Competition between Emerging and Conventional Transportation Modes: A Context-Dependent Analysis

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SHORT SUMMARY

Driven by advances in information technology, the sharing economy has rapidly expanded in the transportation sector. New demand has been identified and addressed by modes such as ride-sourcing and car-sharing, while travelers and the market remain in transition. This study explores travelers' mode choice preferences under the competition between emerging and conventional modes. A stated choice experiment was conducted in Northeast China, resulting in 337 valid responses, and a random parameter error component model was estimated. The results indicate that emerging and conventional modes form distinct groups with shared unobserved components. More importantly, their relationship is condition-dependent rather than uniform. Conventional modes dominate under structured conditions, while emerging modes become more competitive in flexible contexts. This suggests that emerging modes act as conditional competitors rather than direct substitutes. Competition across modes is asymmetrical, and socio-demographic factors such as income and familiarity with ride-sourcing further shape mode preferences.

Keywords: Ride-sourcing, Mode choice, Context effect

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1. INTRODUCTION

New transport modes associated with internet technology, such as ride-sourcing and car-sharing, are emerging and increasingly reshaping urban travel demand. These app-based services provide passengers with flexible schedules, instant matching, and diverse service options through mobile platforms. Benefiting from these features, emerging modes compete with conventional modes such as taxis and may show advantages under specific conditions, providing passengers with more choices to match their travel needs.

Although ride-sourcing and car-sharing have existed for over two decades, their rapid development has mainly been driven by the spread of smart mobile technologies (Chan & Shaheen, 2012; Correia & Antunes, 2012). These modes are expected to reduce private car use and contribute to mitigating congestion and emissions (Kent, 2014; Jin et al., 2018). However, existing studies show that the user groups of emerging and conventional modes largely overlap (Rayle et al., 2016), suggesting that passengers' preferences across different travel contexts are not yet fully understood. In particular, it remains unclear under what conditions emerging modes gain advantage over conventional modes and how these modes interact with each other. Despite the long-term impacts of COVID-19 on travel behavior, the relative relationships between modes remain largely stable due to their fundamental characteristics (Loa et al., 2022). Therefore, further research is needed to better understand travelers' mode choice behavior under different conditions.

This study aims to explore travelers' preferences in mode choice under the competition between emerging modes (ride-sourcing and car-sharing) and conventional modes (taxis and public transport). Both trip characteristics and mode attributes are incorporated in a stated choice experiment, where contextual variables are used to structure the decision environment. In addition to these factors, socio-demographic characteristics and prior travel experience are considered. A mixed logit model with error components is estimated to capture correlations within emerging and conventional modes. The findings provide insights into how travelers match mode characteristics with their travel needs and how different modes compete under varying conditions.

2. METHODOLOGY

Experiment Design

To analyze transportation mode choice behavior, respondents' socio-demographic characteristics (e.g., age and gender), household characteristics (e.g., household size and composition), and prior experience with ride-sourcing were collected. Additional factors include transportation expenditure and car ownership. Respondents were asked to recall their transportation costs in the previous year and report their experience with ride-sourcing. For those who had used ride-sourcing services, information on usage frequency in the past month and average waiting time was collected.

Travel context and alternative-specific attributes were assumed to influence mode choice. As shown in Table 1, four contextual variables were included: time slot, travel purpose, companion, and travel distance. Time was categorized into four periods, which may also reflect perceived safety (Nguyen-Phuoc et al., 2021). Travel purpose included work or study, returning home, shopping and leisure, and trips to other cities. Companion was defined as travelling alone, with a stranger, an acquaintance (e.g., co-workers), or an intimate person (e.g., family members or close friends). Travel distance included four levels ranging from 5 to 20 km.

