What Factors Affect Commuters’ Utility of Choosing Mobility as a Service? An Empirical Evidence from Seoul

Sujae Kim 1, Sangho Choo 2, Sungtaek Choi 3 and Hyangsook Lee 4,*

1 Department of Urban Planning, Hongik University, Seoul 04066, Korea; rtw1119@gmail.com
2 Department of Urban Design & Planning, Hongik University, Seoul 04066, Korea; shchoo@hongik.ac.kr
3 Department of Metropolitan Transport, The Korea Transport Institute, Sejong 30147, Korea; schoi83@koti.re.kr
4 Graduate School of Logistics, Incheon National University, Incheon 22012, Korea
* Correspondence: hslee14@inu.ac.kr

Abstract: Mobility as a Service (MaaS), which integrates public and shared transportation into a single service, is drawing attention as a travel demand management strategy aimed at reducing automobile dependency and encouraging public transit. In particular, there have been few studies that recognize traffic congestion during peak hours and identify related factors for practical application. The purpose of this study is to explore what factors affect Seoul commuters’ mode choice including MaaS. A web-based survey that 161 commuters participated in was conducted to collect information about personal, household, and travel attributes, together with their mode preference for MaaS. A latent class model was developed to classify unobserved latent groups based on trip frequency by means and to identify factors influencing mode-specific utilities (in particular, MaaS service) for each class. The result shows that latent classes are divided into two groups (public transit-oriented commuters and balanced mode commuters). Most variables have significant impacts on choice for MaaS. The coefficient of MaaS choice of Class 1 and Class 2 were different. These findings suggest there is a difference between the classes according to trip frequency by means as an influencing factor in MaaS choice.

Keywords: Mobility as a Service (MaaS); shared transportation; mode choice; commuters; latent class model

1. Introduction

The 4th industrial revolution, first presented at the world economic forum annual meeting 2016 [1], emphasizes the significance of artificial intelligence, big data analysis and platform technologies based on information and communications technology (ICT). In addition, it aims to produce and efficiently utilize services in response to consumer preferences. Evidently, such changes are gradually affecting the shared economy. Presented by Martin Weitzman in 1984, the shared economy is a concept that aims to prevent overproduction and overconsumption by sharing individual resources with others. Previously, shared economy was only utilized in the living community unit, but its scope is expanding with the development of ICT, leading to services such as Uber and Airbnb. In the transportation sector, shared economy mainly appears to be utilized by shared transportation, which is being suggested as a solution to traffic congestion problems [2–4]. Mobility as a Service (MaaS), a transportation service that utilizes public transportation and shared transportation and combines them into single seamless mobility, is drawing attention as an alternative to previous solutions through expanding transportation infrastructure [5]. Advances in the Internet of Things (IoT) and platform technology have made it possible for users to take advantage of information about transportation, emerging as a new transport service—MaaS. Starting in European cities such as Helsinki, Finland, and expanding to North America and Australia [6–15], MaaS aims to increase the convenience and efficiency of transportation by providing integrated services. This convenient service will have a great effect on reducing
traffic congestion and air pollution by utilizing public transit and shared transportation instead of buying cars. In addition, the reservation and payment services of MaaS can be helpful in the post-pandemic phase. These services can reduce contact due to reservations and payments when using public transportation and taxis. Henhser [16] suggested that MaaS could be helpful in the post-pandemic phase by providing multiservice offerings such as delivery service.

Whereas many current studies [17–22] regarding MaaS are focused on the concept of MaaS or its potential demand, there is a lack of empirical studies [1–22] focusing on how MaaS choice can be affected, and even less on commute trips. As MaaS has been considered as one of the solutions to reducing vehicle ownerships [23,24], and alleviating congestion, this study aims to explore influencing factors of MaaS choice, focusing on commuters in Seoul, South Korea. Seoul has highly developed, well-connected public transportation systems, a variety of car- and bike-sharing services subsidized by local governments are available, and the public transit usage accounts for a sizable portion of mode shares [25]. A web-based survey was conducted to collect data, gathering information about choice of MaaS over conventional transportation modes for weekday travel including commute trips, personal and household traits, and travel attributes. Incorporating these factors as explanatory variables, we developed latent class models identifying heterogeneous MaaS choices based on current frequency of transportation.

The remainder of this study is organized as follows. Section 2 widely reviews recently published references to MaaS. Section 3 presents data collection, data manipulation, relevant descriptive analysis, and methodology. Section 4 analyses the result of estimated class membership and class-specific models sequentially, thereby establishing two heterogenous groups by comparing their profiles. In Section 5, the conclusion delivers a brief summary of results and discusses research findings and implications, together with future research directions.

