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Active Transport and Travel Demand in Brisbane: Insights from Survey and Smart Travel Diary Data

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EXECUTIVE SUMMARY

Active transport has significant potential to help reduce congestion, emissions, and the associated health burden of physical inactivity. Despite ongoing infrastructure investments across Australian cities, participation rates remain limited relative to the proportion of short-distance trips that could feasibly be completed by walking, cycling, or public transport. This study examines active transport behaviours in Brisbane by integrating survey responses with a web-based smart travel diary to investigate mode choice patterns, behavioural determinants, and constraints influencing the uptake of active travel modes.

A targeted, or purposive sampling, method was used to focus on collecting data from people who at least sometimes use active transport. Data were collected between July and October 2025 using two complementary instruments: a Qualtrics survey and a web-based travel diary. Following the matching of responses, 613 unique respondents were retained, contributing 1,116 valid trip records (an average of 1.82 trips per participant). The combined dataset enabled detailed study of demographic characteristics, transport resources, confidence in active modes, frequency of walking and cycling, and perceived barriers and motivators associated with active transport participation.

Descriptive analyses indicate that the sample comprised an even split of female and male respondents, with 47% aged between 35 and 54 years, 34% aged 55 years and over, and 19% aged 18–34 years. Educational attainment was high, with 80% of participants holding post-secondary qualifications. Approximately 74% possessed a car licence, and 91% reported access to at least one car. In comparison, ownership of active and micro-mobility modes was lower, with 37% owning a bicycle, 12.6% an e-bike, 11.9% an e-scooter, and 12.4% a motorcycle. Self-reported confidence in using active modes was highest for bicycles (69%), followed by e-bikes (43%) and e-scooters (32%). Walking was the most frequently reported activity, undertaken at least weekly by 89% of respondents, whereas 31% reported cycling at least once per week. The most frequently cited barriers to active transport participation included concerns regarding traffic safety and insufficient separated infrastructure, whereas key motivators included proximity to destinations and the availability of safe and continuous paths.

According to the travel diary data, driving accounted for 31% of all trips, followed by walking (30%), cycling (23%), and transit (16%). When combined, walking and cycling constituted 53% of all recorded trips, indicating a substantial contribution of active modes to total travel activity. The most common trip purposes were commuting, shopping, and fitness-related travel, whereas recreational and escort trips were less prevalent.

A Mixed Logit (MXL) model was estimated to investigate the determinants of mode choice, extending a baseline Multinomial Logit model to account for unobserved heterogeneity and repeated observations per respondent. The MXL specification produced a significantly improved model fit relative to the MNL, as confirmed by the likelihood-ratio test. The model accurately replicated the aggregate modal shares (predicted probabilities: walking 32%, cycling 23%, driving 29%, transit 16%), illustrating strong predictive validity.

The mixed logit results indicate several statistically significant predictors of mode choice (relative to walking). Bicycle ownership was strongly associated with a higher likelihood of cycling and a lower likelihood of driving, and high self-reported cycling confidence increased cycling (and was associated with lower transit use). Car availability increased driving and reduced transit use. Men were more likely to choose cycling. Younger adults (18–34) were more likely to cycle, whereas older adults (55+) were less likely to use transit. Households with children under 15 showed greater reliance on driving. Income effects were also evident: medium-income respondents were less likely to cycle and to use transit than low-income respondents, and higher-income respondents showed a stronger preference for driving. These findings show that both resource availability and sociodemographic characteristics influence mode selection.

Origin–destination analysis illustrated that travel behaviour is embedded within the spatial structure of the city. Distance between origins and destinations emerged as the strongest factor associated with travel flows. After accounting for distance, neighbourhood characteristics remained important: areas with higher concentrations of full-time employment generated and attracted more trips, while destinations with higher proportions of older residents and households with children attracted fewer trips. These findings indicate that travel demand is closely linked to the spatial distribution of employment and population structure rather than being evenly distributed across Brisbane.

Overall, the results provide an empirically grounded understanding of active transport behaviour in Brisbane. The findings emphasise the importance of targeted interventions that address infrastructure quality, safety perceptions, and accessibility barriers, particularly for women, older adults, and families with children.

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1. Introduction

Governments are investing in active transport infrastructure to alleviate urban congestion, reduce greenhouse gas emissions, and enhance public health outcomes (Gössling, 2020; Rabl & De Nazelle, 2012; Woodcock et al., 2009). In Australian cities, however, the uptake of active travel remains modest despite substantial infrastructure spending (Beck et al., 2022). For example, only 1.1% of Australian workers commute by bicycle, and 2.8 % walk to work, despite a substantial proportion living within a short active travel distance (Both et al., 2022). This underutilisation is particularly pronounced in Brisbane, where vehicle kilometres travelled have increased by approximately 60% over the past two decades, much of it attributable to short-distance trips of less than five kilometres, journeys that could feasibly be undertaken through walking, cycling, or public transport alternatives (Infrastructure Australia, 2024). These patterns highlight both the underutilised potential of active travel and the urgent need for empirical research, such as active transport and travel surveys, to better understand behavioural drivers and inform targeted interventions.

The barriers to active transport adoption are multifaceted, spanning individual, social, and environmental determinants. International research consistently highlights the importance of safety perceptions, infrastructure continuity, and proximity to destinations as primary enablers of active travel (Handy et al., 2014; Heinen et al., 2010). At the same time, sociodemographic and household factors such as gender, age, income, and family composition shape the likelihood of adopting active modes (Aldred et al., 2016; Beck et al., 2022). Women and older adults often report heightened vulnerability to traffic and personal safety risks, while families with young children face logistical constraints that reinforce car use (Buehler & Pucher, 2017). Moreover, the rise of micromobility technologies—such as e-bikes and e-scooters—has created new opportunities to extend the reach of active transport, yet empirical understanding of these behaviours in Australian remains limited.

Understanding the behavioural and contextual determinants of active transport in Brisbane is therefore essential for informing policy and infrastructure investment. Previous studies have predominantly relied on travel surveys or census data that offer limited behavioural granularity and fail to capture trip-level decision-making processes. This study advances the evidence base by integrating attitudinal and behavioural data collected through two complementary sources: a population survey administered via Qualtrics and a web-based travel diary. The combined dataset enables an examination of both the motivational and situational factors influencing mode choice, providing a more holistic understanding of active transport participation in an Australian metropolitan context.

The study addresses four key objectives. First, it characterises the demographic and attitudinal profile of active transport users, including confidence in using different modes and perceived barriers and motivators. Second, it analyses trip-level mode share and travel purposes derived from diary entries to identify behavioural patterns across population subgroups. Third, it examines route selection behaviour using spatially referenced diary data, enabling assessment of the geographic distribution of trips and the use of active transport infrastructure within the Greater Brisbane Area. Fourth, it applies discrete choice modelling to estimate the effects of demographic, household, and perceptual variables on mode choice relative to walking.

2. Methods

2.1 Participants and Procedure

Data were collected from 613 Brisbane (Australia) residents between July and October 2025. Recruitment used three parallel channels: (i) Facebook posts in local active-transport groups,

(ii) in-person flyer distribution with a QR code linking to the survey, and (iii) online research panel managed by PureProfile and Dynata, targeting the Greater Brisbane area. A targeted, or purposive sampling, method was used to focus on collecting data from people who at least sometimes use active transport. Eligibility required respondents to: (1) be at least 15 years of age, (2) currently reside within Greater Brisbane, and (3) report at least one destination-oriented active-transport trip in the past seven days, defined as walking, cycling, scootering, or skateboarding to reach a destination (not solely to access public transport). Individuals not meeting these criteria, duplicate entries, and records failing attention or logic checks were excluded prior to analysis.

The questionnaire was administered online via Qualtrics. The survey link was shared through a QR code on flyers and a posted URL on Facebook; panel participants accessed the same instrument via PureProfile and Dynata. Participants were asked to review an information document and a consent form before starting the questionnaire. The participants were notified that their involvement was completely voluntary, their data would be kept anonymous. The survey required approximately 10-15 minutes to complete. Ethical approval was obtained from the Queensland University of Technology Human Research Ethics Committee prior to study commencement.

Two survey screens ensured the target population: an age check (≥15 years) and a Brisbane residency check. Respondents then confirmed at least one destination-oriented active transport trip in the last seven days (walk, cycle, scooter, skateboard — not solely to access public transport).

2.2 Measures

This study combined a brief questionnaire with a web-based smart travel diary. The questionnaire collected sociodemographic, household composition and resources, driving licence status, access to vehicles and micromobility devices, self-reported confidence using active modes, weekly activity level, employment/study status and schedules, active travel frequency and reasons for (non) use, plus perceived barriers and motivators to active transport. Responses were screened with two attention-check items; inconsistent or incomplete cases were excluded when they failed quality checks or contained excessive missingness. Categorical items were recoded into analysis-ready indicators as described below. The full questionnaire is provided in the Appendix A.

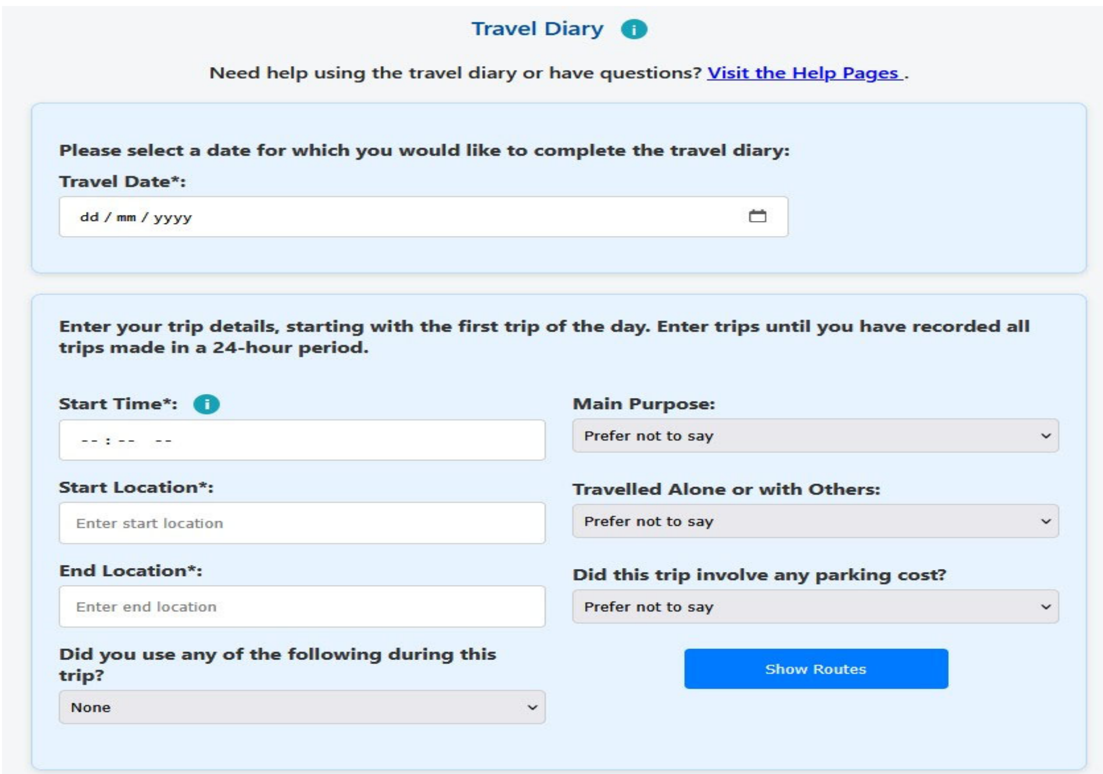

Figure 1. Smart Travel Diary trip-entry interface.

The questionnaire was paired with a purpose-built, web-based smart travel diary that recorded trip-level behaviour and the decision context for each trip (Figures 1–2). After selecting a travel date, participants entered each trip made within the 24-hour period using a structured form with required fields and hover tooltips (Figure 1). For every trip they reported the start time, start and end locations (free-text boxes with geocoding), main trip purpose, whether they travelled alone or with others, use of paid parking (if applicable), and whether they used any special facilities or devices (e.g., e-scooter).

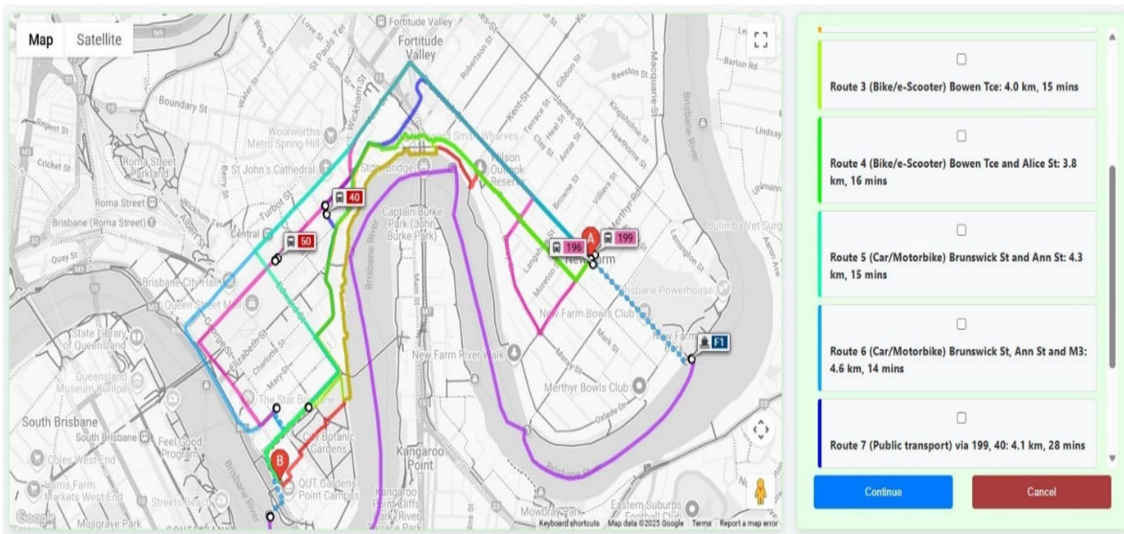

Figure 2. Route alternatives map and selection panel.

After clicking Show routes, an embedded routing engine generated alternative route–mode combinations between the reported origin and destination. These were presented on an interactive map with a side panel listing each option with distance and travel time. Participants then selected the route taken for that trip and could tick any additional routes they typically consider. The route taken could be adjusted with waypoints if needed. To capture decision sets (not just outcomes), the diary also asked respondents to indicate all modes they would normally consider for a similar trip before proceeding.

When a trip was saved, the portal stored trip metadata (timestamps, coordinates, chosen mode/route ID, considered alternatives, distance/time, stated purpose, group travel, and parking cost) and rendered a daily summary table so participants could review, edit, or delete entries before submitting the day. Submissions triggered a confirmation page with a link to return to the diary if participants wished to add further trips.

For modelling, the diary data were linked to questionnaire records via a panel identifier. Each trip observation was expanded to a universal four-alternative choice set (walking [reference], cycling, driving, transit), yielding one long-format row per alternative with a binary "chosen" flag. Availability constraints (e.g., no car licence; no bicycle access) and person/household attributes from the questionnaire were used to derive analysis-ready indicators and, where appropriate, to restrict alternative availability in estimation. The final specification of the baseline and heterogeneity-robust mode choice models includes the following predictors described in Table 1.

