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Research Article

Automated Mobility-on-Demand Service Improvement Strategy through Latent Class Analysis of Stated Preference Survey

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Automated driving technologies have advanced remarkably and are expected to be a part of our lives soon. Because automated driving technology does not require a driver, a significant change in future mobility services is expected. Automated driving technology is closely related to the development of public transit services as it can significantly reduce driver labor costs and provide a more comfortable in-vehicle environment. In particular, the preference for automated mobility-on-demand services that can respond in real time to the dynamic demand through automated driving technology is growing. Previous studies have compared passengers' preferences for automated mobility-on-demand services and other transportation modes and proposed a way to enable more passengers to use automated mobility-on-demand services. However, as the number of pilot operations increases, future research will focus on ways to improve competitiveness among automated mobility-on-demand services. This study conducts a passenger preference survey based on the characteristics of automated mobility-on-demand services. In particular, changes in the in-vehicle environment and seat selection system, which differ from existing mobility-on-demand services due to automated driving technology, are investigated. The latent class modeling approach is used to classify passengers based on stated preference data collected from the survey. The estimation results show that vehicle type and seat choice system have a significant impact on passengers' preference for automated mobility-on-demand services. In addition, considering that a high percentage of passengers do not prefer to improve autonomy in seat reservation and the in-vehicle environment, this study suggests that cost-consuming service improvement strategies are not always appropriate.

1. Introduction

Many problems associated with driving are expected to be solved by automated driving technology (ADT). The main benefits are driving safety and efficiency, and the greatest benefit is that there is no need for a driver above all else. This is expected to alleviate driver shortages and labor costs, which are currently hot topics in logistics [1]. For instance, in Texas, the introduction of ADT was predicted to result in a significant change because labor compensation (salary and fringe benefits) accounts for 70% of the total operating cost of public transit services [2]. Thus, introducing ADT in public transit services could be a significant step toward addressing the long-term labor cost issue.

ADT is expected to significantly improve public transit services by providing real-time services while also lowering operating costs. Recently, the preference for public transit services that can respond to dynamic demand in real time rather than fixed route services has increased, and ADT is being considered a major alternative [3]. In a prior study, ADT was found to be more cost-effective and customizable than human-operated services when applied to mobility-on-demand (MoD) services that required changing routes in real time based on various situations [4]. Thus, ADT should be accompanied by other technologies to provide the desired MoD services because considering it separately is difficult. Previous studies on passenger preference for MoD were based on big data [5, 6] or a stated preference (SP) survey [7, 8]. In particular, in an SP-based study on automated MoD (AMoD) services, the mode choice of passengers was analyzed while considering the traditional travel properties (time, cost, transfer, and the number of stops) of AMoD

[7, 8]. However, it is difficult to explain all the innovations of AMoD solely on the basis of traditional travel properties. Moreover, as traditional travel properties are not unique to AMoD but have the same characteristics as MoD, additional research is needed to investigate the preference for AMoD.

One of the main benefits of AMoD is the efficient use of the in-vehicle environment due to the absence of the driver's seat. At least one more passenger can be accommodated on board, or passengers can have a more comfortable space by rearranging the seats. Given the growing importance of private space, it is expected that the change in the in-vehicle environment due to ADT will have a significant effect on passengers' preferences. Recent related studies have analyzed travel properties using a model that considers individual attitudes as well, and privacy-seeking is noted as one of the main attitudinal factors [9, 10]. The improvement of the in-vehicle environment is closely related to the crowdedness level, which is one of the traditional travel properties. The crowdedness level is an important factor in choosing a vehicle, and providing vehicle crowding information has become an effective way to promote passenger comfort [11]. In general, crowding information about intraregional public transit services is provided on three or four levels, with the service that provides seats to all passengers only informing the number of remaining seats. On the other hand, most interregional public transit services require vehicle and seat reservation, and AMoD is similar to interregional services in that a vehicle must be reserved for boarding. The problem is that not everyone wants to obtain more information on short trips, which can be annoying. A lot of information may be desired for interregional travel with a long travel distance, but there is a possibility that a higher proportion of groups want to receive minimal information about intraregional travel. Considering that higher costs are required to provide more information, this is an important issue consideration before commercializing AMoD.