2. Literature Review

The concept of MaaS was first presented by Sonja Heikkila [26] and began to draw attention through the MaaS platform called Whim, which is operated mainly in Helsinki, Finland. It aims to provide the level of convenience of individual passenger cars by utilizing various means of transportation. Thus, MaaS should be able to provide information on the multi-modal, linking shared transport with public transport on a single platform and a real time travel plan [17,27]. A wide range of studies [28,29] have been carried out to establish the concept of MaaS and its components. MaaS is commonly defined as a service that integrates various means of transportation and is provided through package plans (either as monthly/annually paid packages or pay-as-you-go). In addition, the MaaS system for using, booking and paying the transport provided must be integrated and provided within a single platform. Finally, the platform provides users with real-time information on the means of transportation; in particular, individually customized travel plans are presented based on existing travel records.

Kamargianni et al. [28] evaluated existing pilot projects and services aimed at enabling MaaS according to their integration level. The integration levels were assessed with ticket integration, payment integration, journey planning function, booking function, and mobility package integration. It also presented three components of MaaS: a card or ticket that integrates various means of transportation, a user-tailored package, and a platform for providing information on transportation. Goodall et al. [29] presented key factors that need to be considered in future use of MaaS, which requires government efforts to revitalize MaaS. They emphasized that the MaaS platform should collectively implement travel plans, service reservations, and payments. Jittrapirom et al. [30] synthesized literature to establish the concept of MaaS as a platform for integrating various means and services, organizing and defining its elements. Such MaaS elements are considered as an integration of transportation means, single platform, diverse user, integrated technology, and user-oriented service provision. Mulley et al. [5] conducted an assessment of the transport
package scenario through discussions with Australian Community Transport operators by investigating its availability when providing MaaS to the mobility handicapped. They argued that transportation such as public transit and taxis should be provided according to user needs, and service use and payment could be provided through a single account without a separate ticket or card.

MaaS is mainly implemented in Europe and North America, and is provided by pilot projects and independent platforms [6–15]. Most MaaS can be used by linking public transportation, taxi, bicycle-sharing, car-sharing, etc., with various services such as real-time information, travel plans, reservation, and payment (e.g., Wein mobil, Whim, GVH, Qixxit, Moovel, Oise mobilite, and Mycicero). Some of these platforms do not provide reservation and payment services, and travel plans considering various means and routes are the only ones available (Cowlines and Transit). In the case of the Netherlands, public transportation and bike-sharing are usable (TripKey).

In addition, there are many efforts to motivate the use of MaaS in Europe. Transport for London (TFL), a public transportation management agency, plans to provide public services by utilizing public transportation and bike-sharing systems, linking them to various means such as shared cars and taxis. A platform has also been developed that provides reservation and payment services by integrating fare policies [31]. The Connex in the Netherlands is a MaaS public-private partnership consisting of some 40 public and private organizations, and offers alternatives to maximize the MaaS operating system and transportation efficiency, proposing a fare policy based on the combination of various means [32]. The EU’s MaaS4EU and MaaS Alliance presented the MaaS policy framework as the European integrated MaaS guideline [33,34].

Several studies were conducted to investigate preferences for new MaaS services and analyze factors affecting service choices by using a stated preference (SP) survey. Alonso et al. [35] sought to utilize MaaS based on a demand responsive transport (DRT) system in Amsterdam, the Netherlands. The SP survey composed nine scenarios, dividing various transportation modes into DRT-based services, taxis and private passenger cars. The study adopted a Max Self-Regulation model by separating private passenger car ownership, analyzing factors affecting respondents’ service choice. The result showed that highly educated people over 50 years and workers having a private passenger car are likely to choose DRT-related services. On the other hand, it also showed that those who do not own private passenger cars are likely to choose services that included taxis.

Matyas et al. [19] conducted an SP survey in London to analyze MaaS preferences based on user travel characteristics. This study developed a logit model by collecting travel information and examining the preferences of the MaaS package, including public transportation, taxi, bicycle-sharing and car-sharing. The results showed that respondents had a higher preference for the packages that include previously experienced means of transportation and public transit. Ho et al. [20] analyzed factors influencing MaaS usage in Sydney, Australia. The study designed a SP survey by recording travel information of respondents for a fortnight and organizing respondent-tailored MaaS packages for analysis of potential demand estimation and influential factors. Impacts of those factors were analyzed by adopting a logit model based on the SP survey data. The model results demonstrated that two specific individual attributes including age and the number of children in the household had an influence on the choice of MaaS, whereas other socio-economic traits (gender, household type, membership of car-sharing and vehicle ownership) had a negligible impact. In addition, it turns out that the greater the amount of service provided by means of transportation, the greater the preference for MaaS is, and monetary benefits such as discounted travel cost for taxis and bicycles have a positive influence on MaaS choice. Vij et al. [21] surveyed 3985 Australians to determine their demand and willingness to pay for MaaS in Australia. The survey found that 46% of the Australian population was willing to use MaaS, preferring pay-as-you-go packages to unlimited packages. Latent class choice models were used to estimate consumer preferences for MaaS, and latent classes were classified into place of residence, age, gender, household income,
etc. The latent classes are defined as five groups: MaaS enthusiasts, car dependents, etc. MaaS enthusiasts had the highest probability of purchasing MaaS at 87 percent, and car dependents rarely used MaaS at 1 percent. The MaaS package bundle was preferred for local public transport and taxis and long-distance public transport, and bikeshare was the least popular. The willingness to use MaaS is closely related to age and life cycle stages (e.g., young individuals who have full-time jobs and retired old adults). Matyas and Kamargiani [22] predicted individual preferences in the MaaS package. Since individuals may exhibit different preferences for MaaS, they developed a latent class choice model to address the problem of preference heterogeneity. The data used in the study are related to MaaS surveyed by Greater Manchester. The latent classes were divided into three classes: MaaS package avoiders, MaaS package explorers, and MaaS package enthusiasts. MaaS package avoiders responded that 95 percent would not use MaaS, MaaS package explorers responded that 67 percent would use basic packages, and MaaS enthusiast responded that 84 percent would use extra packages and urban packages. Age, gender, income, education, and travel behavior had a significant impact on purchasing MaaS packages.

