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Modelling daily travel time allocation decision in dual-earner households

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Abstract

This study examines gendered differences in total daily travel time among heterosexual dual-earner couples using a partner-disaggregated linear regression framework. Drawing on data from the Southeast Queensland Household Travel Survey (2017–2024), the analysis models each partner's travel time separately as a function of their individual characteristics, shared household conditions, and built environment attributes. Guided by the Household Responsibility Hypothesis and Sen's Capability Approach, the study conceptualizes travel time as a reflection of household capabilities shaped by gendered divisions of labor, shared resources, and spatial opportunity structures. Findings show that male partners generally spend more time traveling. Trip timing, employment sector, and life stage significantly affect travel burdens. Younger female partners and those employed in male-dominated industries experience longer travel durations. Built environment attributes also show gendered effects: for female partners, greater walkability and access to maintenance services are associated with longer travel time, while public transit and cycling infrastructure reduce travel durations. For male partners, increased access to nearby bus stops and transit services is associated with shorter travel times. These results underscore the persistent gender asymmetries in time use within shared households and infrastructure. The study contributes theoretically by framing travel time as an interdependent household outcome; methodologically by applying a partner-specific linear regression approach; and empirically by informing gender-sensitive transport and land-use policies aimed at promoting more equitable labor market participation.

Keywords: Dual-earner couples; travel time; household capabilities; built environment

1 Introduction and motivation

In recent decades, rising female labor force participation and evolving family norms have transformed household structures and travel behavior. Dual-earner households, wherein both partners engage in paid employment, are now the predominant family configuration in many developed and emerging economies (OECD, 2023), replacing the traditional "breadwinner husbands" and "homemaker wives" model (Broomhill and Sharp, 2005; Cha, 2010). This shift introduces complex trade-offs in employment, caregiving, and travel coordination, as each partner's travel behavior constrains or enables the other's within finite temporal and spatial resources. Yet most transport models treat individuals as independent agents, overlooking the interdependence of household travel decisions. Empirical studies demonstrate significant intra-household correlation in travel patterns (Cools and Moons, 2016), implying that analyzing partners separately may misrepresent household dynamics and weaken policy relevance. Recent studies also indicate that dual-earner couples collectively incur substantially higher travel-time burdens, typically 25-40 % more combined daily travel time than single-earner households at similar income and location levels (Kwon and Akar, 2022; Almås, Attanasio and Carneiro, 2023). Evidence also shows consistent gendered differences where women with children tend to shorten travel times while taking on more errands or childcare-related trips, whereas men's patterns remain steady (Echeverría et al., 2024; Lee et al., 2022). These

patterns raise a fundamental question should longer total travel time reflect greater access to economic and social travel activities, or greater constraints and time poverty? This ambiguity highlights the need for a framework that interprets travel not as an intrinsic good or burden, but as a context-dependent proxy for how individuals convert household, temporal, and spatial resources into real opportunities for participation and well-being.

Two theoretical frameworks guide this investigation. Sen's Capability Approach (Sen, 1995) conceptualises well-being as the freedom to achieve valued functionings (e.g., accessing employment, caregiving, or community life). Within this framework, travel time is not treated as a capability in itself, but as a quantifiable proxy for the functioning of mobility and access. In a capability lens, a longer travel duration may reflect the ability to participate in desired travel activities (a positive opportunity), or conversely it may reveal constrained conversion due to caregiving responsibilities, job inflexibility, or spatial mismatch (a constraint). Similarly, shorter travel duration may indicate convenient access (high capability) or that they are geographically or economically constrained to a narrow radius (low capability). The Household Responsibility Hypothesis (HRH(Johnston-Anumonwo, 1992; Turner and Niemeier, 1997) complements this framing by explaining gendered travel behavior through the unequal distribution of unpaid labor, which limits women's temporal and spatial flexibility. Travel time, therefore, emerges as a negotiated outcome shaped by spouse/partner' individual capabilities, household capability and external opportunity structures (e.g., built environment, transport services). While partners often share residential locations and material resources, divergent employment conditions and caregiving roles result in gendered asymmetries persisting in how travel time is distributed. Existing research often neglects these interdependencies, relying instead on individual-level or commute-only metrics. Together, these frameworks shift the lens as travel time is not inherently beneficial or burdensome but reflects underlying capability conversion processes that determine how individuals, embedded in household contexts, transform resources into well-being, labor market participation, and household economic resilience.