This study investigates factors that passengers consider important when using AMoD services. In particular, the preference for the unique properties of AMoD, such as the in-vehicle environment and seat choice system, is investigated, and the results are estimated through the SP survey. Despite numerous studies on AMoD's market share and passenger preferences in literature reviews, few studies have investigated the unique benefits of AMoD. In this context, this study attempts to derive implications for service strategies by segmenting markets for AMoD properties that have not been reviewed in previous studies. For example, it is expected to be useful for establishing appropriate strategies if the group favoring advanced seat choice systems is dominant or if the group with high sensitivity to specific travel properties is dominant. In addition to the two cases, heterogeneity over several factors is expected to be revealed, and the latent class model (LCM) has been utilized in deriving results. As reviewed in previous studies, LCM has strength in interpreting class profiles and is widely used in transportation fields. Thus, the purpose of this study is to classify latent classes for the preference for properties of AMoD based on data obtained from the SP survey. Finally, based on the estimation results, we propose an appropriate strategy for providing more competitive AMoD services by considering both traditional travel properties and the unique characteristics of AMoD.

The remainder of this paper is organized as follows. In the data collection section, the questionnaire configuration and SP experimental design for collecting the data used in this study are explained, and the sample configuration is described. The methods section describes the configuration of LCM used to classify passengers and the parameter estimation methodology. The last part concludes with the estimation results, class profiles, conclusions, and limitations.

2. Data Collection

The purpose of this study is to investigate properties that make passengers prefer AMoD to the conventional transportation system. However, AMoD is still being piloted in some regions, and most respondents are unfamiliar with the service. Thus, prior to the SP survey, explanations of ADT, MoD, and AMoD are presented to clarify the scope of the experiment and to help respondents understand AMoD services. The remaining questions include SP experiments and questions about respondents' sociodemographics. This survey was conducted online from November 10 to 15, 2021, with respondents aged 20 and older living in 24 regions with a population of 0.3–1 million. Survey regions were selected mainly for areas where AMoD service can be commercialized in the near future. To explain in more detail, large cities with high demand were considered primarily, and areas, where public transit services were sufficiently supplied, were excluded. Regions, where public transit services are well supplied, are likely to be commercialized relatively late due to the low competitiveness of AMoD service. Therefore, Seoul, a representative metropolitan city, was the first to be excluded from the survey region, and Suwon, the largest metropolitan city in Gyeonggi-do, was also excluded for the same reason. The sample is stratified to allocate the number of samples according to the proportion of the population in each region, and 2,258 samples are eventually collected (see Table 1).

The purpose of the SP experiment is to analyze passenger preferences for two AMoD models with different properties. As AMoD has not yet reached the commercialization stage, an SP experiment is designed to analyze the preference for each property (see Figure 1). The respondents choose the more preferred models among the two AMoD models while considering traditional travel properties (arrival time, access time, in-vehicle time, and the number of stops) and in-vehicle environment properties (crowdedness level, seat choice system, and vehicle type) presented in a given hypothetical situation. One respondent responds to four different hypothetical situations.

The attribute level in AMoD is limited to a maximum of 3 levels to avoid having too many cases in the experiment (see Table 2). In the case of traditional travel properties, a realistic level is chosen in consideration of conventional public transit services, and the access and arrival times are

Table 1: Socio-demographics and distribution of sample ($N = 2{,}258$).