In summary, previous studies have largely focused on general travelers with various travel purposes, but to the best of the authors’ knowledge, this is one of first studies specifically focusing on regular commuters’ behavior. Given that those commuters generate frequent, routine trips, resulting in peak-hour traffic congestion in urban areas, this study analyzes what factors affect mode preferences to Maas and to what extent those associations can be postulated, narrowing our focus down to commuters. In addition, preference for new transportation service may have different influencing factors depending on travel attributes. In other words, it is necessary to consider the heterogeneity of the traveler. However, it is also notable that there is few prior research that deals with traveler’s heterogeneity. In this study, we derive the influencing factors of MaaS choice by developing a latent class model, which classifies the latent classes and estimates the influence of each class.

3. Data and Methodology

3.1. Data Collection

Data for this study was obtained from a web-based survey emailed in December 2018 to 173 randomly selected Seoul commuters aged between 20 and 60, following the choice-based sampling method to represent mode shares of population. The beginning of the survey consists of screen questions asking for the location of residence, commuting status, and age. Survey participants who were not eligible for the survey ended the survey without further processing. As shown in Table 1, the sample distribution of the survey and the 2016 Household travel survey (HHTS) were compared to verify the representation of the sample in the survey. The sample distribution of the survey was similar to 2016 HHTS in terms of gender, age, and commute means. Therefore, the sample of the survey is representative. Survey participants were asked to report their personal attributes (e.g., gender and age), household attributes (e.g., the number of household members and monthly household income), travel attributes including the primary travel mode, trip frequencies by means, and MaaS choice. MaaS was defined as an app-based service that provides booking and payment services simultaneously, as suggested in many studies [17,19–22]. After excluding cases with missing values, 161 cases were retained in the final dataset. It showed that (1) 64.6% of respondents were male; (2) almost one third of the respondents were 30 to 39 years, followed by those who aged 40 to 49 (26.7%) and 50 to 59 (21.8%); shares of commute means of transportation were 29.8%, 33.6%, 34.8% for car, bus, and subway, respectively, followed by taxi (1.2%) and bicycle (0.6%).
The sample of commuters living in Seoul in a 2016 household travel survey conducted in Korea.

Table 1. Distribution of the survey sample and 2016 household travel survey.

| Category      | 2016 HHTS (%) | Sample (%) |
|---------------|---------------|------------|
| Gender        |               |            |
| Male          | 62.7          | 64.6       |
| Female        | 37.3          | 35.4       |
| Age group     |               |            |
| 20–29         | 14.4          | 18.6       |
| 30–39         | 34.7          | 32.9       |
| 40–49         | 28.0          | 26.7       |
| 50–59         | 22.9          | 21.8       |
| Commute means |               |            |
| Car           | 28.7          | 29.8       |
| Bus           | 33.2          | 33.6       |
| Subway        | 36.4          | 34.8       |
| Taxi          | 0.6           | 1.2        |
| Bicycle       | 1.1           | 0.6        |

*The sample of commuters living in Seoul in a 2016 household travel survey conducted in Korea.

We present MaaS, which enables multiple transportation as a single package in this study. Since MaaS presented in this study is currently unavailable in Seoul, MaaS choice needs to be identified via a stated preference (SP) method. Transportation services in MaaS are configured based on the trip frequency for a week. Figure 1 show the survey questions for a respondent who reported private car used 5 trips for a week and spent 12 min driving 8 km per trip. Public transportation, taxi, and bicycle was used 12 trips, 2 trips, and 2 trips for a week, respectively. The SP survey for general mode choice utilizes varying fare and time of the mode to construct a utility function based on the results of mode choice. With this approach, we acquire multiple reports for each respondent, achieving more accurate results. Thus, this survey was repeated five times for each individual with different MaaS packages, resulting in a total of 805 collected cases.

Part II: Fill your current travel record for a week

| Mode | Car | PT | Taxi | Bicycle | CS |
|------|-----|----|------|---------|----|
| Total number of trips for a week | 5   | 12 | 2    | 2       | 0  |
| Average distance per trip (km)  | 8   | -  | -    | -       | -  |
| Average duration per trip (min) | 12  | -  | -    | 30      | 0  |
| Total fare for a week (won)     | 48,700 | 16,200 | 20,000 | 0       | 0  |

*PT: Public transportation, CS: Car sharing

Figure 1. The survey question about the travel record for a week.

