PUBLIC TRANSPORT SYSTEMS FOR THE ELDERLY IN NEW ZEALAND RURAL SMALL TOWNS

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ABSTRACT

Given the growing elderly population, ensuring adequate public transportation for individuals aged 65 and older is a significant global concern. This research investigates the travel behaviour and mode-choice preferences of senior citizens in New Zealand (NZ) to enhance transport accessibility in low-density regions through the implementation of on-demand public transport services, such as Demand Responsive Transport (DRT). Public transportation options in most rural, small, and medium-sized towns throughout NZ are either limited or non-existent. The focus of this study is on Thames and Tokoroa, two medium-sized rural towns in the Waikato region, characterised by higher-than-average proportions of residents aged 65 and above. These populations have seen substantial growth over the past two decades and are projected to double by 2043. As in many rural areas, elderly residents in these towns face mobility challenges due to the limited availability, affordability, and accessibility of transportation services. To address these issues, a combined Revealed Preference (RP) and Stated Preference (SP) survey was administered to 324 respondents to capture travel behaviours and mode-choice attitudes. Responses were analysed using multinomial Logit and Mixed Logit models, and a three-class Latent Class (LC) model was employed to explore heterogeneity in preferences. The findings corroborate a strong demand for on-demand public transport services in rural NZ and indicate that socio-demographic factors, individual mobility characteristics, and perceptions of transportation service quality influence elderly travel choices. The modelling further identified distinct subgroups within the elderly population, each exhibiting different priorities and sensitivities concerning transport options. Although the sample size is modest, it is proportionate to the target towns. A larger sample may enhance the robustness of the models; however, the current findings already afford vital insights for designing transport policies tailored to older adults in rural settings. These insights are increasingly vital as NZ's aging population continues to expand and mobility needs become more intricate.

INTRODUCTION

New Zealand Elderly People in Rural Areas

Aotearoa New Zealand (NZ) continues to urbanise, yet growth is also reshaping smaller towns and rural districts. The estimated resident population is projected to exceed six million before 2040, with net international migration contributing a substantial share of the increase (Stats NZ, 2025a). At the same time, population ageing is marked: the number of people aged 65+ is expected to reach one million by 2028, with further growth in later decades (Stats NZ, 2022). Projections indicate sustained increases in the 85+ cohort as well, underscoring a long-run shift in age structure (EHINZ, 2025). Although NZ is predominantly urban, rurality remains salient for ageing and service access. Recent indicators suggest around 15–16% of residents live in rural areas, and rural communities tend to have older age profiles and higher dependency ratios than urban centres (EHINZ, n.d.; Ministry of Health, 2023). The Government's Rural Health Strategy explicitly recognises geographic inequities. It sets a ten-year direction to improve access, including through digital, mobile, and outreach services, and by better supporting access to care at a distance (Ministry of Health, 2023).

Mobility is a key determinant of social participation and health in later life. Licence holding remains high even at older ages, about 73% of those aged 75+ hold a driver's licence, but travel patterns shift with age as driving declines and reliance on non-driving modes and walkable access rises (Ministry of Transport, n.d.-a; Ministry of Transport, n.d.-b). In sparsely populated settings, fixed-route public transport often entails long access walks, low frequency and high per-rider costs, intensifying barriers for older adults with mobility limitations (Ministry of Health, 2023). A range of policy instruments and community services partly mitigates transport disadvantage for older people. The Super Gold scheme provides free off-peak urban public transport for eligible cardholders (Ministry of Transport, n.d.-c). The Total Mobility scheme subsidises door-to-door trips for people who cannot use conventional public transport because of disability or impairment (NZTA, 2025). In many rural districts, St John's Waka Ora Health Shuttle fills critical gaps by providing donation-supported transport to health and wellbeing appointments (St John, n.d.). While valuable, these supports are patchy across regions, capacity-constrained, and often oriented to specific purposes (e.g., medical trips), leaving wider everyday mobility needs unmet in low-density areas (NZTA, 2025; Doran, 2024).

Emerging on-demand transport services, such as demand-responsive transport (DRT) models, illustrate alternative pathways for rural and small-city contexts. In Timaru, the MyWay by Metro on-demand service, piloted in 2020, has been made permanent, with authorities citing record patronage and improved network performance relative to the previous fixed-route system (Environment Canterbury, 2024; 2025). While Timaru is an urban case, its low-density travel patterns share features with rural settlements; the evidence suggests that flexible, stop-to-stop or door-to-door services can improve access where traditional routes are inefficient (Environment Canterbury, 2024; 2025). Digital readiness is increasingly intertwined with mobility, both for planning and booking trips and for accessing services remotely when travel is impractical. The Better Later Life strategy highlights digital inclusion as a priority, and the Office for Seniors has convened a Digital Inclusion Action Group to expand training for older adults (Office for Seniors, 2025a; 2025b). While internet use among older New Zealanders has risen (e.g., recent estimates suggest ~84% of those 65+ use the internet), digital exclusion persists for some, particularly in rural areas where connectivity can be variable (Wrapson, 2024; DIA, 2022). These realities have direct implications for app-based DRT, telehealth, and information provision in rural communities.

