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Travel Preferences Among Car Drivers At Urban And Regional Multimodal Mobility Hubs: A Stated Choice Experiment

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Abstract

Multimodal mobility hubs are emerging as an effective solution for integrating various transport modes and reducing reliance on private cars. Their successful design and implementation require a thorough understanding of factors affecting user preferences and behaviors concerning the hubs and the transport modes they offer. This study used a stated choice experiment to examine the travel preferences of car drivers in the Netherlands, distinguishing between urban and regional hubs. The design included hub characteristics, mode attributes, and contextual variables. The results from an error component multinomial logit models show that private cars remain the preferred mode when offered either type of hubs. Factors like sunny weather, shorter travel distances, and free parking at hubs increased hub attractiveness. Buses and trains were preferred in urban and regional hubs, respectively, compared to shared e-bike, share e-scooter and shared car. Younger, highly educated, and middle-income respondents show greater inclination toward shared modes, indicating a promising target group for mobility hub adoption.

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1. Introduction

As cities and regions aim to reduce car dependency and promote more sustainable forms of mobility, increasing attention is being paid to multimodal travel solutions that combine different transport options (Liao et al., 2024). Multimodal mobility hubs have emerged as a key physical infrastructure to facilitate this shift. These hubs are transfer

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points where several transport modes are co-located. However, definitions vary widely. While the basic function of the hub is to enable mode transfers, scholars and practitioners increasingly emphasize its broader role as a socio-economic node, contributing to spatial development and improving accessibility (Frank et al., 2021; Witte et al., 2021). Yet, substituting the private car with more sustainable options requires a substantial behavioral shift, particularly as car use is often habitual and shaped by chained activities and situational constraints (Daisy et al., 2018). For many users, the private car is not merely a transport mode. It symbolizes autonomy, flexibility, and social status, while offering unmatched door-to-door convenience (Kent, 2014; Burlando et al., 2019). Intermodal or multimodal trips, by contrast, often involve higher perceived disutility due to added travel time, transfer effort, and the need to coordinate across access, main, and egress stages (Schakenbos et al., 2016). Factors such as cost, physical and cognitive effort, and the ability (or lack thereof) to multitask during travel also influence mode choice (Le et al., 2020). Moreover, contextual conditions like weather can significantly impact decisions, with adverse conditions often pushing users toward car use (Hyland et al., 2018).

In this context, multimodal hubs offer promising alternatives, but the challenge is making these options equally appealing. To be effective, hubs must reduce key sources of friction, such as long access distances, long transfer times, and inadequate facilities, while also increasing perceived utility. By incorporating diverse services, hubs can become spaces where people can conduct various activities beyond just traveling (Bell, 2019), thereby transforming otherwise idle waiting times into productive or pleasant experiences (Fan et al., 2016). For example, cafes or co-working spaces can provide comfortable waiting environments, while supermarkets or parcel pickup points enable passengers to complete errands en route. This is especially relevant given that private car use often facilitates chaining multiple purposes into one efficient tour (Hunecke et al., 2021). By offsetting travel disutility with added utility from secondary activities, strategically located and well-equipped hubs can offer both functional modal connections and thus citizens mobility needs and also serve as attractive nodes that support users' daily routines.

Despite growing policy and academic interest in mobility hubs, empirical evidence on how their specific features influence travel behaviour, particularly in different spatial contexts, remains limited. Previous studies focus on hub location strategies (Blad et al., 2022), user segmentation in neighbourhood hubs (van der Meer, 2022), or the potential of shared electric mobility in eHUBS (Liao et al., 2024). To date, only limited research has examined how multimodal hubs, and their characteristics, particularly those offering both shared and public transport options, can actively substitute private car use in both urban and regional environments.

This study addresses that gap by providing a comprehensive analysis of how contextual conditions, hub features, and transport mode attributes influence user preferences for multimodal mobility hubs. Using a stated choice experiment (SCE) and collecting data from frequent car drivers, it examines the potential of hubs to substitute private car use, focusing on the influence of integrated services and facilities. By comparing urban and regional hubs, the study provides new insights into how shared mobility and value-adding amenities can enhance hub attractiveness across spatial contexts.

The remainder of the paper first presents the experiment design and sample, followed by the model specification, estimation results, and concludes with key insights and future research directions.