The MaaS choice, the dependent variable of this study, was surveyed in binary form (Figure 2). The left image of Figure 2 (first alternative) is the travel record for a week reported by the respondent in Figure 1. The right image of Figure 2 is the MaaS package (second alternative) that consists of public and shared mode, excluding private car, based on the first alternative. When composing a bundle of MaaS packages, it is configured to provide similar levels of usage to each means of the first alternative. The various scenarios under the bundle of each MaaS package were repeated five times. In addition, personal, household, and travel attributes were surveyed as explanatory variables. Personal and household attributes consist of gender, age, education level, job type, commute means, the number of household members, the number of cars, and household monthly income. Transportation facility attributes include access time from home to a public transportation station and a bicycle sharing station, whether a car sharing station is located near the home, and the number of bus stop in the TAZ where the home is located. Travel attributes take into consideration car, public transportation, taxi, and bicycle trip frequency for a week.
Lastly, the proportion of the residential area and commercial area, the total floor area of neighborhood commercial facility and business facility in the TAZ were encompassed by land use attributes. Note that multiple correlation analyses were conducted to only select uncorrelated explanatory variables, meaning that there were no multicollinearity issues.

3.2. Key Descriptive Statistics of the Sample

The descriptive statistics on the key variables are presented in Table 2. Almost 73% of respondents selected MaaS. The respondents tended to be more often male, white collar, and have no car sharing station near residence. Subway, bus, and car are used as commute means, in decreasing order. Weekly trip frequency by means was 2.7 trips for cars, 7.4 trips for PT, 0.7 trips for taxis, and 0.5 trips for bicycles. Respondents used public transportation the most, and rarely used bicycles. The number of household members and cars was 3.1 and 1.0, respectively. Access times to PT station and car sharing station from the residence were 9.9 min and 16.4 min, respectively.
Table 2. Descriptive statistics of the sample.

| Variable                        | Count | Share |
|---------------------------------|-------|-------|
| Choice of MaaS                   |       |       |
| Yes                             | 591   | 73.4% |
| No                              | 214   | 26.6% |
| Gender                          |       |       |
| Male                            | 520   | 64.6% |
| Female                          | 285   | 35.4% |
| Job type                        |       |       |
| Professional                    | 130   | 16.1% |
| Service worker                  | 45    | 5.6%  |
| Sales worker                    | 55    | 6.8%  |
| White collar                    | 545   | 67.7% |
| Other                           | 30    | 3.7%  |
| Commute means                   |       |       |
| Car                             | 240   | 29.8% |
| Bus                             | 270   | 33.5% |
| Subway                          | 280   | 34.8% |
| Taxi                            | 10    | 1.2%  |
| Bicycle                         | 5     | 0.6%  |
| Presence of car sharing station |       |       |
| Yes                             | 220   | 27.3% |
| No                              | 585   | 72.7% |
| Education level                 |       |       |
| high school diploma             | 35    | 4.4%  |
| attending college and university| 25    | 3.1%  |
| college and university degree   | 600   | 74.5% |
| attending graduate school       | 10    | 1.2%  |
| completed graduate degree       | 135   | 16.8% |
| Household monthly income        |       |       |
| less than 1 million won         | 5     | 0.6%  |
| 1–2 million won                 | 45    | 5.6%  |
| 2–3 million won                 | 120   | 14.9% |
| 3–5 million won                 | 280   | 34.8% |
| 5–10 million won,              | 305   | 37.9% |
| 10 million won or more          | 50    | 6.2%  |

| Variable                        | Mean  | S.D.  |
|---------------------------------|-------|-------|
| Personal and household attributes|       |       |
| Education level                 | 3.2   | 0.9   |
| Number of household members     | 3.1   | 1.2   |
| Number of cars                  | 1.0   | 0.5   |
| Household monthly income        | 4.2   | 1.0   |
| Transportation facility attributes|      |       |
| Access time to a PT station     | 9.9   | 8.7   |
| Access time to a bike-sharing station | 16.4 | 17.8 |
| Number of bus stops             | 28.4  | 15.1  |
| Land use attributes             |       |       |
| Proportion of the residential area (%) | 0.6 | 0.4  |
| Proportion of the commercial area (%) | 0.0 | 0.1  |
| Neighborhood commercial facility area (ha) | 6.2 | 5.7  |
| Business facility area (ha)     | 0.5   | 1.5   |
| Travel attributes               |       |       |
| Car trip frequency              | 2.7   | 3.1   |
| PT trip frequency               | 7.4   | 5.1   |
| Taxi trip frequency             | 0.7   | 1.1   |
| Bicycle trip frequency          | 0.5   | 1.6   |

1 The survey grouped education level numbered 1 to 5 (high school diploma, attending college and university, college and university degree, attending graduate school, and completed graduate degree). “For the models presented, we assume for convenience that each one-unit increase in education level has the same effect on the utility of choosing MaaS” as in Kim and Mokhtarian [36]. 2 The survey grouped household monthly income into levels numbered 1 to 6 (less than 1 million won, 1–2 million won, 2–3 million won, 3–5 million won, 5–10 million won, and 10 million won or more, 1 dollar is 1116 Korean won in December 2018). We applied the same as the education level.

