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Assessment of the environmental impact and policy responses for urban air mobility: A case study of Seoul metropolitan area

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ABSTRACT

Urban air mobility (UAM) is expected to be a new alternative future transportation system to overcome the limitations of infrastructure investment and resolve traffic congestion cost issues in urban areas. This study aims to estimate the parameters of the mode choice model incorporating the cleaner transportation mode and evaluate the environmental impact by calculating the reduction of greenhouse gas emissions from ground traffic. A stated preference survey is employed to estimate the parameters for each travel mode, including the emerging travel mode. The awareness and experience of the air travel modes remove the hesitation concerning travel mode choice having positive values, but concerns about taking new types of air mobility reduce the probability of choosing urban air mobility. The macroscopic travel demand forecasting program simulates the travel demand of urban air mobility to calculate the reduction of CO_2 emissions between before and after the introduction. While about 30 thousand of urban air mobility travel demand are generated after the introduction of urban air mobility in the urban area, it reduces about 90 thousand tons of CO_2 emissions from the ground traffic. The introduction of urban air mobility causes modal shifts from ground traffic, reducing climate change and global warming. Policymakers should evaluate the feasibility of introducing urban air mobility, including environmental impact assessment, and an appropriate transit fare policy is required for the proliferation of urban air mobility.

1. Introduction

The development of smart mobility services has changed the overall transportation system and the paradigm to provide various types of transportation services (Shaheen et al., 2020). At the same time, as electricity-based vehicles have become more common, interest in the environmental impact of transportation has increased (Casals et al., 2016; Wu et al., 2018; Schäfer et al., 2019). Urban Air Mobility (UAM) has been proposed as a mode of transportation that provides more advanced services based on the on-demand service in the urban transportation system. Since it is expected that UAMs with higher specified vehicles, longer distances, and heavier loads will be developed, Grandl et al. (2018) have predicted that it will be able to start service in 2025 and by 2035 operate a total of 23,000 UAMs with a scale of about 1000 units in cities with populations in the range of about 5–10 million people. The performance specification of UAM is capable of operating at a maximum speed of 160 kph, operating up to 750 km, and withstanding a load of 240 kg (Becker, 2017). UAM provides passengers efficient transportation services with reduced travel time for long-distance travel. Since UAM must be facilitated with a specific port between the origin and destination, the efficiency occurs when the travel distance is more significant than a certain distance, specifically more than 25 km (Grandl et al., 2018). Fig. 1 depicts the structure in which UAM imputes the existing travel journey.

Recently, among the developments of UAM, vertical take-off and landing (VTOL) aircraft and vertiport have been introduced to operate UAM systems in urban areas. Many companies have been focusing on developing various types of electrified VTOL (eVTOL) because it is considered a travel mode that is safer, more reliable, more economical, and eco-friendlier than conventional aero-mobility vehicles (Airbus, 2018). They are in the process of developing and testing the prototype of eVTOL for commercial use and are planning to obtain certification in 2023 and start commercial operations in 2024 (Joby Aviation, 2020; Lilium, 2020). In addition, researchers have demonstrated the environmental benefit from the introduction of electrified UAM services in the urban area by calculating the CO_2 emissions (Afonso et al., 2021; Mudumba et al., 2021). South Korean government has a plan to introduce the eVTOL service in the Seoul metropolitan area using the route in

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Han river, which is the fixed corridor connecting to major vertiports for safe flying by 2025, to launch the fully autonomous UAM service by 2035 (eVTOL, 2021; The Korea Herald, 2022). In this study, it is assumed that fully-electrified VTOL will be introduced in Seoul metropolitan area by 2035, and an investigation was conducted to determine the environmental impact of the change in the mode share by shifting from the ground traffic to UAM.