Within Waikato, two contrasting settings illustrate the rural ageing challenge. In the Thames Coromandel District, ageing is pronounced; for example, Thames Central recorded a median age of 58.6 years in the 2023 Census (Stats NZ, 2024a). Due to the location's popularity with retirees, the population in this age group has increased sharply over the last 20 years, mainly from higher net migration from the Auckland region. It is predicted to rise to 43 per cent from 27.1 per cent in 2043. Further south, Tokoroa functions as an inland service town with surrounding rural settlements; 2023 Census summaries indicate population growth since 2018 alongside a substantial and rising share of older adults (Stats NZ, 2024b; 2024c). Kiernan (2014) found that Tokoroa was one of the major single-employer towns in NZ. The downsizing of the local forestry and milling industry mainly affected the young population, as they moved in search of jobs and opportunities, while the elderly preferred to stay on their property and in their town. Based on the latest census, the total population of Tokoroa has been declining since the late 1980s, driven by declines across all age groups below 65 years, with net migration losses exceeding natural increase. These cases underscore how settlement form, service geography and age structure interact to shape mobility needs, and why flexible transport and age-friendly design are central to equitable access in rural Aotearoa.

Needs of Demand Responsive Transport for the Elderly in New Zealand Rural Areas

Ageing is associated with fewer trips and shorter daily travel distances as driving activity declines, while reliance on non-driving modes and walkable access increases (Alsnih and Hensher, 2003; Rosenbloom, 2001). In many countries, older adults still make a large share of their trips by car, but licensing and self-regulation (e.g., avoiding night driving) lead to reduced trip frequency and lengths at older ages, patterns documented in the United States, Australia and Europe (Alsnih and Hensher, 2003; Rosenbloom, 2001). Public transport use among older people is typically low where access is poor, and most walking trips are short (often under 500 m), highlighting the importance of door-to-door or short-walk options (Alsnih and Hensher, 2003). In general, public transport is not a frequently used mode of transport for the elderly, and 80% of their walking trips involve distances of under 0.5 km (Alsnih and Hensher, 2005; Rosenbloom, 2001).

In New Zealand (NZ), the accessibility challenge is acute in rural settlements and small towns, where fixed-route bus services are sparse or absent, taxis (if present) can be costly, and distances to services are non-trivial. These constraints interact with ageing, particularly for people no longer able or willing to drive, creating a clear need for flexible, short-walk alternatives that complement existing community transport and Total Mobility provision. Recent local experience reinforces this: MyWay by Metro in Timaru has transitioned from trial to a permanent on-demand service (2025), while Baybus OnDemand (Tauranga South) is continuing its trial into 2026; Greater Wellington's Metlink On Demand ran a multi-year trial in Tawa/Porirua to 2024. Together, these cases show that app (and phone) based, stop-to-stop or door-to-door services can fill gaps where fixed routes struggle, provided booking, coverage, and fares are well designed (Environment Canterbury, 2025; Bay of Plenty Regional Council, 2025).

Demand Responsive Transport (DRT) has been trialled in many parts of the world for over 30 years. In some countries, DRT serves a specific purpose, for example, meeting the needs of mobility-impaired passengers and elderly people, while in others, it is used for commercial operations or to address the 'last mile' problem. Classic and contemporary literature frames DRT as an intermediate public transport mode between bus and taxi that flexes routes and schedules to meet realised demand, spanning community transport through to area-wide networks (Enoch et al., 2004; Khattak and Yim, 2004; Zahedi et al., 2024; UITP, 2025). DRT is especially pertinent where fixed routes are financially marginal due to low density, dispersed trip ends, and peak-off-peak imbalance, common features of rural NZ (Bakker, 1999; Enoch et al., 2004). Operationally, DRT typically involves advance or real-time booking, algorithmic pooling to virtual stops, and dynamic routing; key cost drivers include fleet size and type, staffing, dispatch/booking costs and user mix (Ambrosino, 2004; Khattak and Yim, 2004).

