILITY	0.015***	0.002	0.008*	0.005	0.014***	0.003
ASC_BIKE	-0.073**	0.247	-0.140***	0.273	-0.107***	0.033
ASC_SCO	-0.205***	0.250	-0.237***	0.277	-0.256***	0.035
ASC_SQ x MARRIAGE	-0.337**	0.131	0.110	0.195	-0.406***	0.131
COST x INCOME	0.037***	0.009	0.006	0.011	0.026***	0.009
TIME x AGE	-0.032***	0.007	0.001	0.048	-0.028***	0.006
AVA x MARRIAGE	-0.003	0.001	-0.001	0.002	-0.005***	0.001
Model Statistics						
Log-Likelihood	-2837.72		-1732.13		-3109.20	
Pseudo- R^2	0.052		0.023		0.055	
AIC/N	1.904		1.928		1.753	
Observations	4408		3672		4696	

*** p<0.01, ** p<0.05, *p<0.1

Baseline preferences vary more strongly across cities. ASCs differ noticeably, suggesting different underlying propensities to switch to E-bikes or E-scooters relative to the status quo. These shifts likely reflect unobserved local factors, including infrastructure provision, system maturity, operating conditions, and city-specific travel norms. Socio-demographic interaction effects further reinforce spatial heterogeneity. Income moderates cost sensitivity in Auckland and Hamilton, but not in Christchurch, while age-related differences in time sensitivity appear only in Auckland and Hamilton. Taken together, these patterns support the estimation of separate city models rather than relying solely on pooled interaction structures. Overall, the city-specific MNL models preserve behaviourally plausible signs across cities while revealing meaningful variation in magnitudes and significance, consistent with spatial heterogeneity in micromobility preferences.

To capture unobserved preference heterogeneity, city-specific MIXL models are estimated, and the results are reported in Table 4. Relative to MNL, MIXL relaxes the fixed-coefficient assumption by allowing selected parameters to vary across individuals, thereby representing latent taste variation.

In the pooled MIXL specification, travel time and availability are treated as random parameters because pooling observations across cities combines distinct travel environments, service densities, and network conditions. That cross-city structural variation is expected to generate heterogeneous sensitivities to time and reliability that observed variables alone cannot fully explain (Train, 2009; Hensher et al., 2015).

Once estimation is restricted to a single city, the setting becomes more homogeneous. With less structural variation in travel conditions, within-city dispersion in time and availability sensitivity is limited and is adequately captured through fixed parameters and observed interactions; when specified as random, these attributes produce unstable estimates or insignificant variance. Service cost, however, continues to exhibit statistically significant unobserved heterogeneity within each city, even after accounting for income effects. This pattern is consistent with persistent differences in affordability perceptions and willingness to pay. For that reason, cost is retained as the only random parameter in the city-specific MIXL models, capturing meaningful intra-city heterogeneity while maintaining parsimony and estimation stability (Hess and Train, 2017). Across Auckland, Christchurch, and Hamilton, mean cost coefficients remain negative and highly significant, and the corresponding standard deviations are also significant. The implication is clear: individuals differ materially in cost sensitivity, and willingness to pay for micromobility access varies widely. Allowing cost to vary improves fit relative to the city-specific MNL models, reflected in higher pseudo-R^2 values and lower AIC/N. A further benefit is that travel time, which is insignificant in the city-specific MNL models, becomes negative and statistically significant in the MIXL specifications. This shift suggests that opposing individual-level time preferences can cancel out in fixed-coefficient models, masking the effect at the aggregate level; once taste variation is introduced, underlying time sensitivity becomes detectable (Train, 2009). Accessibility and availability continue to show expected signs and remain statistically significant in most cases: longer access distance reduces the probability of choosing micromobility, while higher availability increases it. Compared with the socio-demographic interactions, the random parameter(s) explain a larger share of behavioural variation, indicating an important role for unobserved heterogeneity in micromobility preferences.

Table 4 City-specific Mixed Logit (MIXL) Modelling Results

	Auckland		Christchurch		Hamilton	
Attributes	Coeff.	S.E	Coeff.	S.E	Coeff.	S.E
Random parameters in utility functions						
SERVICE COST	-6.106***	0.406	-4.111***	0.450	-5.577***	0.225
Nonrandom parameters in utility functions						
TRAVEL TIME	-0.095**	0.002	-0.160***	0.005	-0.131***	0.002
ACCESSIBILITY	-0.007***	0.005	-0.004*	0.002	-0.006***	0.003
AVAILABILITY	0.018***	0.373	0.010*	0.006	0.011**	0.301
ASC_BIKE	-0.262***	0.378	-0.258**	0.108	-0.284***	0.308
ASC_SCO	-0.403***	0.096	-0.360***	0.109	-0.441***	0.079
ASC_SQ x MARRIAGE	-0.767***	0.187	0.022	0.245	-0.525***	0.170
COST x INCOME	0.047	0.030	-0.012	0.032	0.056**	0.026
TIME x AGE	0.003	0.014	0.036**	0.015	0.010	0.012
AVA x MARRIAGE	-0.004*	0.002	-0.002	0.003	-0.004	0.002
Derived standard deviations of random parameter distributions						
SERVICE COST	5.560***	0.348	4.303***	0.354	4.670***	0.289
Model Statistics						
Log-Likelihood	-2169.27		-1426.72		-2541.51	
Pseudo- R^2	0.340		0.282		0.354	
AIC/N	1.457		1.588		1.424	
Observations	4408		3672		4696	

*** p<0.01, ** p<0.05, *p<0.1

Overall, the city-specific MIXL models provide a more behaviourally flexible representation of choice than the corresponding MNL models while preserving interpretability through separate city estimation. Taken together with the pooled results, the modelling sequence shows that both spatial differences between cities and unobserved individual-level variation contribute to observed micromobility adoption patterns.