2.1 Data Analysis

The analysis proceeded in three stages. First, descriptive statistics were used to summarise participant characteristics, transport resources, confidence in active modes, reported barriers and motivators, and trip purposes. Frequencies and percentages were calculated for categorical variables, while means and ranges were reported for continuous measures.

Second, mode choice behaviour was examined using a discrete choice modelling approach to identify key behavioural and demographic factors associated with selecting walking, cycling, driving, or public transport for individual trips. A mixed logit model was applied to account for repeated trips made by the same participant and to capture differences in preferences across individuals. Mixed logit is particularly suited to discrete-choice data with repeated observations because it captures unobserved preference heterogeneity and accommodates panel structures (Greene & Hensher, 2003; Paz et al., 2019). Walking was treated as the reference mode. The analysis focused on estimating the direction and relative strength of associations between mode choice and factors such as vehicle access, cycling confidence, age, gender, household composition, and income. Additional technical details are provided in Appendix B.

Table 1. Predictors included in the mode choice model

Variable (analysis label)	Description / coding
Male	Respondent identified as male (1=yes; 0=no).
Has car	Household owns or has access to ≥1 car (1=yes; 0=no).
Has bicycle	Household owns or has access to ≥1 bicycle (1=yes; 0=no).
Conf bicycle high	Cycling confidence reported as "somewhat" or "extremely" confident (1=yes; 0=no; neutral/low coded 0).
Any under15	Household includes at least one member aged <15 years (1=yes; 0=no).
Age Younger	Respondent in younger age group (18–34 years) based on survey categories (1=yes; 0=no).
Age Older	Respondent in older age group (≥55 years) based on survey categories (1=yes; 0=no).
Inc Med	Household income in the survey's medium band (1=yes; 0=no).
Inc High	Household income in the survey's high band (1=yes; 0=no).

Note: This table includes only the factors that are statistically correlated with mode choices. Detailed wording of all data items considered in the analyses is provided in Appendix A.

Third, an origin-destination (OD) flow analysis was conducted using count-based regression models to examine how spatial separation and neighbourhood characteristics shape travel patterns across Brisbane. Travel flows were aggregated considering the Statistical Area Level 2 (SA2) and analysed between origin-destination pairs.

The SA2 groups are geographic areas defined by the Australian Bureau of Statistics (ABS) and correspond to medium-sized regions intended to represent local communities. These areas are commonly used as functional spatial units for consistent statistican analysis across the state. This level of spatial aggregation offers several advantages, including adherence to national statistical standards and the provision of relatively homogeneous data granularity across regions.

A Poisson regression model was employed to examine how distance, access to cars and bicycles, income, age structure, employment status, and household composition are associated with the number of trips between the OD pairs. Model covariates were selected using an iterative specification process guided by statistical significance and goodness-of-fit criteria. Additional methodological details are provided in Appendix B, and the variables included in the OD analysis are listed in Table 2.

Table 2. Descriptions of variables used in the OD analysis.

Domain	Description / coding
Car access	% of individuals with ≥1 car in the household
Bike access	% of individuals with ≥1 bicycle in the household
Children	% of households with children <15 years
Age groups	% aged 15–34 years (younger adults) % aged ≥54 years (older adults)
Income	% of individuals in the low-income category % of individuals in the high-income category
Employment	% employed full-time % not working
Distance	Distance between origin and destination (km)

Note: All variables except distance are included twice, once for origin areas and once for destination areas.

One of the main reasons for working at this level of aggregation is the presence of sparsity in the OD flows. High levels of spatial granularity generate a large number of OD pairs with near-zero counts, resulting in many parameters relative to the number of observations. Under these conditions, model estimation tends to produce inflated standard errors and statistically insignificant coefficients. Aggregation increases the expected count per OD pair, thereby improving the asymptotic properties of the count model. Moreover, finer levels of granularity exacerbate multicollinearity among covariates, leading to unstable coefficient estimates in both sign and magnitude (Stillwell, et al., 2018; Parenteau, et al., 2011).

2.2 Sample Size

The required sample size for this study was determined using standard approaches commonly applied in population-based transport and travel behaviour research, specifically Yamane's method and Cochran's method for estimating proportions. Estimates were calculated at a 95% confidence level and assumed a conservative scenario in which the true population proportion is unknown. This approach produces a relatively large sample for common studies where the models include around 15 or less variables. Applications requiring models including larger number of variables require additional data with the sample size increasing dramatically with the number of required estimates.

Sample size requirements were assessed for a 5% margin of error, which is widely accepted in transport planning and policy research as providing an appropriate balance between statistical precision and practical feasibility.

Given an estimated adult population of approximately 2.2 million residents aged 15 years and older across the Greater Brisbane region, Yamane's approach indicates that a sample of approximately 400 respondents is sufficient to achieve a 5% margin of error under simple random sampling assumptions. Similarly, Cochran's method yields a required sample size of approximately 384 respondents under the same confidence and precision criteria. Given the large population size, finite population corrections were negligible and therefore not applied. To account for potential clustering, repeated participation, and response dependencies commonly observed in online survey and travel diary data collection, a modest increase in the required sample size was considered appropriate. The achieved sample of 613 respondents therefore exceeds the minimum requirements under both Yamane's and Cochran's methods for a 5% margin of error, providing adequate statistical power and precision for the analyses undertaken in this study. However, this relatively small sample size only enables the analysis and estimation of models including around 30 (613/20) parameters. This is sufficient to meet the requirements and objectives of most studies such as the one undertaking in this project. The estimation of large models involving more than 30 parameters requires additional data collection.

3. Results

3.1 Descriptive Analyses

A total of 613 unique participants contributed 1,116 diary trips. On average, participants reported 1.82 trips each. In total, 300 participants (48.9%) submitted more than one diary trip; the remainder (n = 313; 51.1%) provided a single trip. The average of fewer than two trips per participant suggests that some travel days were only partially reported, which is common in voluntary diary studies where participants may record only their main or most memorable trips.

3.1.1 Demographic and Household Characteristics

The sample for descriptive analysis consisted of 613 participants who were successfully matched across both survey and diary datasets. Each participant ID contributed only once to the analysis, ensuring uniqueness. Percentages are calculated relative to valid responses. Table 3 shows demographic characteristics of participants.

Overall, the sample comprised an approximately equal proportion of female and male participants (49% female, 49% male; 0.2% other/prefer not). The age distribution indicated that most participants were middle-aged (35–54 years; 47%), followed by older adults aged 55 years and above (34%), and younger adults aged 34 years or below (19%). In terms of educational attainment, post-secondary qualifications were most common, with 30% holding a bachelor’s degree, 25% a diploma or certificate, and 25% a postgraduate qualification, while 19% reported completion of high school and 0.5% preferred not to state their education level. Approximately 14% of participants reported that they were currently studying. Employment patterns indicated that nearly half of the sample were employed full-time (48%), while 21%

were not working or reported another employment status. Part-time employment accounted for 18% of respondents, and 13% were retired. Students without paid work represented the smallest group at 0.7%. Most participants held a car licence (74%), while 7% had no licence.

Table 3. Comparison between study sample and Brisbane population aged 15 years and over.

Variable	Category	Study Sample (%)	Brisbane Population (%)	χ^2 (df)	p-value
Gender	Male	49%	49%	0.01 (1)	0.93
	Female	49%	50%		
Age group	18 – 34 years	19%	27%	12.6 (2)	< 0.001
	35 – 54 years	47%	45%		
	55 years and over	34%	27%		
Education level	Low (High school or below)	19%	42%	215 (2)	< 0.001
	Medium (Certificate/Diploma)	25%	31%		
	High (Bachelor/Postgraduate)	55%	27%		
Household income	Low (< $65 k)	25%	37%	10.8 (2)	< 0.001
	Medium ($65 – 130 k)	45%	34%		
	High (> $130 k)	30%	29%		
Currently studying	Yes	14%	22%	9.7 (1)	0.002
	No	86%	78%		
Employment status	Full-time	61%	57%	1.8 (2)	0.35
	Part-time	22%	26%		
	Not employed	17%	17%		

Note: Population proportions are drawn from Australian Bureau of Statistics (ABS) (2021) Census Quick Stats and Community Profiles. p-values are based on chi-square goodness-of-fit tests comparing study sample versus population proportions.

A series of chi-square goodness-of-fit tests were conducted to assess the representativeness of the study sample relative to the Brisbane population aged 15 years and older (Australian Bureau of Statistics, 2021). As shown in Table 3, gender and employment distributions were broadly consistent with Census figures ($p > 0.05$). However, significant differences emerged for age ($p < 0.001$), education ($p < 0.001$), household income ($p < 0.001$), and current study status ($p = 0.002$). The sample contained a higher proportion of older adults, tertiary-educated individuals, and medium-to-high income households, and fewer students than the Brisbane average. These differences are consistent with the study's online recruitment channels and its focus on active transport, which may have attracted participants with higher educational attainment and stronger engagement in health-promoting behaviours. While these demographic skews do not compromise internal validity, they should be considered when interpreting findings.

3.1.2 Mode Ownership, Self-reported Confidence and Use

Ownership of household transport assets was highest for cars (90.9%), followed by bicycles (37.2%). However, ownership of e-bikes, e-scooters, and motorcycles was approximately 12% (12.6%, 11.9%, and 12.4%, respectively).

As shown in Figure 3, confidence in using bicycles, e-bikes, and e-scooters was highest for bicycles (69% confident; 34% somewhat, 35% extremely), lower for e-bikes (43%; 28%, 15%), and lowest for e-scooters (32%; 21%, 11%).

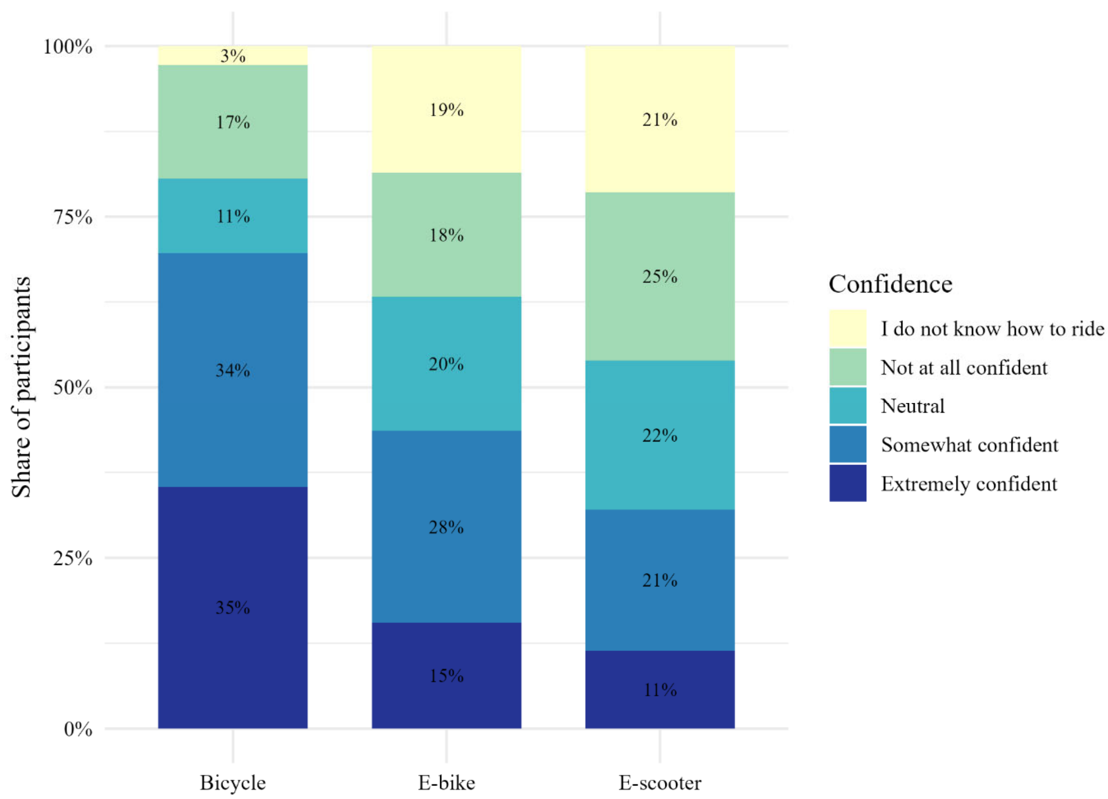

Figure 3. Confidence using different active transport modes. Stacked bar chart showing levels of confidence (from not confident to very confident) for bicycles, e-bikes, and e-scooters.

"Not at all confident" responses were 17% for bicycles, 18% for e-bikes, and 25% for e-scooters, and "Neutral" responses were 11%, 20%, and 22%, respectively. Inability to ride was rare for bicycles (3%) but more common for e-bikes (19%) and e-scooters (21%). Overall, confidence was highest for bicycles, lower for e-bikes, and lowest for e-scooters, with lack of riding skills concentrated in the micromobility modes.

Walking was the most frequently used mode, with 57% reporting daily walking and 32% walking 1–2 times per week, while only 1% reported no walking (Figure 4). Cycling showed moderate uptake, with 11% cycling daily and 20% weekly, and 42% were non-users. Micromobility use was limited overall; for e-bikes, 70% were non-users (8% daily, 7% weekly), and for e-scooters, 65% were non-users (10% daily, 8% weekly). At least-weekly use followed a clear gradient, highest for walking at 89%, then cycling at 31%, then e-scooters at 18%, and lowest for e-bikes at 15%.

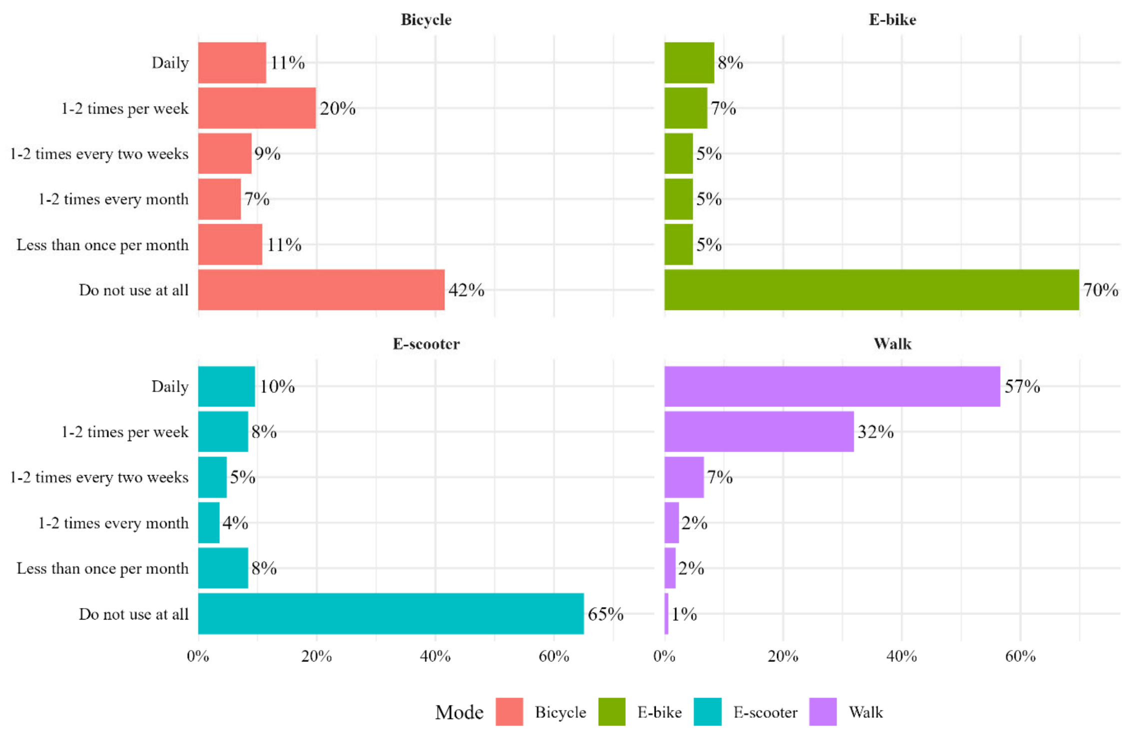

Figure 4. Frequency of active travel mode use.