Furthermore, the statistical differences of the continuous explanatory variables between the two groups (MaaS chooser vs. non-chooser) were analyzed using t-tests. In addition, chi-square tests were performed to identify the significant relationship between the categorical explanatory variables and MaaS choice (Table 3). All travel attribute variables showed statistical differences at a 90% significance level. Most of personal and
household attributes (except for gender and the number of household members), transportation facility attributes (except for the number of bus station), and land use attributes (except for proportion of residential area) were significant at a 90% significance level.

Table 3. Descriptive analysis by MaaS choice.

| Variable                              | t-Value | p-Value | \( \chi^2 \) | p-Value |
|---------------------------------------|---------|---------|---------------|---------|
| Personal and household attributes     |         |         |               |         |
| Gender                                | 0.632   | 0.427   | 0.632         | 0.427   |
| Education level category              | 2.258   | 0.024   | 23.420        | 0.001   |
| Job type                              |         |         | 55.027        | 0.000   |
| Commute mean                          | 0.836   | 0.403   |               |         |
| Number of household members           | 6.026   | 0.000   |               |         |
| Number of cars                        | 3.210   | 0.001   |               |         |
| Household monthly income category     |         |         |               |         |
| Transportation facility attributes    |         |         |               |         |
| Access time to PT station (min)       | 1.669   | 0.096   |               |         |
| Access time to bicycle sharing station (min) | 3.670   | 0.000   |             |         |
| Presence of car sharing station       | −1.301  | 0.194   | 3.523         | 0.061   |
| Number of bus stop                   |         |         |               |         |
| Land use attributes                   |         |         |               |         |
| Proportion of the residential area (%)| −0.791  | 0.429   |               |         |
| Proportion of the commercial area (%) | −2.421  | 0.016   |               |         |
| Neighborhood commercial facility area (ha) | −1.696  | 0.090   |             |         |
| Business facility area (ha)           | 2.699   | 0.007   |               |         |
| Travel attributes                     |         |         |               |         |
| Car use                               | 51.629  | 0.000   |               |         |
| PT use                                | 20.249  | 0.000   |               |         |
| Taxi use                              | 67.516  | 0.000   |               |         |
| Bicycle use                           | 31.284  | 0.000   |               |         |

3.3. Methodology

We adopted a logistic regression model since the dependent variables are binary. The logistic regression model estimates relationships between a dependent variable in the form of a dichotomous scale with a value of 0 or 1, and explanatory variables [37]. Since the binomial dependent variable and explanatory variables do not have linearity, a conventional linear regression model is not an appropriate tool. If the independent variable X and the dependent variable Y are linear, the effect of X is constant, but if the two variables follow the logistic function, X affects Y differently depending on the position of X. The expected value of Y using X is expressed as E(Y|X), and if Y is a discrete variable, E(Y|X) has a concept of probability. Therefore, it is represented by E(Y|X) = p(X) to indicate the prediction of the probability of Y according to the X value. The p(X) is the probability that a particular selection will appear for a given explanatory variable, in the form of a S-shaped logistic curve with a minimum value of 0 and a maximum value of 1. The odds, the ratio of probability that an outcome will occur over probability not to occur, are expressed as Equation (1) [37]:

\[
\text{odds} = \frac{p}{1-p}
\]  

(1)

The probability is expressed by utilizing odds, and the relationship between dependent and explanatory variables in a nonlinear form through logit transformation is linear. Accordingly, the logistic regression model can be expressed as Equations (2)–(4) [37]:

\[
E(Y|X) = p(X) = \frac{\exp(\alpha + \beta X)}{1 + \exp(\alpha + \beta X)} = \frac{1}{1 + \exp(-\alpha + \beta X)}
\]  

(2)

\[
\frac{p}{1-p} = \frac{\frac{1}{1+\exp(-\alpha+\beta X)}}{\exp(-\alpha+\beta X)} = \frac{1}{\exp(-(\alpha+\beta X))} = \exp(\alpha + \beta X),
\]  

(3)
\[ \log \left( \frac{p}{1-p} \right) = \alpha + \beta X. \] (4)

This model can be classified according to the number and attribute of the dependent variables. In particular, a binomial logistic model can be used when analyzing the two alternatives where a particular event occurs for a single situation and is divided into two categories (one for a particular event and one for a non-occurrence). It also uses the utility theory of the probability choice model. In the probability choice model, utility can be expressed as an attraction to alternatives through their attributes. According to the utility theory, each probability \((U_i)\) to choose an alternative consists of an observable deterministic utility \((V_i)\) and an unobserved random utility \((\varepsilon_i)\) as Equation (5):

\[ U_i = V_i + \varepsilon_i \] (5)

In analyses based on individual choices, deterministic and random utility theories are used to account for causes of differences in individual choices for alternatives. The probability of choice is indicative of the logistic distribution according to the effect of the explanatory variable and the increase in utility in choosing alternatives in the logistic regression model. Thus, the logit transformation method is used to estimate the binomial logistic regression model by substituting utility as a probability variable.