To operationalize this framing, the study models total daily travel time for male and female partners in heterosexual dual-earner households using a partner-disaggregated econometric framework. Each partner's travel time is estimated independently based on their demographic profile, employment characteristics, household conditions, and built environment context. The analysis uses data from the South-East Queensland Household Travel Survey (SEQHTS, 2017–2024) and is limited to cohabiting, heterosexual couples in which both partners are employed (full- or part-time), with gender operationalized as binary based on self-reported sex in the survey data. The dependent variable captures total travel duration across all trip purposes. While the empirical approach does not implement a fully recursive or joint modeling structure, it serves as a diagnostic step toward modeling intra-household interdependencies. The study establishes baseline insights into gendered asymmetries in total travel time and provides a foundation for future models that captures intra-household interdependencies, where one partner's travel time may constrain or enable the other's. The contributions of this study are threefold. First, it advances theoretical understanding by framing travel time allocation as a household-level, interdependent decision-making process rather than an independent individual outcome. Second, it applies a partner-disaggregated empirical approach to reveal partner-level variation in travel behavior. Third, it offers initial empirical insights highlighting the need for interventions that are both gender-responsive and household-aware. The study contends that recognizing the household context in travel behavior research is critical for designing policies that promote equitable participation in the labor market without incurring disproportionate travel-time burdens.

The remainder of the paper is structured as follows. Section 2 outlines the methodological ramework, including data sources, processing steps, and the econometric modeling approach. Section 3 presents the results and discussion. Section 4 concludes with a summary of key findings, study limitations, and directions for future research.

2 Methods

2.1 Data acquisition and processing

This study uses data from the Southeast Queensland Household Travel Survey (HTS, 2017–2024), covering eight Local Government Areas (LGAs) including Brisbane, Gold Coast, Sunshine Coast, Ipswich, Logan, Moreton Bay, Redland, and Noosa. The dataset includes linked trip, person, and household-level variables (e.g., trip duration, mode, employment, vehicle ownership), collected at the SA2 level under ASGS (Edition 3). Dual-earner households were identified by filtering for co-residing adult partners (respondent and spouse) who were both employed (full- or part-time), excluding households with non-partner co-residents or individuals not in the labor force. Employment status was validated using Australian labor force classifications. The final sample comprises 2,130 male and 2,130 female partners, with trips confined to the SEQ region for contextual consistency. Each partner was uniquely identified, and sample weights were applied to generate representative estimates. To spatially contextualize travel behavior, HTS household records are linked to the Land Use and Public Transport Accessibility Index (LUPTAI, 2019–2023), which provides multimodal accessibility scores (walking, cycling, and public transport) to 33 destination types at the SA2 level. Land-use mix is measured using SA2-level entropy indices. Household locations in the HTS data enable each household to be precisely matched to its corresponding SA2, allowing for the integration of accessibility indicators and land-use mix without spatial generalization. Additionally, local public transport access is measured using 400-meter buffer-based bus stop counts around household locations, computed in ArcGIS 10.6. All datasets were merged into a unified SPSS database for analysis.

2.2 Empirical context

2.2.1 Dependent variable

The dependent variable is the natural logarithm of total daily travel time (in minutes) per partner, covering all trip purposes. Log-transformation corrects for skewness and supports linear regression assumptions. As shown in Table 1, mean logged travel time is slightly higher for male partners (4.296) than for females (4.159).

Table 1: Summary statistics of the Dependent variable

Dependent Variables	Variable Description	Female Partner (N=2130)				Male Partner (N=2130)			
		Mean	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
Travel time (Partner-specific)									
Travel Time (mins)	Log (Total time spent on all trips across various purposes (work, maintenance, leisure, and other) by a male or female partner in a dual-earner household)	4.159	0.696	1.099	6.356	4.296	0.703	1.609	6.494

2.2.2 Independent variables

Independent variables are grouped into five domains to capture intra-household and spatial factors shaping total daily travel time in dual-earner households:

- Partner-Specific Travel Characteristics: Trip initiation timing variables (e.g., early morning, morning peak, off-peak, evening) capture temporal organization of travel within the context of shared household schedules.