POLICY AND PRACTICAL IMPLICATIONS

Policy and practical implications are drawn from a combined reading of the revealed preference (RP) survey and the discrete choice model results (MNL and MIXL). The RP survey describes observed travel behaviour, while the models identify the preference structures and heterogeneity driving mode choice across cities. RP results show clear differences in CBD trip purpose by city (Table 5). Auckland has the most mixed-use profile, with work travel alongside substantial shares of entertainment, education and shopping trips. Christchurch is more education-oriented (alongside work), consistent with student-driven travel patterns. Hamilton is the most retail-focused, with shopping accounting for more than one-third of CBD trips. These contrasts suggest that CBD access needs vary systematically across cities rather than aligning with a single national pattern.

Table 5 Trip Purpose to CBD (%)

	Work	Education	Shopping	Home	Entertainment	N/A
Auckland	33.6	16.2	17.3	8.0	24.3	0.7
Christchurch	33.8	24.4	15.9	4.1	18.1	3.7
Hamilton	26.9	12.1	37.3	1.4	21.8	0.5

The mode choice models help explain these observed RP patterns. Across cities, both the MNL and MIXL results consistently identify service cost and accessibility as the strongest determinants of choice. Cost enters with a negative and statistically significant coefficient, indicating high sensitivity to out-of-pocket disutility. Accessibility is also negative and significant, reinforcing the importance of addressing first/last-mile barriers such as the walk to reach a vehicle. Availability is positive and significant, indicating that greater coverage and more reliable vehicle availability increase the likelihood of choosing micromobility or PT-linked options. Travel time is weak or insignificant in several city-specific MNL models. For short CBD-oriented trips, this suggests perceived convenience, access conditions, and monetary cost outweigh marginal differences in in-vehicle time. The MIXL specifications add an important behavioural insight: cost sensitivity varies substantially across individuals. Treating cost as random reveals statistically significant heterogeneity in willingness to pay that is not fully explained by observed socio-demographics. Spatial differences also appear in the city-specific models. Variation in ASCs indicates different baseline tendencies to switch modes across Auckland, Christchurch, and Hamilton, even after controlling for observed attributes. These differences plausibly reflect local context in urban form, infrastructure quality, and existing micromobility systems. Consistent with this, the city-specific MIXL models improve fit relative to MNL (including higher pseudo-R^2), confirming the presence of unobserved heterogeneity within each city. The RP mode shares align with the modelling outcomes. Table 6 shows that car access dominates CBD travel in all three cities (to varying degrees), with public transport consistently ranking second.

Table 6 Mode to Access the CBD (%)

	PT (Bus/Train)	Car	Bicycle	Walk	Others
Auckland	35.4	48.8	4.7	9.6	1.5
Christchurch	20.9	59.7	12.9	6.1	0.4
Hamilton	22.1	62.7	3.7	6.6	4.7

Walking is relatively more prominent in Auckland, and cycling is more prevalent in Christchurch, patterns that correspond with the estimated accessibility and availability effects in the models. Taken together, the RP/SP surveys, MNL, and MIXL modelling results indicate that while certain behavioural drivers, particularly cost sensitivity, accessibility, and availability, are common across cities, their magnitudes and baseline preferences differ substantially across urban contexts. These findings support the need for city-specific approaches to CBD access that reflect local travel purposes, infrastructure conditions, and heterogeneous user preferences, rather than uniform policy prescriptions.

CONCLUSIONS

This study examined Central Business District (CBD) access mode choice in three New Zealand cities using longitudinal revealed-preference data and a structured sequence of discrete-choice models. Estimation began with pooled specifications to identify common behavioural drivers, then moved to city-specific multinomial logit (MNL) and mixed logit (MIXL) models to capture spatial variation and preference heterogeneity. Across all stages, service cost, accessibility, and availability emerged as robust determinants of choice, whereas travel time showed weaker and more context-dependent effects, particularly for short, CBD-oriented trips. City-specific MNL results revealed substantial differences in baseline preferences, as reflected in alternative specific constants (ASCs), underscoring the role of local context in shaping CBD access behaviour. These differences align with observed variation in trip purposes, mode shares, and urban form across Auckland, Christchurch, and Hamilton. MIXL models improved fit and revealed significant unobserved heterogeneity, particularly in cost sensitivity. Allowing the cost coefficient to vary across individuals captured wide differences in willingness to pay that were not fully explained by observed socio-demographics, highlighting the value of modelling preference heterogeneity in urban travel behaviour. Overall, the city-specific MIXL specifications provided the most behaviourally realistic representation of CBD access choices while remaining interpretable. Taken together, the findings show that while key behavioural mechanisms are shared across cities, their relative importance and baseline preferences vary systematically with local conditions. This modelling approach demonstrates the benefit of combining pooled and city-specific discrete choice models to balance generalisability with spatial realism in the analysis of urban mobility.

A limitation of this study is that road safety conditions and regulatory constraints governing micromobility use are not explicitly modelled. Factors such as perceived crash risk, helmet requirements, speed limits, and restrictions on riding and parking locations may influence micromobility adoption and could vary substantially across cities and over time. While these aspects are partially reflected in ASCs and availability measures, future research would benefit from incorporating explicit safety and regulatory indicators to further refine behavioural interpretation.

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