Identifying Key Factors and Forecasting Demand to Implement Shared Taxi Services using Stated Preference Survey

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1. Introduction

In Japan, rural areas and simi-rural areas face transportation problems due to shifts in demographic and economic constraints. As the country's population ages, rural areas encounter steep decline in both the availability and accessibility of public transportation services. This is a common problem across the rural regions with the low population density and especially for regions where only bus and traditional taxis operates as public transportations. Although buses run on reasonable prices, they provide limited access to places and limited frequency due to the reduction of the services. The taxi on the other hand offers more convenience and comfort compared to bus (Qiu et al., 2022) but they are economically viable for regular use. This forces the residents to rely heavily on the private cars and on the other hand, left many people without reliable and affordable options to get around for those without the private car adoption. These issues are vastly reflected across rural areas and semi-rural areas Japan where depopulation and ageing population made traditional transportation less useful or practical.

Despite these challenges, local governments have successfully managed to set up ridesharing programs that serve to fill in the transportation gaps caused by discontinued bus routes and provided residents with fairly reliable and affordable transportation alternatives. Nonetheless, the shared taxi service, either as a straightforward replacement for reduced bus service or as an additional option for taxi, promises to very much reduce single-occupancy vehicle use delivering a more convenient and affordable alternative for those previously locked into more expensive alternatives such as traditional taxi service or long queens waiting for less frequent bus service. Considering this context, the primary research objectives are as follows:

- To identify key factors to implement shared taxi services in the rural and semi-rural regions by using SP survey and developing a discrete choice model.
- To predict the demand of the ride sharing services and analyze how changes in Level of Service (LOS), affect the probability of choosing ridesharing services.
- To provide practical insights and recommendations for policy makers and service providers to design an efficient ridesharing system.

2. Literature Review

Much research has been done on the influencing factors on the adoption of ride-sharing services by focusing on demographic attributes, socioeconomic status and perceived individual convenience and security. Soltani et al. (2021) investigate the determining factors influencing ridesharing adoption and non-adoption in Adelaide, Australia by using a quantitative survey of 408 respondents and multinomial logit (MNL) modelling. Loa and Habib (2021) investigated the role of attitudinal and perceptional factors impacting the adoption and usage frequency of ride-hailing services in Toronto, Canada. The study collected 1069 respondents from a web-based survey and applied binary logistic regression models to differentiate between exclusive and shared ride-hailing adoption and a zero-inflated ordered probit (ZIOP) model to access usage frequency. Akbari et al. (2020) explored the behaviors of passengers who decided to adopt ridesharing services in Iran. The Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB) and Partial Least Squares Structural Equation Modeling (PLS-SEM) are used to analyze an online survey respondent of 318 Iranian users. Wang et al. (2019) investigate the factors that impact the willingness of the non-users to use ride-sharing services with perceived value and perceived risk as determining factors in their decision-making process. Similarly, Huang et al. (2023) study the factors that affect people's willingness to share rides. The study centers in Manhattan, New York City and utilizes data from transportation network companies (TNCs) such as Uber and Lyft. Similarly, Cahyo et al. (2019) discuss the factors affecting the choices of passengers between ride-sourcing and ride-splitting services. The authors analyze the impacts of fare savings, extra travel time, and security concerns based on gender on the passengers' choices in selecting the mode of travel. With a similar trend, Elnadi and Gheith (2022) explore what causes the users of ride-hailing services to continue their usage in Egypt. The study integrated the Technology Acceptance Model (TAM), Innovation Diffusion Theory (IDT) and Partial Least Squares Structural Equation Modeling (PLS-SEM) to evaluate the 379 survey responses from ride-hailing.

Existing research on ride sharing services conducted by various scholars are for urban areas and cities where ridesharing is widely used. The willingness to share factors and time and cost tradeoffs for shared taxis in rural areas, especially in the context of Japan are still unexplored. Here, this research aims fill the research gap by providing insights to understand the important factors and customers preferences towards shared taxi service in rural society of Japan.

3. Methodology

Creating a survey is one of the most important components of this research as it serves as a base for the research objectives. The main purpose of this survey design is to capture the preferences and behavior of the respondents if the shared taxi is introduced as a new transport mode. In this research the SP survey serves as a main data collecting tool to obtain the responses of the preferences from the respondents across hypothetical scenarios. The variables were chosen based on a balance of literature review and expert suggestions to ensure that the survey covers a wide range and yet simple for the respondents. Variables are categorized into alternative-specific variables (i.e., varying across the alternatives of the experiment stated in the survey) and case-specific independent variables (i.e., varying by respondent). In this study, there are total 5 variables and with each variable having three attribute levels, there were a total of 243 possible scenarios. To ensure that most important variations are included without overwhelming the participants and resources, orthogonal design was created by using orthogonal array in SPSS software and the scenarios are reduced from 243 to 16.