3.1.3 Gender Differences in Mode Use

Figure 5 displays trip mode shares by gender. Across genders, driving and walking constituted the largest shares of trips and were similar in magnitude. Cycling comprised a higher proportion of men's trips (29% vs 17% for women), while transit comprised a slightly higher proportion of women's trips (18% vs 14% for men).

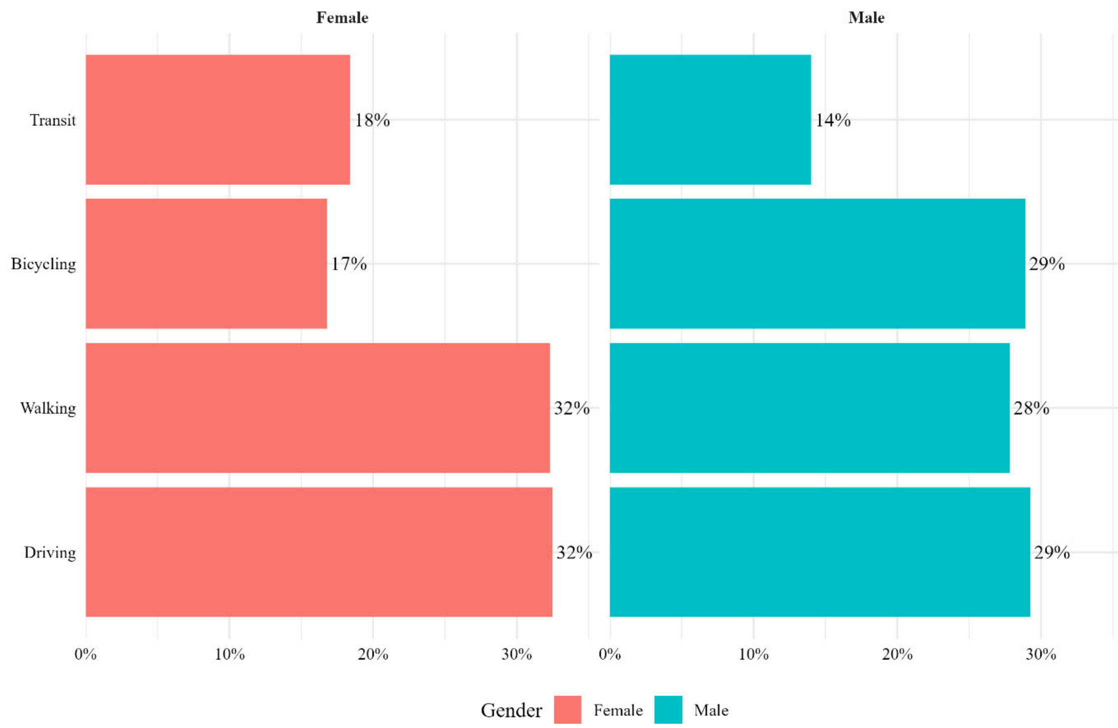

Figure 5. Mode share by gender. Distribution of reported travel modes (e.g., walking, driving, cycling, transit) expressed as percentages within each gender group.

3.1.4 Barriers and Motivators to Active Travel

Around 25% of participants reported reducing or stopping active transport over the past 12 months. Figure 6 shows barriers to use active transport across total sample. The most frequently cited barrier was too much car traffic/safety concerns (18%), followed by lack of physically separated lanes (6%) and inadequate lighting (4%). Smaller shares reported unpleasant travel paths (4%) and destinations too far (4%), with weather, taking other people, health/fitness, carrying heavy items, and hilly terrain each at 2%, and too many rules and lack of secure/safe parking at 1%.

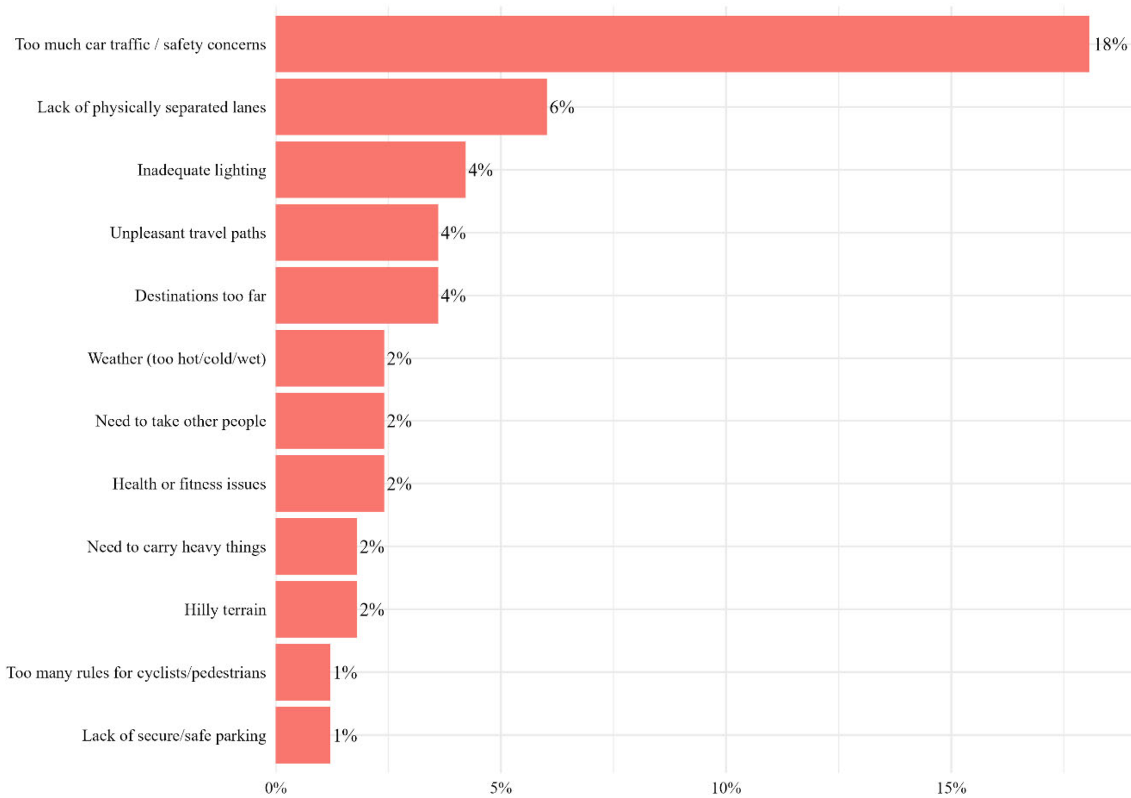

Figure 6. Barriers to use active transport.

Conversely, several motivators were reported as encouraging active transport use (Figure 7). The leading motivators were being closer to destinations (18%), more separated walking/cycling paths (13%), and reduced travel time (8%). Additional motivators—more car-free zones, more greenspace, and better lighting at night—each attracted 2%, while more/safer parking, more people walking/cycling, and greater driver awareness were each 1%.

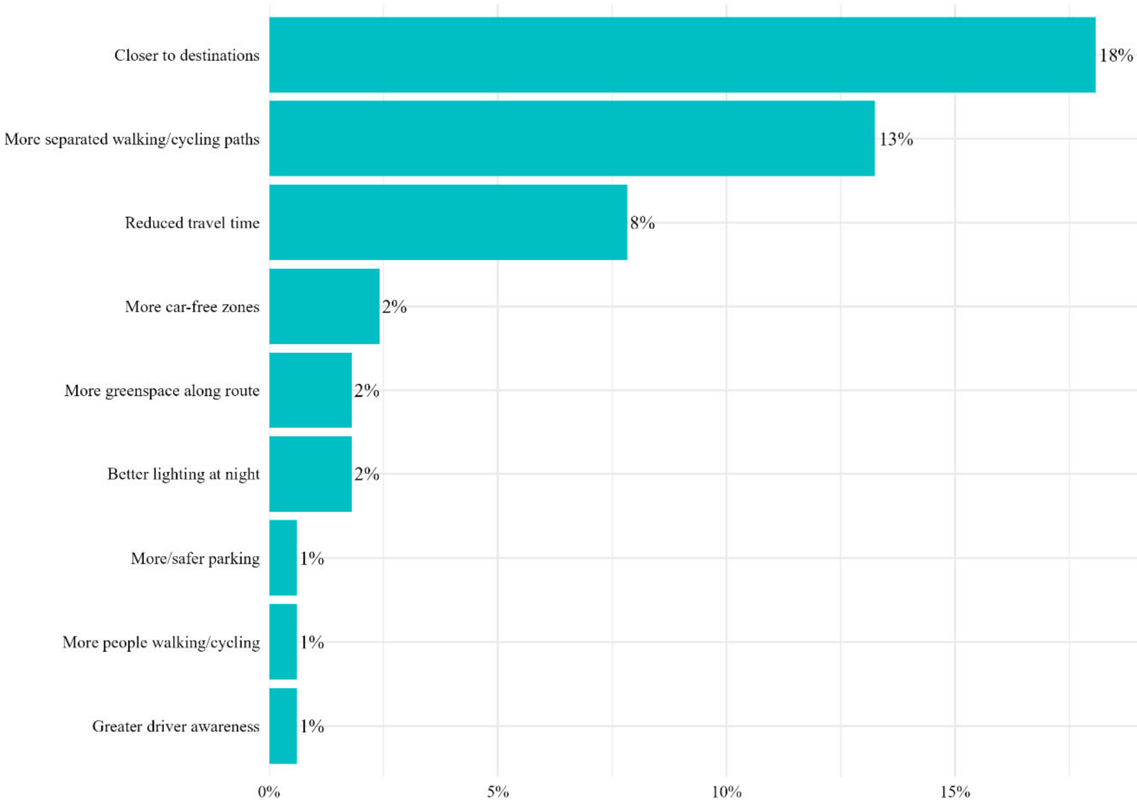

Figure 7. Motivators to use active transport.

3.2 Travel Behaviour Characteristics of Participants

3.2.1 Mode Share

Figure 8 shows the percentage of trips by mode. Across all recorded trips, driving (31%) and walking (30%) accounted for the largest shares, followed by cycling (23%) and transit (16%). Taken together, active modes (walking and cycling) represented 53% of trips, indicating that more than half of reported travel was by non-motorized modes.

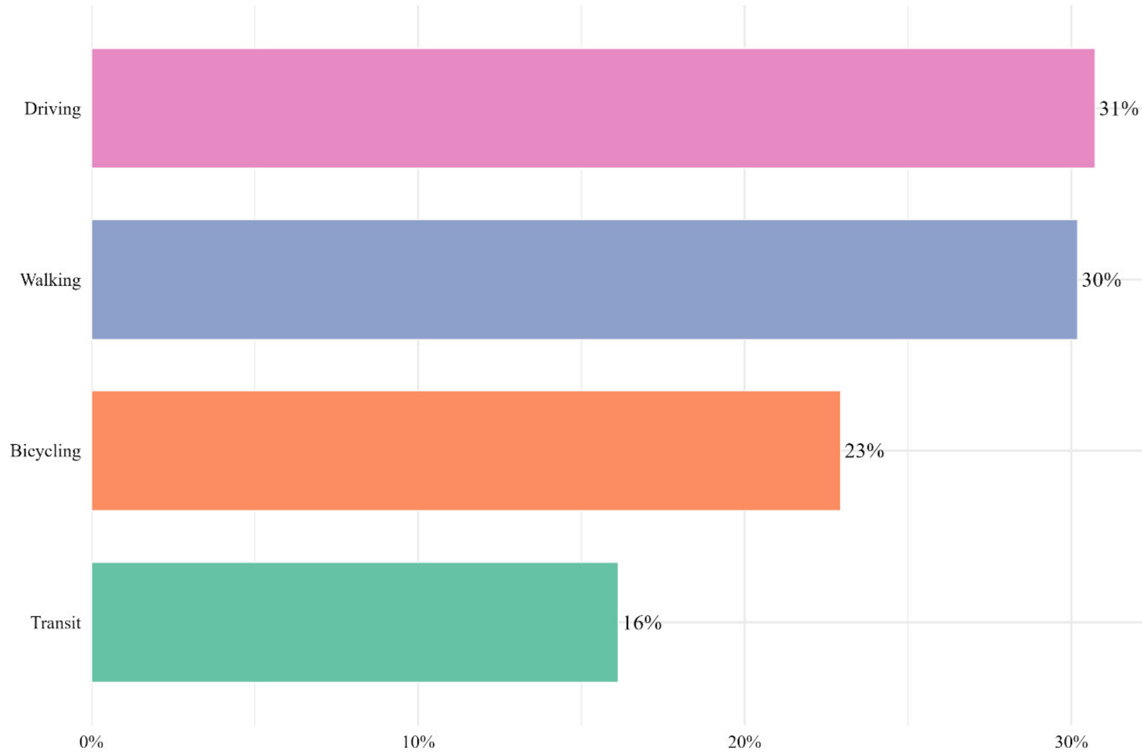

Figure 8. Mode share of trips.

Figure 9 illustrates differences in mode share across self-reported weekly physical activity levels. Among participants reporting minimal activity (<2 hours/week), driving accounted for just over half of trips (51%), while walking (20%), transit (14%), and cycling (16%) were less common. Among lightly active participants (approximately 2–3 hours/week), reliance on driving decreased to 36%, accompanied by higher shares of walking (30%) and transit (19%), while cycling remained relatively stable (15%). For moderately active participants (approximately 3–4 hours/week), walking (34%) and cycling (27%) together exceeded driving (25%). Among very active participants (≥4–5 hours/week), cycling represented the largest share of trips (33%), followed by walking (30%), with driving further reduced to 22% and transit remaining stable (15%).