Variable	Category	Frequency	Distribution (%)
Gender	Male	1,082	47.9
	Female	1,176	52.1
Age	20–29 years	355	15.7
	30–39 years	670	29.7
	40–49 years	753	33.3
	50–59 years	388	17.2
	>60 years	92	4.1
Education	Less than middle school	19	0.8
	High school graduate	465	6.0
	Attending University	135	20.6
	College graduate or higher	1,639	72.6
Occupation	Manager	143	6.3
	Expert	252	11.2
	Office worker	669	29.6
	Service worker	275	12.2
	Salesperson	165	7.3
	Agricultural, forestry, and fishery workers	16	0.7
	Technicians or craftworkers	79	3.5
	Device/Machine operation or assembly workers	79	3.5
	Simple labor worker	108	4.8
	Soldier	4	0.2
	Student	104	4.6
	Inoccupation	268	11.9
	Etc	96	4.3
Residence	Seongnam city, Gyeonggi-do	157	7.0
	Hwaseong city, Gyeonggi-do	149	6.6
	Bucheon city, Gyeonggi-do	136	6.0
	Namyangju city, Gyeonggi-do	123	5.4
	Ansan city, Gyeonggi-do	111	4.9
	Anyang city, Gyeonggi-do	106	4.7
	Pyeongtaek city, Gyeonggi-do	104	4.6
	Siheung city, Gyeonggi-do	90	4.0
	Gimpo city, Gyeonggi-do	87	3.9
	Paju city, Gyeonggi-do	86	3.8
	Uijeongbu city, Gyeonggi-do	83	3.7
	Gwangju city, Gyeonggi-do	75	3.3
	Hanam city, Gyeonggi-do	68	3.0
	Wonju city, Gangwon-do	113	5.0
	Cheongju city, Cungcheongbuk -do	102	4.5
	Cheonan city, Chungcheongnam-do	94	4.2
	Asan city, Chungcheongnam-do	55	2.4
	Jeonju city, Jeollabuk-do	95	4.2
	Pohang city, Gyeongsangbuk-do	81	3.6
	Gumi city, Gyeongsangbuk-do	69	3.1
	Gimhae city, Gyeongsangnam -do	87	3.9
	Yangsan city, Gyeongsangnam-do	70	3.1
	Jinju city, Gyeongsangnam-do	64	2.8
	Sejong-Si	53	2.3
Income	<420 USD per month	255	11.3
	420–840 USD per month	97	4.3
	840–1,680 USD per month	281	12.4
	1,680–2,520 USD per month	604	26.7
	2,520–3,360 USD per month	486	21.5
	3,360–4,200 USD per month	292	12.9
	4,200–5,880 USD per month	155	6.9
	5,880–8,400 USD per month	58	2.6
	>8,400 USD per month	30	1.3
Driving license	Acquired	2,001	88.6
	Not acquired	257	11.4
Car ownership	Owned	2,032	90
	Not owned	226	10

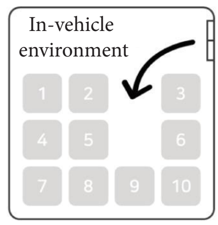
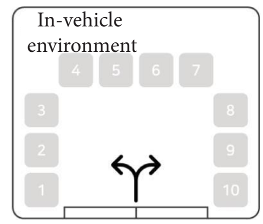
	Van type	Shuttle type
Vehicle Type	 	 
Arrival time	15 min left	5 min left
Access time	3 min	7 min
In-vehicle time	20 min	30 min
Number of stops	Maximum 4	Maximum 6
Congestion level	3/10	8/10
Seat choice system	Seat choice available	Seat choice after boarding
Mode choice	□	□

Figure 1: An example of stated choice experiments.

Table 2: Attribute level.

Variable	Level
Vehicle type	Van type (conventional type) and shuttle type (driverless type)
Arrival time (min)	5, 10, 15
Access time (min)	3, 5, 7
In-vehicle time (min)	20, 25, 30
Number of stops	2, 4, 6
Crowdedness level	3/10 (not crowded), 8/10 (crowded)
Seat choice system	Seat choice available, automatic seat assignment, seat choice after boarding

set similarly to taxi services. Because this experiment compares AMoD models with different travel properties, it is assumed that the travel costs in AMoD models are the same. Vehicle types are classified according to the absence of a driver's seat, with the van type selected as a type considered suitable for AMoD among currently commercialized models, and the shuttle type is chosen to provide passengers with a more comfortable space by removing the driver's seat. Finally, seat choice systems are classified into three categories: seat choice available, automatic seat assignment, and seat choice after boarding; the hierarchy is established sequentially on the basis of a passenger's autonomy for seat reservation.