This research focuses on three cities of Niigata Prefecture: Nagaoka City, Minamiuonuma City and Myoko city. These cities share many similar city characteristics but have different mobility patterns. One immediate similarity is that all three of these cities depend very heavily on private cars. As access to public transportation is limited in some of the areas, over 70% of the residents rely on private cars. This heavy reliance on private cars results in traffic congestions, emission of toxic gases and social isolation for those without access to private cars especially senior citizens and low-income citizens. Ranking system is used instead of just one choice to mitigate the contradictions of non-private car owners and to encourage the private car owners to give public transportation a chance under the right scenario.

The survey was distributed from late October to early November across three cities. For the offline survey, the survey forms were tri folded, put it in an envelope and delivered to residences in the city. The residents are given two options to fill the survey form. The first option is to fill the survey form on paper, enclose the survey and send it via post office. The second option is through the QR code provided in the first page of the survey. For Myoko city, 150 paper surveys and 1200 QR codes, for Minamiuonuma city, 150 paper surveys containing QR codes survey and for Nagaoka City, 850 paper surveys with QR codes were distributed. After filtering out the collected data, a total of 252 responses are feasible for this research.

4. Model Results and Discussion

Two discrete choice models: Conditional Logit Model (CLM) and Panel Mixed Logit Model (PMLM) are chosen to compare due to their ability to capture various dimensions of traveler behavior. The results from the contitional logit model is shown in **Table 1** and the results from the panel mixed logit model is shown in **Table 2**.

Table.1 Results from Conditional Logit Model

Variables	Coefficients	Std.Error	z value	p value	Odds Ratio
Alternative Specific Independent Variables					
Wait time	**-0.0402881**	0.0078773	- 5.11	**0.000**	**0.9605127**
Travel time	-0.0468475	0.0649429	-0.72	0.471	0.9542329
Travel fare	**-0.0017374**	0.0003114	-5.58	**0.000**	**0.9982641**
Case Specific Independent Variables					
Variables	**Coefficients**	**Std.Error**	**z value**	**p value**	**Odds Ratio**
Distance	**0.0916913**	0.0422033	2.17	**0.030**	**1.0960**
Age	0.0206356	0.02069	1.00	0.319	1.020
Gender	0.2592818	0.6319629	0.41	0.628	1.296
Private Car	**-6.791168**	1.140368	-5.96	**0.000**	**0.0011**
Taxi Usage	0.2561917	0.3564681	0.72	0.472	1.292
Distance to BS	-0.0010574	.0005482	-1.93	0.054	0.9989
Cons	**2.673932**	1.322128	2.02	**0.043**	**14.497**
Private Car as Base Alternative					
Distance	-0.014	0.1185	-0.12	0.908	0.9864
Age	-0.0056	0.0073	-0.77	0.441	0.9944
Gender	**0.8068**	0.3535	2.28	**0.022**	**2.2408**
Private Car	0.1883	0.6248	0.30	0.763	1.2072
Taxi Usage	0.2157	0.3600	0.60	0.549	1.2407
Distance to BS	-0.0004	0.0004	-0.94	0.350	0.9996
Cons	**-1.8778**	0.9462	-1.98	**0.047**	**0.1529**
Bus as Base Alternative					
Distance	**-0.5180**	0.1294	-4.00	**0.000**	**0.5957**
Age	**-0.0464**	0.0125	-3.72	**0.000**	**0.9547**
Gender	0.7003	0.8484	0.83	0.409	2.01
Private Car	0.5785	1.3431	0.43	0.667	1.78
Taxi Usage	-0.3379	0.43004	-0.79	0.432	0.7132
Distance to BS	-0.00047	0.000825	-0.58	0.564	0.9995
Cons	**3.681**	1.508	2.44	**0.015**	**39.71**
Regular Taxi as Base Alternative					