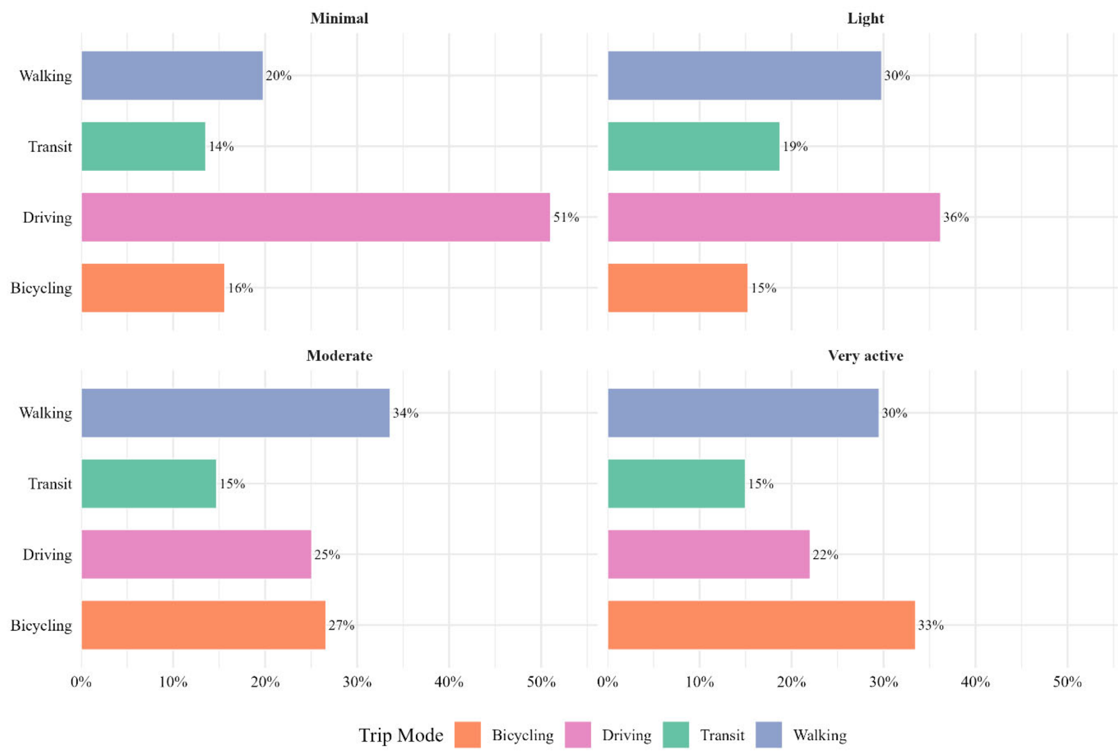

Figure 9. Trip mode share by weekly activity level.

Figure 10 illustrates the proportion of participants using each travel mode, stratified by age group and gender. Walking participation was relatively consistent across age categories, though slightly higher among women. Cycling displayed a markedly different pattern, with substantially higher participation among younger males, particularly those aged 15–24 years, while female participation remained comparatively lower across all age groups.

Driving increased steadily with age among both genders, peaking among participants aged 45–64 years, suggesting greater reliance on private vehicles in middle to later adulthood. Transit use was most prevalent among young adults (25–34 years) and declined with age, consistent with patterns of car ownership and employment-related travel. Overall, males were more likely than females to use active modes, whereas females demonstrated slightly higher participation in walking and driving at mid-life stages.

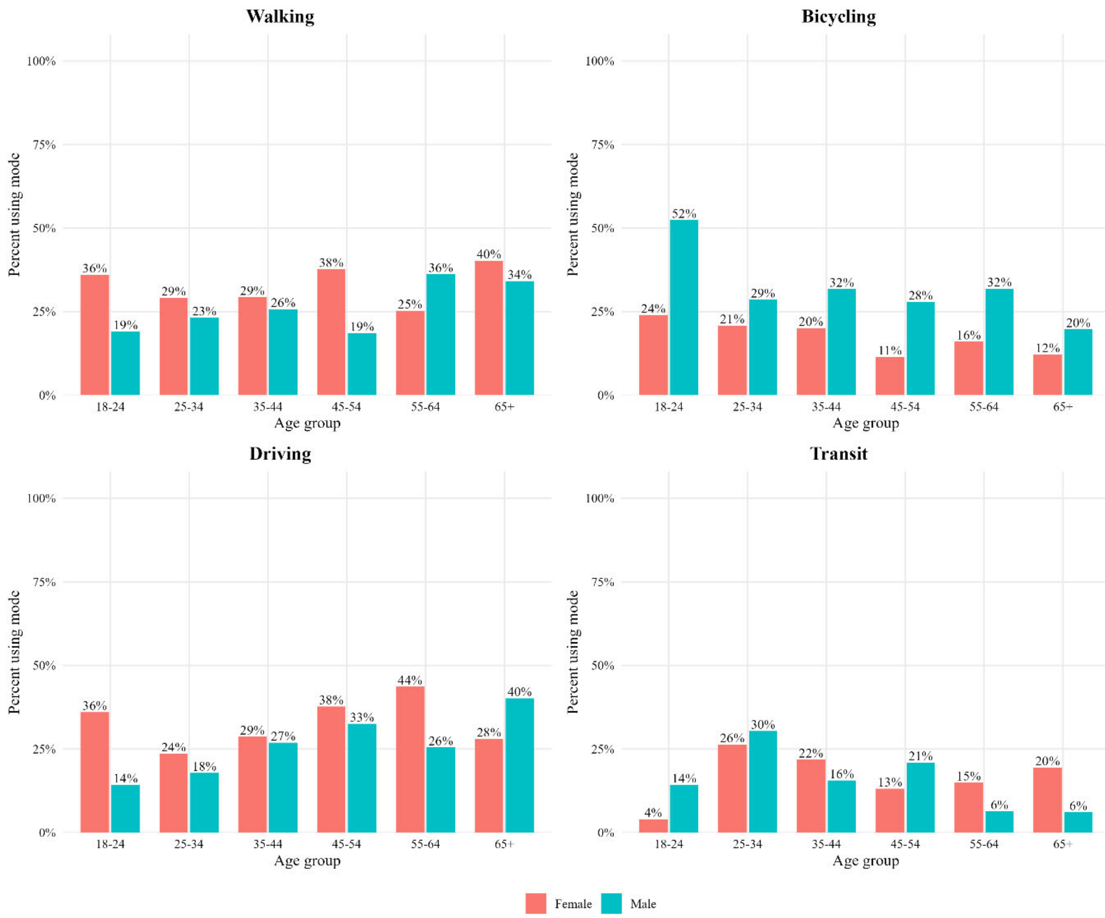

Figure 10. Mode use by age group and gender.

3.2.2 Trip Purpose

The distribution of trip purposes shows that home-based and work-related travel are more prevalent among the sample (Figure 11). Approximately one-quarter of trips (25.9%) were return-home journeys, followed by commuting to workplaces (19.4%) and shopping or personal business (15.6%). Fitness and sporting activities accounted for 12.2% of trips, while other discretionary purposes such as recreation, visiting family or friends, and leisure represented smaller shares. Educational and secondary work trips comprised less than 3% of total trips. These findings may show that the dataset primarily captures routine daily travel behaviour, with a moderate representation of discretionary activities.

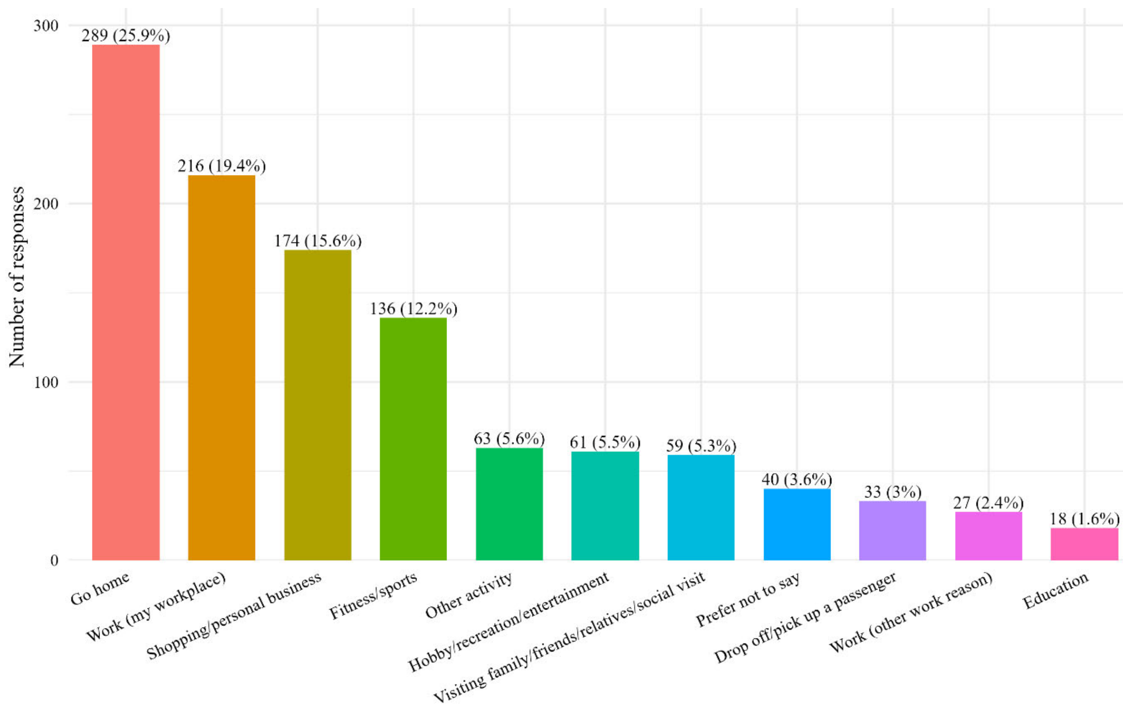

Figure 11. Trip purposes reported by participants.

Figure 12 shows the variation in transport mode choice across trip purposes. Walking and driving together accounted for most trips, though their relative shares differed by context. Walking was more frequently used for exercise or sport (54%), shopping and errands (44%), and recreation or leisure (26%), suggesting that active modes are more common for short or discretionary journeys. Driving was more frequent for escort trips (42%), workplace commutes (32%), and return-home trips (36%), reflecting reliance on private vehicles for structured or time-sensitive travel.

Transit use was higher for social visits (31%) and recreation (25%), while cycling had a moderate but consistent presence across all purposes, ranging from 10–30%, particularly for exercise or sport (30%) and go-home (25%) trips. Taken together, the findings indicate that active modes are primarily used for proximity-based and lifestyle trips, whereas motorised travel remains more common for commuting and household responsibilities.

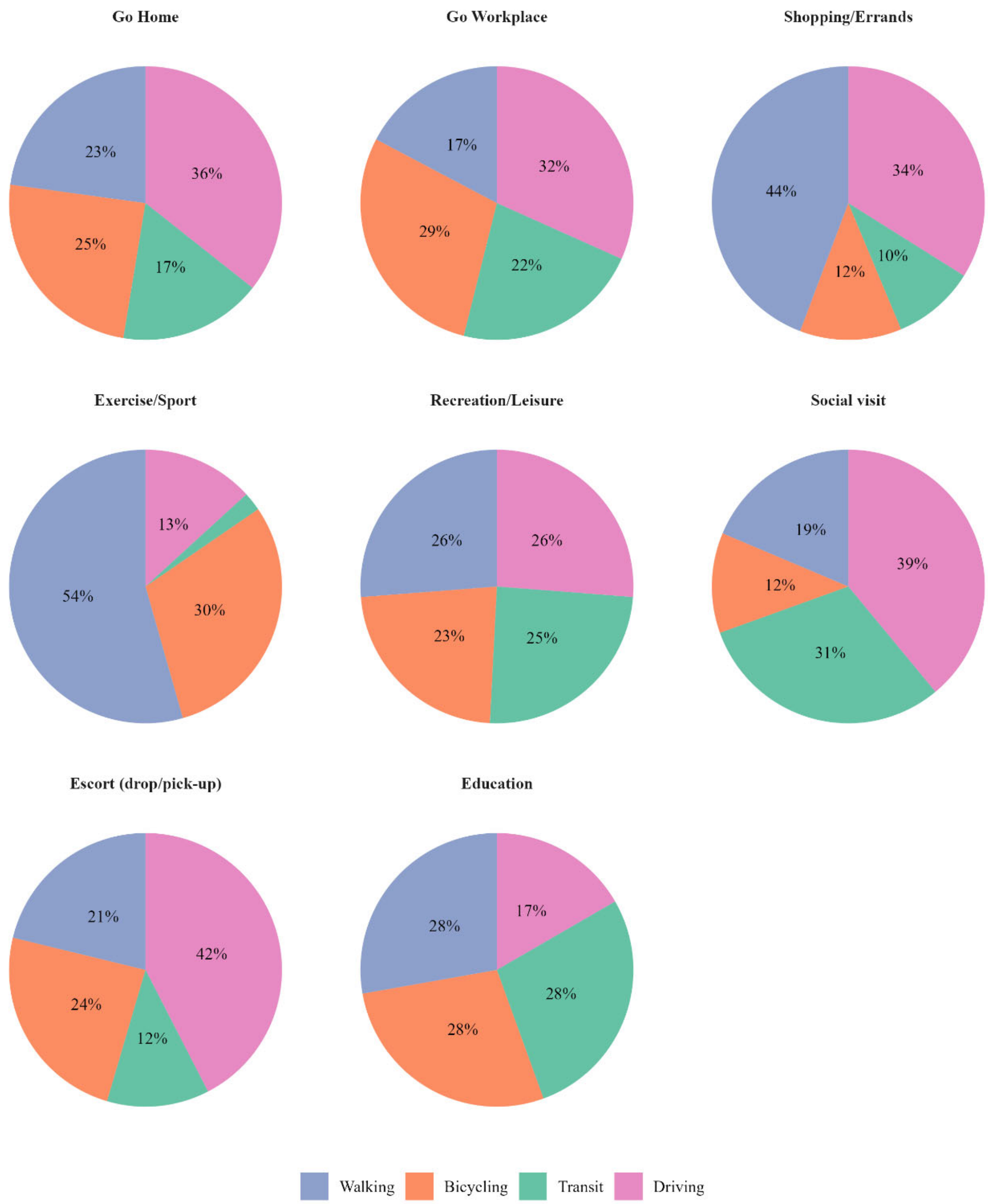

Figure 12. Modal share of trips by trip purpose.

As shown in Figure 13, a substantial majority of participants (71%) reported travelling alone, while 16.4% travelled with one other person and 6.5% travelled with two or more companions. Only 6.1% preferred not to disclose this information. The predominance of solo travel suggests that most journeys were individual, short, or purpose-driven, such as commuting or personal errands. This pattern aligns with previous findings that everyday urban mobility is largely characterised by independent travel behaviour.

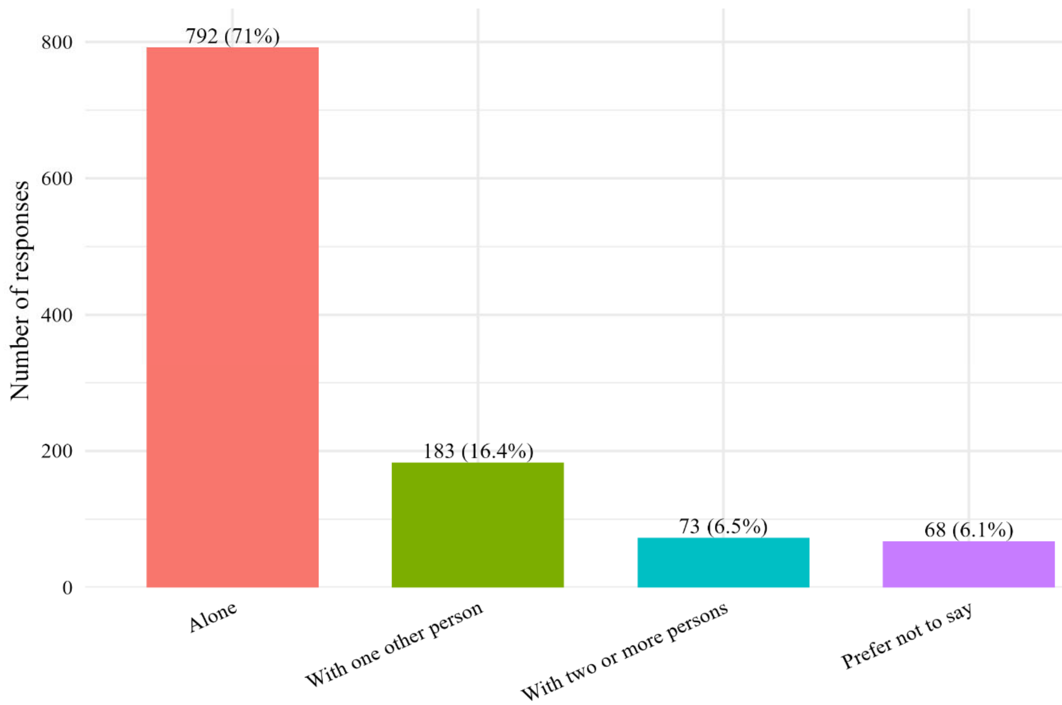

Figure 13. Distribution of travel companionship among participants.