Table 1 Selected attributes and attributes levels

Attributes	Attributes level
Contextual attributes	
Time slot	Peak time (6am-9am & 4:30pm-7:30pm)
	Daytime (9am-4:30pm)
	Evening (7:30pm-11pm)
	Mid-night (11pm-6am (+1))
Travel purpose	Work or study; transfer to other city; shopping or leisure; go home
Companion	Intimate people; acquaintances; strangers; alone
Destination distance	5 km; 10km; 15 km; 20 km
Travel mode attributes	
Driving time	15 min; 30 min; 45 min; 60 min
Service level [Ride-sourcing]	Professional service;
	Use clean energy vehicle;
	Plentiful riding sources and extensive coverage area;
	Multiform life services
Type of vehicle [Ride-sourcing & Car-sharing]	Economy; Comfort; Business; Luxury
Access time	5 min; 10 min; 15 min; 20 min
Estimated costs	[Ride-sourcing] CNY 1.5/km; CNY 2/km; CNY 2.5/km; CNY 3/km
	[Car-sharing] CNY 1/km; CNY 1.5/km; CNY 2/km; CNY 2.5/km
	[Mass transit] CNY 1; CNY 2; CNY 3; CNY 4
	[Taxi] CNY 2/km; CNY 2.5/km; CNY 3/km; CNY 3.5/km

The experiment aims to examine choice behavior between emerging and conventional modes. Four motorized public transportation modes were included: two emerging modes—ride-sourcing (RS) and car-sharing (CS), and two conventional modes, taxi (TA) and mass transit (MT). Car-sharing differs from ride-sourcing and taxis in that users rent and drive the vehicle themselves. Non-motorized and private modes were excluded, while an "other" option was included to ensure a complete choice set.

Emerging modes provide differentiated service levels compared to conventional taxis. Vehicle type, ranging from economy to luxury, was included for both ride-sourcing and car-sharing, with cost rate varying independently to examine price sensitivity across vehicle types. Service attributes were specified for ride-sourcing only. Based on existing practices (Mo et al., 2020), four service levels were considered: professional service (full-time drivers with standardized service), use of clean energy vehicles, plentiful service supply with wide coverage, and multiform life services (e.g., food delivery or other platform services). All attributes were specified at four levels. A fractional factorial design was applied, generating 128 profiles from 17 attributes. Each respondent was presented with four randomly selected choice scenarios.

Model specification

An error component logit model with random parameters was estimated to capture individual's transportation mode choice behavior and the heterogeneity in driving time preferences between different respondents. Five transportation modes are distinguished: U_{RS}, U_{CS}, U_{PT}, U_{TA} and U_{OTH} are the utility of respectively ride-sourcing, car-sharing, taxi, mass transit and other. Two error components W_m ($m = 1, 2$) are specified and correspondingly named W_{cov}, W_{emg} for respectively the group of emerging modes, conventional modes. These error components are assumed normally distributed with zero mean and $Var[W_m] = \theta_m^2$, the standard deviation θ_m of the m^{th} error component is to be estimated. The utility for each option in situation s of individual n can be written as

$$U_{RS} = \boldsymbol{x}_{RS}\boldsymbol{\beta} + W_{emg} + \varepsilon_{RS} \quad (1)$$

$$U_{CS} = \boldsymbol{x}_{CS}\boldsymbol{\beta} + W_{emg} + \varepsilon_{CS} \quad (2)$$

$$U_{PT} = \boldsymbol{x}_{PT}\boldsymbol{\beta} + W_{cov} + \varepsilon_{PT} \quad (3)$$

$$U_{TA} = \boldsymbol{x}_{TA}\boldsymbol{\beta} + W_{cov} + \varepsilon_{TA} \quad (4)$$

$$U_{OTH} = \varepsilon_{OTH} \quad (5)$$

where $\boldsymbol{x}_j$ is the vector of explanatory variables including socio-demographic characteristics and designed attributes, and $\boldsymbol{\beta}$ is the vector of parameters to be estimated. ε_j is the error term in EV1 distribution.

3. RESULTS AND DISCUSSION

The estimation results are presented in Table 1. The alternative "other" is treated as the reference alternative and all variables are effect-coded. We consider the coefficients for driving time as random parameters that follow a normal distribution. Results based on 1500 Halton draws lead to a loglikelihood of -1665.531 and Rho-squared value of 0.164, which are satisfactory. Results of the constants for all transportation modes are all positive and significant. This means that, compared with the reference alternative "other", passengers are more likely to choose the public transportation modes in experiment.