Note: Orange bold words are $p < 0.05$ statistically significant; BS = Bus Stop

Table.2 Results from Panel Mixed Logit Model

Variables	Coefficients	Std.Error	z value	p value	Odds Ratio
Alternative Specific Independent Variables					
Wait time	**-0.0402881**	0.0078773	- 5.11	**0.000**	**0.9605127**
Travel time	-0.0468475	0.0649429	-0.72	0.471	0.9542329
Travel fare	**-0.0017374**	0.0003114	-5.58	**0.000**	**0.9982641**
Case Specific Independent Variables					
Variables	**Coefficients**	**Std.Error**	**z value**	**p value**	**Odds Ratio**
Distance	0.0917	0.0644	1.42	0.154	1.0960
Age	**0.0206**	0.0067	3.09	**0.002**	**1.0208**
Gender	0.2593	0.2498	1.04	0.299	1.296
Private Car	**-6.7912**	0.3676	-18.48	**0.000**	**0.0011**
Taxi Usage	0.2562	0.2164	1.18	0.236	1.2920
Distance to BS	**-0.0011**	0.0003	-4.05	**0.000**	**0.9989**
Cons	**2.6739**	0.7647	3.59	**0.000**	**14.4969**
Private Car as Base Alternative					
Distance	-0.0137	0.1703	-0.08	0.936	0.9864
Age	-0.0056	0.0040	-1.39	0.165	0.9944
Gender	**0.8068**	0.1773	4.55	**0.000**	**2.2408**
Private Car	0.1883	0.2902	0.65	0.516	1.2072
Taxi Usage	0.2157	0.1291	1.67	0.095	1.2407
Distance to BS	**-0.0004**	0.0002	-2.14	**0.033**	**0.9996**
Cons	**-1.8779**	0.8400	-2.24	**0.025**	**0.1529**
Bus as Base Alternative					
Distance	**-0.518**	0.1302	-3.98	**0.000**	**0.5957**
Age	**-0.0464**	0.008	-5.77	**0.000**	**0.9547**
Gender	0.7003	0.2707	1.89	0.059	2.0143
Private Car	0.5785	0.5992	0.97	0.334	1.7834
Taxi Usage	-0.3379	0.2319	-1.46	0.145	0.7132
Distance to BS	-0.0005	0.0003	-1.40	0.163	0.9995
Cons	**3.6817**	0.9687	3.8	**0.000**	**39.7135**
Regular Taxi as Base Alternative					

Note: Orange bold words are p <0.05 statistically significant; BS = Bus Stop

The alternative specific variable from both models indicates that wait time ($p<0.05$) and travel fare ($p<0.05$) are the statistically significant factors when a respondent is choosing a transport mode. This aligns with many existing research such as Yang et al. (2021), Göransson and Andersson (2023), Du et al. (2024), Yoon et al. (2017), Deka & Carnegie, (2021), etc. In both models, the private car ownership is statistically significant.

Although distance is statistically significant for CL model the direction of both models suggest that shared taxi is preferable with longer distances when compared to private cars. For the PML model, age and distance to BS are significant meaning that older people are more likely to choose shared taxi and the distance to bus stop can indirectly affect the probability of choosing private car as respondents living further from bus stops are more likely to choose private cars than shared taxis. Although gender is statistically significant in both models, revealing that females are more likely to choose shared taxis over bus, the distance to bus top is only statistically significant for PML model. Many research state that males are more likely to use shared taxis, but the research conducted by Huang et al. (2023) stated that in Manhattan, female are more likely to choose shared taxis. Distance to bus stop is found to be the new factor which adds to the existing body of literature. When comparing the regular taxi to shared taxi, both models show that distance and age are significant factors. This supports two research conducted by Soltani et al. (2021) and Loa and Habib (2021), who states that younger generation are more likely to adopt ride sharing services. On the other hand, Huang et al. (2023) states that longer distance decreases the WTS which aligns with the model results. Although the log-likelihood value for both the models is the same, due to the nature of the survey and Wald chi-square statistic being higher, the PML model indicates that the variations are better captured by PML model. The detailed of goodness-of-fit metrics are shown in **Table 3**.

Table.3 Goodness-of-Fit Measures

Metrics	Conditional Logit	Panel Mixed Logit
Number of Observations	7868	7868
Number of Cases	1969	1969
Number of Panels	-	**246**
Log-Likelihood (LL)	-967.28176	-967.28176
Wald-Chi Square	164.74	**701.54**
Prob>Chi Square	0.000	0.000
LR Chi Square	2132.04508	2132.04508
McFadden's Pseudo R^2	0.5242	0.5242

5. Demand Estimation

For the demand estimation, which is the second research objective, Nagaoka city respondents were split from the main model for more accurate demand estimation. The p value and value of McFadden's Pseudo R^2 from **Table.4** indicates that the fitted model can explain 55% better than the null model. For demand estimation, only the alternative specific variables (**Table.5**)were used because they are the decision factors when it comes to choosing a transport mode and for service planning, these factors can be adjusted and estimate the demand.