Figure 14 presents the distribution of bicycle and micromobility device use during the reported trips. Most respondents (70.9%) indicated no use of bicycles or micromobility devices. It should be noted that “None” was the default response option, therefore, records for participants who did not actively answer this question were also classified as “None” or “no use of bicycle or micromobility”. Pedal-powered bicycles were the most common mode among users (16%), followed by e-bikes (7.5%) and e-scooters (5.6%).

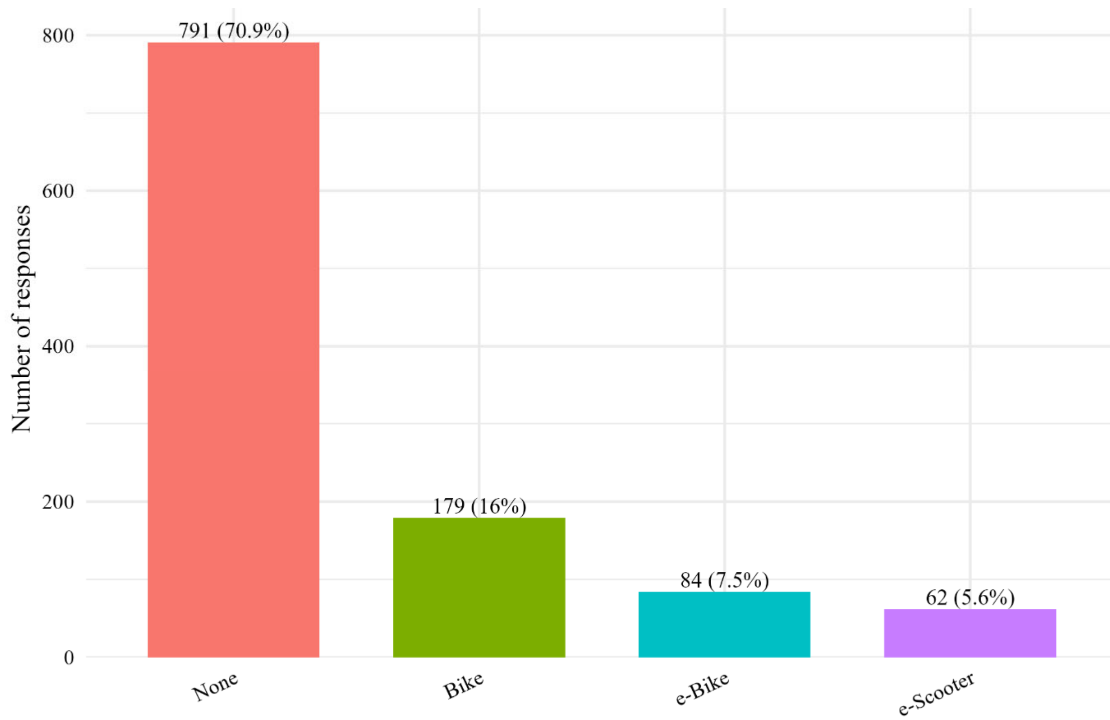

Figure 14. Reported use of bicycles, e-bikes, and e-scooters among participants.

Most respondents reported either not using parking (59.5%) or accessing free parking (31.4%) at their trip destination (Figure 15). Only a small proportion of participants incurred parking costs, with 4.4% preferring not to disclose, 2.2% paying less than \$5, 2% paying \$5–10, and 0.5% paying more than \$10. The predominance of no or free parking may reflect a travel pattern dominated by non-motorised or low-cost transport modes and short-distance trips.

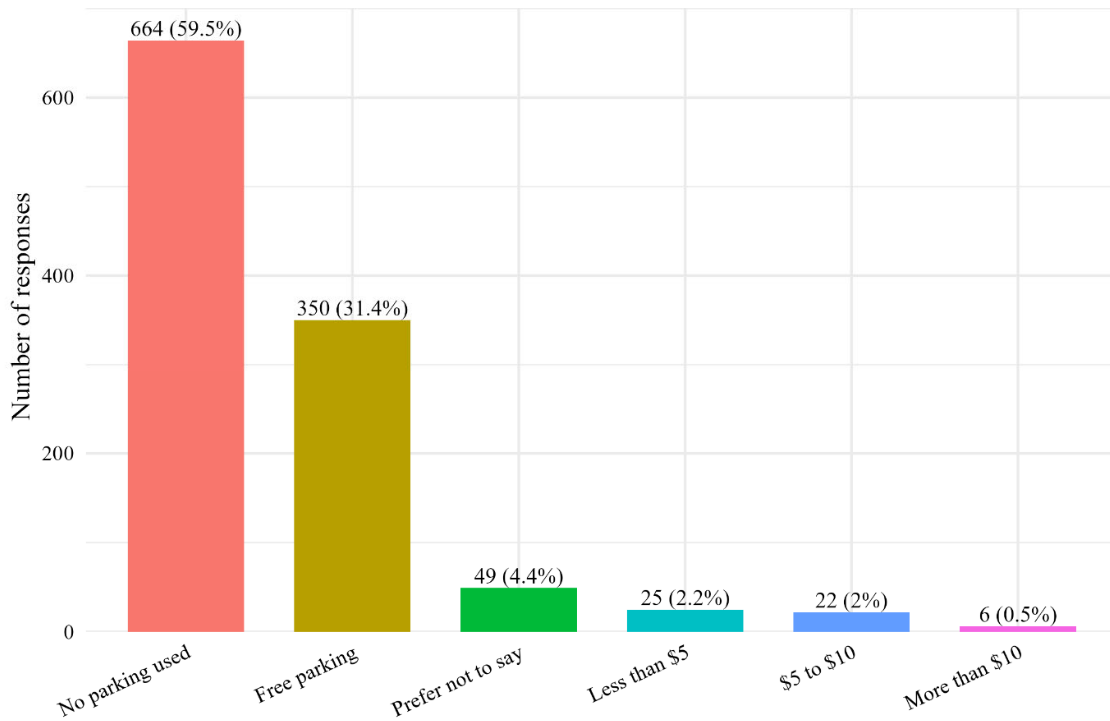

Figure 15. Reported parking cost at trip destination.

3.2.3 Spatial Distribution of Reported Trips

Spatial visualisations of participant-recorded travel routes were generated from the web-based diary data to examine the geographical coverage and mode-specific patterns of movement across the Greater Brisbane Area. Two complementary map layers were produced (Figures 16 and 17). The first depicts all recorded trips by selected mode (walking, cycling, driving, and transit), while the second isolates active micromobility trips, including bicycles, e-bikes, and e-scooters.

The trip-level data reveal a dense concentration of travel activity within the Brisbane inner city and southern corridors, consistent with areas of higher population and employment density. Walking and cycling trips cluster strongly around central Brisbane, South Bank, and major university precincts, while driving and transit trips exhibit longer-distance trajectories connecting outer suburbs such as Logan, Redcliffe, and Caboolture. The spatial extent of these routes indicates that participants frequently used active transport for shorter, intra-urban movements, whereas driving and public transport predominated for inter-suburban and peripheral destinations.

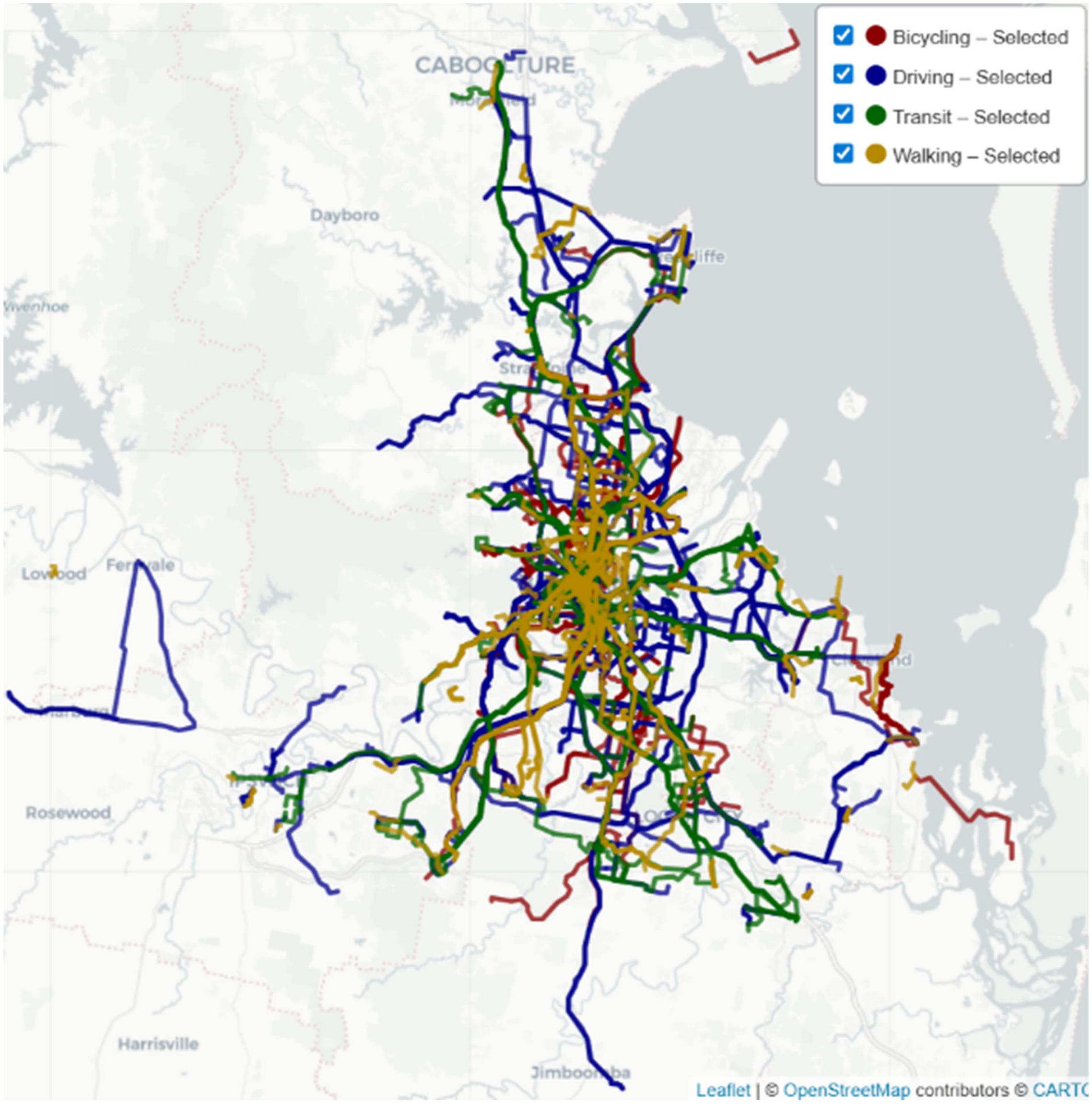

Figure 16. Reported trip routes across the Greater Brisbane Area by selected mode. Each line represents a route recorded by a participant in the web-based travel diary.

The micromobility-specific map shows clear overlap between conventional bicycle and e-bike routes, particularly along the Bicentennial Bikeway, the Brisbane River loop, and arterial corridors linking southside suburbs to the CBD. E-scooter trips display a more fragmented spatial pattern but are similarly concentrated around central activity hubs and riverside corridors, reflecting their use for last-mile connectivity and leisure-oriented travel. Overall, active travel modes are more prevalent within the inner metropolitan zones, while motorised and public transport options appear the outer urban catchments.

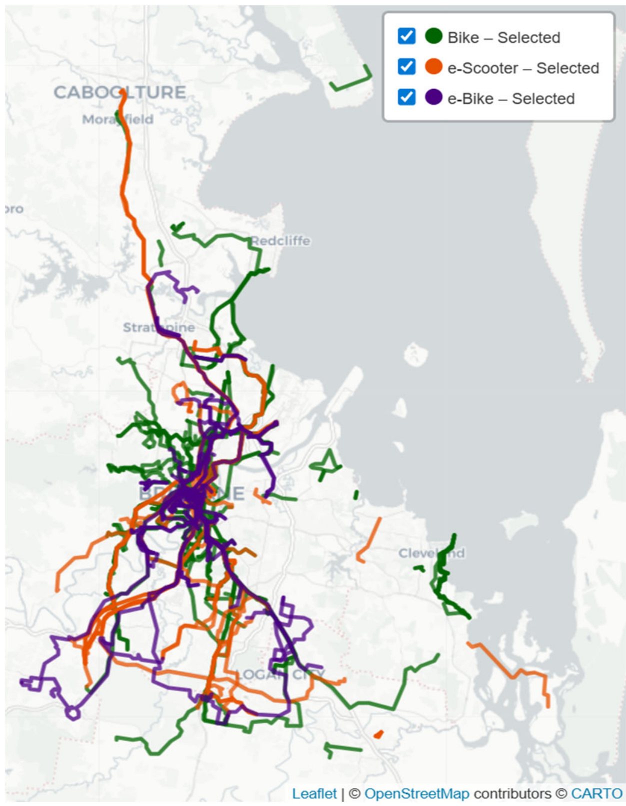

Figure 17. Spatial distribution of active micromobility trips.

3.3 Mode Choice Analysis

3.3.1 Model Fit and Predicted Shares

This section examines the factors that influence how people choose between walking, cycling, driving, and public transport for their daily trips. The analysis focuses on identifying which individual, household, and contextual characteristics are most strongly associated with each travel mode, with the aim of informing practical transport planning and policy decisions.

The final model provided a strong representation of observed travel behaviour and accurately reproduced the overall distribution of travel modes in the sample. A parsimonious mixed logit model (MXL) reached a maximised log-likelihood of −1,089, compared with −1,361 for a MNL, corresponding to a McFadden's pseudo-R^2 of 0.3 versus 0.14. A likelihood-ratio test against the intercept-only null model was highly significant (χ^2 = 649.48, $p < 0.001$), demonstrating strong joint explanatory strength and validating the inclusion of random alternative-specific constants (ASCs) for cycling, driving, and transit. In terms of aggregate predictive performance, the mean predicted choice probabilities from the MXL closely mirrored observed mode shares: walking ≈ 0.32, cycling ≈ 0.23, driving ≈ 0.29, and transit ≈ 0.16.

3.3.2 Factors Influencing Mode Choice

Table 4 provides the estimated model including key explanatory factors of mode choice behaviour relative to walking. The results should be interpreted in the context of the study sample, which includes a high proportion of participants who already engage in walking and other active travel. The results highlight several clear and policy-relevant patterns. The coefficients for cycling ($\beta = -4.12$, $p < 0.001$) and driving ($\beta = -3.55$, $p < 0.001$) were negative, indicating that respondents tended to favour walking over these modes. In contrast, the positive ASC for transit ($\beta = 1.92$, $p = 0.008$) indicated a general inclination toward public transport among a subset of individuals. The standard deviations of the random ASCs were large and highly significant (cycling SD = 3.37; driving SD = 4.08; transit SD = 3.15; all $p < 0.001$), revealing substantial unobserved heterogeneity in baseline preferences that persisted after accounting for the measured predictors.