2. Data collection

The data used in this study were collected through a web-based survey administered in March 2023 among frequent car drivers in the Netherlands. Respondents were recruited via a market research company. The survey was structured into several sections, including screening for car ownership and driving frequency, questions about private and shared transport mode usage, a SCE, and socio-demographic information. Attitudinal questions were included but not analysed in this study. The SCE explored whether respondents would switch from their private car to a multimodal mobility hub, and if so, which hub-based mode they would choose. Each task presented a hypothetical trip scenario defined by contextual factors (e.g. weather, purpose, trip distance). Respondents first chose between using their privately owned car vs. the hub; if the hub was selected, they were then asked to choose among shared e-bike, e-scooter, shared car, and public transport (i.e. bus for urban hubs, train for regional ones, reflecting typical service availability). Fig 1 shows an example of the choice task.

You need to travel 7 km for work while it is raining. You also have to do the groceries that day. Would you travel by your own car or via the hub?						
Situation 1: Trip by own car		Situation 2: Traveling via the hub				
Travel time	19 minutes	Distance from home to hub	2 km			
Parking costs	€20	Parking costs if you park your car at the hub	€8			
Fuel costs	€2.31	Transfer time to get to transportation mode	7 minutes			
 Private car		Available transport modes	 Bus	 Shared e-bike	 Shared e-scooter	 Shared car
		Travel time from hub to destination	12 minutes	14 minutes	14 minutes	10 minutes
		Costs for the trip	€3.35	€3.51	€3.51	€5.55
		Arrival frequency per hour	4	Always available	Always available	Always available
		Facilities at the hub	Available (✓) or not available (-)			
		Supermarket	✓			
		Parcel pick-up point	✓			
		Café	-			
		Gym	✓			
		Drugstore and medicine pick-up point	✓			
		Social extended reality office	✓			
		Daycare	✓			

Fig. 1. Example of the choice task in the stated choice experiment for the urban context (translated from Dutch)

Two experimental contexts (urban and regional hubs) were tested using consistent alternatives and attributes, with context-specific level adjustments. The attributes covered four dimensions: trip context, private car characteristics, hub features, and mode-specific variables (Table 1). For the hub-based alternatives, several design elements were introduced to capture the role of service integration, such as transfer time and the presence of specific facilities (e.g. supermarket, parcel pick-up, gym). In particular, the hub journey was modelled in two legs: origin-to-hub and hub-to-destination. The second leg was derived by subtracting the first from the total direct trip distance and applying a detour factor. Mode attributes included per-kilometre tariffs and, for public transport, arrival frequency. While respondents did not see tariff values or the hub–destination distance directly, they were shown the resulting travel cost and time, calculated using mode-specific tariffs and speeds. For the private car, fuel-type-based cost was shown to enhance realism, though not varied experimentally. This setup ensured internal consistency and reduced cognitive load for respondents. Attributes were defined using either 2, 4, or 8 levels. Four levels were used for most attributes to capture potential non-linear effects while keeping the design manageable. A balanced and orthogonal fractional factorial design of 64 rows, blocked into 8 subsets, was used. Respondents were randomly assigned to one block and one hub type.

After data cleaning, the final sample consisted of 888 respondents, with a nearly even split between the urban ($n=441$) and regional ($n=447$) subgroups, yielding 3,528 and 3,576 choice observations, respectively. All respondents were frequent car drivers—defined as driving at least once per week and owning at least one car—resulting in a sample that is not representative of the general Dutch population but highly relevant for the study's focus on car use reduction. In terms of gender, 53% of respondents were male and 47% female, with a slightly higher proportion of men in the urban subsample (55% vs. 50% in the regional). Age distribution was broadly similar across contexts. In the total sample, 12% were aged 18–34, 17% were 35–44, 21% were 45–54, 26% were 55–64, and 24% were over 64. Monthly net income varied, with 14% earning less than €1,667, 24% between €1,668 and €2,500, another 24% between €2,501 and €3,333, and 21% earning more than €3,334. An additional 16% either did not know or preferred not to disclose their income. Those who were assigned to urban hub choice tended to be slightly more represented in the higher income brackets. Educational attainment was consistent across the two subsamples: 13% of respondents reported a low education level, 41% middle, and 46% high. Regarding car use, 25% reported using a private car one to two days per week, 31% three to four days, and 44% five or more days. A large majority (87%) used petrol or diesel vehicles, with only 13% relying on electric, hybrid, or other alternatives. Familiarity with shared mobility services was moderate to high, especially in urban areas. In the total sample, 57% were familiar with (e-)bike sharing, 62% with (e-)scooter sharing, and 67% with (e-)car sharing. Urban respondents reported higher familiarity for each mode, particularly for (e-)bike (60% in urban hub experiment vs. 55% regional hub experiment) and (e-)scooter sharing (64% urban vs. 59% regional).