Table 5.2 Goodness-of-fit Measures for Nagaoka Model

Metrics	Value
Log-Likelihood (LL)	-360.20793
Prob>Chi Square	0.0000
LR Chi Square	883.19724
McFadden's Pseudo R^2	0.55079

Table.5 Nagaoka City PML Model Estimations

	Coefficients	**Std.Error**	**z value**	**p value**
Wait time	**-0.0822907**	0.0156866	- 5.25	**0.000**
Travel fare	**-0.0023467**	0.0005997	-3.91	**0.000**

The coefficient values can be used to formulate the utility equation for different transport modes. After that, the probability equation can be formulated. Different wait time and costs are generated in the utility equation and analyzed how the probability of shared taxi changes over different level of service. **Figure.1** shows the sensitivity analysis between short distance around 2 km distance. From this sensitivity analysis, the demand for the shared taxi can be calculated.

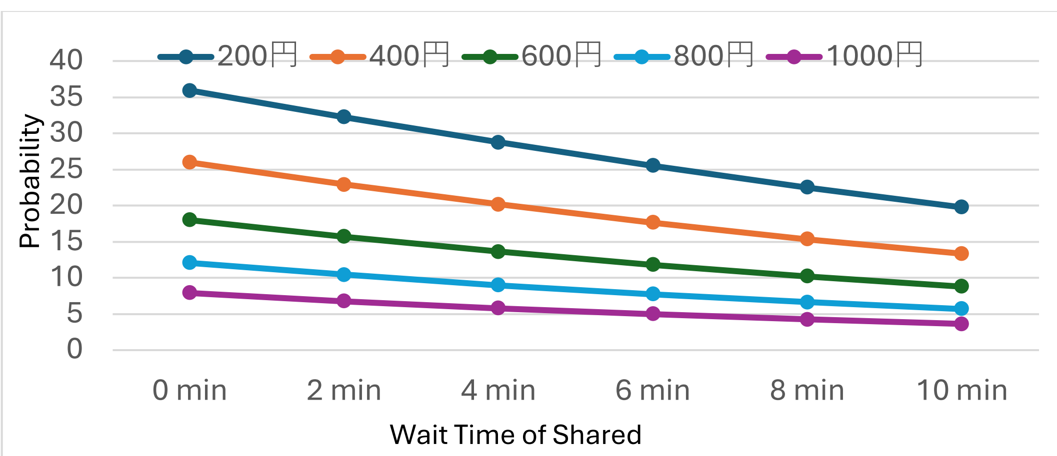

Figure.1 Probability of Choosing Shared Taxi at Short Distance (2km)

However, the share of the other transport modes as shown in **Figure.2**, is needed to be addressed. There are total of 9 modes in Nagaoka City but only 3 modes are included in the survey. The combined percentage of other modes that are not included in the survey are about 23.3 percent. So, in order to not overestimate the demand, it is assumed that the share other modes are remianed the same and the combined percentage is subtracted from the probability of choosing shared taxis. After the subtraction, least amount of demand for the shared taxi service can estimated. **Figure.3** and **Figure.4** demostrates the difference between the mode split from the model and potential mode split in the Nagaoka city when shared taxi is implemented at 300 yen.