With these AMoD properties, a hypothetical choice situation is created using an efficient design that provides a situation that minimizes D-error. As a result, 36 hypothetical choice situations are created, and they are divided into 9 blocks consisting of 4 situations. Finally, 9,032 responses from 2,258 respondents in 4 choice situations are collected.

3. Methods

The LCM considers heterogeneity and assumes that each individual belongs to a finite number of groups. Compared to the mixed logit models, which assume parameters following continuous distribution, the latent class models are less flexible than the mixed logit model [12], and it is useful in marketing analysis where group classification is required. The reason for this is that each group's individual can be identified without any assumptions, and it is widely used in various transportation planning fields [13–16]. Latent class analysis has also been in some recent studies on public transit services based on ADT [7, 17]. However, the preference between AMoD and conventional modes of transportation [7] or various modes of transportation with ADT [17] has mainly been studied, and only a few studies have compared AMoD models on the basis of unique properties of AMoD.

This study compares various AMoD models, focusing on the unique characteristics of AMoD models, to investigate passengers' preferences for each property of AMoD. In addition, to derive good empirical results, the membership variable, which is a group classification variable of the LCM, is composed mainly of socio-demographics. In previous studies, various implications could be derived through a model that considers attitudinal factors, but the goal of this study is to increase utilization by increasing the intuition of the estimation results through quantitative factors. For example, privacy-seeking, one of the representative attitude factors, can indirectly explain the preference for the comfort of the in-vehicle environment and the preference for driving a personal vehicle. Rather, in this study, it is expected that it is more useful to examine whether each group's usual travel behavior is a choice rider or a captive rider who only uses public transit by adopting vehicle ownership, which is a direct indicator.

Thus, the class membership part consists of four socio-demographics (age, gender, car ownership, and income level), and the choice model part consists of AMoD travel properties (arrival time, access time, in-vehicle time, and the number of stops) and in-vehicle environment properties (vehicle type, crowdedness level, and seat choice system) (see Figure 2).

In the LCM, the probabilities of an individual n choosing alternative i, which can be calculated by the product of class membership probability and choice probability conditional on class membership, can be expressed as equation (1), where $P_n(i|q)$ is the prior probability for class q for individual n.

$$P_{\text{in}} = \sum_{q \in Q} P_{nq} P_n(i|q). \tag{1}$$

In this study, the multinomial logit model, which assumes all selection situations independently, is used, and the class membership model is expressed by equation (2), where X_n^Z is a $(Z \times 1)$ vector of covariate associated with individual n, and θ_q is a $(1 \times Z)$ vector of the unknown parameter characterizing class q for attributes X_n^Z.

$$P_{nq} = \frac{\exp\left(\theta_q X_n^Z\right)}{\sum_{\varphi \in Q} \exp\left(\theta_\varphi X_n^Z\right)}. \tag{2}$$

The conditional probability $P_n(i|q)$ is the joint probability that individual n chooses alternative i related to class q in all choice situations, as expressed in equations (3) and (4), where $P_{nt}(i|q)$ is the probability $P_n(i|q)$ in choice situation t. X_{int}^G is a $(G \times 1)$ vector of attributes of travel properties of individual n choosing mode i in choice situation t, and β_{iq} is a $(1 \times G)$ vector of parameters related to mode i and class q for attributes X_{int}^G.

$$P_n(i|q) = \prod_{t \in T} P_{nt}(i|q). \tag{3}$$

$$P_{nt}(i|q) = \frac{\exp\left(\beta_{iq} X_{int}^G\right)}{\sum_{j \in J} \exp\left(\beta_{jq} X_{jnt}^G\right)}. \tag{4}$$

4. Results

Before determining the optimal number of classes, the following goodness-of-fit indicators are reviewed: log-likelihood (LL), Bayesian information criterion (BIC), consistent Akaike information criterion (CAIC), and ρ^2 (see Table 3). As verified in previous studies, the three-class model with the lowest BIC and CAIC is chosen as the final model [18, 19]. LatentGOLD, a software package estimating the latent class model, was used to estimate the simulation results.