Table 2 Error component model results

Levels	Ride-sourcing	Car-sharing	Taxi	Mass transit
Constant	1.118***(0.001)	0.314(0.364)	1.308***(0.000)	1.806***(0.000)
Random parameter of trip attributes				
Driving time				
15 min	0.400**(0.025)	0.400**(0.025)	0.400**(0.025)	0.632***(0.001)
30 min	0.079(0.654)	0.079(0.654)	0.079(0.654)	0.056(0.782)
45 min	0.018(0.925)	0.018(0.925)	0.018(0.925)	-0.179(0.297)
60 min	-0.497	-0.497	-0.497	-0.508
Standard deviation of 15 min	0.682*(0.076)	0.682*(0.076)	0.682*(0.076)	0.923***(0.006)
Standard deviation of 30 min	0.024(0.996)	0.024(0.996)	0.024(0.996)	0.094(0.972)
Standard deviation of 45 min	0.833***(0.005)	0.833***(0.005)	0.833***(0.005)	0.371(0.616)
Non-random parameter of trip attributes				
Access time/Waiting time				
5 min	0.381**(0.035)	0.479**(0.035)	0.481***(0.006)	0.319*(0.073)
10 min	-0.073(0.668)	-0.239(0.415)	-0.016(0.935)	-0.205(0.249)
15 min	-0.036(0.848)	-0.265(0.386)	-0.187(0.331)	-0.072(0.674)
20 min	-0.272	0.025	-0.278	-0.041
Cost rate				
Low	0.404**(0.036)	0.577**(0.019)	0.506***(0.006)	0.042(0.833)
Medium1	0.300*(0.100)	0.055(0.823)	0.195(0.320)	-0.088(0.627)
Medium2	-0.095(0.620)	-0.350(0.248)	-0.198(0.317)	-0.060(0.745)
High	-0.609	-0.282	-0.503	0.106
Type of car				
Economy	0.141(0.419)	0.156(0.559)	-	-
Comfort	-0.030(0.865)	-0.188(0.521)	-	-
Business	-0.018(0.925)	-0.034(0.895)	-	-
Luxury	-0.093	0.067	-	-
Services				
Professional services	-0.164(0.396)	-	-	-
Use clean energy vehicles	0.303*(0.074)	-	-	-
Plentiful riding sources and extensive service areas	0.123(0.476)	-	-	-
Multiple versatile services	-0.262	-	-	-
Context variables				
Time slot				
Peak time (6am-9am & 4:30pm-7:30pm)	-0.404(0.200)	-0.557(0.172)	-0.841**(0.014)	0.257(0.349)
Daytime (9am-4:30pm)	-0.109(0.745)	-0.113(0.776)	-0.432(0.231)	0.593*(0.069)
Evening (7:30pm-11pm)	0.238(0.444)	0.385(0.313)	0.555*(0.057)	0.167(0.552)
Midnight (11pm-6am (+1))	0.275	0.285	0.717	-1.017
Travel purpose				
Work or study	-0.292(0.331)	-0.253(0.506)	-0.392(0.197)	-0.065(0.811)
Transfer	0.964***(0.004)	0.532(0.212)	1.035***(0.001)	0.181(0.566)
Shopping or leisure	-0.521(0.102)	-0.250(0.491)	-0.475(0.102)	-0.220(0.467)
Go home	-0.151	-0.029	-0.167	0.104
Companion				
Together with intimate people	-0.387(0.153)	-0.231(0.518)	-0.310(0.287)	-0.469*(0.072)
Together with acquaintance(s)	0.653**(0.036)	0.774**(0.022)	0.139(0.652)	-0.208(0.484)
Together with other person(s)	0.163(0.656)	0.036(0.938)	0.517(0.164)	0.692*(0.057)
Alone	-0.429	-0.580	-0.346	-0.015
Destination distance				
5 km	0.077(0.791)	-0.254(0.486)	-0.034(0.913)	-0.082(0.779)
10 km	-0.174(0.548)	-0.319(0.371)	-0.030(0.916)	-0.041(0.876)