Collectively, these cases in Table 1 illustrate that a rural DRT system can shorten access walks and reduce booking and transfer friction for older individuals. Furthermore, DRT offers cost-effective coverage in areas where fixed routes underperform. Additionally, DRT serves as a feeder service to regional lines and essential services such as healthcare and shopping, provided that fares, zones, and booking channels are designed to be age-friendly. Evidence consistently shows that 'service design' and 'cost control' determine viability: pooling efficiency, vehicle choice, dispatch costs and demand density are pivotal. Pricing must balance 'affordability' (to attract patronage) with 'revenue sufficiency', particularly in early years when returns are lower (Khattak and Yim, 2004; Ambrosino, 2004). Where fixed-route services are not viable in rural areas, shared DRT at higher fares (subsidy-backed or concession-aligned) is often more appropriate than low-fare fixed routes with low load factors (Bakker, 1999; Enoch et al., 2004).

Table 1 Rural DRT Examples in NZ and Overseas: Booking and Accessibility.

Service, Place & Country	Booking Window (Lead Time)	Pick-up Type & Typical Walk	Notes for Users	Sources
MyWay by Metro, Timaru, NZ	Real-time/ASAP via app or phone.	Virtual stop assigned within a short walking distance	Short-walk virtual stops reduce access burden; phone/app options help non-smartphone users.	https://www.environmentcanterbury.govt.nz/transport/myway-by-metro/
Baybus OnDemand, Tauranga South, NZ	ASAP or up to 7 days in advance.	Virtual stop < 150 m from user.	Very short walks (~150 m) are age-friendly; an advance booking option supports medical/shopping trips.	https://www.baybus.co.nz/bus-routes-and-timetables/babbus/
Metlink On Demand, Tawa/Porirua, NZ	Real-time bookings during trial.	Directed to the nearest virtual stop.	Trial ended Dec 2024; useful design precedent for short-walk access.	https://www.metlink.org.nz/on-demand/
HertsLynx, Hertfordshire, UK	3 min before travel up to 30 days ahead.	300+ virtual stops across zones with a short walk.	Very flexible booking + short walks; a strong fit for older users who need spontaneity.	https://www.hertfordshire.gov.uk/services/transport-and-parking/public-transport/buses
Wiltshire Connect, Wiltshire, UK	Up to 7 days ahead; as little as 30 min on the day.	Virtual stop with in-app walking directions (typically 30 min pick-up).	Clear walking guidance + short-notice booking = accessible for seniors.	https://www.wiltshireconnect.co.uk/
Tees Flex, Tees Valley, UK	Real-time, pooled/shared rides.	Virtual stop nearby/ short walk.	Rural zones, shared rides, and short access walks are built in.	https://teesvalley-ca.gov.uk/transport/tees-flex/
TFI Local Link (Door-to-Door), Rural Ireland	Phone booking in advance (day-before for Door-to-Door).	Door-to-door or deviated (minimal walk).	Best for those with limited mobility, minimal walking, but less spontaneous than app-based DRT.	https://www.transportforireland.ie/local-link/
MyBus (SPT), Rural/Small-town, Scotland	Advance booking by phone/app.	Door-to-door, as close as possible to the destination.	Door-to-door greatly reduces walking; driver assistance from pavement.	https://www.spt.co.uk/travel-with-spt/bus/mybus/
FlexiRide, Various towns, Victoria, AU	Up to 1 week in advance; real-time day-of.	Virtual stop within a short walk; app guides to pick-up.	Short-walk design; mixed advance/ASAP booking suits users' routine/spontaneous trips.	https://www.ptv.vic.gov.au/more/travelling-on-the-network/flexiride/
Flexilink, Sunshine Coast, AU	≥ 2 hours ahead (or by 9 pm the night before the first AM trip).	No fixed stops, safe pick-up arranged along the route, and a short walk.	Low-tech phone booking with near-door pick-ups; predictable lead-time helps planning.	https://www.sunshinecoast.qld.gov.au/living-and-community/transport-and-roads/public-transport/flexilink
Bay Transit Express, Rural Virginia, USA	On-demand (no advance required), allows pre-book in app.	Nearby pick-up points within small zones (a short walk).	Rural micro-transit pilots reported short waits and improved access for seniors.	https://www.baytransit.org/express/

For older residents in rural NZ, DRT answers a specific set of needs: short-walk access, reliable booking, feeder links to clinics/shops and inter-town services, and inclusive channels (phone + app). Local trials (Timaru, Tauranga South; Metlink On Demand) and overseas rural programmes (Ireland, UK, Scotland, Australia, US) provide transferable templates for service design, coverage and funding, especially where the aim is age-friendly, cost-aware mobility in places that fixed routes alone cannot serve well. Older adults in rural NZ exhibit a strong preference for short access walks and short/real-time booking windows. Our preliminary study shows that the disutility of walking distance is large and increases with age, while additional advanced booking time has, at most, a modest effect once access is controlled. Recent deployments demonstrate how DRT can be configured to meet these needs: virtual-stop models that keep walks within 150-200 metres (e.g., Baybus OnDemand, HertsLynx, Tees Flex, Wiltshire Connect) and door-to-door models for eligible users (e.g., TFI Local Link, MyBus) combined with real-time or short-notice booking and phone support (e.g., HertsLynx: 3 min-30 days; Wiltshire Connect: ≤30 min; Virginia's rural microtransit: no advance required) (Baybus, HertsLynx, Wiltshire, Tees Valley, SPT, TFI Local Link, DRPT). These design choices directly address older users' key barriers in low-density settings: long walks, infrequent services, and rigid schedules.