Based on the estimation results, the travel property coefficients of the discrete choice model part are all negative values or insignificant (see Table 4). In other words, the five attributes (arrival time, access time, in-vehicle time, number of stops, and crowdedness level) included in the model are factors that increase the disutility of travel when it increases, so the estimation result should be a negative value. Since the coefficient for the crowdedness level of class 3 has a positive value but is not significant, as a result, estimates for all attributes were appropriately derived. In particular, all time-related coefficients are significant. When the share of a specific class is extremely low, it is difficult to interpret, but the smallest class accounts for 9.65% (class 3), which is an appropriate level.

For the vehicle type option, all three classes have different preferences: class 1 prefers van type, class 3 prefers shuttle type, and class 2 does not have a significant effect on the choice. The shuttle type is expected to be chosen by a passenger that considers the improvement of the in-vehicle environment important. However, in class 3, the shuttle type is preferred even though the crowdedness level does not affect the chosen one. Moreover, class 1 and class 2 had no significant preference for shuttle types, even though the crowdedness level influenced the choice. Thus, the research hypothesis on the close relationship between vehicle types and the improvement of the in-vehicle environment is not appropriate. For the seat choice system, class 1 prefers automatic seat assignment, class 2 prefers seat choice available, and class 3 does not prefer automatic seat assignment. The group most similar to the 1-class model estimation result is class 3 in terms of vehicle type and class 2 in terms of seat choice system (see Table 5). When a decision is made on the basis of the 1-class model result regarding vehicle type, it is not appropriate to consider the market share of class 3.

The improvement of AMoD service is divided into two aspects: an increase in the number of service vehicles and an extension of the service coverage. It is necessary to apply two improvement measures based on the difference in the relative sensitivity of travel time properties. More specifically,

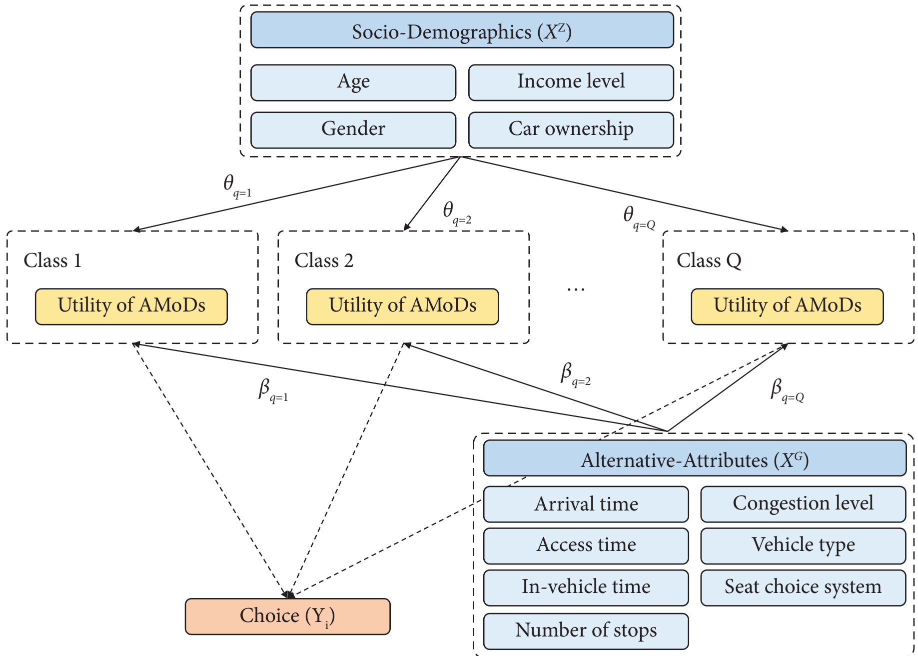


Figure 2: Framework for the proposed LCM of AMoD preference.

Table 3: Quantitative fit of 1–6-latent class membership models.