Levels	Ride-sourcing	Car-sharing	Taxi	Mass transit
15 km	0.322(0.357)	0.663*(0.086)	0.358(0.300)	0.175(0.550)
20 km	-0.226	-0.090	-0.295	-0.052
Socio-demographic variables				
Monthly income				
0 - 4000	0.221(0.343)	0.342(0.248)	0.355(0.110)	0.449**(0.041)
4001 - 8000	0.327(0.159)	0.304(0.263)	-0.147(0.477)	-0.024(0.911)
More than 8000	-0.547	-0.646	-0.208	-0.425
Monthly transportation cost				
Not record	-0.874***(0.001)	-0.699**(0.019)	-0.747***(0.005)	-0.497*(0.051)
1 - 500	0.127(0.709)	-0.145(0.691)	0.206(0.502)	0.412(0.134)
501 - 1000	0.512(0.163)	0.773*(0.058)	0.948***(0.004)	0.578*(0.063)
>1000	0.235	0.070	-0.407	-0.493
Household structure				
Living with children	0.646*(0.054)	0.783**(0.027)	0.915***(0.007)	0.553*(0.094)
Living with parents	-1.094***(0.004)	-0.920**(0.026)	-1.337***(0.000)	-1.238***(0.000)
Living with children and parents	1.240*(0.053)	1.062(0.105)	0.983*(0.096)	1.233**(0.033)
Living with partner or alone	-0.792	-0.926	-0.562	-0.548
Household car ownership				
Have no car	1.046***(0.003)	1.261***(0.000)	1.237***(0.000)	1.085***(0.000)
Have 1 car	-0.605**(0.013)	-0.790***(0.009)	-0.802***(0.001)	-0.780***(0.001)
Have 2 or more car	-0.441	-0.471	-0.436	-0.306
Driving licence				
Have no licence		-0.274(0.224)		
Have a non-local licence		0.377(0.148)		
Have a local licence		-0.103		
RS riding experience				
Yes	0.424**(0.041)	0.300(0.139)		
No	-0.424	-0.300		
RS monthly riding frequency				
0 times	-0.415**(0.044)			
1 - 3 times	-0.184(0.353)			
4 - 6 times	-0.197(0.416)			
7+ times	0.797			
RS waiting time				
0 - 5 min	0.286(0.388)			
6 – 10 min	0.241(0.472)			
11 - 15 min	-0.939(0.163)			
16+ min	0.412			
Standard deviations of error components				
Emerging modes (RS, CS)	0.911***(0.000)			
Conventional modes (TA, MT)	0.589**(0.045)			
LL (β)	-1665.531			
LL (0)	-1993.417			
Rho2	0.164			

Note: * Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

Two error components were specified to capture unobserved correlations within emerging modes (ride-sourcing and car-sharing) and conventional modes (taxi and mass transport), respectively. The statistically significant standard deviations of both components indicate the presence of correlated unobserved utility components shared by alternatives within each group. This suggests that alternatives within the same group are influenced by common unobserved factors not captured by the observed attributes and therefore exhibit similarity at the unobserved level.

The parameters of driving time are treated as random parameters. Results show that the utility of driving time progressively decreases with increasing driving time for all modes, with slightly higher sensitivity observed for mass transit. A significant effect is found for 15 minutes driving time, indicating that this level has a higher utility than the average driving time. The results of the standard deviation further indicates that significant taste variation exists in the utility of short driving times (15 minutes) for all modes and longer driving times (45 minutes) for all transportation modes but mass transit. This suggests that respondents differ in their preferences for both short and long travel times across most modes. These findings imply that mass transit is more sensitive to increases in travel time, while other modes maintain relatively stable utility at longer durations.

As shown in Figure , taxis exhibit the largest variation in choice probability in response to cost (17.4%), followed by ride-sourcing (14.9%). The choice probability of taxis and car-sharing decrease rapidly from low to lower-medium cost rate, whereas ride-sourcing starts to decline at higher-medium cost rate shows the largest decrease at the highest cost rate. These patterns indicate that taxis and car-sharing are more sensitive to cost changes at lower levels, while ride-sourcing becomes less attractive mainly at higher cost levels. This suggests that different modes compete under different cost conditions rather than uniformly across all price levels.