Table 1. Overview of attributes and attributes levels used in the stated choice experiment

Category	Attribute	Attribute levels
Contextual attributes	Weather	Sun / Rain
	Primary travel purpose	Work / Leisure
	Other activities	Groceries / Picking up a package / Business meeting / Dropping-off-off and picking-up children from daycare
Status quo (private car) attributes	Direct travel distance from origin to destination (km)	Urban: 3 / 7 / 11 / 15 Regional: 10 / 25 / 40 / 55
	Parking costs at destination (€)	0 / 4 / 8 / 12 / 16 / 20 / 24 / 28
Hub attributes	Distance from origin to hub (km)	Urban: 0.5 / 1 / 1.5 / 2
	Distance from origin to hub as percentage of direct distance (%)	Regional: 30 / 40 / 50 / 60
	Detour multiplier (ratio travel distance via hub to OD distance)	0.80 / 1 / 1.20 / 1.40
	Transfer time (min)	1 / 3 / 5 / 7
	Parking costs at hub (€)	0 / 8
	Supermarket	Yes / No
	Parcel pick-up point	Yes / No
	Café	Yes / No
	Day care	Yes / No
	Gym	Yes / No
	Drugstore/medicine pick-up	Yes / No
	Social XR office	Yes / No
Transport mode attributes	Arrival frequency (min): Bus	Urban: 2 / 4
	Arrival frequency (min): Train	Regional: 2 / 4
	Tariff (€/km): Bus	0.13 / 0.17 / 0.21 / 0.25
	Tariff (€/km): Train	0.15 / 0.20 / 0.25 / 0.30
	Tariff (€/km): E-scooter	0.50 / 0.65 / 0.80 / 0.95
	Tariff (€/km): E-bike	0.40 / 0.50 / 0.60 / 0.70
	Tariff (€/km): Shared car	0.51 / 0.66 / 0.81 / 0.96

3. Modelling approach

This study applies an error component mixed logit (EC-MNL) model within the Random Utility Maximization framework (McFadden, 1973) to estimate mode choice behaviour and capture unobserved heterogeneity due to shared characteristics of the four hub-based alternative modes and the two micromobility options available within the hubs. Separate models were estimated for urban and regional contexts to explore potential differences in preferences.

The utility U_{njt} that respondent n assigns to alternative j in choice task t is defined as:

$$U_{njt} = V_{njt} + \varepsilon_{njt} \quad (1)$$

where V_{njt} denotes the systematic utility and ε_{njt} is an independently and identically distributed extreme value type I error term. The systematic utilities are specified as follows:

$$V_{n,SQ,t} = \beta^D D_{nSQ,t} + \gamma Z_n \quad (2)$$

$$V_{njt} = ASC_j + \beta^X X_{njt} + \beta^H H_{nt} + \beta^T T_{njt} + \gamma Z'_n + \sum_p I_{jp} \sigma_p v_{np} \quad (3)$$

In Eq.2, $V_{n,SQ,t}$ represents the utility of the private car alternative; $D_{nSQ,t}$ captures trip-specific attributes (e.g. parking cost at destination, travel distance), and Z_n includes respondent-specific characteristics (e.g. car use frequency, fuel type of their car). For the hub-based alternatives (Eq. 3), ASC_j is an alternative specific constant; X_{njt} includes mode-specific attributes; H_{nt} is the vector of hub-related features; T_{njt} is the vector of contextual variables

and $\mathbf{Z}'_n$ is the vector containing sociodemographic characteristics of respondents. β^X , β^H , β^T and γ are the corresponding vectors of coefficients. The last term in Eq.3 captures error components. $v_{np} \sim N(0,1)$ are standard normal draws, σ_p are standard deviations to be estimated, and I_{jp} are group-specific indicator variables. Two error components are used in the model: one shared across all hub-based alternatives (bus/train, bike, scooter, shared car), and another specific to the micromobility modes (shared e-bike and e-scooter), to account for unobserved similarities within these groups. The estimation accounts for the panel structure of the data by linking repeated observations from each individual through a panel likelihood formulation. Estimation was conducted using Maximum Simulated Likelihood with 500 Halton draws, implemented in Apollo for R (Hess & Palma, 2019).