METHODOLOGY

Logistic Regression and Latent Class Model

A latent class (LC) model is a model for cross-classified contingency tables that explains associations among variables in terms of conditional independence given an unobserved or latent classification (Lazarsfeld and Henry, 1968; Bhat, 1997; Magidson and Vermunt, 2004; Colombo et al., 2009). The LC choice model, introduced by Lazarsfeld and Henry (1968) and developed by Kamakura and Russell (1989), enables simultaneous choice modelling and market segmentation to identify segment-specific preference parameters, individual profiles for each segment, and segment sizes. The Multinomial Logit Model (MNL) assumes a common preference structure across individuals, whereas LC models incorporate heterogeneous preferences into the deterministic utility function through a simultaneous estimation process. An LC model calibrates class-specific parameter sets, and the likelihood that a respondent belongs to a class is a probabilistic function of individual characteristics and preferences. The probability of the mode j being chosen by the individual i, given that it belongs to their membership of class s, can be expressed as:

$$P(y_i = j|\, s) = \frac{\exp\,(\beta_s x_{ij})}{\sum_{q=1}^{J_i} \exp\,(\beta_s x_{ij})} \tag{1}$$

where the utility function is

$$U_{ij|s} = \beta_s x_{ij} + \varepsilon_{ij|s} \tag{2}$$

The vector β_s is specified as a class-specific vector of parameters for the class s $(s = 1, 2, \ldots, S)$. Following the approaches and assumptions utilised by Swait and Adamowicz (1994) and Boxall and Adamowicz (2002), the choice probability within the class $P(y_i = j|\, s)$ is given by the MNL, and the choice set contains a set of alternatives, including mode j.

$$M_{is} = \frac{\exp\,(\theta_s z_i)}{\sum_{s=1}^{S} \exp\,(\theta_s z_i)} \tag{3}$$

The probability of an individual i belonging to a class membership s is M_{is}which is determined by the MNL's form as a function of respondents' characteristics. To identify the model, the Sth parameter vector, represented by a constant term, is normalised to zero.

Several statistical criteria can be used to determine the best number of classes, e.g., Akaike Information Criterion (AIC), Consistent Akaike Information Criterion (CAIC), and Bayesian Information Criterion (BIC), and this requires a balanced evaluation of the indices (Shen, 2009). These indices are defined as follows:

$$\mathrm{AIC} = -2\left[LL(\hat{\beta}) - \mathrm{S}\cdot K_s - (S-1)K_c\right] \tag{4}$$

$$\mathrm{CAIC} = -2\mathrm{LL}(\hat{\beta}) - [\mathrm{S}\cdot K_s + (S-1)K_c - 1][\ln(2N) + 1]$$

$$\mathrm{BIC} = -2LL(\hat{\beta}) + [\ln(\mathrm{N})][\mathrm{S}\cdot K_s + (S-1)K_c]$$

where $LL(\hat{\beta})$ is the value of the log-likelihood function at convergence for the estimated parameters

$\hat{\beta}$, K_s is the number of elements in the utility function of the class-specific choice models, K_c is the total number of parameters in the model, and N is the total number of observations in the sample. The Consistent AIC (CAIC; Bozdogan, 1987), a derivative of the AIC (Akaike, 1987), penalises models with a larger number of parameters relative to the sample size *N.* LC models with different numbers of segments should be estimated and assessed across a range of class sizes. The information criterion indices mentioned above (AIC, CAIC, and BIC) are used to compare several plausible models, with the lowest value of a given index indicating the best-fitting model (Nylund et al., 2007). Louviere et al. (2000) also suggested that the value of *S* that minimises each of the AIC and CAIC measures indicates which model should be preferred.

Data Collection and Survey Sample

The study was scoped to rural and small-town New Zealand, with an initial exploratory phase to build a broad understanding of mobility barriers for older adults. This study first administered a brief revealed-preference (RP) questionnaire to establish existing travel patterns and pain points and to guide the selection of attributes for the subsequent experiment. Using insights from the RP stage, this study narrowed the focus to two rural case settings, Thames (Thames–Coromandel District) and Tokoroa (South Waikato District), and compiled contextual evidence from Stats NZ, Waka Kotahi NZ Transport Agency, the Ministry of Transport, the two district councils, and local taxi operators. A concise literature review on rural mobility, ageing and demand-responsive transport (DRT) informed the wording, attribute ranges and framing of the stated preference (SP) instrument.