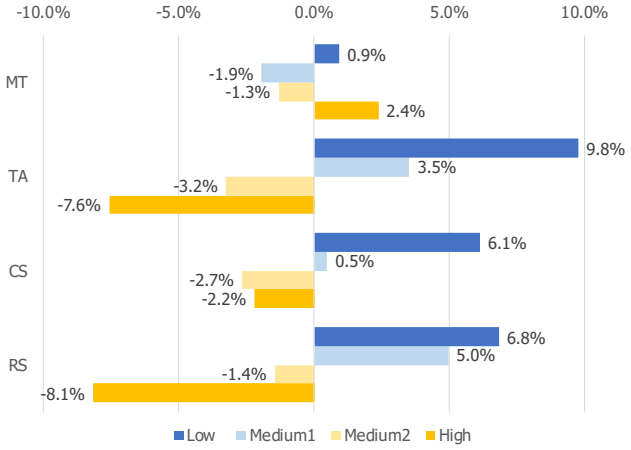


Figure 1 Mode choice probability change affected by alternative-specific cost rate change

Results indicate that distance is not a critical factor influencing most modes, except car-sharing. The significant and positive effect of the 15 km level suggests that car-sharing may be more attractive for longer trips within the city. The use of clean energy vehicles in ride-sourcing shows a positive effect, suggesting that this feature may enhance its relative attractiveness.

An interesting finding related to the contextual effects concerns the effects of time slot. Results indicate that the utility of mass transit is highest during the day, while the utility of ride-sourcing and other car-based modes is highest in the evening and at midnight. Time slot significantly affects taxis and mass transit, but not ride-sourcing and car-sharing, indicating that emerging modes are less sensitive to temporal variations.

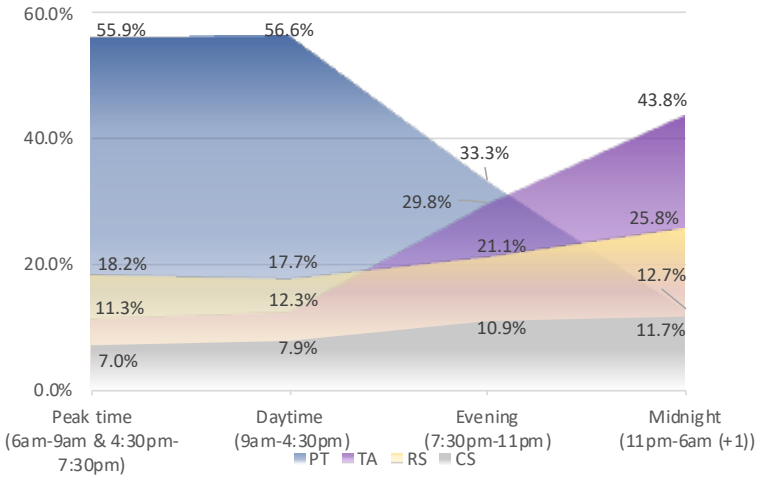


Figure 2 Effect of time slot on choice probability

As depicted in Figure , the choice probability of mass transit remains above 50% from morning to off-work time (6:00–19:30) and then declines sharply in the evening and at midnight. By contrast, taxi usage is lower than ride-sourcing during daytime but increases rapidly in the evening, reaching its highest level at midnight. The probability of emerging modes changes relatively little across time periods, with slightly higher values in the evening and at night. These patterns are consistent with a substitution relationship between mass transit and taxis, particularly when mass transit becomes less available or less convenient. Emerging modes, in contrast, show relatively stable usage patterns and appear to serve as flexible alternatives across time periods.

Travel purpose also affects mode choice. The transfer category (travel to transportation hubs such as train stations or airports) shows significant positive effects for ride-sourcing and taxis, suggesting that these modes are more competitive for transfer trips, while respondents are less likely to use car-sharing.

Companion is another important factor. Individuals travelling with acquaintances show a higher preference for emerging modes, particularly car-sharing, which has a significantly higher utility than ride-sourcing. This may be related to the provision of a more private and comfortable shared space. In contrast, conventional modes are more preferred when individuals travel with strangers, especially mass transit. This may reflect a higher perceived level of safety in public or shared environments. Overall, these results indicate that emerging modes gain relative advantage in socially flexible contexts, while conventional modes remain more competitive in situations involving unfamiliar social interactions.