Number of classes	Number of parameters	LL	AIC	BIC	CAIC	ρ^2
1	8	−4734.626	9485.252	9531.030	9539.030	0.307
2	21	−4383.002	8808.004	8928.171	8949.171	0.521
3	34	−4298.388	8664.777	**8859.333**	**8893.333**	0.608
4	47	−4257.929	8609.859	8878.804	8925.804	0.649
5	60	−4221.470	8562.941	8906.275	8966.275	0.683
6	73	−4191.595	8529.190	8946.914	9019.914	0.721

Table 4: Estimation results of discrete choice model part from 3-class model.

Attributes	Class 1		Class 2		Class 3	
	Coefficient	*z*-value	Coefficient	*z*-value	Coefficient	*z*-value
Vehicle type (van = 1)	0.4489	(4.1329)***	−0.0314	(−0.5174)	−7.2495	(−3.7679)***
Arrival time (min)	−0.5074	(−13.9365)***	−0.0168	(−2.0988)***	−0.3292	(−2.2734)***
Access time (min)	−0.0924	(−3.0674)***	−0.0919	(−6.6829)***	−0.6236	(−2.6748)***
In-vehicle time (min)	−0.2266	(−11.4521)***	−0.0401	(−7.0957)***	−0.3705	(−2.0677)***
Number of stops	−0.0160	(−0.3944)	−0.0404	(−3.0601)***	−0.2173	(−1.3153)
Crowdedness level (crowded = 1)	−0.0451	(−2.5188)***	−0.0754	(−7.1544)***	0.1097	(0.3339)
Automatic seat assignment	0.4993	(3.1957)***	0.3741	(5.3558)***	−1.9785	(−1.9785)***
Seat choice available	0.1020	(0.7245)	0.6093	(8.9863)***	−0.3717	(−0.5042)
Class shares	0.5492	0.3543	0.0965			

Note. ***An estimate with a p value less than 0.01.

groups with higher sensitivity to access time will have higher preferences as the service area expands, and if the sensitivity to arrival time is high, there is a need to increase the number of service vehicles. The relative sensitivity of the time attribute versus the in-vehicle time of the discrete choice model part is reviewed (see Table 6). As the result, class 1 is more sensitive to arrival time and less sensitive to access time than other classes. To improve the preference of class 1, it will be necessary to allocate more service vehicles so that passengers can board a vehicle quickly. On the other hand, to improve the preference of the other two classes, where access time is more important, the coverage of service should be broadened. According to the estimation results, more respondents (class 1) need a policy that increases the number of service vehicles, and the same result is obtained for the 1-class model.

The results of the class membership model part show that four membership variables are used, but only two attributes

Table 5: Estimation results of discrete choice model part from 1-class model.

Attributes	Coefficient	Z value
Vehicle type (van = 1)	−0.1658	(−6.0377)***
Arrival time (min)	−0.1477	(−43.4059)***
Access time (min)	−0.0766	(−10.1372)***
In-vehicle time (min)	−0.0720	(−23.1482)***
Number of stops	−0.0360	(−4.7269)***
Crowdedness level (crowded = 1)	−0.0468	(−8.4630)***
Automatic seat assignment	0.2625	(6.9667)***
Seat choice available	0.2770	(7.7737)***

Note. ***An estimate whose p value is less than 0.01.

Table 6: Coefficient ratio of travel time properties from the 3-class model.

Attributes	Class 1	Class 2	Class 3
Arrival time/in-vehicle time	2.2392	0.4190	0.8885
Access time/in-vehicle time	0.4078	2.2918	1.6831

Table 7: Estimation results of class membership model part.

Attributes	Class 1		Class 2		Class 3	
	Coefficient	z value	Coefficient	z value	Coefficient	z value
Age	0.0892	(0.9439)	0.1387	(1.3646)	—	—
Gender	0.1935	(0.8458)	0.0461	(0.1844)	—	—
Income level	0.0524	(−0.7435)	0.1820	(2.3403)***	—	—
Car ownership	1.4912	(5.1213)***	0.1535	(0.5483)	—	—

Note. ***An estimate with p value less than 0.01.

Table 8: Descriptive statistics on car ownership.