Survey instrument

This study implemented a combined RP+SP survey in 2022. The instrument comprised two parts:

- Part A – Respondent profile and transport context. Age, gender, location, household income, driver licensing/ability, household vehicle ownership and smartphone access/usage. These items were chosen both to characterise the sample and to support interaction terms in modelling (e.g., cost × income, access × age, booking × smartphone).
- Part B – Choice experiment. Each respondent completed eight choice tasks. Every task presented three labelled alternatives reflecting realistic options in the study area:
    - Option 1 – Current bus (walk access). \$2 per boarding; average walk ≈500 m to a stop; no booking.
    - Option 2 – Fixed DRT (stop-to-stop). \$6 or \$8 per boarding; average walk ≈100 or 150 m to a designated pick-up; 1 or 2 hour advanced booking time.
    - Option 3 – Flexible DRT (door-to-door). \$10 or \$12 per boarding; door-to-door pick-up/drop-off; < 1/2 hour advanced booking time.

The attributes and levels were therefore:

- Service cost (\$/boarding): 2, 6/8, 10/12.
- Accessibility (walk distance): 100 metres; 500 metres; door-to-door.
- Advanced booking time (hours): none (current bus), 1/2 (fixed DRT), 0.5/1 (flexible DRT).

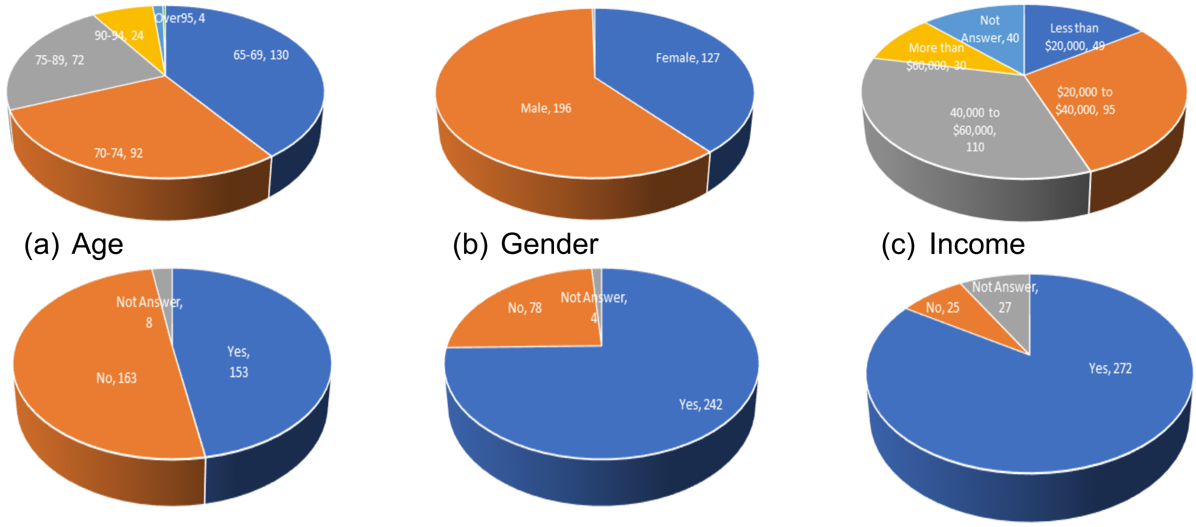
Attribute ranges were piloted to ensure credible trade-offs in rural contexts (shorter walks and shorter lead times where feasible), while maintaining cost spreads that reflect likely operating costs of stop-to-stop and door-to-door services.

Sampling frame and fieldwork

The population of interest for this study comprised residents aged 65 and above residing in Thames, Tokoroa, and adjoining localities. The targeted sample size was set at 400. However, a total of 324 complete responses were obtained, attributable to the area's low population density and the seasonal availability of older residents. Recruitment efforts involved community channels such as libraries, senior centres, and community groups, as well as in-person interviews conducted in town centres and health/shopping precincts. Participants could complete the survey either on paper or digitally, with assistance from an interviewer if needed. Table 2 summarises the key characteristics of the 324 respondents. In brief:

- Age: nearly two-thirds of respondents were in the 65–69 year age group.
- Gender: male respondents represented a slight majority.
- Income: the most prevalent income bracket was $40,000–$ 60,000, followed by $20,000–$ 40,000.
- Vehicle Ownership: 84% reported owning one or more household vehicles.
- Smartphone ownership: 47% possessed a smartphone.
- Fitness to drive: 75% self-assessed as fit to drive.
- Usual mode of non-medical errands: 51% primarily drove themselves; public transport and family/whānau were the next most frequently cited alternatives.