4. Results

Models were estimated with effect-coded categorical variables and accounted for panel structure. The final specifications, shown in Tables 2 and 3, achieved adjusted ρ^2 values of 0.510 (urban hub) and 0.636 (regional hub). A backward elimination approach was used, starting from a full model and iteratively removing the least significant socio-demographic parameters until only statistically significant ones remained.

The results reveal distinct patterns in the evaluation of private car and hub-based alternatives across urban and regional contexts. In urban areas, car utility declines for short trips and rises for longer ones, while in regional areas, utility peaks at mid-range distances (~40 km) and decreases beyond. Parking costs (which were defined as hypothetical parking cost at the destination) reduce car utility in both contexts, but urban users show a steady sensitivity to increasing fees, whereas regional users respond mainly to high-cost thresholds (e.g. €20). Habitual car use increases preference for private car, while fuel type shows no significant effect. Trip cost was shown to respondents but excluded from the model due to strong correlation with distance.

Table 2. Estimated coefficients (t-values) for private car and multimodal hub attributes in urban (U) and regional (R) contexts. Bold indicates significance at least 10% level.

Private car	Multimodal hub	
	U	R
Distance O-D: Km 3 (U) / 10 (R)	-0,23 (-2,07)	-0,22 (-1,86)
Distance O-D: Km 7 (U) / 25 (R)	-0,21 (-2,31)	-0,01 (-0,06)
Distance O-D: Km 11 (U) / 40 (R)	0,04 (0,39)	0,40 (3,58)
Distance O-D: Km 15 (U) / 55 (R)	0,40	-0,17
Parking €0	1,53 (9,48)	0,89 (5,20)
Parking €4	0,99 (6,53)	0,58 (3,58)
Parking €8	0,50 (3,60)	0,42 (2,62)
Parking €12	0,24 (1,72)	0,98 (5,51)
Parking €16	-0,39 (-3,00)	-0,1 (-0,62)
Parking €20	-0,69 (-5,22)	-0,79 (-5,63)
Parking €24	-1,27 (-9,43)	-0,66 (-4,62)
Parking €28	-0,91	-1,33
Fuel: Diesel	-0,02 (0,18)	-0,03 (-0,14)
Fuel: Other	0,02	0,03
Frequency 1–2 days/week	0,73 (4,38)	0,38 (2,02)
Frequency 3–4 days/week	-0,29 (-1,62)	0,03 (0,15)
Frequency ≥ 5 days/week	-0,44	-0,41
<i>Standard deviations of errors components</i>		
Hub alternatives	2,17 (16,14)	2,39 (14,61)
Micromobility alternatives	1,63 (11,11)	2,66 (9,18)

Preferences for multimodal hub attributes also show some contextual differences. In urban areas, utility peaks at 1 km access distance and declines beyond, indicating a strong sensitivity to proximity. In regional settings, preferences are weaker and less consistent, though a moderate distance is preferred. Free parking significantly increases hub utility

in urban areas, but has little effect regionally. Moreover, in regional settings, the effect of transfer time is approximately linear, with disutility decreasing as transfer durations increase. Only the 1-minute transfer time is statistically significant, suggesting that regional travelers may be more tolerant of walking within hubs, possibly viewing it as an opportunity to engage with hub facilities. In contrast, the urban estimates are more variable and non-linear, with only moderate transfer times (3 minutes) showing a significant negative effect. Facility impacts differ across urban and regional settings. In urban hubs, amenities such as parcel pickup points, gyms, daycare, and a social XR office positively influence utility, suggesting that respondents value services that support quick errands or flexible work. In regional hubs, supermarkets, cafés, gyms, and the XR office are particularly attractive. The consistently strong effect of the XR office, described to respondents as a shared space with extended reality tools for remote collaboration (and illustrated with a reference image), suggests openness to integrating flexible and tech-enabled working environments into hub settings. Conversely, the negative effect of drugstores in regional hubs indicates that not all services contribute equally to perceived hub value.