- Partner Demographics and Employment Segmentation: Includes age cohort categories and employment sector classifications (female-dominated, male-dominated, and mixed industries), accounting for life-course positioning and occupational structures that influence individual travel capabilities.
- Household Capabilities: Measured through the number of children across three age groups (1–4, 5–12, 13–17 years), these indicators represent caregiving intensity and intra-household time-use constraints that affect travel flexibility.
- Macro-Spatial Household Context: Includes household location by Local Government Area (LGA) and land-use entropy at the SA2 level, capturing variations in spatial diversity, regional accessibility, and built environment integration.
- Built Environment and Service Accessibility: Encompasses infrastructure measures (e.g., bikeway density, motorway density), local access indicators (e.g., bus stops within 400m), and multimodal accessibility indices (cycling, walking, public transport) to key activity destinations.

These domains support a multidimensional analysis of how individual traits, shared resources, and spatial conditions shape gendered travel outcomes. Descriptive statistics for each domain are reported in Table 2 and subsequent tables, disaggregated by gender where relevant.

Table 2: Summary statistics for independent variables

Independent Variables	Variable Description	Female Partner (N=2130)				Male Partner (N=2130)			
		Mean	SD	Min	Max	Mean	SD	Min	Max
Travel Characteristics									
Partner-Specific Time-of-Day Travel Segments									
Early morning (4:00 am -6:59 am)	Trip made by a partner, beginning between 4:00 am and 6:59 am, is typically classified as early morning travel.	0.350	0.477	0.000	1.000	0.448	0.497	0.000	1.000
Morning peak (7:00 am-8:59 am)	Trip made by a partner, beginning between 7:00 am and 8:59 am, corresponding with morning peak travel hours.	0.375	0.484	0.000	1.000	0.313	0.464	0.000	1.000
Business hours off-peak (9:00 am- 2:59 pm)	Trip made by a partner, beginning between 9:00 am and 2:59 pm, during standard business hours but outside peak congestion periods.	0.190	0.393	0.000	1.000	0.171	0.377	0.000	1.000
Evening peak (3:00 pm -5:59pm)	Trip made by a partner, beginning between 3:00 pm and 5:59 pm, aligning with evening peak travel demand.	0.072	0.258	0.000	1.000	0.053	0.223	0.000	1.000
Night off-peak (6:00 pm- 8:59 pm)	Trip made by a partner, beginning between 6:00 pm and 8:59 pm, categorized as early night-time travel during off-peak conditions.	0.012	0.108	0.000	1.000	0.014	0.116	0.000	1.000
Late PM off-peak (9:00 pm- 11:59 pm)	Trip made by a partner, beginning between 9:00 pm and 11:59 pm, classified as late night off-peak travel.	0.000	0.022	0.000	1.000	0.001	0.031	0.000	1.000
Midnight AM off peak (12 am to 3:59 am next day)	Trip made by a partner, beginning between 12:00 am and 3:59 am the following day, reflecting overnight or midnight off-peak travel.	0.000	0.022	0.000	1.000	0.000	0.022	0.000	1.000
Partner Demographics and Employment Segmentation									
Age									
18-29 years	The partner belongs to the 18–29 year age cohort	0.134	0.341	0.000	1.000	0.102	0.303	0.000	1.000
30-39 years	The partner belongs to the 30–39 year age group	0.216	0.412	0.000	1.000	0.211	0.408	0.000	1.000
40-49 years	The partner belongs to the 40–49 year age group	0.166	0.372	0.000	1.000	0.159	0.366	0.000	1.000
50-59 years	The partner belongs to the 50–59 year age group	0.300	0.459	0.000	1.000	0.288	0.453	0.000	1.000
60-69 years	The partner belongs to the 60–69 year age group	0.173	0.379	0.000	1.000	0.215	0.411	0.000	1.000

Table 2: Summary statistics for independent variables (Continued.)