Table 2. Sample Demography



(a) Age (b) Gender (c) Income

(d) Smartphone Users (e) Fit to Drive (f) Auto Ownership

MODELLING RESULTS AND ANALYSIS

Multinomial Logit (MNL) and Mixed Logit (MIXL) Models

This section outlines the mode choice models developed for respondents from both cities. Multinomial logit (MNL) and mixed logit (MIXL) models were estimated using three generic attributes (cost, accessibility, and advanced booking time) and three socio-economic attributes (age, gender, and smartphone usage). The models were estimated using data from 1,208 observations of 151 survey respondents in Thames and 1,384 observations from 173 respondents in Tokoroa, with separate utility functions for each mode (SQ: Bus with a walk; Option 1: Fixed-route BRT service; Option 2: Flexible BRT service).

This study first estimates a baseline multinomial logit (MNL) model with generic coefficients on fare (COST), walk distance to the pick-up (ACCESSIBILITY), and advance booking time (ADV_BOOKING). The specification includes socio-economic taste shifters, income (INCOME) and age (AGE), and alternative-specific constants (ASCs) for two DRT variants, Fixed DRT (scheduled around short-walk virtual stops around 100-150 metres with 1-2 hour pre-booking) and Flex DRT (operating at the address level, door-to-door with 0.5-1 hour pre-booking). Each DRT constant can shift for smartphone owners (S_PHONE_FIXED, S_PHONE_FLEX). To accommodate repeated choices per respondent and preference heterogeneity, this study then estimates a mixed logit (ML) in which COST is random (triangular, sign-constrained negative) and ACCESSIBILITY and ADV_BOOKING are fixed; all models treat bus with a walk as the base alternative. The MNL attains a log-likelihood of -1846.01 (McFadden pseudo-R^2 = 0.062; AIC/N = 2.052). The mixed logit model

(MIXL) improves fit substantially: log-likelihood = -1522.48, McFadden pseudo-R² = 0.233, AIC/N = 1.695. The likelihood gain (ΔLL = 323.5) remains decisive after penalising for the additional parameter(s), so this study relies on the ML for inference and uses the MNL as a baseline check. Coefficient estimates for the attributes and variables are presented in Table 3.

Table 3. 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				
COST	-0.560***	0.047	-0.959***	0.114
Nonrandom parameters in utility functions				
ACCESSIBILITY	0.290***	0.095	0.277**	0.121
ADV_BOOKING	-0.196	0.002	-0.003*	0.002
ASC_FIXED (Fixed DRT)	3.016***	0.415	4.983***	0.501
ASC_FLEX (Flexible DRT)	4.968***	0.574	7.347***	0.718
AGE	-0.936***	0.132	-0.828**	0.355
INCOME	0.038***	0.008	0.078**	0.035
S_PHONE_FIXED	-0.463***	0.117	-0.444***	0.290
S_PHONE_FLEX	-0.847***	0.126	-1.033**	0.496
Derived standard deviations of random parameter distributions				
COST			0.442***	0.034
Model Statistics				
Log-Likelihood	-1846.01		-1522.47	
Pseudo- R^2	0.0627		0.2333	
AIC/N	2.052		1.695	
Observations	2592			

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

Across specifications, fare enters utility negatively and significantly. In the MIXL, the mean random COST coefficient is -0.959 with a significant spread of 0.442 (triangular), implying meaningful heterogeneity while preserving a negative sign for essentially all draws. The average ACCESSIBILITY coefficient is +0.277, but the interaction with AGE is -0.828 (both significant), so the effective access slope is negative for realistic ages (i.e., extra walking reduces utility, and the penalty grows with age). ADV_BOOKING has a small but statistically significant negative mean effect in the MIXL. Thus, booking lead time is statistically detectable but substantively minor once access distance and price are controlled. INCOME systematically moderates price sensitivity, indicating that higher-income respondents are less fare-averse. Both DRT options carry large, positive baseline utilities relative to the bus with a walk (MIXL: ASC_FIXED = 4.98, ASC_FLEX = 7.35). Smartphone ownership reduces these baselines: S_PHONE_FIXED = −0.444 and S_PHONE_FLEX = −1.033. When interpreted as odds ratios, these shifts correspond to $exp^{-0.444}$ ≈ 0.64 and $exp^{-1.033}$ ≈ 0.36. This indicates that smartphone owners have a 36% reduction in the odds of selecting the fixed DRT and a 64% reduction in the odds of selecting the flexible DRT compared to non-owners, while holding fare, walking distance, and booking time constant. A plausible interpretation is that smartphone users may expect ride-hail standards: fast confirmations, accurate ETAs with short pick-up windows, live tracking, few cancellations with easy rebooking, and the same experience across the app and phone.