Evidence on observable influences was consistent with established behavioural mechanisms. Men showed a significantly greater likelihood of selecting cycling relative to walking ($\beta = 1.16$, p = 0.003), whereas no systematic gender differences were observed for driving or transit. Access to a car increased the probability of driving ($\beta = 2.07$, $p = 0.018$) and reduced the likelihood of transit use ($\beta = -2.60$, $p < 0.001$). Bicycle ownership strongly increased cycling ($\beta = 3.50$, $p < 0.001$) and reduced driving ($\beta = -1.21$, $p = 0.009$), which aligned with expectations that access to cycling equipment encouraged active travel. Higher self-reported cycling confidence increased the likelihood of choosing this mode ($\beta = 1.18$, $p = 0.019$) and reduced the probability of selecting transit ($\beta = -1.11$, $p = 0.008$), suggesting that exposure and experience may shift mode choice toward active modes. Predictors are illustrated in Figure 18.

Table 4. Mixed Logit estimates with random alternative-specific constants (cycling, driving, transit) and fixed covariate effects relative to walking.

Coefficient	Estimate	Std. Error	z-value	p-value
Fixed effects (means)				
(Intercept): cycling	−4.117	1.039	−3.959	<0.0001 ***
(Intercept): driving	−3.554	1.037	−3.426	<0.0001 ***
(Intercept): transit	1.916	0.728	2.630	0.008 **
Male: cycling	1.164	0.399	2.912	0.003 **
Has car: driving	2.070	0.876	2.362	0.018 *
Has car: transit	−2.595	0.722	−3.594	<0.0001 ***
Has bicycle: cycling	3.501	0.643	5.444	<0.0001 ***
Has bicycle: driving	−1.207	0.468	−2.578	0.009 **
Conf bicycle high: cycling	1.176	0.504	2.333	0.019 *
Conf bicycle high: transit	−1.107	0.415	−2.667	0.007 **
Any under15: driving	0.776	0.376	2.061	0.039 *
Age older: transit	−2.070	0.589	−3.515	<0.0001 ***
Age younger: cycling	1.294	0.513	2.521	0.011 *
Income med: cycling	−1.103	0.508	−2.169	0.030 *
Income med: transit	−1.795	0.563	−3.188	0.001 **
Income high: driving	1.722	0.515	3.338	<0.0001 ***
Random parameters (standard deviations)				
sd.(Intercept): cycling	3.371	0.585	5.759	<0.0001 ***
sd.(Intercept): driving	4.081	0.626	6.517	<0.0001 ***
sd.(Intercept): transit	3.154	0.595	5.297	<0.0001 ***

Note: Significance markers indicate approximate confidence levels: *** p<0.001 (~99.9% CI), ** p<0.01 (~99% CI), * p<0.05 (~95% CI). Positive coefficients indicate higher utility relative to walking for the stated mode.

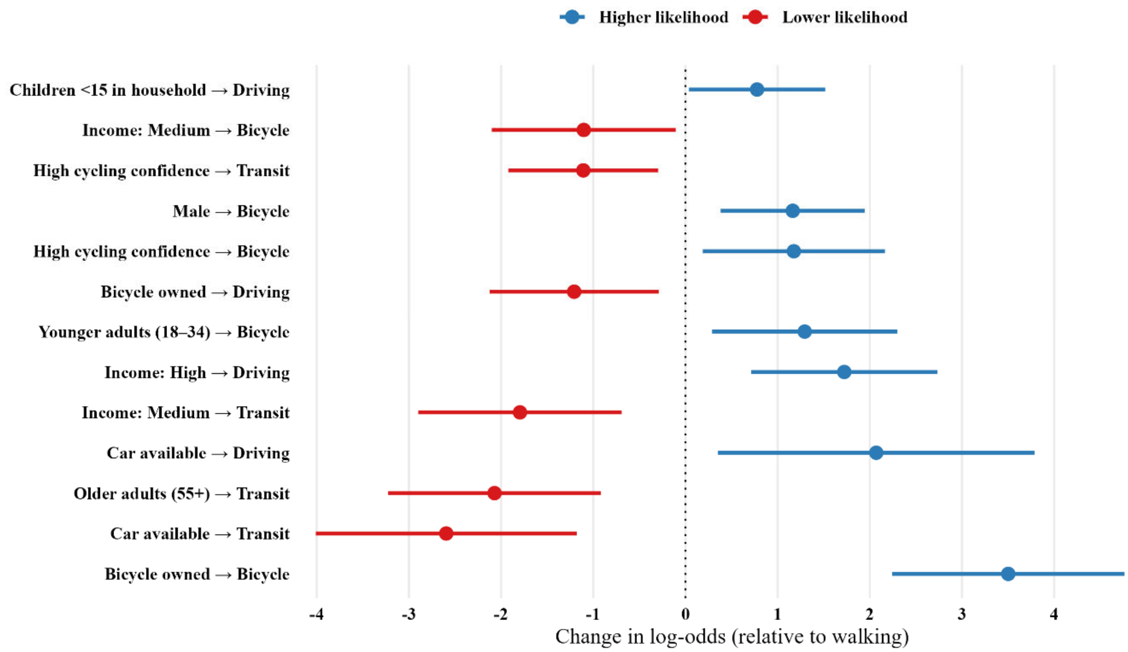

Figure 18. Estimated effects of predictors on mode choice from the mixed logit model (relative to walking). Positive coefficients indicate a higher likelihood of choosing the respective mode, while negative coefficients represent a lower likelihood. Error bars show 95% confidence intervals.

Household and life-cycle patterns were also evident in the results. The presence of children under 15 years increased the likelihood of driving (β = 0.78, p = 0.039), a finding that aligned with escorting responsibilities and scheduling constraints within family households. Older adults aged 55 years and above were less likely to use transit (β = −2.07, p < 0.001), which suggested potential comfort, accessibility, or familiarity barriers associated with public transport. Younger adults aged 18–34 years were more likely to use a bicycle (β = 1.29, p = 0.012) and exhibited a marginally lower propensity to drive (β = −0.96, p = 0.086). Socioeconomic patterns were apparent, with respondents in the medium-income group being less likely to bicycle (β = −1.10, p = 0.030) and less likely to use transit (β = −1.80, p = 0.001), whereas those in the high-income group were more likely to drive (β = 1.72, p < 0.001).

3.4 Origin-Destination Travel Patterns Across Brisbane

This section examines how trips are distributed between different parts of Brisbane and how neighbourhood characteristics and distance influence the number of trips between areas. The analysis focuses on identifying which types of areas tend to generate more trips, which attract more trips, and how spatial separation constrains travel across the city.

3.4.1 Factors Associated with Travel Flows Between Areas

Table 5 summarises the associations between neighbourhood characteristics, distance, and the number of trips between origin–destination (OD) pairs. The results are presented as percentage effects on the expected number of trips. These effects are derived by exponentiating the estimated coefficients to obtain incidence rate ratios. For ease of interpretation, effects are reported as the expected percentage change in OD flows associated with a 1% increase in each explanatory variable, holding all other variables constant. Distance is interpreted per one-kilometre increase. Further methodological details are provided in Appendix B.

Several variables show statistically significant associations with travel flows. Distance plays a central role in shaping movement across the city. A one-kilometre increase in distance between an origin and destination is associated with an approximate 0.38% reduction in the number of trips ($\beta = -0.0038$), providing clear evidence of distance-decay effects in urban travel behaviour.

Destination population characteristics also matter. Areas with higher proportions of older residents attract fewer trips: a 1% increase in the share of people aged 54 years and older at the destination is associated with a reduction in flows of approximately 0.88% ($\beta = -0.8795$). Similarly, destinations with higher shares of households with children under 15 years receive fewer trips, with a 1% increase associated with a reduction of around 0.38% ($\beta = -1.1261$).

In contrast, employment intensity is positively associated with travel flows. Areas with higher proportions of full-time employment generate and attract more trips. A 1% increase in the share of full-time employed residents at origins is associated with a 0.41% increase in trips, while a corresponding increase at destinations is associated with a 0.54% increase in trips.

Table 5. Poisson regression model estimates with % effect per coefficient at SA2 grouping level of granularity

Variable	Coefficient	Std. Error	z-value	p-value	% Effect
Constant	1.2789	0.1389	9.200	<0.0001 ***	--
% employed full-time (origin)	0.4052	0.1394	2.906	0.003***	0.41%
% employed full-time (destination)	0.5335	0.1597	3.340	0.001***	0.54%
% aged ≥54 years (older adults) (destination)	-0.8795	0.1769	-4.972	<0.0001 ***	-0.88%
% of households with children <15 years (destination)	-1.1261	0.2151	-5.234	<0.0001 ***	-0.38%
Distance	-0.0038	0.0009	-4.055	<0.0001 ***	-0.38%

Overall, the results indicate that spatial separation between origins and destinations is the strongest constraint on travel flows. Once distance is accounted for, neighbourhood demographic and socioeconomic characteristics—particularly age composition, household structure, and employment concentration—provide additional explanatory power in shaping how trips are distributed across Brisbane.

3.4.2 Construction of the Origin–Destination Dataset

In addition to modelling aggregate travel flows, the OD analysis was extended using participant-selected routes to examine internal and external movement patterns between SA2 zones, providing further insight into how active and mixed-mode travel is distributed across Brisbane.

The origin–destination analysis was conducted using a refined subset of travel diary routes to ensure spatial accuracy and consistency. The initial dataset contained 1,116 recorded trips. A waypoint indicator was used to identify whether participants followed the default Google-suggested route or manually edited their route to reflect their actual path. Trips with edited waypoints were retained, as these represent deliberate user-selected routes rather than automated shortest paths. After removing incomplete, invalid, or implausible records, the final OD dataset consisted of 523 trips. Each trip was spatially linked to Statistical Area Level 2 (SA2) zones using the recorded start and end coordinates of the selected routes. This process enabled aggregation of individual trips into OD pairs suitable for spatial flow analysis.

In total, the refined dataset included 334 SA2 zones and 401 unique OD pairs, where each OD pair represents the number of trips between a specific origin and destination zone. Most OD pairs occurred infrequently, with only 81 pairs containing more than one trip, highlighting the dispersed and low-frequency nature of many everyday travel movements captured in the diary data.

3.4.3 Internal and External Origin–Destination Flows

Origin–destination flows were analysed under two scenarios: internal flows (Figure S2; Appendix B), where trips begin and end within the same SA2 zone, and external flows (Figure S3; Appendix B), where trips occur between different SA2 zones. This distinction helps differentiate highly localised mobility from broader cross-area travel patterns.

Internal flows were identified across 36 SA2 zones within Southeast Queensland. These internal trips typically involved short distances and relatively low travel times, indicating highly localised travel behaviour.

Brisbane City recorded the highest number of internal trips (seven). In Brisbane City, internal trips were evenly split between walking and cycling, with one transit trip, and none exceeded 22 minutes in duration. Distances ranged from 330 metres to 4.9 km, illustrating that internal trips are well suited to active modes. In contrast, Robertson's internal trips were primarily undertaken by walking, with one short driving trip. Although distances were similar across modes, driving required substantially less time, highlighting how time efficiency may influence mode choice even for short trips.

External flows were more spatially dispersed and were examined by focusing on the top five origin and destination SA2 zones with the highest number of unique connections. Visualising all OD pairs simultaneously was not informative due to the large number of low-frequency flows.

As an origin, Brisbane City generated the greatest number of external connections, accounting for 41 OD pairs and 66 trips. These trips covered a wide distance range (1.3 km to 70.6 km, average 12.6 km) and involved a mix of modes. Public transport was the most frequently used mode, followed by cycling and walking, while micromobility modes (e-bikes and e-scooters) together accounted for a substantial share of trips. Most external trips originating in Brisbane City were undertaken for the purpose of returning home. South Brisbane ranked second, with 14 OD pairs and 15 trips, where public transport was the most frequently used mode. Remaining origin zones generated fewer than ten OD pairs each, indicating a strong concentration of inter-area connectivity around inner-city locations.

When examined from the destination perspective (Figure S4; Appendix B), Brisbane City again emerged as the primary trip attractor, receiving 78 trips across 46 unique origin zones. The majority of these trips were work-related, with public transport and cycling playing a prominent role. Average trip distances exceeded 11 km, indicating that Brisbane City attracts travel from across a wide metropolitan catchment.

Other key destinations—including South Brisbane, Fortitude Valley, West End, and Chermside—showed more moderate but still distinct flow patterns, often reflecting employment concentration and mixed-use activity. Across all destinations, most OD pairs involved only one or two trips, reinforcing the importance of considering both intensity and diversity of travel connections rather than total volumes alone.

4. Discussion and Conclusion

This study provides empirical evidence on how individual characteristics, household circumstances, and spatial structure jointly shape travel behaviour in Brisbane. The findings indicate that mode choice is strongly structured by access to transport resources and individual capability, rather than attitudes alone. Bicycle ownership and higher cycling confidence substantially increased the likelihood of cycling, while car access strongly increased driving and reduced public transport use. These patterns suggest that travellers' feasible choice sets are constrained by material access and accumulated experience, which condition behavioural responses to infrastructure and policy interventions. As a result, even among individuals who already engage in active travel, shifts toward or away from specific modes depend on whether people possess the resources, skills, and familiarity required to adopt those modes in daily practice. This highlights that behavioural change is unlikely to occur through attitudinal interventions alone, without parallel investments that expand practical access and reduce capability barriers.

Household and life-course constraints further explain observed patterns. Participants living in households with children under 15 years were more likely to drive, reflecting time pressures and escorting requirements that limit the feasibility of active and public transport modes. Age-related effects also emerged, with younger adults more likely to select cycling and older adults less likely to use public transport. These differences likely arise from variation in physical comfort, confidence, and accumulated travel habits, as well as age-related differences in daily routines and accessibility needs. This suggests that active transport interventions must account for life-course differences rather than assuming uniform behavioural responses across age groups.

The origin–destination analysis reinforces these findings by demonstrating that travel behaviour in Brisbane is strongly shaped by the city's spatial structure, with distance acting as the primary constraint on everyday mobility. This finding highlights the importance of proximity and network connectivity in enabling active travel, particularly for short and medium-distance trips. Even after accounting for distance, neighbourhood composition continues to influence travel demand. Areas with higher proportions of older residents and households with children attract fewer trips, suggesting that mobility needs in these locations are more localised and sensitive to time, comfort, and accessibility constraints. In contrast, employment-dense areas generate and attract substantially more travel, reflecting the concentration of work-related activities. From a policy perspective, these results indicate that active transport investments are likely to be most effective when aligned with employment centres and mixed-use areas, while residential neighbourhoods with higher care responsibilities or ageing populations may require targeted design responses—such as improved local connectivity, safer crossings, and shorter, barrier-free routes—rather than uniform infrastructure provision.

Taken together, the results show that active transport behaviour cannot be explained solely by individual preferences or infrastructure provision in isolation. Instead, travel decisions reflect the interaction of resource access, household constraints, and the spatial distribution of destinations. Policies aimed at increasing active transport participation therefore need to move beyond uniform interventions and adopt place-based, life-course-sensitive approaches that align infrastructure investment with employment centres, support localised mobility in residential areas, and reduce practical barriers to mode adoption across different population groups.