Independent Variables	Variable Description	Female Partner (N=2130)				Male Partner (N=2130)			
Partner Demographics and Employment Segmentation									
Age									
>70 years	The partner is 70 years or older, with likely reduced or ceased labor market engagement.	0.010	0.101	0.000	1.000	0.024	0.154	0.000	1.000
Employment Sector									
Female-dominated jobs	The partner is employed in a sector with a predominantly female workforce, including industries such as education and training, health care and social assistance, administrative and support services, arts and recreation services, and retail trade.	0.596	0.491	0.000	1.000	0.227	0.419	0.000	1.000
Male-dominated jobs	The partner is employed in a sector with a predominantly female workforce, including industries such as education and training, health care and social assistance, administrative and support services, arts and recreation services, and retail trade.	0.114	0.317	0.000	1.000	0.442	0.497	0.000	1.000
Gender Mixed job	The partner works in sectors with a relatively balanced gender distribution, including accommodation and food services, financial and insurance services, information media and telecommunications, public administration and safety, rental and real estate services, and professional, scientific, and technical services.	0.291	0.454	0.000	1.000	0.331	0.471	0.000	1.000

Table 2: Summary statistics for independent variables (Continued.)

Independent Variables	Variable Description	Mean	SD	Min	Max
Household Capabilities					
Number of children	Total number of young children (toddlers/preschoolers) aged 1–4 years in the household	0.025	0.185	0.000	3.000
	Total number of school-aged children aged 5–12 years in the household	0.056	0.294	0.000	3.000
	Total number of adolescents aged 13–17 years in the household	0.034	0.224	0.000	3.000
Macro-Spatial Household Capabilities					
Local Government Area (LGA)					
Noosa	Number of dual-earner couple households (with both male and female partners) residing in the Local Government Area of Noosa.	0.040	0.196	0.000	1.000
Sunshine Coast	Number of dual-earner couple households residing in the Local Government Area of Sunshine Coast.	0.132	0.338	0.000	1.000
Moreton bay	Number of dual-earner couple households residing in the Local Government Area of Moreton Bay.	0.107	0.309	0.000	1.000
Brisbane	Number of dual-earner couple households residing in the Local Government Area of Brisbane.	0.233	0.423	0.000	1.000
Ipswich	Number of dual-earner couple households residing in the Local Government Area of Ipswich.	0.104	0.305	0.000	1.000
Logan	Number of dual-earner couple households residing in the Local Government Area of Logan.	0.117	0.321	0.000	1.000
Redland	Number of dual-earner couple households residing in the Local Government Area of Redland.	0.119	0.324	0.000	1.000
Gold coast	Number of dual-earner couple households residing in the Local Government Area of the Gold Coast.	0.149	0.356	0.000	1.000
Entropy					
Land use mix at household location	Measures the mix of land use types surrounding the household's location at the SA2 level (e.g., residential, commercial, civic, industrial, transport infrastructure). Land use= $-([\sum_{j=1}^{k} P^j lnP^j])/\ln k$, where Pj, is the proportion of land use type j and k is the number of land use categories.	0.359	0.187	0.000	0.922

Table 2: Summary statistics for independent variables (Continued.)

Independent Variables	Variable Description	Mean	SD	Min	Max
Built Environment and Transport Access Attributes					
Road and Pathway Network Density (Z-scores)					
Bikeway density	total length of bikeways (km) per km² SA2 area. Represents the availability of non-motorised cycling infrastructure near households.	0.000	1.000	-0.526	6.179
Busway density	total length of busway, which is wholly dedicated as a bus-only transitway that does not include bus lanes on roads with other trafficability (km), which is per unit SA2 area (km2)	0.000	1.000	-0.151	9.179
Connector density	total length of collector roads (km) per km² SA2 area, indicating access to mid-tier roads.	0.000	1.000	-1.193	8.712
Ferry density	the total length of public ferry routes (km) per km² SA2 area. Reflects water-based transit	0.000	1.000	-0.138	15.439
Highway density	total length of arterial highways (km) per km² SA2 area. Represents long-distance vehicle accessibility.	0.000	1.000	-0.405	8.471
Local road density	total length of service-level local roads (km) per km² SA2 area.	0.000	1.000	-1.913	2.611
Mall road density	total length of pedestrian-prioritized mall roads (km) per km² SA2 area, allowing limited vehicle	0.000	1.000	-0.062	27.475
Motorway density	total length of motorways that are a major interstate through route and/ or the principal connector road between capitals and/or major regions and/or key towns/commercial centres/inter-transport hubs (km) per unit SA2 area (km2)	0.000	1.000	-0.435	10.979
Restricted road density	total length of restricted road which provides access within the property and not part of the public road network (km) per unit SA2 area (km2)	0.000	1.000	-1.133	6.485
Secondary road density	total length of secondary road /sub arterial road (km) per unit SA2 area (km2)	0.000	1.000	-1.305	5.493
Track Density	total length of track which provide access tracks and fire trails(km) per unit SA2 area (km2)	0.000	1.000	-0.414	9.336
Walkway density	total length of designated pedestrian walkways (km) per km² SA2 area.	0.000	1.000	-0.694	19.001
Modal Access and Proximity Measures					
Bus Stop Count (per Household Vicinity)	Total number of bus stops located within a 400-meter buffer around the residence of dual-earner couple households	3.540	3.566	0.000	24.000
Distance to Central Business District (CBD)	Z score (Euclidean distance (in km) between the residential location of dual-earner couple households and the nearest Central Business District (CBD))	0.000	1.000	-1.269	2.725