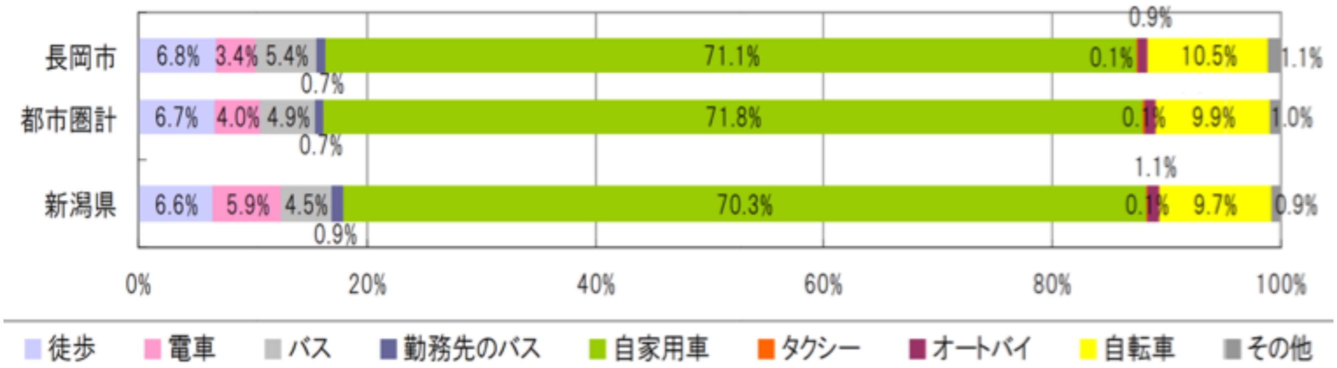

Figure.2 Mode Split of Nagaoka City

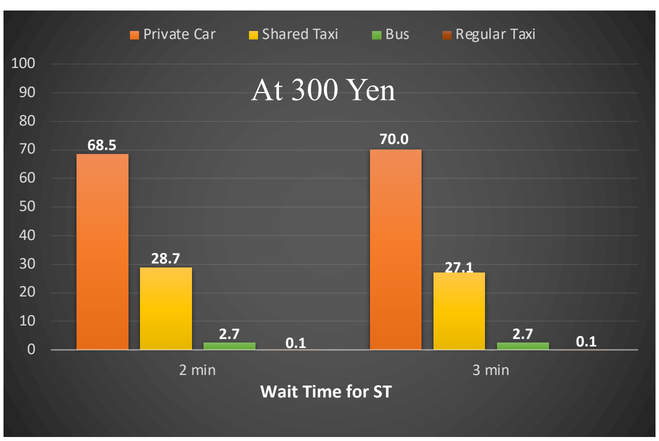

Figure.3 Mode Split From the Model

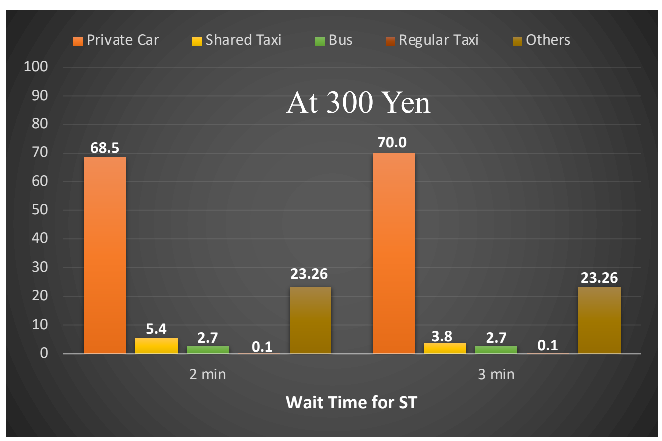

Figure.4 Potential Mode Split in Nagaoka City

6. Practical Implications

This is the 3rd and final research objective of the research, which is to provide practical insights and recommendations for service providers. There are 4 suggestions for the practical implications.

1) Although wait time and fare are both significant factors, the service providers should piroritize wait time as respondents are willing to pay 23 yen to reduce wait time by 1 minute.
2) Since the shared taxis in Niigata prefecture operates with shared taxi stops similar to buses, maximizing the taxi stops across service area is also important to increase attractiveness and satisfaction of the users.
3) Older people are more likely to choose shared taxi over private car which means that service providers should consider the needs of senior citizens.
4) Survey indicated that senior citizens have trouble using smart phone apps so, this factor is also important for the passengers to use the service despite of their technological limitations.

7. Conclusion

The limitations of the research are as follows.

- The research area is focused on rural areas which limits the applicability to urban areas with different mobility patterns.
- The probability of the shared taxi is based on the SP survey where choice of respondents made in the survey and actual behavior may differ.
- External factors such as weather conditions or time of the day can be influencing factors for the probability of choosing shared taxis.
- Service providers need to consider the mode shifts that may come from other alternatives such as walking or bicycle for demand estimation.
- Survey was conducted over a limited period which will not be account for seasonal variations which can result in different travel behaviors.

The followings are some of the future research suggestions.

- Expand the study area to bigger urban setting cities like Niigata city or Joetsu city.
- Conduct RP survey on existing shared taxi services and compare the accuracy of factors.
- Adding more factors such as weather conditions and urgency.
- Compare the ride sharing services with other shared mobilities such as the carpooling.

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