The logit model assumes that the population has the same utility function. However, respondents may have different utility in choosing MaaS. This research hypothesis motivates is to apply a latent class modeling approach. The latent class model proposes that the populations are divided into several unobserved (“latent”) classes, and observations allocated to each class can capture unobserved heterogeneity [38]. The latent layer model is divided into the membership model and the class-specific choice model. The former describes the probability \(P_n(c)\) that the observation \(n\) belongs to latent class \(c\), and the latter predicts the probability \(P_n(i|c)\) that the observation \(n\) chooses alternative \(i\) (MaaS package), conditional on the observation \(n\) belonging to class \(c\). The probability \(P_n(i)\) can be expressed as Equation (6) [39]:

\[ P_n(i) = \sum_{c=1}^{C} P_n(c) \times P_n(i|c), \] (6)

where, \(n\) is observation \((n = 1, 2, \ldots , N)\), \(i\) is alternative (the MaaS package alternative is binary choice between 0 and 1, in this study.), and \(c\) is latent class \((c = 1, 2, \ldots , C)\). \(P_n(c)\) and \(P_n(i|c)\) can be specified as Equation (7) and Equation (8), respectively:

\[ P_n(c) = \frac{e^{\alpha_c z_n}}{\sum_{k=1}^{C} e^{\alpha_k z_n}} \] (7)

\[ P_n(i|c) = \frac{e^{\beta_i x_n}}{\sum_{j=1}^{C} e^{\beta_j x_n}} \] (8)

where, \(\alpha_c\) is a corresponding vector of parameters, \(z_n\) is a vector to determine the class \(c\) probabilities for observations \(n\). The latent class model estimates the membership model and class-specific choice model simultaneously by the maximum likelihood procedure, estimating models to describe the heterogeneity of latent classes [37,39,40].

4. Model Estimation Result

4.1. Model Selection

It is important to determine the number of latent classes in estimating and choosing the final latent class model. In this study, the latent class was determined based on the trip frequency of commute means. However, since the number of latent classes according to the criterion is not known [41,42], researchers must manually determine the optimal number of latent classes by comparing models stratified by the number of classes. Quantitative
indicators and qualitative criteria are needed to determine the optimal number of latent classes. Log-likelihood, Akaike information criterion (AIC), and Bayesian information criterion (BIC) were considered as quantitative indicators. A model with the highest log-likelihood and the lowest AIC and BIC is generally accepted as the optimal model. A few recent studies [36,43] also consider conceptual considerations and model interpretability. In this research, we selected the model with two latent classes (Table 4) with the lowest BIC (in terms of log-likelihood and AIC, the four-class model exhibited the best outcome, but they were not chosen due to model convergence failure and interpretability).

Table 4. Model indices by the number of classes.

| Number of Classes | Log-Likelihood | AIC       | BIC       |
|-------------------|----------------|-----------|-----------|
| 1                 | −388.118       | 816.236   | 910.053   |
| 2                 | −300.614       | 689.228   | 895.625   |
| 3                 | −246.388       | 628.776   | 947.753   |
| 4                 | −189.356       | 548.712   | 974.434   |

4.2. Estimation Results

4.2.1. Membership Model

Table 5 shows the estimation results of the class membership model with two classes. The class probabilities of the two classes are 54.3% and 45.7%, respectively, and the MaaS choice probability of Class 1 and Class 2 are 82.6% and 62.5%, respectively. That is, those who belong to Class 1 are more likely to choose MaaS compared to those in Class 2. Among the trip frequency, three out of four covariates (other than PT) were statistically significant at the 99% significance level; respondents belonging to Class 2 are more likely to use personal vehicles including cars and bicycles and less likely to use taxis than those belonging to Class 1.

Table 5. Estimation results of class membership model.

| Category               | Class 1       | Class 2       |
|------------------------|---------------|---------------|
| Class probability      | 54.3%         | 45.7%         |
| MaaS choice probability| 82.6%         | 62.5%         |

| Coef. | z-value | Coef. | z-value |
|-------|---------|-------|---------|
| Constant     | -       | -2.335 *** | -2.75 |
| Car trip frequency | -       | 0.920 *** | 4.54 |
| PT trip frequency | -       | 0.076 | 1.34 |
| Taxi trip frequency | -       | -1.192 *** | -4.19 |
| Bicycle trip frequency | -       | 1.191 *** | 4.43 |

Note: *** indicates significance at the 99% level.