Table 2: Summary statistics for independent variables (Continued.)

Independent Variables	Variable Description	Cycle		Walking		Public Transport	
Service Accessibility Environment							
Accessibility to services from household location							
Work-related services	Z-score (average travel time (seconds) by cycling, walking, or public transport to reach employment-related destinations such as employment centers, industrial zones, and office-based blue- and white-collar job clusters)	-2.175	1.182	-2.979	1.010	-3.788	1.145
Maintenance-related services	Z-score (average travel time (seconds) to reach everyday maintenance destinations like banking institutions, community centers, childcare centers, health clinics, general practitioners, hospitals, post offices, supermarkets, and mixed retail hubs	-2.020	3.966	-2.661	3.560	-2.521	3.186
Leisure related services	Z-score (average travel time (seconds) to access broader civic services like welfare support, education providers (primary and secondary schools), universities, and vocational institutions (e.g., TAFE))	-2.761	2.646	-2.234	3.317	-2.534	2.678
Other related services	Z-score (average time (seconds) taken to arrive by cycling, walking, or public transport to reach other services like welfare facilities, education, primary and secondary schools, universities, TAFE,	-1.380	1.821	-1.916	1.897	-1.517	2.395

Note: Binary variables are coded as 1 if the attribute applies to the respondent, and 0 otherwise. For example, “Household located in Redland = 1” indicates residence in Redland LGA.

2.3 Modelling framework

This study adopts a partner-disaggregated linear regression framework to model the total daily travel time of male and female partners within dual-earner households. Each partner's travel time is modeled separately as a function of their own demographic attributes, household composition, and spatial-environmental factors. This structure enables the identification of partner-specific underlying mechanisms that shape total daily travel time. The dependent variable is the natural logarithm of total daily travel time (in minutes) for each partner, aggregating across all trip purposes. Log-transformation addresses the skewness typical of travel time distributions and satisfies assumptions of linearity and homoscedasticity required for consistent estimation. The general functional form of the model is specified as follows:

$$\log(y_i) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} + \varepsilon_i \quad \text{Equation 1}$$

Where $\log(y_i)$ is the natural logarithm of total daily travel time for partner i ; $X_{1i}, X_{2i} \ldots X_{ki}$, i are covariates reflecting individual demographics, employment segmentation, caregiving responsibilities, land use entropy, transport network densities, and modal accessibility; , β_0 is the intercept; β_1, β_2, …,β_k are the coefficients to be estimated, and ϵi the error term, assumed to be normally distributed with zero mean and constant variance. Model estimation is performed using Maximum Likelihood Estimation (MLE) under normality assumptions for residuals. All estimations are implemented using GAUSS, a matrix-based programming environment optimised for econometric modelling.

3 Results and discussion

able 3 shows partner-specific linear regression estimates of daily travel time using maximum likelihood estimation in Aptech GAUSS. The models yielded log-likelihood values of −1.03726 (female) and −1.03256 (male). Positive coefficients indicate longer travel time and negative coefficients indicate shorter durations. While constant terms are statistically significant, they primarily serve as baselines for interpreting covariate effects.