Attributes	Class 1	Class 2	Class 3
Owned	1,301 (93.9%)	582 (86.1%)	149 (75.6%)
Not owned	84 (6.1%)	94 (13.9%)	48 (24.4%)
Total	1,385 (100.0%)	676 (100.0%)	197 (100.0%)

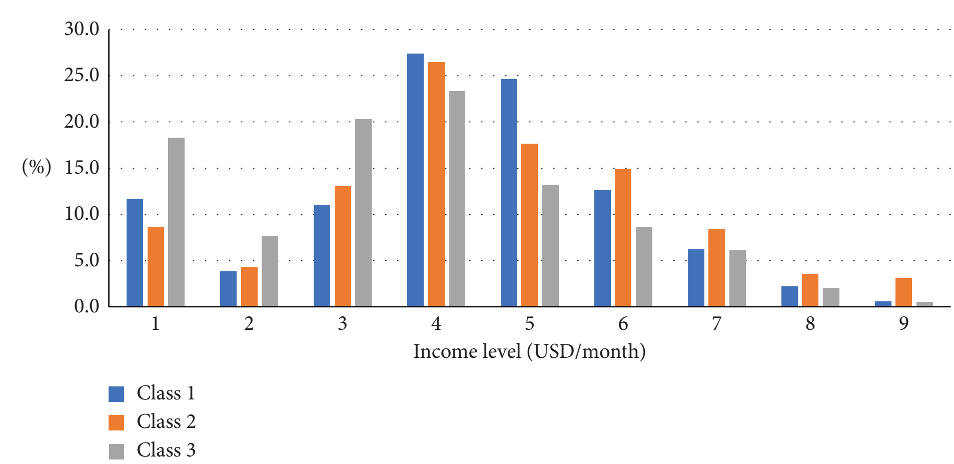


Figure 3: Descriptive statistics on income level.

(income level and car ownership) are significant (see Table 7). Car owners are more significantly distributed in class 1 than class 3, and the higher the income level, the more distributed car owners are in class 2 than class 3. According to the car ownership descriptive statistics of respondents belonging to each class, class 1 has the highest rate, whereas

Table 9: Descriptive statistics on the number of drives per week.

Attributes	Class 1	Class 2	Class 3
Less than 2 times	547 (39.5%)	278 (41.1%)	113 (57.4%)
More than 3 times and less than 5 times	481 (34.7%)	178 (26.3%)	36 (18.3%)
More than 6 times	357 (25.8%)	220 (32.5%)	48 (24.4%)
Total	1,385 (100.0%)	676 (100.0%)	197 (100.0%)

Note. Respondents who do not own a car are counted not to drive.

Table 10: Summary of characteristics per class.

Attributes	Class 1 (competitive class)	Class 2 (choice rider)	Class 3 (captive rider)
Car ownership	1st	2nd	3rd
Income level	2nd	1st	3rd
Drives per week	2nd	1st	3rd
Vehicle type	Van type preferred	—	Shuttle type preferred
Seat choice system	Automatic seat assignment preferred	Seat choice available preferred	Seat choice after boarding is preferred

class 3 has the lowest (see Table 8). Income level descriptive statistics of each class are as follows: the 1–3 levels for class 3 (less than 1,680 USD per month), 4 and 5 levels for class 1 (more than 1,680 USD and less than 4,200 USD per month), and 6–9 levels for class 2 (more than 4,200 USD per month), which is the most (see Figure 3). The descriptive statistics on the number of drives per week are also reviewed, considering the country's high preference for public transit services regardless of whether a car is owned (see Table 9).

According to the three descriptive statistics and the class membership model part results, the characteristics of each class are labeled: class 1 as a competitive class, class 2 as choice riders, and class 3 as captive riders (see Table 10). First of all, since the income level and the number of drives per week are indicators that can represent public transit usage behavior, the higher the two indicators, the more preferred personal transportation to public transit. In addition, preferences for a more advanced seat choice system were derived in the same order. This represents the importance of providing detailed seat information, and the desire to receive more information can be interpreted as preferring personal transportation to public transit.

