14th Symposium of the European Association for Research in Transportation

Behavioral Determinants of Ridesharing Participation: Policy and Platform Design Implications

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SHORT SUMMARY

Despite its potential to reduce congestion, peer-to-peer ridesharing adoption remains limited, pointing to an incomplete understanding of the behavioral determinants shaping travelers' willingness to participate. To address this, the present study develops a stated preference survey to estimate willingness to engage in ridesharing as drivers or passengers under varying attributes. Findings indicate that students and academically educated commuters are more likely to rideshare, whereas higher income and flexible arrival times are associated with lower passenger participation. Additional time burdens like detours, walking, and waiting generate greater disutility than origin-to-destination travel time. Drivers are less sensitive to time and fuel costs when driving alone, but these factors become salient when considering ridesharing with a passenger, suggesting role-specific behavioral barriers. Results imply that platforms should prioritize matching algorithms that minimize detours, access, and waiting times. From a policy perspective, driver-targeted incentives can strengthen supply, while effective passenger-focused mechanisms remain an open challenge.

Keywords: Incentives | Mode choice modeling | Ridesharing | Shared mobility | Stated-preference data

1. INTRODUCTION

Despite decades of policy efforts, most metropolitan commute trips still occur in single-occupancy vehicles, contributing to congestion and emissions (Kay et al., 2013). Transit and active modes offer sustainable alternatives but are not feasible for all trips. As an intermediate alternative, ridesharing—defined as the shared use of a private vehicle by two or more travelers with similar origins, destinations, and departure times—has regained attention for its potential to improve seat utilization (Shaheen and Cohen, 2019). However, the factors influencing travelers' willingness to participate in ridesharing remain insufficiently understood.

The present study focuses on peer-to-peer ridesharing, as distinct from commercially operated services like ride-hailing. Ridesharing can yield environmental and social benefits as it utilizes existing trips (with minor detours) rather than generating new vehicle travel (Yao and Bekhor, 2021). Yet ridesharing adoption remains limited, partially due to technical challenges like coordination and scheduling (Shoshany-Tavory et al., 2020). Digital ridesharing platforms (e.g., *Scoop*) mitigate these challenges by designing algorithms that efficiently match drivers and passengers, but their market penetration remains limited (Kang et al., 2024; Mitropoulos et al., 2021). This limited success may reflect travelers' low willingness to share rides and the insufficient alignment of matching mechanisms with user preferences (Lavieri and Bhat, 2019). Thus, understanding travelers' behavioral determinants—who participates, in what role (driver/passenger), and under which conditions—is critical to increasing adoption.

Stated preference (SP) surveys have been widely employed to examine travelers' willingness to participate in ridesharing (Su et al., 2026). In SP surveys, respondents are presented with hypothetical travel scenarios and are asked to choose among alternatives. This enables the direct isolation of specific factors affecting travel behavior and the examination of user preferences for emerging and/or infrequently used mobility alternatives, such as ridesharing, for which revealed preference (RP) data remain scarce (Yang et al., 2009).

Existing studies identify three main groups of influencing factors for ridesharing participation: individual, trip-related, and system factors (Mitropoulos et al., 2021). For individual factors, ridesharing participants tend to be younger and single or married without children (Tahmasseby et al., 2016). Evidence on income effects is mixed: some studies associate ridesharing with lower-income groups (Bulteau et al., 2019), while others find higher adoption among higher-income individuals (Neoh et al., 2017). Gender also plays a role, as women's participation depends on perceived security (Ciari and Axhausen, 2012). Trip-related factors include purpose, distance, and spatiotemporal characteristics. In fact, ridesharing is most common for longer-distance commute trips (Lee et al., 2016). Finally, system factors include platform design characteristics (e.g., pricing schemes, user experience) and external incentives (e.g., parking benefits, financial incentives; Olsson et al., 2019).

Despite this growing body of research, behavioral modeling of ridesharing remains challenging due to the interdependence of supply and demand. Unlike traditional mode choice contexts, each potential traveler in ridesharing may act as either a passenger, a driver, or opt out. The resulting feedback between traveler decisions and platform performance further complicates analysis and policy design. Recent studies have begun addressing these complexities by incorporating behavioral realism into ridesharing modeling, such as rejection and cancellation behaviors (Fielbaum et al., 2024; Yao and Bekhor, 2022). Yet many important behavioral aspects remain underexplored. Although it is well established that travelers seek to minimize time and cost, their responses to specific time and cost components, and the relationships between them, are still insufficiently understood. Key open questions include how critical detour time is for a driver's willingness to pick up a passenger, how sensitive passengers are to walking and waiting times compared with those of public transportation (PT), and the importance of the driver–passenger cost-sharing split. Addressing these questions requires further empirical investigation.