Socio-demographic characteristics further shape mode choice behavior. Mass transit is strongly preferred by lower-income groups, and its attractiveness decreases with increasing income. In contrast, interest in emerging modes is higher than average among individuals with medium income levels (CNY 4001–8000). This suggests that emerging modes gain relative advantage among middle-income users.

Monthly transportation expenditure also affects mode choice. Individuals without a clear transportation budget are less likely to use public transportation. When costs are below CNY 500, preferences for most modes become positive, with the highest levels observed between CNY 500 and 1000. At higher expenditure levels (above CNY 1000), taxis and mass transit become less

attractive, while ride-sourcing becomes relatively more appealing. This indicates that ride-sourcing gains a relative advantage among higher expenditure groups.

A remarkable result related to household structure. Living with parents is negatively associated with public transportation use, suggesting greater dependence on private cars. Households with children show demand for all public transportation modes, with a relatively higher preference for ride-sourcing. It is probably because families with children in China often have a high travel demand, with their destinations distributed throughout the city. Average household car ownership in China is less than 1 by the end of 2022, implying other household members depend on mass transit and ride-sourcing (and other modes).

Car ownership reduces reliance on public transportation. Individuals with access to private cars are less likely to use these modes, while non-car owners rely more on mass transit and ride-sourcing. Zheng *et al.* (2019) found that ride-sourcing may reduce car ownership by providing an alternative to private vehicles., and this has been observed in many countries (Bilgin et al., 2023; Wadud & Namala, 2022; Ward et al., 2019; Widita & Diwangkari, 2022).

Experience with ride-sourcing positively influences its utility as well as that of car-sharing. Higher riding frequency is associated with higher utility, while lower frequency levels show negative coefficients due to effect coding. This indicates that frequent users are more likely to choose ride-sourcing. The effect of waiting time experience is not significant, suggesting limited influence on future choices.

4. CONCLUSIONS

This study explored the influence of factors that potentially affect travelers' inclination to use different transportation modes, considering emerging and conventional transportation modes. Using the data collected in a stated choice experiment, we estimated a random parameter error component model. The results reveal that alternatives within each group share common unobserved components, indicating that emerging and conventional modes form distinct behavioral clusters. While public transportation remains the preferred option under experimental conditions, emerging modes account for a substantial share of choices, highlighting their growing role in the transport system.

A key finding of this study is that the relationship between emerging and conventional modes is condition-dependent rather than uniform. Instead of acting as universal substitutes, these modes interact differently depending on travel conditions. Under structured conditions, such as daytime travel or situations involving unfamiliar social settings, conventional modes—particularly mass transit—maintain a clear advantage. In contrast, under more flexible or constrained conditions, such as nighttime travel or socially flexible contexts, emerging modes become more competitive and may serve as effective alternatives.

The results further show that competition across modes is asymmetrical. Strong substitution patterns are observed within conventional modes, particularly between mass transit and taxis when service availability changes. Emerging modes, however, do not consistently replace conventional modes but instead gain advantage under specific conditions, such as moderate cost levels, transfer trips, or among certain user groups. This suggests that emerging modes complement the existing transport system by filling gaps where conventional modes are less effective, rather than directly displacing them.

Socio-demographic characteristics reinforce these patterns. Higher-income and higher-expenditure travelers are more likely to adopt emerging modes, while lower-income groups remain more dependent on public transportation. In addition, familiarity with ride-sourcing increases its attractiveness, indicating that experience plays a role in strengthening its position in the market.

Overall, this study highlights that transportation mode choice is shaped by the interaction between travel conditions and user characteristics. Emerging modes should therefore be understood as conditional competitors that enhance system flexibility rather than as direct replacements for conventional modes.

These findings have implications for both policymakers and platform operators. Improving service availability during off-peak periods, promoting environmentally friendly vehicle technologies, and enhancing flexibility in service provision may strengthen the role of emerging modes while maintaining the essential function of conventional modes.

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