5. Discussion and Conclusions

This study investigates the heterogeneity of passengers' preferences for AMoD on the basis of travel properties and in-vehicle environmental factors. Because previous studies have compared the preferences of other transportation modes and AMoD, the findings have been used to discuss the policy strategy necessary to induce demand for other transportation modes into AMoD. However, with the development of ADT, the number of AMoD pilot operation areas is increasing in various locations, and a competitive demand induction policy among AMoD models is expected to become an important topic. Therefore, this study focused on estimating the service that passengers expect from AMoD through SP analysis of different AMoD models with different characteristics.

The characteristics of AMoD investigated in this study are divided into traditional travel properties and in-vehicle environmental factors. Because all traditional travel properties of AMoD are independent of ADT, they are indistinguishable from MoD, and a unique characteristic of AMoD is the in-vehicle environment factor. Because the vehicle type can differ from the conventional type without the driver's seat, the SP preference is investigated by dividing the vehicle type into van type and shuttle type. According to the estimation results, the SP preference was classified into three latent classes with different preferences, and more than 50% of the respondents preferred the van type. Although this is considered to be a limitation of the experimental design, it was assumed that class 3 that preferred the shuttle type prefers a new type of vehicle to the effect of in-vehicle environment improvement. Moreover, with less than 10% of total respondents belonging to class 3 with early adopter tendencies, it is considered that most passengers prefer a familiar vehicle type to a new vehicle type. In other words, there may be no need to spend money to change the form of a service vehicle simply because ADT is introduced. The preference for a seat choice system for employing MoD is also investigated, and the preference for the most cost-consuming strategy is not high, as that for the vehicle type. Approximately 1/3 of the respondents belong to the class with the highest preference for "seat choice available," which is expected to require the most autonomy and the highest system maintenance cost. The ratio between the estimated coefficients of time properties suggested two policy strategies to improve preference. The sensitivity of the classes to arrival and access times differs, and more than 50% of the respondents consider arrival time to be more important than access time. Thus, the estimation results suggest that a policy to increase the number of service vehicles is needed to improve arrival time rather than to expand service coverage to improve access time.

The contribution of this study is to suggest a strategy to meet the needs of passengers to provide competitive services by considering not only the characteristics of MoD but also the unique characteristics of AMoD. The estimation results suggest that high-cost policies do not always enhance competitiveness among AMoD models. In addition, different strategies should be used to strengthen the competitiveness of MoD and AMoD, and it is expected that a low-cost strategy for AMoD will obtain a high preference for a specific service. Second, the practical applicability of the estimation results is improved by composing the class membership variables that classify classes only with direct indicators. In other words, direct indicators such as income level and vehicle ownership can be applied to real-world problems by integrating them with the characteristics of the regions being piloted.

The limitations of this study are due to the lack of a detailed experimental design. First, the respondents did not properly recognize the effect of the shuttle type on the in-vehicle environment improvement. By providing the seat map, we expected respondents to perceive the van type as a closed structure and the shuttle type as an open structure (see Figure 1). More specifically, corner seats of the van type are expected to be less comfortable because they are all blocked in all directions when high crowdedness level. However, based on the estimation results, additional explanations are required for the respondents' recognition. As a result, contrary to the expectation, the preference for the new vehicle type is estimated rather than the in-vehicle environment improvement. Second, it is necessary to consider regional characteristics such as the level of public transit service infrastructure in the surveyed regions. For example, if the headway of the surveyed public transit service is long, the service may be less sensitive to arrival time, and the preference for the shuttle type in terms of a vehicle type may be increased in areas with high crowdedness levels. In future research, the level of public transit service infrastructure should be considered by linking information about each respondent's residence or the most frequent travel departure point with graphic information system data. Third, it is necessary to consider a passenger's current travel behavior (travel purpose, mode of transportation, etc.) and the purpose of using AMoD. In this study, the most used transportation mode of each class was indirectly estimated through class membership attributes, but more appropriate results could be derived from direct indicators such as the frequency of public transit service use.

Data Availability

The data used to support the findings of this study have not been made available because these data still need to be used in other unfinished studies.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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