3.1 Temporal characteristics

The COVID/Lockdown variable captures macro-temporal disruptions external to household-level factors. The negative coefficient for FY 2021–2022 indicates reduced total travel time for both partners. This aligns with pandemic-related shifts such as increased remote work, fewer trips, and restricted access to services. Interpreted within a Capability lens, this disruption temporarily reconfigures the functioning of commuting and caregiving access, reducing travel burdens but also limiting participation in valued activities (e.g., work, socialization). Travel time here reflects both a loss of opportunity and relief from previous constraints, depending on partner roles.

3.2 Partner-specific travel characteristics

Trip start time significantly shapes travel durations. For male partners, departures during the Early AM period (4:00–6:59 AM) and the PM peak (3:00–5:59 PM) are associated with longer travel times. These periods coincide with high congestion levels and are aligned with occupational sectors such as construction, logistics, and trades, which often require early start times. In the Australian context, while the conventional workday begins around 9:00 AM, many male-dominated sectors commence shifts before 7:00 AM. Conversely, evening off-peak trips (6:00–8:59 PM) are associated with shorter durations for both partners, likely reflecting lower congestion and localised activities. These associations indicate that functionings related to employment access are filtered through gendered occupational schedules and temporal constraints. Early AM travel reflects reduced temporal flexibility and elevated opportunity costs, while evening mobility suggests more autonomous or discretionary travel. Time-efficient access is unequally distributed, even within shared temporal contexts. Within shared households, time-efficient access is unevenly distributed across partners, shaped by structural role differentiation rather than individual preference.

3.3 Partner demographics and employment role

Despite sharing household and spatial conditions, partner-specific attributes such as age, gender, and employment sector are structurally associated with differential travel time outcomes. Female partners aged 30–39 exhibit longer travel durations, reflecting life-course intersections between peak employment engagement and intensified caregiving demands. These longer durations do not uniformly indicate either constraint or opportunity, rather, they signify trade-offs negotiated within the context of role performance and external obligations. In contrast, shorter travel times among older female partners (60–69) likely reflect transitions into retirement, part-time work, or localized activity routines. Employment in male-dominated sectors for women and mixed-sector fields for men is also linked to longer travel duration. These patterns align with spatial entrapment theory (Cortis *et al.*, 2023), where structural conditions, not individual choice, limit the capacity to transform resources into equitable mobility and labour market access.

3.4 Household capabilities

Household-level factors, while shared, produce differentiated travel outcomes across partners. The results indicate that by sharing the same household structure and caregiving environment, an increase in the number of children aged 13–17 is positively associated with longer travel durations for both female and male partners. In the Australian context, adolescent partial autonomy (e.g., school travel, part-time work, learner driving) may afford greater parental flexibility, enabling longer commutes or discretionary travel. However, this does not automatically imply enhanced capability. Travel time becomes a visible outcome of household-level resource negotiations and opportunity trade-offs.

3.5 Macro-spatial household capabilities

Spatial context acts as a structuring influence on the conversion of household resources into mobility. Female partners residing in Redland experience longer travel durations, likely due to Redland's spatial morphology characterized by dispersed residential development, limited connectivity, and low-density land use. However, higher land-use mix at the household location is associated with shorter travel for both partners, highlighting the benefits of compact, mixed-use urban environments for time-efficient travel. These findings reflect how spatial morphology functions as a conversion factor. Certain environments facilitate more flexible, time-efficient mobility, while others impose constraints that differentially affect household members. Travel time here serves as a proxy for how spatial structure shapes the realization of travel-related functionings.

3.6 Built environment and transport access attributes-Conversion Efficiency Mediated by Infrastructure and Gender Roles

Though partners share the same spatial setting, travel time responses differ by gender. Greater distance from the central business district (CBD) is linked to shorter travel times for female partners, which is a counterintuitive but contextually plausible outcome. This aligns with Australian literature, noting that women's spatial employment distribution tends to be more dispersed and less CBD-oriented compared to men (Currie *et al.*, 2010). For male partners, more bus stops within 400m and better public transport access to work services are associated with shorter travel times, reflecting efficient conversion of infrastructure into work-related travel participation. At the trip origin, higher pedestrian density is associated with longer travel durations for female partners. Similarly, walkable access to maintenance services increases their travel time. In contrast, higher bikeway density and greater cycling accessibility reduce travel time for women. This aligns with prior research showing that women are more likely to cycle when protected and connected cycling infrastructure is present (AitBihiOuali and Klingen, 2022; Giacomantonio, Mitra and Ravensbergen, 2024). These findings illustrate how system-level accessibility and localized infrastructure jointly shape travel-time functionings.