The present study aims to promote the understanding of travelers' willingness to participate in ridesharing rather than drive alone, and to examine the factors influencing their choice of role as either

driver or passenger. Using SP data and a choice modeling approach, we strive to identify the role of several key behavioral determinants of participation, with particular attention given to the relative importance of time and cost attributes. Specifically, we investigate how different time components (namely, detour time, walking and waiting time, and parking search time) affect the probability of ridesharing choices. Similarly, we examine the effects of cost-related components (namely, fuel and parking costs) as well as incentives on travelers' decisions to share rides. By examining travelers' mode choice for commute trips as a function of these attributes, we aim to deepen our understanding of ridesharing behavior. This improved understanding is expected to support more effective and informed policy and platform design, enabling the development of ridesharing matching mechanisms and incentive schemes that can increase uptake, promote more sustainable mobility choices, and ultimately reduce congestion.

2. METHODOLOGY

An SP survey was developed to collect respondents' hypothetical mode choices for their regular commute. The questionnaire consisted of three components: (a) socio-demographic characteristics (gender, age, employment, education level, living situation, etc.); (b) a revealed preference (RP) section capturing current commute behavior (typical mode, travel time, arrival time flexibility, mode use frequency, etc.); and (c) the SP scenarios. Participation was restricted to adults who (i) commute to work or school, (ii) hold a valid driver's license, and (iii) have a one-way commute travel time between 10 and 40 minutes, ensuring that all respondents could realistically choose among the alternatives presented. Participants were recruited across Israel, with a quota of 40% for residents of the Tel-Aviv metropolitan area to ensure adequate representation of travelers from the country's most congested region.

In the SP experiment, each respondent was presented with six scenarios in which she had to select one of four alternative modes: driving alone, ridesharing (RDSH) as a driver, ridesharing as a passenger, or PT. The experimental design included seven attributes (i.e., independent variables) grouped into three categories:

- **Travel time components** included basic time (in-vehicle origin-to-destination time), detour time (for ridesharing drivers to pick up a passenger), walking and waiting time (for ridesharing and PT passengers), and parking search time (for drivers). In-vehicle time was pivoted around the respondent's self-reported typical commute time. Travel time for the ridesharing alternatives was occasionally reduced to reflect the use of HOV lanes.
- **Travel cost components** included fuel cost or PT fare, and parking fees. Ridesharing drivers and passengers split fuel costs unevenly (60% allocated to drivers and 40% to passengers; or vice versa).
- **Incentives** included:
    - For drivers: no incentive, voucher for coffee-and-pastry, priority parking (operationalized as reduced cost and parking search time), or bonus payment (surge pricing).
    - For passengers: no incentive, voucher for coffee-and-pastry, or a free ride every ten trips.

Attribute levels were assigned across scenarios following a randomized experimental design to ensure sufficient variation and minimize correlations among attributes, while ensuring all combinations were realistic and meaningful. See **Figure 1** for an example of one SP scenario.

	Drive Alone	Ridesharing Driver	Ridesharing Passenger	Public Transport
				
Total travel time	**27 min**	**28 min**	**38 min**	**37 min**
Basic time	25	25	25	30 (HOV)
Detour time	-	3	-	-
Walking and waiting	-	-	13	7
Parking search	2	0	-	-
Total travel cost	**57 NIS**	**36 NIS**	**15 NIS**	**8 NIS**
Fuel/ticket costs	37	22	15	8
Parking fees	20	14	-	-
Incentive	-	Priority parking	Voucher for coffee and pastry	-

Figure 1. Example of an SP scenario displaying the four alternative modes and their associated attributes - time, cost, and incentives.

The survey was programmed in *Qualtrics* online survey platform and distributed through a panel provider. Two comprehension check questions were included to verify that respondents understood the concept of ridesharing and associated benefits.

Using the SP data collected, we estimated discrete choice models to quantify preferences and trade-offs underlying ridesharing participation. A mixed logit (ML) model with a panel specification was estimated to account for unobserved heterogeneity and correlation across the six choices provided by each respondent. Nested logit (NL) models with several different nesting structures were estimated to test for correlated alternatives.

3. RESULTS

Data collection was conducted in July 2025, yielding 363 complete survey responses. Following data cleaning, during which responses exhibiting two or more indicators of inconsistent or non-credible behavior were excluded, the final sample consisted of 325 valid responses. Mean survey completion time was 9.6 minutes (SD = 2.5). The sample was almost evenly split by gender (164 females; 161 males) with an average age of 43.5 years (SD = 15.0). A large majority of respondents (89.6%) reported having frequent/consistent access to a car. For the typical RP mode choice, 71% reported commuting as car drivers, 5% as car passengers, and 18% by PT. Reported RP commute times averaged 24.8 minutes (SD = 9.6). All alternatives in the SP scenarios were chosen with sufficient frequency to support model estimation (25% drive-alone, 19% PT, 23% ridesharing driver, and 33% ridesharing passenger). To analyze participants' SP choices, we first estimated a ML model with a panel-specific error component to study sensitivities of the different factors. All models were estimated using *PandasBiogeme* software (Bierlaire, 2023). **Table 1** presents the estimation results for the ML model.