4.2.2. Class-Specific Choice Model

The two-class model, together with a pooled model as reference are both presented in Table 6. The latent class model exhibited an improved goodness-of-fit (rho-squared of the pooled and latent class models were 0.304 and 0.461, respectively). Both models share key variables, which are statistically significant at the 90% level in common. With respect to the individual and household attributes, respondents who are male or have more household members tend to choose MaaS (it is consistent with the results of Ho et al. [16]). Coefficients of the education level, household monthly income, and number of cars are negative in class 1 model. Matyas et al. [19] partly explained one of those relationships; they revealed a negative relationship between MaaS preference and household monthly income and stated that respondents with low income are likely to own fewer private vehicles, resulting in preferences for public transit and Maas. Regarding the transportation facility attributes, accessibility to public transportation (in Class 1) and shared transportation service (in Class 2) were positively associated with MaaS choice. Given that MaaS provides
shared transportation service, those relationships seem fairly obvious, which aligns with the results from Matyas et al. [19]. Ho et al. [20] suggested that the lower the car trip frequency is, the higher the preference for MaaS is. Similar results were found in Class 1 (albeit it was not significant at the 90% level).

Table 6. Estimation results of the MaaS choice models.

| Variable                              | Pooled Model | Latent Class Model | Class 1 | Class 2 |
|---------------------------------------|--------------|--------------------|---------|---------|
| Constant                              | 0.539        | 5.327 ***          | 0.733   |         |
| Gender (male)                         | 0.226        | 2.166 ***          | 1.370 **|         |
| Education level category              | -0.338 ***   | -1.162 **          | -0.042  |         |
| Job type (white collar)               | 0.158 *      | 0.444              |         |         |
| Commute means (car)                   | -0.386 *     | -1.014             | -0.226  |         |
| Number of household members           | 0.229        | 1.350 ***          | 1.170 **|         |
| Number of cars                        | -0.126       | -3.233 ***         | -2.392  |         |
| Household monthly income category     | -0.549 **    | -0.713 *           | 0.002   |         |
| Access time to PT station (min)       | -0.011       | -0.300 ***         | -0.033  |         |
| Access time to bicycle sharing station (min) | -0.014 ***   | 0.105 ***          | -0.044 **|         |
| Presence of car sharing station       | 0.601 ***    | 0.616              | 2.164 ***|         |
| Number of bus stop                    | 0.446 *      | 0.110 ***          | 0.025   |         |
| Proportion of the residential area (%)| 3.015 **     | 3.195 ***          | 1.857 **|         |
| Proportion of the commercial area (%) | 0.043 *      | 2.835              | 1.548 **|         |
| Neighborhood commercial facility area (ha) | -0.099     | 0.011              | 0.053   |         |
| Business facility area (ha)           | 0.006        | 0.343              | -0.145  |         |
| Car use                               | -0.256       | -1.399             | -2.824  |         |
| PT use                                | 1.376 ***    | 1.752 ***          | 1.703 **|         |
| Taxi use                              | 0.986 ***    | 5.307 ***          | 1.081 * |         |
| Bicycle use                           | 0.138        | -5.237 ***         | 0.584   |         |

Model Summary

- Number of case: 805
- Log-likelihood (0): -558.0
- Log-likelihood (β̂): -388.1
- ρ²: 0.304

Note: *, **, *** indicate significance at the 90%, 95%, and 99% significance levels.

MaaS is a service to reduce the use of private cars through the efficient use of public and shared transportation. Those who own and use private cars tend not to change transit mode, so MaaS is considered to have a low preference for these people. In other words, those living in areas with good accessibility to public transportation are likely not to use their own cars and are likely to use MaaS.

4.2.3. Class Profiles

To understand the fundamental characteristics of each latent class, we examined to what extent the personal and household attributes, transportation facility attributes, land use attributes, and travel attributes differ by class using expected values [43] (Table 7). The probability that the respondent belongs to the latent class is expressed as Equation (9); it is a weighted average to which the prior probability suggested by Bhat [44] is applied.

\[
x_n = \frac{\sum_{n=1}^{N} P_n(c)x_n}{\sum_{n=1}^{N} P_n(c)}
\] (9)
Table 7. Expected values of selected variables by latent class.