Three conclusions follow. First, service cost matters, and lower-income riders feel it most. Sensitivity to service cost is clearly negative, with stronger effects among those on lower incomes. Second, walking distance is the biggest operational lever, especially for older people. Third, booking time still matters, but plays a smaller role once access is addressed. People are generally positive about DRTs, particularly the flexible, door-to-door option, but smartphone owners are less inclined to use it unless the app and phone experience is strong. Therefore, service/operation design should focus on bringing pick-ups closer to reduce walking, offering targeted fares or concessions for low-income riders, and improving the digital experience with reliable ETAs, easy rebooking, and smooth support across both app and phone channels.

Latent Class Modelling

The latent class (LC) model is an efficient method when analysts do not know the distribution of taste heterogeneity in the sample. The most common form of the LC choice model is the latent class multinomial logit (LC-MNL) model. Two, three, and four-class LC-MNL models were estimated. To determine the number of classes, the BIC and AIC statistics were primarily considered. Practically, the three-class specification provides the best model fit, since although the AIC decreases as more classes are added, the BIC starts to increase again. Improvements in the other criteria decrease as the number of classes increases from two to three, and from three to four. However, for the 4-class model, all estimated parameters for one class were found to be not statistically significant, rendering interpretation for that class impossible. Also, given the relatively small sample size, the model produced many insignificant parameter estimates as the number of classes increased. Therefore, a three-class model was chosen, and the results are shown in Table 4 because it yields more statistically significant parameters while allowing for a better comparison of respondents' perceptual heterogeneity.

Table 4 Latent Class Model Estimations

	MNL	Latent Class Multinomial Logit (LC-MNL)		
Attributes		Class 1	Class 2	Class 3
COST	-0.560(0.047)***	-1.784(0.242)***	-0.919(0.082)***	-0.586(0.166)***
ACCESSIBILITY	0.290(0.095)***	-0.662(0.438)	-0.386(0.135)***	1.754(0.450)***
ADVANCE BOOKING TIME	-0.196(0.001)	-0.009(0.006)	-0.399(0.122)	0.001(0.005)
ASC_FIXED (Fixed DRT)	3.016(0.415)***	2.186(2.024)	5.456(0.587)***	5.125(1.802)***
ASC_FLEX (Flexible DRT)	4.968(0.574)***	6.570(2.660)**	7.679(0.810)***	8.695(1.549)***
AGE	-0.936(0.132)***	0.522(0.391)	-0.958(0.260)***	-6.801(1.953)***
INCOME	0.038(0.008)***	0.220(0.033)**	0.098(0.017)***	0.218(0.062)***
S_PHONE_FIXED	-0.463(0.117)***	-1.478(2.660)**	-1.065(0.217)***	2.412(1.549)
S_PHONE_FLEX	-0.847(0.126)***	-4.786(1.086)***	-1.551(0.269)***	0.943(1.245)
Class membership probability		0.266	0.575	0.158
Model Statistics				
Log Likelihood	-1846.01	-1472.73		
Pseudo R^2	0.0650	0.2585		
AIC	2.052	1.661		
BIC		1.749		

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

Each of the estimated models consists of generic variables, two ASCs and socio-economic variables. The generic attributes are the variables used in the choice experiment, which include cost, accessibility, and advanced booking time. The interaction terms are variables describing respondents' socio-economic characteristics. Those functional forms interact only with ASC or generic attributes. Model estimation initially used the generic attributes and ASC parameters. After the parameters of the first model were obtained, socio-economic variables were added, and other models were specified. However, there is always a trade-off between the benefits of adding more socio-economic characteristic terms and the complications of statistical validation that arise from doing so (Ortuzar and Willumsen, 2001). Therefore, the final model included all generic variables and ASCs based on statistical fit and predictive performance, including parameter significance and improvements in the Log Likelihood (LL), McFadden pseudo-R^2, and AIC.