5. Recommendations

This section translates the empirical findings of this study into practical recommendations to support transport planning and policy development in Brisbane. Drawing on integrated survey, travel diary, and spatial origin–destination analyses, the results show that travel choices are shaped by access to transport assets, individual capability, household responsibilities, and the spatial distribution of destinations. In particular, cycling uptake is strongly enabled by bicycle access and user confidence, while car availability reinforces driving and reduces public transport use. Household factors—especially the presence of children—constrain participation in active travel, and spatial analysis confirms that distance and employment concentration are primary drivers of travel demand. Together, these findings indicate that effective active transport policy requires coordinated action across infrastructure provision, capability building, and place-based planning, rather than reliance on uniform or attitudinal interventions alone. The recommendations below are intended to inform near-term investment priorities while also supporting longer-term strategies to improve accessibility, equity, and network performance across Brisbane's transport system.

Planning and Infrastructure

Prioritise environments that support short-distance trips: Evidence from both the mode choice and origin–destination analyses indicates that distance remains the primary constraint on everyday travel behaviour. Planning efforts should therefore prioritise improvements to walking and cycling conditions in locations where trip lengths are already short and where employment, services, education, and daily activities are accessible within feasible active travel distances. Targeting these environments is likely to deliver higher uptake and more consistent use of active modes.

Concentrate active transport investment around employment-rich destinations: Origin–destination results show that areas with higher concentrations of full-time employment generate and attract substantially more trips. Investment in high-quality walking and cycling infrastructure, end-of-trip facilities, and network connectivity should therefore be focused on major employment centres, universities, hospitals, and mixed-use precincts. Aligning active transport provision with employment locations is likely to maximise usage and reinforce mode shift for routine travel.

Capability, Access, and Behavioural Support

Pair infrastructure investment with initiatives that build individual capability: Mode choice results indicate that cycling confidence is a strong predictor of cycling uptake, independent of infrastructure availability. Infrastructure delivery should therefore be accompanied by complementary initiatives such as skills training, confidence-building programs, and targeted information campaigns. These measures can help translate infrastructure investment into actual behavioural change.

Support access to active transport equipment: Bicycle ownership emerged as a key enabler of cycling and was associated with reduced reliance on driving. Policies that reduce cost and access barriers—such as shared bicycle schemes, targeted subsidies, or pilot programs for lower-participation groups—may reinforce infrastructure investments and broaden participation in active travel.

Improve accessibility and comfort of public transport for older adults: Lower public transport use among older participants suggests potential barriers related to comfort, accessibility, or familiarity. Enhancing pedestrian access to stops, improving seating, lighting, and wayfinding, and addressing first- and last-mile barriers may improve usability and support continued mobility for older residents.

Place-Based and Integrated Approaches

Adopt place-based transport strategies tailored to neighbourhood characteristics: The origin–destination analysis demonstrates that travel flows vary systematically with neighbourhood age structure, household composition, and employment patterns. Transport interventions should therefore be tailored to local context rather than applying uniform solutions across Brisbane. Place-based approaches are better suited to addressing diverse mobility needs across different communities.

Integrate land-use and transport planning to reduce structural travel constraints: The strong role of spatial proximity highlights the importance of aligning transport investment with land-use decisions that support compact, mixed-use development. Coordinated planning that brings housing, employment, and services closer together can reduce travel distances and increase the feasibility of walking, cycling, and public transport.

Future work should build on the findings of this study by strengthening longitudinal evidence, expanding spatial and population coverage, and deepening understanding of behavioural responses to active transport investments. Repeated application of the integrated survey and smart travel diary approach following major infrastructure interventions—such as new bridges, corridors, or precinct upgrades—would enable direct measurement of behavioural change over time, including induced and discretionary travel that is not captured in traditional household travel surveys, thereby improving evaluation and forecasting accuracy. Further research should also examine how emerging modes, particularly e-bikes, e-scooters, and shared micromobility, reshape feasible travel distances and mode substitution patterns across population groups, with explicit consideration of comfort, safety perceptions, and regulatory constraints. Finally, integrating revealed and stated preference methods would allow testing of hypothetical policy scenarios, such as improved network separation, reduced parking availability, or enhanced end-of-trip facilities, supporting a more comprehensive, evidence-based framework for designing, prioritising, and evaluating active transport investments in Brisbane and other Australian cities.

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Appendix A: Survey Items and Response Categories

Q1. Age

How old are you?

□ Under 15

□ 15–17

□ 18–24

□ 25–34

□ 35–44

□ 45–54

□ 55–64

□ 65+

Q2. Greater Brisbane residency

Do you currently live in the Greater Brisbane area?

□ Yes □ No

Q3. Active transport in the last week

In the past week, have you walked, cycled, scootered, or skateboarded to reach a destination — not just to access public transport?

□ Yes □ No

Q4. Gender

Please select your gender.

□ Male □ Female □ Prefer to describe: ______ □ Prefer not to answer

Q5. Highest level of education

□ Years 9 and below

□ Years 10/11/12

□ Certificate I/II

□ Certificate III/IV

□ Advanced Diploma/Diploma

□ Bachelor degree

□ Graduate Diploma/Graduate Certificate

□ Postgraduate degree

□ Prefer not to answer

Q6. Attention check

To make sure you're reading the questions carefully, please select "Agree."

□ Strongly disagree □ Disagree □ Neutral □ **Agree** □ Strongly agree

---

Q7. Current employment status *(Select all that apply)*

□ Employed (paid work) — typically ≥35 hours/week

□ Employed (paid work) — typically <35 hours/week

□ Student receiving Youth Allowance/Stipend

□ Volunteer/unpaid work

□ Unpaid caring (children, older people, people with illness/disability)

□ Retired or on an age pension

□ Not currently working due to a long-term health condition or disability

□ Not currently working due to short-term illness or injury

□ Not currently working for another reason

□ Prefer not to answer

(Display Q8–Q10 if Q7 includes either employed option.)

Q8. Occupation

Which of these best describes your work?

□ Manager □ Professional □ Technician/Trades □ Community & Personal Service

□ Clerical/Administrative □ Sales □ Machinery Operator/Driver □ Labourer

□ Don’t know □ Prefer not to answer

Q9. Industry

Which industry best describes your workplace?

□ Agriculture/Forestry/Fishing □ Mining □ Manufacturing □ Electricity/Gas/Water/Waste

□ Construction □ Wholesale trade □ Retail trade □ Accommodation & Food Services

□ Transport/Postal/Warehousing □ Information Media & Telecommunications

□ Financial & Insurance Services □ Rental/Hiring/Real Estate

□ Professional/Scientific/Technical □ Administrative & Support Services

□ Public Administration & Safety □ Education & Training

□ Health Care & Social Assistance □ Arts & Recreation Services

□ Other Services □ Don’t know □ Prefer not to answer

Q10. Work travel days *(Select all that apply)*

□ I only work from home/other locations

□ My work schedule changes every week

□ Monday □ Tuesday □ Wednesday □ Thursday □ Friday □ Saturday □ Sunday

□ Prefer not to answer

Q11. Are you currently studying?

□ Yes □ No □ Prefer not to answer

(Display Q12–Q13 if Q11 = Yes.)

Q12. Study enrolment

□ Secondary school

□ University/TAFE/College (full-time)

□ University/TAFE/College (part-time)

□ Something else: ______

□ Prefer not to answer

Q13. Study travel days *(Select all that apply)*

□ None of the days

□ My class schedule changes every week

□ Monday □ Tuesday □ Wednesday □ Thursday □ Friday □ Saturday □ Sunday

□ Prefer not to answer

Q14. Driver's licence *(Select all that apply)*

□ No licence □ Car licence □ Motorcycle licence □ Other licence □ Prefer not to answer

Q15. Vehicles available in the household

How many of the following are currently available for you to use (in working order)?

- Cars/utes/vans: 0 / 1 / 2 / 3 / 4+

- Motorcycles: 0 / 1 / 2 / 3 / 4+
- Bicycles: 0 / 1 / 2 / 3 / 4+
- E-bikes: 0 / 1 / 2 / 3 / 4+
- E-scooters: 0 / 1 / 2 / 3 / 4+

Q16. Confidence using selected modes

Please indicate your level of confidence when using the following modes.

Response scale: **Extremely confident / Somewhat confident / Neutral / Not at all confident / I do not know how to ride**

- Bicycle
- E-bike
- E-scooter

Q17. Assistance with travel activities

Do you currently require any help or assistance with your daily travel activities?

□ Yes □ No □ Prefer not to answer

(Display Q18 if Q17 = Yes.)

Q18. Main reason(s) for assistance *(Select all that apply)*

□ Short-term health condition (<6 months)

□ Long-term health condition (≥6 months)

□ Disability

□ Old or young age

□ Difficulty with English language

□ Other: ______

□ Prefer not to answer

Q19. Weekly activity level

Which of the following best describes your weekly level of activity?

□ Minimal — mostly sedentary; <2 h/week of physical activity

□ Lightly active — short walks/light exercise; ~2–3 h/week

□ Moderately active — regular workouts/jogging; ~3–4 h/week

□ Very active — vigorous exercise/strenuous activity; ~4–5 h/week

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Q20. Household composition

Including yourself, how many people currently live in your household?

- Under 15 years: 0–5+
- 15–17 years: 0–5+
- 18 years or over: 0–5+

Q21. Household weekly income (before tax; approximate)

(Annual equivalents in parentheses)

□ Negative income

□ Nil income

□ $1–$149 ($1–$7,799)

□ $150–$299 ($7,800–$15,599)

□ $300–$399 ($15,600–$20,799)

□ $400–$499 ($20,800–$25,999)

□ $500–$649 ($26,000–$33,799)

□ $650–$799 ($33,800–$41,599)

□ $800–$999 ($41,600–$51,999)

□ $1,000–$1,249 ($52,000–$64,999)

□ $1,250–$1,499 ($65,000–$77,999)

□ $1,500–$1,749 ($78,000–$90,999)

□ $1,750–$1,999 ($91,000–$103,999)

□ $2,000–$2,499 ($104,000–$129,999)

□ $2,500–$2,999 ($130,000–$155,999)

□ $3,000–$3,499 ($156,000–$181,999)

□ $3,500–$3,999 ($182,000–$207,999)

□ $4,000–$4,499 ($208,000–$233,999)

□ $4,500–$4,999 ($234,000–$259,999)

□ $5,000–$5,999 ($260,000–$311,999)

□ $6,000–$7,999 ($312,000–$415,999)

□ $8,000 or more ($416,000 or more)

□ Prefer not to answer

Q22. Frequency of active travel use

How often do you use the following modes?

Response scale: **Daily / 1–2× per week / 1–2× every two weeks / 1–2× per month / Less than once per month / Do not use at all**

- Walk
- Bicycle
- E-bike

- E-scooter
- Other (e.g., skateboard, unicycle, Segway)

(Display Q23 if ***all*** *modes selected "Do not use at all", or adapt to show if any primary target mode = "Do not use at all".)*

Q23. Reasons for not using active travel *(Select up to three)*

□ Using active travel would increase my travel time

□ Inconvenient because trips often combine multiple errands (e.g., shopping, pickup/drop-off)

□ Unable to use due to age/health condition/long-term injury

□ Lack of/insufficient active transport infrastructure

□ I feel it is unsafe to use active travel modes

□ Discomfort (e.g., weather, hills, helmet requirements)

□ Other: ______

Q24. Reduced or stopped active transport in the past 12 months

Have you reduced or stopped using active transport (cycling, walking, e-bikes/e-scooters, etc.) in the past 12 months?

□ Yes □ No

Q25. Attention check

To make sure you're reading the questions carefully, please select "Disagree."

□ **Disagree** □ Strongly disagree □ Neutral □ Agree □ Strongly agree

(Display Q26 if Q24 = Yes.)

Q26. Reasons for reducing/stopping active transport *(Select up to three)*

□ Accident not related to active travel

□ Accident related to active travel

□ Safety concerns

□ Change in relationship/family/work/study location or status

□ To reduce travel time

□ Health concerns

□ Closures or changes in active travel paths

□ Construction activities along usual route

□ Police enforcement of cycling rules

□ Other: ______

Q27. Barriers to walking or cycling more often *(Select all that apply)*

□ Too much car traffic / worried about accidents

□ Inadequate lighting

□ Lack of physically separated lanes/dedicated infrastructure

□ Unpleasant routes (e.g., noisy main roads, lack of greenspace)

□ Distances are too far to ride/walk

□ Often need to escort others

□ Health or fitness issues

□ Terrain is too hilly

□ Usually need to carry heavy things

□ Lack of secure/safe parking

□ Too many rules for cyclists and pedestrians

□ Weather conditions (too hot/cold/wet)

□ Other: ______

Q28. Changes that would make active transport more likely *(Select up to three)*

□ Being closer to work, school, shops, etc.

□ Reduced travel time

□ More bicycle/walking paths physically separated from car traffic

□ More greenspace along the route

□ More car-free zones

□ Availability of public bicycle sharing

□ Better lighting at night

□ Increased driver awareness of bicycle/pedestrian safety and sharing the road

□ Having more bicyclists and pedestrians present

□ Secure end-of-trip facilities at destinations (parking, showers, lockers)

□ More/safer places to park

□ Other: ______

Appendix B: Technical Modelling and Methods

Analysis of Mode Choice

Mode choice was analysed using a mixed logit (MXL) model, estimated in R with the mlogit package. A baseline multinomial logit (MNL) was first fitted to obtain sensible starting values and to benchmark fit. However, all results reported in the paper refer to the final MXL as the preferred specification. Mixed logit is particularly suited to discrete-choice data with repeated observations because it captures unobserved preference heterogeneity and accommodates panel structures (Greene & Hensher, 2003; Paz et al., 2019). Unlike a standard MNL, which imposes homogeneous tastes and the independence-from-irrelevant-alternatives assumption, the MXL relaxes these by allowing selected parameters to vary randomly across individuals (Train, 2009).

Walking served as the reference alternative. In the final MXL specification, the alternative-specific constants (ASCs) for cycling, driving, and transit were treated as random coefficients, capturing dispersion in baseline preferences for these modes. All other explanatory variables—such as gender, age group, household composition, vehicle or bicycle ownership, cycling confidence, and income bands—were modelled as fixed effects. Estimation used simulated maximum likelihood via the BFGS algorithm with 2,000 Halton draws, and a panel structure to account for multiple trip observations per respondent. The results table reports coefficient estimates (means of random parameters), robust standard errors, z-statistics, and p-values. For the MXL, the estimated standard deviations of the random ASCs are also reported to quantify unobserved heterogeneity by mode. Model fit is summarised by the maximised log-likelihood, McFadden's pseudo-R^2, Akaike (AIC) and Bayesian (BIC) information criteria. Model-specification checks included comparisons between the preliminary MNL and the final MXL, alternative specifications (e.g., three-level versus binary income), and the removal of nonvarying or weakly identified predictors. Model parsimony was pursued by iteratively fixing non-contributing interaction terms to zero and comparing each restricted specification with the less-restricted model using likelihood-ratio tests. Terms were retained only when their inclusion significantly improved overall fit.

Origin-Destination (OD) analysis

The variables included in the OD analysis are presented in Table 2. These variables encompass demographic and household characteristics obtained from the survey, as well as the distance between each origin–destination pair. The distance measure was derived using the Haversine formula, which computes great-circle distances based on the georeferenced coordinates of the origin and destination points. All variables are indexed by $j \in \{origin, destination\}$, as each reflects attributes associated with either the origin area or the destination area.