| Variable                        | Pooled Model | Class 1: PT-Oriented | Class 2: Balanced Mode |
|---------------------------------|--------------|----------------------|------------------------|
| Travel attributes               |              |                      |                        |
| Car frequency                   | 2.7          | 0.9                  | 4.8                    |
| PT frequency                    | 7.4          | 9.3                  | 5.3                    |
| Taxi frequency                  | 0.7          | 0.8                  | 0.6                    |
| Bicycle frequency               | 0.5          | 0.1                  | 1.0                    |
| Personal and household attributes|              |                      |                        |
| Gender (male)                   | 64.6%        | 54.2%                | 76.9%                  |
| Education level category        | 3.2          | 3.2                  | 3.3                    |
| Job type (white collar)         | 67.7%        | 68.4%                | 66.8%                  |
| Commute means (car)             | 29.8%        | 6.9%                 | 56.9%                  |
| Number of household members     | 3.1          | 2.9                  | 3.3                    |
| Number of cars                  | 1.0          | 0.9                  | 1.2                    |
| Household monthly income category| 4.2          | 4.1                  | 4.4                    |
| Transportation facility attributes|             |                      |                        |
| Access time to PT station (min) | 9.9          | 8.2                  | 11.9                   |
| Access time to bicycle sharing station (min) | 16.4 | 12.8 | 20.6 |
| Car sharing station             | 27.3%        | 24.9%                | 30.2%                  |
| Number of bus stop              | 28.4         | 29.3                 | 27.3                   |
| Land use attributes             |              |                      |                        |
| Proportion of the residential area | 0.6          | 0.5                  | 0.6                    |
| Proportion of the commercial area | 0.0          | 0.0                  | 0.0                    |
| Neighborhood commercial facility area | 6.2          | 6.3                  | 6.1                    |
| Business facility area          | 0.5          | 0.5                  | 0.6                    |

Looking at the characteristics of each latent class, the access time to the PT station and the bicycle sharing station for class 1 was 8.2 min and 12.8 min, respectively, which exhibited better access to transportation facilities compared to Class 2 (PT = 11.9 min, bicycle sharing = 20.6 min). Accordingly, Class 1 mainly uses public transportation for commuting (9.3 trips/week) as expected. Class 2 is mostly men (76.9%), and more than half of them used cars for commute (56.9%). Additionally, commuters in Class 2 did not have a certain preference for commute mode (car = 4.8 trips/week, PT = 5.3 trips/week). Thus, we label the two groups as “public transit-oriented commuter” and “balanced mode commuter”, respectively.

5. Conclusions and Discussion

In the context of travel behavior, previous studies have dealt with MaaS, which provides seamless multi-modal services on an app, but there are few studies that identify key factors affecting MaaS choice, and related studies rarely focus on commute trips. Thus, this study first defined MaaS as an app-based service that combines conventional public transit and shared transportation and provides booking and payment services simultaneously, then aimed to explore the MaaS choice mechanism of Seoul commuters. A SP survey was designed and conducted to collect personal, household and travel attributes, as well as the mode choice of MaaS service. Based on collected data, MaaS choice models were developed. In particular, we adopted a latent class modeling approach to distinguish different unobserved groups, thereby identifying heterogenous impacts of explanatory variables on likelihood of choosing MaaS. The results showed that Seoul commuters are classified into two latent groups based on mode use frequency. Commuters in Class 1 are more likely to prefer public transportation whereas Class 2 commuters tend not to have a specific mode preference (they used cars and public transportation equally). Various attributes, including personal and household traits, and transportation facility, were statistically significant at the 90% significance level. Comparing the two classes of the latent class model, we found that the coefficient of most variables was similar (whether positive or negative), but statistically significant variables were different. The coefficients of the number of cars and access time to PT station were negative, whereas coefficient of the number of bus stop was positive. Through such analysis, this study has developed the latent class model to derive influence factors considering the heterogeneity of MaaS choice and personal, household, and built environment (e.g., land use and transportation facilities) attributes.
As a result, the following implications are obtained: First, it is possible to employ a MaaS system suitable for the characteristics of the employed area by reflecting the built environment variables. Previous studies [19–22] calculated the utility of the MaaS choice depending on the MaaS package bundle without reflecting regional characteristics. It is important to observe what means are included in the MaaS package, but it is also necessary to study the characteristics of the areas in which MaaS will be employed. In addition, this study develops a MaaS choice model that reflects the heterogeneity of the commuter. As a result of model development, commuters were divided into two groups (the public transit-oriented and the balanced mode commuter groups), and the influencing factors of MaaS choice for each group were analyzed differently. These results confirm the heterogeneity of commuter’s travel behavior. Therefore, the results of this study emphasize the importance of considering users and built environment characteristics when planning and employing MaaS systems in the future.

Of course, this study has some limitations due to budget and time constraints. First, there are additional factors affecting the likelihood of choosing MaaS such as personality and travel attitudes which could be considered when conducting future surveys. A more sophisticated model could be developed through the survey of such additional samples. Moreover, expansion of the research area to wider spatial areas, not confined to Seoul, would be beneficial for further research. In Seoul, the public transport system is well-equipped, which is advantageous for the introduction of MaaS. However, further research on the introduction of MaaS should also include other cities because of the varying context of each city. In this respect, research [45,46] using hierarchical models that can deal with spatial correlation issues is also needed. Lastly, as MaaS becomes more concrete in the future, an enhanced SP survey design considering more realistic traffic conditions such as waiting time is required. In addition to the weekly package analyzed in this study, future efforts should consider various types of period packages (e.g., one-time packages or monthly packages) and the recently popular e-scooter. Further sophisticated modeling strategies considering such aspects would be useful for exploring the heterogenous impact on the likelihood of choosing MaaS. Overall, there is little doubt that MaaS is in its early stages, and further research is in demand.

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