Table 1. Mixed logit estimates for commute mode choice (t-statistics in parentheses; coefficients with |t| < 1.5 shown in gray).

	Drive alone	**RDSH driver**	**RDSH passenger**	**PT**
Alternative specific constant	--	**0.473** (0.585)	**2.780** (3.75)	**1.850** (2.16)
Panel error component	**2.500** (14.70)			
Individual characteristics				
	Drive alone	**RDSH driver**	**RDSH passenger**	**PT**
Female*	-	**0.175** (0.43)	**-0.466** (1.10)	**-0.694** (1.66)
High income*	-	**-0.415** (0.90)	**-0.732** (1.56)	**-0.702** (1.49)
Student*	-	**1.490** (2.46)	**1.030** (1.25)	**-0.412** (0.55)
Academic*	-	**1.270** (3.06)	**1.160** (2.72)	**0.226** (0.52)
Flexible arrival time*	-	**-0.493** (1.02)	**-0.875** (1.64)	**-0.882** (1.62)
Choice inertia				
	Drive alone	**RDSH driver**	**RDSH passenger**	**PT**
Commute by PT on RP*	-	-	-	**1.960** (3.21)
Commute as car driver on RP*	**1.390** (2.83)	**1.420** (3.83)	-	-
Commute as car passenger on RP*	-	-	**-1.400** (1.33)	-
High frequency bus use on RP*	-	-	-	**1.470** (2.94)
High frequency train use on RP*	-	-	-	**0.633** (1.04)
High frequency car driver on RP*	**1.280** (2.09)	-	-	-

Time coefficients				
	Drive alone	**RDSH driver**	**RDSH passenger**	**PT**
Basic time	**-0.033** (1.16)	**-0.051** (2.76)	**-0.052** (3.47)	**-0.070** (6.73)
Detour time * Has children	-	**-0.288** (2.18)	-	-
Walking & waiting time	-	-	**-0.119** (8.09)	**-0.110** (5.65)
Parking search time	**-0.038** (1.53)	**-0.084** (4.03)	-	-
Cost coefficients				
	Drive alone	**RDSH driver**	**RDSH passenger**	**PT**
Fuel/ticket cost	**-0.030** (1.52)	**-0.063** (4.37)	**-0.057** (4.54)	**-0.113** (2.33)
Fuel/ticket cost * Own a hybrid/electric car	**-0.0003** (0.03)	**0.023** (1.53)	-	-
Parking cost	**-0.021** (5.22)	**-0.055** (5.80)	-	-
Incentives				
	Drive alone	**RDSH driver**	**RDSH passenger**	**PT**
Voucher for coffee and pastry*	-	**0.863** (3.68)	**0.039** (0.251)	-
Priority parking*	-	**0.581** (1.91)	-	-
Bonus payment*	-	**0.77** (2.91)	-	-
# observations	1,950			
Initial Log-likelihood	-2,182.192			
Final Log-likelihood	-1,889.137			

*Dummy Variable

As shown in Table 1, the estimated panel error component is highly significant, suggesting meaningful unobserved heterogeneity across individuals. Two individual characteristics are positively associated with the probability of choosing to rideshare, namely having an academic education and being a student. In contrast, individuals with higher incomes and those who report flexible arrival time at their destination are less likely to rideshare as passengers. Age, employment status, vehicle availability, and other individual characteristics are not found to significantly influence the likelihood of choosing to rideshare. Further, strong choice inertia effects are observed among car drivers and PT users, indicating a tendency to retain habitual behavior rather than switch to new (ridesharing) alternatives. Consistent with this pattern, current car drivers are more likely to select the driver's role in ridesharing.

All time coefficients are negative and significant for the ridesharing and PT alternatives. In contrast, basic (origin-to-destination) time is not significant for the drive-alone alternative (although significant for the ridesharing driver alternative). This suggests that solo drivers may be less sensitive to time unless they consider taking on a ridesharing passenger. The interaction term between detour time and having children is negative and substantial in magnitude, indicating that parents are particularly sensitive to detour time. Moreover, the coefficients for parking search time (for ridesharing drivers) and for walking and waiting time (for ridesharing passengers) are approximately twice as large as the basic travel time coefficient, as expected. These relative magnitudes suggest that users are especially sensitive to additional time burdens, such as detours, walking, and waiting, compared to in-vehicle travel time.