The significant correlation parameters confirm unobserved similarities across hub-based modes, with a distinct additional correlation between shared micromobility options, reflecting their perceived similarity by users.

Table 3 shows that alternative-specific constants are negative and highly significant for all hub-based modes, indicating a strong baseline preference for private car use. The strongest disutility is found for micromobility (especially in regional areas), suggesting limited substitution potential in less dense settings.

Contextual factors significantly shape preferences. Sunny weather increases the utility of micromobility modes, especially in urban areas and consistent with prior research on weather sensitivity (Curtale and Liao, 2023), while train use also benefits from sunny weather in regional settings. In contrast, work-related travel lowers the likelihood of choosing hub alternatives in urban areas, with negligible effects in regional contexts. Secondary activities matter: business meetings consistently raise utility across modes and settings, suggesting value in integrating professional tasks via hubs. Grocery shopping encourages train and e-bike use in regional areas but lowers shared e-car utility in urban settings. Parcel pickup and daycare trips generally reduce the appeal of shared options, with the exception of shared car use in regional hubs, which may offer greater flexibility. As expected, longer detours via the hub reduce utility, with significant negative effects for bus and shared e-car in urban areas and shared e-bike in regional areas, confirming that added travel time decreases the appeal of hub-based modes. To improve clarity and avoid collinearity with trip cost and distance, detour was modelled as a binary variable (longer vs. equal/shorter), simplifying interpretation. Arrival frequency significantly increases utility only for regional trains, indicating greater sensitivity to wait times in low-frequency settings. Lastly, higher trip costs consistently lower the likelihood of choosing hub alternatives, confirming cost sensitivity. It is important to note that trip cost was specified as a generic coefficient across hub-based alternatives to avoid multicollinearity, particularly since cost was derived from distance and per-kilometre tariffs. Initially, mode-specific tariff levels were included in the model to reflect pricing heterogeneity, but they were subsequently removed due to statistical insignificance and limited interpretability.

Sociodemographic effects reveal clear age-related patterns. For regional train, utility declines linearly with age, while urban bus shows a weaker trend, i.e. significantly negative for the 55–64 group, but increasing again for 65+. Shared e-bikes are strongly preferred by the youngest users, especially in regional settings, while urban shared scooters show a sharp decline in preference with age, echoing prior findings on micromobility adoption (Van Der Meer et al., 2023). Education shows a consistent influence on mode preferences. Higher education is linked to greater utility for regional train, shared e-bike (both contexts), and urban shared car, likely reflecting openness to innovative or sustainable options. For urban bus, the middle education group shows the strongest effect. Overall, preferences decline for individuals with lower education levels, in line with prior findings suggesting that this group may be less inclined to adopt shared or public transport modes (Bösehans et al., 2023). Income effects are more mode-specific: medium-income individuals prefer regional trains and shared cars, while low-income respondents are less inclined to use shared scooters in urban contexts.

5. Conclusions

This study explored frequent car users' preferences for mobility hub alternatives in urban and regional settings using a SCE and EC-MNL model. Results highlight the need for both push measures (e.g. parking costs) and pull strategies (e.g. better hub access and integrated services) to reduce car reliance.

Table 3. Estimated coefficients (t-values) for public transport and shared mobility modes in urban (U) and regional (R) contexts. Bold indicates significance at least 10% level.