Forecasting the demand for newly introduced travel modes is essential for establishing effective transportation planning. A stated preference (SP) survey is considered an appropriate method to explore the behavioral change for a newly introduced travel mode in the future (Louviere et al., 2000). Researchers have analyzed the behavioral change for UAM use by constructing the SP survey (Peeta et al., 2008; Fu et al., 2019; Al Haddad et al., 2020; Eker et al., 2020), and others have studied the change in travel demand of UAM concerning the modal split, incorporating assumptions for estimating the travel demand (Garrow et al., 2017; Kreimeier and Stumpf, 2017; Zhang et al., 2018; Balac et al., 2019; Bulusu et al., 2021; Straubinger et al., 2021). Those studies focused on the behavioral characteristics to implicate the transport policy for improving the use of UAM after its introduction in intra-city and inter-city areas; however, they still highlighted the significant factors of travel time and cost for passengers to consider their choosing an on-demand, aerial mobility service. It is necessary to estimate the mode-specified parameters that incorporate travel time and cost from the SP data to identify the choice behaviors of UAM as an alternative in urban travels.

Moreover, greenhouse gas (GHG) emissions from the transport sector were estimated at 605.8 million tons in 2018, accounting for 13% of the total emissions, 96% of which was attributable to traffic on the roads in Korea (IEA, 2022). Many studies have explored the reduction of GHG emissions associated with the travel demand for UAM to introduce the system in many cities, including Chicago (Mudumba et al., 2021), Dallas (Mudumba et al., 2021), Houston (Kohlman and Patterson, 2018), and Munich (Afonso et al., 2021). Researchers have studied the environmental impact of UAM to identify the benefit from the reduction of GHG emissions (Schäfer et al., 2019; Afonso et al., 2021). Another study focused on the effect of reducing GHG emissions on urban areas by comparing UAM and automobile trips, incorporating both autonomous use and combustion engine use (Mudumba et al., 2021). Studies have focused on CO_2 emissions with respect to various other constraints, i.e., 1) types of aircraft (Wroblewski and Ansell, 2019); 2) fleet size (Chao et al., 2017); and 3) environmental impacts (Kohlman and Patterson, 2018; Mudumba et al., 2021). This study focuses on the system-wide reduction of CO_2 emissions associated with UAM constrained to fleet size and travel cost introduced into the Seoul metropolitan area.

Even though many researchers have studied the behavioral characteristics of UAM use to prepare for the impact of modal share after the introduction of UAM, there are still limitations of the process for estimating the travel demand of UAM and assessing the environmental impact. This study focuses on establishing a mode choice model following the introduction of UAM and evaluating the environmental impact considering the modal split in the existing transportation network. Using the choice experiment method, the SP survey is constructed based on the logit structure by recruiting the respondents traveling in Seoul metropolitan areas daily. This study estimates the mode-specified parameters for the mode choice model to analyze the modal split after introducing UAM in an urban area, and the value of travel time for each mode is derived through the comparisons of parameters between the travel time and cost. The estimated parameters are employed to evaluate the environmental impact of the introduction of UAM in the urban transport network using a transportation simulation program. The results give us the prospect for reducing emissions considering various scenarios after the introduction of UAM. This study contributes to the evaluation of the introduction of UAM in metropolitan areas based on three estimation methods, i.e., 1) estimating the parameters by building the logit-based model; 2) predicting the travel demand for UAM using the mode choice model, and 3) evaluating the environmental impact by focusing on the reduction in CO_2 emissions.

Section 2 presents the methodology for conducting the research. Section 3 presents the questionnaire for the choice experiment and illustrates the descriptive statistics. Section 4 shows the estimated results for the parameters of the mode choice model and demonstrates the environmental impact and policy implications of the UAM. Section 5 concludes this research and suggests future research.

2. Methodology

2.1. Multinomial logit model

The econometric methods have been employed to estimate the electric vehicle use considering traveler characteristics by integrating with the survey method (Sang and Bekhet, 2015; Guo et al., 2020). A logit-based model structure was used for the analysis that used data with a discrete choice modeling structure based on the SP survey (Train, 2009). In this study, we used the two types of logit-based mode choice models, i.e., 1) the multinomial logit (MNL) model applied to the simple mode choice model (Fu et al., 2019; Al Haddad et al., 2020; Rimjha et al., 2021) and 2) the random parameter multinomial logit (RPML)