The OD analysis was conducted using the SA2 spatial scale to take advantage of this level of granularity, which ensures greater homogeneity across spatial units and supports robust model fitting and statistical inference. Figure S1 illustrates the spatial distribution of suburbs, grouped according to definitions provided by the Australian Bureau of Statistics.

Figure S1. Map with aggregation of suburbs considering SA2 levels according to guidance of Australian Bureau of Statistics. Each colour denotes an aggrupation of suburbs at the SA2 level for the OD analysis.

Suburbs represent administratively defined localities that capture fine-grained spatial patterns within metropolitan areas and include residential, commercial, and mixed-use environments. SA2 regions grouped constitute medium-sized areas intended to represent functional communities. They are constructed by aggregating smaller SA1 units, often spanning multiple suburbs, into coherent spatial entities.

Poisson regression model

A Poisson regression model is a type of generalized linear model (GLM) designed for the analysis of count data, where the dependent variable Y represents the number of events. The model is appropriate when the outcome variable is non-negative and discrete, and it relies on the assumption of equidispersion, meaning that the variance of Y is approximately equal to its mean. In the Poisson specification, the expected count λ_i is linked to a vector of explanatory variables x_i through a log-link function, ensuring that $\lambda_i > 0$. This formulation implies multiplicative effects of covariates on the expected count, which is a natural and interpretable feature for modelling event frequencies.

To assess the suitability of the proposed modelling approach, given the assumptions imposed on the outcome variable and the covariate structure, a dispersion test was employed to validate the use of the Poisson regression model. The test evaluates whether the equidispersion assumption, $E[Y] = Var(Y)$, holds by examining whether the conditional variance of the outcome deviates from its mean under the fitted Poisson specification. The null hypothesis states that, conditional on the covariates, the variance of the outcome equals the mean, implying the absence of an overdispersion parameter.

Furthermore, potential multicollinearity among covariates was assessed using Variance Inflation Factors (VIFs), which quantity the extent to which the variance of a coefficient estimate is inflated due to linear dependence among predictors. Addressing multicollinearity is essential because model parameters are estimated via maximum likelihood, and their standard errors are derived from the Fisher information matrix. High correlations among predictors can adversely affect the conditioning of this matrix, leading to unstable coefficient estimates and inflated standard errors. Consequently, excessive multicollinearity can compromise statistical inference drawn from the model estimates.

Given that the initial design matrix comprised more than 20 predictors, a variable-selection procedure was applied. Specifically, backward stepwise selection based on a Poisson regression framework and the Bayesian Information Criterion (BIC) was used to identify the most relevant covariates explaining OD flow counts. The procedure begins with a fully specified Poisson model and iteratively removes predictors whose exclusion leads to an improvement in BIC. This approach seeks a parsimonious model that balances goodness of fit and model complexity, as lower BIC values indicate a more favourable trade-off between these two components with an strong penalization on the parameters estimated compared to other methods of penalization. The use of BIC is appropriate in this context because Poisson models are estimated via likelihood-based methods, ensuring consistency between the estimation and model-selection criteria.

Inference in a Poisson regression model focuses on the estimated coefficients β_k, which are interpreted on the log-count scale. Given that some of the features are shares or proportions, the interpretation must be drawn differently from the traditional IRR approach. For this purpose, an $\alpha\%$ of change is set (commonly employing 1% or 10%) and the multiplicative effect is calculated through $(\exp\{\beta_k \times \alpha\%) - 1)\%$, yielding the percentage of change per $\alpha\%$ percentage of change in x_k. On the other hand, features that are real-valued, the exponentiation $(\exp\{\beta_m\} - 1)\%$ yields the change per 1-unit increase in the feature x_m. An IRR greater than 1 denotes that the predictor is associated with an increase in the expected count, whereas an IRR less than 1 indicates a decrease in the outcome. An IRR equal to 1 implies no associations with the outcome.

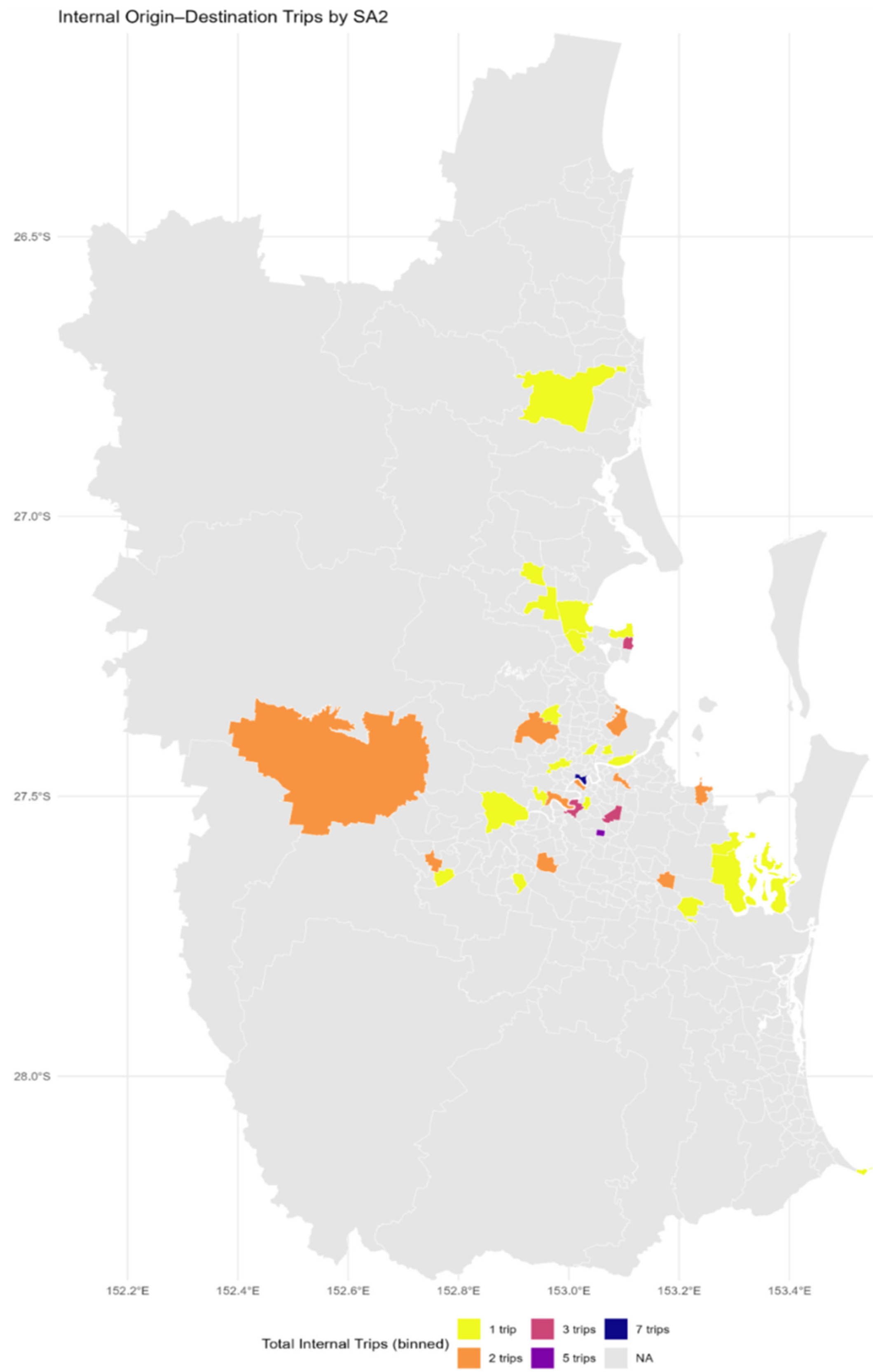

Figure S2: Internal flows in 36 SA2 zones for SEQ.

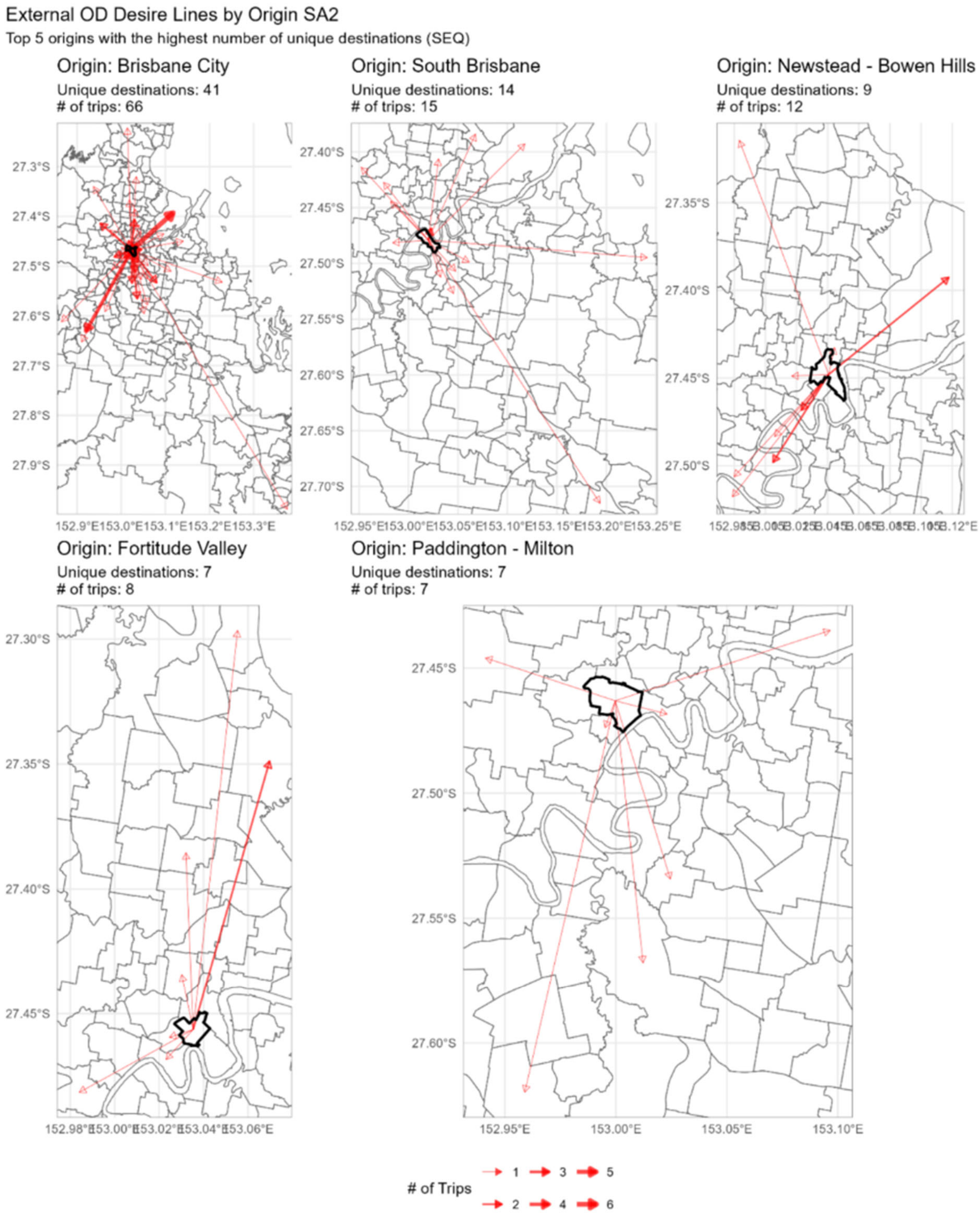

Figure S3: Origin based top 5 SA2 zone external flow desire lines.

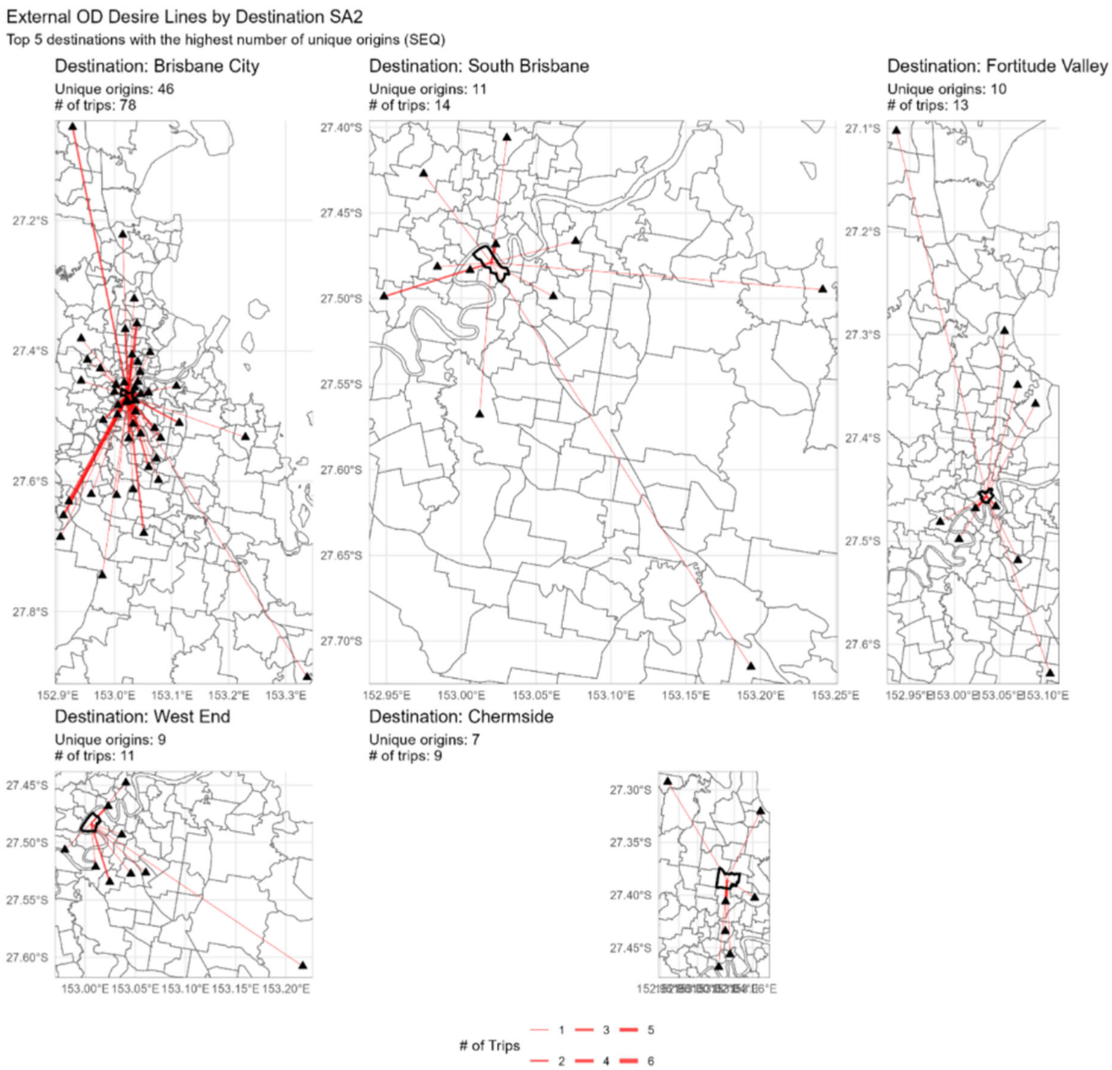

Figure S4: Destination based top 5 SA2 zone external flow desire lines.