	Public transport		Shared e-bike		Shared e-scooter		Shared e-car	
	U (Bus)	R (Train)	U	R	U	R	U	R
ASC	-2,12 (-8,87)	-3,04 (-12,33)	-2,87 (-10,01)	-6,33 (-13,64)	-4,43 (-13,17)	-7,28 (-13,58)	-2,36 (-7,82)	-3,86 (-13,19)
Weather: Sun	0,02 (0,38)	0,15 (2,26)	0,68 (8,7)	0,53 (4,15)	0,48 (3,28)	0,51 (2,8)	-0,08 (-0,92)	0,03 (0,35)
Weather: Rain	-0,02	-0,15	-0,68	-0,53	-0,48	-0,51	0,08	-0,03
Main purpose: Work	-0,10 (-1,55)	0,00 (0,004)	-0,15 (-2,07)	0,01 (0,11)	-0,1 (-0,72)	-0,13 (-0,73)	-0,24 (-2,77)	0,00 (0,01)
Main purpose: Leisure	0,10	0,00	0,15	-0,01	0,10	0,13	0,24	0,00
Other activities: Grocery	-0,16 (-1,40)	0,3 (2,67)	-0,02 (-0,19)	0,53 (2,62)	-0,4 (-1,51)	0,14 (0,44)	-0,28 (-1,79)	0,02 (0,12)
Other activities: Picking up a package	0,00 (0,01)	-0,11 (-0,94)	0,03 (0,21)	-1,02 (-4,00)	0,27 (1,16)	-0,42 (-1,31)	-0,31 (-1,96)	-0,23 (-1,34)
Other activities: Business meeting	0,68 (6,17)	0,35 (3,08)	0,63 (4,89)	0,52 (2,58)	0,83 (3,57)	0,29 (1,02)	0,82 (5,79)	0,16 (0,95)
Other activities: Daycare	-0,54	-0,54	-0,63	-0,02	-0,70	-0,01	-0,23	0,05
Detour: Longer	-0,18 (-2,73)	-0,1 (-1,45)	-0,06 (-0,82)	-0,37 (-2,9)	0,17 (1,2)	-0,16 (-0,89)	-0,18 (-2,03)	0,09 (0,85)
Detour: Equal or shorter	0,18	0,10	0,06	0,37	-0,17	0,16	0,18	-0,09
Arrival frequency: 2 min	0,02 (0,43)	0,17 (2,73)	-	-	-	-	-	-
Arrival frequency: 4 min	-0,02	-0,17	-	-	-	-	-	-
Trip cost (€)	-0,14 (-5,93)	-0,04 (-3,34)	-0,14 (-5,93)	-0,04 (-3,34)	-0,14 (-5,93)	-0,04 (-3,34)	-0,14 (-5,93)	-0,04 (-3,34)
Age: 18 - 34 year	0,13 (0,71)	0,86 (3,87)	0,34 (1,17)	0,85 (2,19)	1,33 (3,39)	-	-	-
Age: 35 - 44 year	0,24 (1,48)	0,39 (2,11)	0,13 (0,48)	-0,26 (-0,77)	1,3 (3,76)	-	-	-
Age: 45 - 54 year	-0,14 (-0,95)	-0,15 (-0,87)	-0,01 (-0,03)	0,16 (0,52)	0,45 (1,31)	-	-	-
Age: 55 - 64 year	-0,52 (-3,48)	-0,37 (-2,19)	-0,64 (-2,51)	0,43 (1,3)	-1,67 (-3,39)	-	-	-
Age: > 64 year	0,29	-0,73	0,18	-1,17	-1,41	-	-	-
Education: Higher	0,35 (2,02)	0,35 (2,53)	0,92 (4,78)	0,82 (3,31)	-	-	0,42 (2,22)	-
Education: Middle	0,45 (2,65)	-0,13 (-0,96)	0,19 (0,99)	0,06 (0,25)	-	-	0,29 (1,53)	-
Education: Lower	-0,80	-0,22	-1,10	-0,88	-	-	-0,71	-
Income: < 1667 €	-	-0,54 (-1,74)	-	-	-1,05 (-2,36)	0,63 (1,24)	-	-0,56 (-1,52)
Income: 1668 - 2500 €	-	0,57 (2,49)	-	-	0,05 (0,16)	0,55 (1,41)	-	0,97 (3,83)
Income: 2501 - 3333 €	-	0,32 (1,32)	-	-	0,1 (0,39)	1,55 (4,05)	-	0,09 (0,32)
Income: >= 3334 €	-	-0,18 (-0,70)	-	-	0,47 (1,57)	-1,62 (-1,89)	-	-0,62 (-1,95)
Income: don't know/prefer not to say	-	-0,17	-	-	0,43	-1,11	-	0,12

Preferences vary by context and user profile, with younger, highly educated, and mid-income individuals more receptive to shared modes. These findings suggest that designing urban and regional hubs require specific customization

in terms of hubs features and location optimization, as our results suggest differences in preference for users of this two different hubs. While the experimental design helped understand key decision drivers, certain limitations remain. First, the current model assumes a simultaneous evaluation of all five alternatives, while in practice, users may follow a sequential decision-making process, such as first deciding whether to use the hub at all, then choosing among the hub-based modes. Second, while using a generic price coefficient and a simplified detour dummy improved model stability, it may have constrained behavioral richness. Finally, unfamiliarity with the concept of multimodal hubs could have influenced stated preferences. Future research will explore Latent Class Models to investigate whether distinct decision-making heuristics are applied (e.g. hub-first versus mode-first strategies). Additionally, Hybrid Logit Models could incorporate latent constructs to better explain users preferences. These modeling extensions will deepen insights and support the design of more user-responsive multimodal mobility hubs.