Table 3: Model estimate results

Characteristics	Female Partner (N=2130)			Male partner (N=2130)		
	β̂	Std. Err.	p-value	β̂	Std. Err.	p-value
Constant	4.211	0.037	0.000	4.349	0.040	0.000
Temporal Characteristics						
Financial Year 2021-2022	-0.109	0.050	0.028	-0.171	0.049	0.000
Trip Characteristics						
Trip Start Time (Base: All other times)						
Trip start time: Early AM (4–6:59 am)	-	-	-	0.164	0.031	0.000
Trip start time: PM peak (3–5:59 pm)	-	-	-	0.298	0.068	0.000
Trip start time: Evening PM off-peak (6:00 pm –8:59 pm)	-0.267	0.138	0.052	-0.670	0.128	0.000
Partner Demographics and Employment Segmentation						
Trip maker characteristics (Base: Age-18-29, 40- 49, 50- 59, and >70 years)						
Age between 30 and 39 years	0.090	0.037	0.016	-	-	-
Age between 60 and 69 years	-0.088	0.040	0.029	-	-	-
Employment type (Base: Female dominated)						
Male-dominated industry sector	0.108	0.047	0.021	-	-	-
Mix industry sector	-	-	-	0.084	0.032	0.008
Household Capabilities						
Number of children aged 13-17 years in the household	0.132	0.067	0.047	0.078	0.030	0.010
Number of vehicles in the household	-	-	-			
Macro-Spatial Household Context						
Area Characteristics (Base: Household located in Brisbane, Gold Coast, Ipswich, Logan, Moreton Bay, Sunshine Coast, and Noosa)						
Household located in Redland	0.114	0.045	0.011	-	-	-
Land-use mix at household location	-0.166	0.086	0.052	-0.313	0.082	0.000
Built Environment and Transport Access Attributes						
Modal Access and Proximity Measures						
Distance to CBD from household location (z-score)	-0.046	0.016	0.005	-	-	-

Table 3: Model estimate results (Continued.)

Characteristics	Female Partner (N=2130)			Male partner (N=2130)		
	β	Std. Err.	p-value	β	Std. Err.	p-value
Built Environment and Transport Access Attributes						
Modal Access and Proximity Measures						
Number of bus stops within a proximity of 400 m of the household location.	-	-	-	-0.015	0.004	0.000
Road and Pathway Network Density (Z-scores)						
Walkway density (z-score) at trip origin location	0.034	0.015	0.026	-	-	-
Bikeway density (z-score) at trip origin location	-0.030	0.016	0.065	-	-	-
Accessibility to Services (z-scores)						
Work-related services (cycling) from the household location	-0.107	0.022	0.000	-	-	-
Maintenance-related services (walking) from the household location	0.083	0.024	0.001	-	-	-
Work-related services (public transport) from the household location	-	-	-	-0.033	0.016	0.031
Log likelihood at Constant	**-2251.13**			**-2271.35**		
Log likelihood at Convergence	**-2208.81**			**-2200.29**		
Note: "–" indicates that the variable was not included in the final model for that partner due to statistical insignificance at the 90% confidence level (p > 0.10)						

4 Conclusion

This study employed a partner-disaggregated linear regression framework to model total daily travel time among male and female partners in heterosexual dual-earner households. Grounded in the Household Responsibility Hypothesis and Sen's Capability Approach, it conceptualizes travel time not as an intrinsic capability but as a proxy functioning shaped by intra-household negotiations and resource distributions. Descriptive analysis indicated that male partners spend more time overall, compared to female partners. Model estimation results reveal partner-specific characteristics such as age, employment sector, and trip timing exert differentiated effects on travel durations. Female partners in mid-career and caregiving life stages, especially those employed in male-dominated sectors, tend to experience longer daily travel times. In contrast, greater autonomy among adolescent children appears to enhance functional travel for both partners, though it may introduce new coordination demands. Built environment characteristics also demonstrate complex interactions with gendered travel patterns. While proximity to public transport and mixed-use environments generally support more efficient travel for both partners, high walkability unexpectedly correlates with longer travel durations for female partners.