As shown in Table 4, model fit is strong, with log-likelihood, McFadden pseudo-R^2, and AIC/N, all showing substantial improvement over the simple MNL baseline. Class membership shares are 25.23%, 53.03%, and 21.74% for Classes 1-3, respectively. Across all classes, COST is negative and statistically significant, and the INCOME interaction is positive, indicating that higher-income respondents are less price-averse. Advanced booking time has no reliable effect in any class. Class 2 (53.03%) users are mainstream riders. Cost sensitivity is moderate (COST = -0.92), and income weakens it (INCOME = +0.098). Walking distance matters substantially once age is considered: the main effect is positive (ACCESSIBILITY = +0.386), but the age term is negative (AGE = -0.958), so the net effect is clearly negative for realistic ages; each additional metre of distance walked reduces utility, with a larger penalty for older riders. Baseline preferences for both DRT designs are significant and positive (ASC1 = +5.46; ASC2 = +7.68). Smartphone ownership lowers these baselines (S_PHONE_FIXED = -1.07, S_PHONE_FLEX = -1.55), suggesting a comparative reluctance among phone users, conditional on attributes. For Class 1 (26.6%), price hawks with Flexible DRT tilt. Fare is very salient (COST = -1.78), again moderated by income (INCOME = +0.221). Access and its age interaction are imprecisely estimated, but there is a strong positive baseline for Flexible DRT (ASC_FLEX = +6.57), while Fixed DRT is not clearly favoured. Smartphone ownership substantially depresses baseline inclination to DRT (S_PHONE_FIXED = -1.48, S_PHONE_FLEX = -4.79). Class 3 (15.8%) users are DRT enthusiasts, extremely walk-averse, and age-dependent. Price matters least here (COST = -0.586), yet income still softens it (INCOME = +0.218). The access pattern is striking, with ACCESSIBILITY = +1.75 and a very negative age interaction (AGE = -6.80), suggesting very large disutility from extra walking among older riders. Baselines for both DRT options are again high (ASC_FIXED = +5.13, ASC_FLEX = +8.70), and smartphone shifts are not reliably different from zero.

Several policy implications emerge from this analysis, highlighting various strategies to improve service effectiveness. To effectively reduce walking distances, which are the primary factor for most users and particularly critical for Class 3, it is advisable to implement closer virtual stops. Additionally, offering flexible or door-to-door pick-ups for older users will enhance accessibility, while ensuring the availability of safe pedestrian routes is essential for promoting overall safety and convenience. Implementing targeted pricing is essential, as users exhibit significant variability in their cost sensitivity and a systematic income effect. Therefore, providing concessions or discounted passes to economically disadvantaged riders is likely to be more effective than blanket fare reductions across the board. To mitigate the negative effects of smartphone use in the two larger classes, it's essential to enhance the digital experience by simplifying booking processes, providing clearer estimated arrival times (ETAs), and offering reliability guarantees. This approach will help ensure that app users perceive DRT more favourably compared to ride-hailing options. Additionally, since booking time has minimal impact, prioritising operational improvements in access and fare policies is more efficient than attempting to reduce advance-booking requirements.

CONCLUSIONS

The elderly share in rural Thames and Tokoroa is high and growing. As driving ability declines with age, safe and reliable mobility becomes a prerequisite for social participation. Existing fixed-route services in these towns provide limited coverage and require long walks to access, creating pronounced barriers for older residents.

This study combined an exploratory revealed-preference (SP) survey with a stated preference choice experiment among 324 residents aged 65+ in Thames and Tokoroa. The models estimated included a multinomial logit benchmark, a mixed logit with random costs, and a fixed-parameter latent class

(LC) model. Alternatives in the SP reflected two recommended DRT archetypes for rural settings: a fixed/stop-to-stop service (short-walk virtual stops, min. 1-2 hour booking) and a flexible/door-to-door service (< 0.5 hour booking), with the existing bus + walk as the base.

Three empirical messages are consistent across specifications. First, service cost disutility is negative and heterogeneous; lower-income riders are markedly more price-sensitive. Second, walking distance is the dominant lever, with the penalty increasing with age; advance booking time has a smaller, but significant, negative effect. Third, there is a strong intrinsic preference for DRT, especially for the flexible option, while smartphone ownership lowers the baseline inclination toward both DRT variants, suggesting expectations around digital reliability and user experience that sit outside the attribute set.

The LC modelling results show two clear groups. Most respondents are 'mainstream': they value a short walk and are price-sensitive. A smaller group are 'DRT enthusiasts': they strongly dislike walking, especially as they age, and are less price-sensitive. For service design, the message is direct. Bring pick-ups closer and use door-to-door where feasible. Offer concessions or targeted fares for lower-income riders. Strengthen the digital experience for phone users with reliable ETAs, easy rebooking, and a consistent experience by app or by phone.

Future work should test these ideas in real services. Pilot the two DRT options in rural towns, track changes in access distance, wait times, cost per trip, and user satisfaction, and compare before-and-after results. Expand the survey to other regions and run a larger, panel sample so we can see how preferences change over time. Add attributes that capture reliability more directly (e.g., pick-up window width, estimated arrival time accuracy, cancellations, and live tracking) and model class membership using demographics and digital readiness. Finally, link the choice models to operational factors (e.g., fleet size, zones, dispatch rules) to identify designs that meet older users' needs while remaining affordable.

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