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References

- Bell, D. (2019). Intermodal mobility hubs and user needs. *Social Sciences*, 8(2).
- Blad, K., de Almeida Correia, G. H., van Nes, R., & Annema, J. A. (2022). A methodology to determine suitable locations for regional shared mobility hubs. *Case studies on transport policy*, 10(3), 1904–1916.
- Bösehans, G., Bell, M., Thorpe, N., Liao, F., Homem de Almeida Correia, G., & Dissanayake, D. (2023). eHUBs—Identifying the potential early and late adopters of shared electric mobility hubs. *International Journal of Sustainable Transportation*, 17(3), 199–218.
- Burlando, C., Ivaldi, E., Parra Saiani, P., & Penco, L. (2019). To own or not to own? Car ownership and consumer awareness: Evidence from an Italian survey. *Research in Transportation Business and Management*, 33.
- Curtale, R., & Liao, F. (2023). Travel preferences for electric sharing mobility services: Results from stated preference experiments in four European countries. *Transportation Research Part C: Emerging Technologies*, 155, 104321.
- Daisy, N. S., Millward, H., & Liu, L. (2018). Trip chaining and tour mode choice of non-workers grouped by daily activity patterns. *Journal of Transport Geography*, 69, 150–162.
- Fan, Y., Guthrie, A., & Levinson, D. (2016). Waiting time perceptions at transit stops and stations: Effects of basic amenities, gender, and security. *Transportation Research Part A: Policy and Practice*, 88, 251–264.
- Frank, L., Dirks, N., & Walther, G. (2021). Improving rural accessibility by locating multimodal mobility hubs. *Journal of Transport Geography*, 94.
- Hess, S., & Palma, D. (2019). Apollo: A flexible, powerful and customisable freeware package for choice model estimation and application. *Journal of choice modelling*, 32, 100170.
- Hunecke, M., Richter, N., & Heppner, H. (2021). Autonomy loss, privacy invasion and data misuse as psychological barriers to peer-to-peer collaborative car use. *Transportation Research Interdisciplinary Perspectives*, 10.
- Hyland, M., Frei, C., Frei, A., & Mahmassani, H. S. (2018). Riders on the storm: Exploring weather and seasonality effects on commute mode choice in Chicago. *Travel Behaviour and Society*, 13, 44–60.
- Kent, J. L. (2014). Driving to save time or saving time to drive? The enduring appeal of the private car. *Transportation research part A: policy and practice*, 65, 103–115.
- Le, H. T. K., Buehler, R., Fan, Y., & Hankey, S. (2020). Expanding the positive utility of travel through weeklong tracking: Within-person and multi-environment variability of ideal travel time. *Journal of Transport Geography*, 84.
- Liao, F., Tian, Q., Arentze, T., Huang, H. J., & Timmermans, H. J. (2020). Travel preferences of multimodal transport systems in emerging markets: The case of Beijing. *Transportation Research Part A: Policy and Practice*, 138, 250–266.
- Liao, F., Dissanayake, D., & de Almeida Correia, G. H. (2024). Modelling the complementarity and flexibility between different shared modes available in smart electric mobility hubs (eHUBS). *Transportation Research Part A: Policy and Practice*, 190, 104279.
- McFadden, D. (1972). Conditional logit analysis of qualitative choice behavior.
- Schakenbos, R., Paix, L. La, Nijenstein, S., & Geurs, K. T. (2016). Valuation of a transfer in a multimodal public transport trip. *Transport Policy*, 46, 72–81.
- Van Der Meer, R., Leferink, T., Geržinič, N., Annema, J. A., & van Oort, N. (2023). Identifying potential use of emerging neighbourhood mobility hubs using behavioural modelling. In 8th International Conference on Models and Technologies for ITS.
- Witte, J.-J., Alonso-González, M., & Rongen, T. (2021). Kennisinstituut voor Mobiliteitsbeleid | KiM Verkenning van het concept mobiliteitshub.