While this study identifies key mechanisms shaping total travel durations, several limitations remain. First, the current specification treats each partner's model independently, without capturing intra-household correlation. As an initial diagnostic step, this approach provides a baseline. Future research will apply recursive or simultaneous equation models to account for interdependencies and feedback loops. Second, the model employs linear functional forms and excludes interaction terms these will be incorporated in future specifications to capture nonlinearities and heterogeneity in capability conversion. Third, although some household-level variables (e.g., vehicle ownership) are included, time-budget constraints and pooled household resources are not fully modeled. Fourth, potential endogeneity from residential self-selection and job-location sorting is not addressed in this version. These methodological enhancements are planned for future iterations.

From a policy perspective, the findings support a shift toward gender-equitable and household-aware transport strategies. Recommendations include supporting women re-entering the workforce through targeted mobility programs, implementing flexible zoning to reduce caregiving-related travel burdens, promoting shared mobility options such as pooled car use or family ride credits that accommodate household coordination, and integrating childcare facilities within transit-oriented developments. Future work will develop quantitative policy scenarios and time-saving estimates to assess the effectiveness of such interventions. Overall, this study establishes an empirical and conceptual foundation for future intra-household travel modeling. By highlighting the structural and gendered dimensions of mobility constraints, it contributes to a growing body of transport research that centers equity, caregiving, and real freedom to access opportunities.

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References

AitBihiOuali, L. and Klingen, J. (2022). 'Inclusive roads in NYC: Gender differences in responses to cycling infrastructure', *Cities*, 127. Available at: https://doi.org/10.1016/j.cities.2022.103719.

Almås, I., Attanasio, O. and Carneiro, P. (2023) 'Household decisions and intra-household distributions', in. Available at: https://doi.org/10.1016/bs.hefam.2023.01.008.

Broomhill, R. and Sharp, R. (2005) 'The Changing Male Breadwinner Model in Australia: a New Gender Order?', *Labour and Industry*, 16(1). Available at: https://doi.org/10.1080/10301763.2005.10722033.

Cha, Y. (2010) 'Reinforcing separate spheres: The effect of spousal overwork on men's and women's employment in dual-earner households', *American Sociological Review*, 75(2). Available at: https://doi.org/10.1177/0003122410365307.

Cools, M. and Moons, E. (2016) 'Handling intrahousehold correlations in modeling travel: Comparison of hierarchical models and marginal models', *Transportation Research Record*, 2565, pp. 8–17. Available at: https://doi.org/10.3141/2565-02;WGROUP:STRING:PUBLICATION.

Cortis, N. *et al.* (2023) *Gender-based Occupational Segregation: A National Data Profile*. UNSW Social Policy.

Currie, G. *et al.* (2010) 'Investigating links between transport disadvantage, social exclusion and well-being in Melbourne - Updated results', *Research in Transportation Economics*, 29(1). Available at: https://doi.org/10.1016/j.retrec.2010.07.036.

Giacomantonio, S., Mitra, R. and Ravensbergen, L. (2024) 'Bicycle facilities and women's cycling frequency – An intersectional analysis of gendered travel behaviour', *Transportation Research Part A: Policy and Practice*, 184, p. 104094. Available at: https://doi.org/10.1016/J.TRA.2024.104094.

Johnston-Anumonwo, I. (1992) 'The influence of household type on gender differences in work trip distance', *Professional Geographer*, 44(2). Available at: https://doi.org/10.1111/j.0033-0124.1992.00161.x.

Kwon, K. and Akar, G. (2022) 'Have the gender differences in commuting been shrinking or persistent? Evidence from two-earner households in the U.S.', *International Journal of Sustainable Transportation*, 16(12). Available at: https://doi.org/10.1080/15568318.2021.1971345.

OECD (2023) *Patterns of employment and the distribution of working hours for couples with children*. Available at: https://www.oecd.org/en/data/datasets/oecd-family-database.html (Accessed: 18 April 2025).

Sen, A. (1995). 'Functionings and Capability', in *Inequality Reexamined*. Oxford University PressOxford. Available at: https://doi.org/10.1093/0198289286.001.0001.

Turner, T. and Niemeier, D. (1997) 'Travel to work and household responsibility: New evidence', *Transportation*, 24(4). Available at: https://doi.org/10.1023/A:1004945903696.