A similar pattern emerges for the fuel/ticket cost coefficients, which are larger and more robust for the ridesharing and PT alternatives, while the effect is weaker for the drive-alone alternative. This suggests that cost considerations become more salient when individuals evaluate shared travel alternatives rather than driving alone. Notably, parking cost is the only cost component that is significant for the drive-alone alternative, possibly due to its direct out-of-pocket nature. In addition, individuals who own a hybrid/electric vehicle exhibit an attenuated sensitivity to travel costs when considering ridesharing as drivers, indicating a lower marginal disutility of cost compared to owners of conventional vehicles. Although fuel cost was specified as an absolute value independent of vehicle type, respondents who own a hybrid/electric vehicle may have discounted its relevance, as it is less salient in their daily travel experience. A dummy variable capturing the uneven cost split between ridesharing driver and passenger is not significant in this model, likely due to correlation with the other cost coefficients. However, it shows the expected significant disutility when no additional explanatory variables are included.

As for the incentives evaluated, the coffee-and-pastry voucher, priority parking, and bonus payment all exhibit meaningful positive effects on the likelihood of choosing to rideshare as a driver, indicating their potential effectiveness in encouraging driver participation. However, the incentive of a free ride every ten trips had a negligible effect on the utility of the ridesharing passenger and was therefore excluded from the model. Similarly, the coffee-and-pastry voucher does not have a significant effect on the likelihood of choosing the ridesharing passenger alternative.

Four NL structures were examined to test for correlation across behaviorally related alternatives (number of nest alternatives shown in parentheses):

1. Driver nest (2); passenger nest (2).
2. Car-based nest (3); PT nest (1).
3. Travel-with-others nest (3); travel-alone nest (1).
4. Ridesharing nest (2); drive-alone nest (1); PT nest (1).

None of the estimated nesting parameters were statistically different from 1 ($\lambda \approx 1$), indicating no evidence of correlated unobserved utility across alternatives. This result implies that the ML specification adequately captures choice behavior without additional nesting structures.

4. DISCUSSION

The present study provides various behavioral insights into commuters' willingness to participate in ridesharing based on SP data. First, individuals with academic education and students are more likely to rideshare, whereas higher-income individuals and those reporting flexible arrival times are less inclined to do so as passengers. Second, the additional time requirements associated with ridesharing (e.g., detours, walking and waiting, parking search) play a central role in mode choice, generating greater disutility than the actual origin-to-destination travel time. In particular, parents demonstrate elevated sensitivity to detour time. Third, drivers are less sensitive to time and fuel costs when driving alone than when considering ridesharing with a passenger.

The observed asymmetry between solo driving and ridesharing in drivers' sensitivity to time and cost attributes provides additional insight into their decision-making processes. This pattern may reflect behavioral mechanisms such as increased salience and mental accounting, whereby costs and time become more psychologically prominent when explicitly linked to sharing with others (Thaler, 1985). The prospect of coordination and social interaction may therefore amplify perceived burdens relative to solo driving, leading costs to be evaluated in more context-dependent terms rather than strictly according to normative economic value.

The present findings carry important implications for ridesharing platform design. Given the high sensitivity to detours, access and waiting times, the success of ridesharing platforms depends critically on efficient matching algorithms that minimize additional time requirements for both drivers and passengers. Reducing detour times, improving pickup-point coordination, and limiting waiting times are likely to have a substantial impact on participation. Future research can investigate how trade-offs between passenger walking time and driver detour time affect participation.

From a policy perspective, the results indicate that driver participation can be effectively encouraged through targeted incentives such as vouchers, bonus payments (e.g., surge pricing), and parking priority. These mechanisms directly address the additional burdens associated with providing rides and can help strengthen the supply side of the ridesharing market. In contrast, the lack of significant passenger-focused incentives suggests that encouraging the demand side might be more complex. It is possible that, relative to the PT alternative, ridesharing is already sufficiently attractive to passengers, reducing the marginal impact of additional rewards. Identifying mechanisms that meaningfully increase passenger participation (if needed at all) remains an important direction for future research.

Although based on data from a specific national context, the findings identify systematic behavioral patterns that offer insights for ridesharing policy and platform design beyond the local setting. Due to the scarcity of real-world (RP) data on ridesharing, the present analysis relies on users' stated choices under hypothetical yet controlled scenarios that enable the systematic examination of key behavioral determinants. Future research should examine the extent to which these behavioral patterns persist in real-world settings, using the limited RP data currently available.

This study demonstrates that successful ridesharing implementation requires differentiated strategies that address the distinct preferences of both drivers and passengers. Designing policies and platforms that effectively balance driver supply with passenger demand is critical for achieving stable and sustainable ridesharing adoption.

ACKNOWLEDGEMENTS

The authors gratefully acknowledge support from the Israel Science Foundation (ISF), Grant No. 2071474.

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