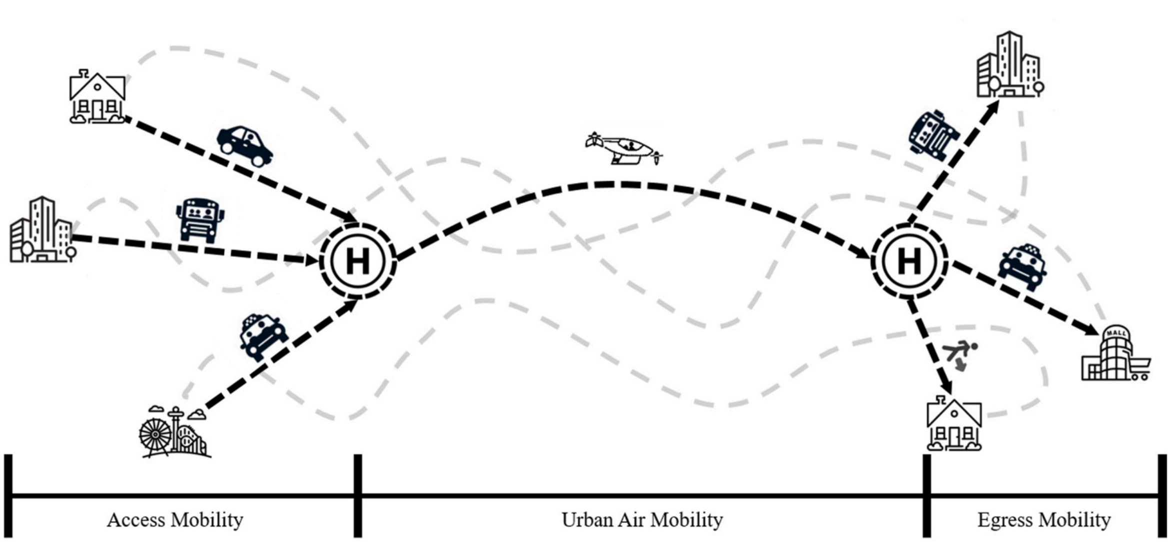


Fig. 1. Change of Travel Journey using On-demand UAM service.

model, which considered the respondents' heterogeneity in multiple-choice situations (Merkert and Beck, 2017; Boddupalli, 2019). Constructing a logit-based mode choice model involves each individual's choice sets and estimates how the choice was made between the travel attributes of each travel mode. The utility function of the MNL model is shown in Eqs. (1) and (2), and it is composed of systematic and random error components that incorporate the travel time, travel cost, and socioeconomic travel attributes.

$$U_j = V_j + \varepsilon_j \quad j = 1,\ 2,\ 3,\ \ldots\ldots,\ A \tag{1}$$

$$V_j = \alpha_j + \beta_{TT} TT_j + \beta_{TC} TC_j + \boldsymbol{\beta_{SE} SE_j} \quad j = 1,\ 2,\ 3,\ \ldots\ldots,\ A \tag{2}$$

where U_j is the utility function of j, which is composed of two components; V_j is the observed utility component of j; ε_j is the unobserved error component of j; α_j is the alternative-specific constant for each travel mode; β_j s are the coefficients of the travel attributes; TT_j is the travel time attribute; TC_j is the travel cost attribute; and $\boldsymbol{SE_j}$ is the matrix of socioeconomic attributes for individual travelers.

The probability of each travel mode being chosen is determined by the ratio of the utility function for each alternative, calculated by the differences in the systematic term. The alternative-specific constants represent the unrevealed preference of the respondents for the specific travel modes in the discrete choice model. The sum of individual mode choice probabilities represents the mode share of the entire transport network system, and Eq. (3) is used to calculate the modal share of each travel mode, as specifically illustrated in the following sub-section.

$$P(j) = \frac{exp\left(\alpha_j + \beta_{TT} TT_j + \beta_{TC} TC_j + \boldsymbol{\beta_{SE} SE_j}\right)}{\sum_t exp(\alpha_t + \beta_{TT} TT_t + \beta_{TC} TC_t + \boldsymbol{\beta_{SE} SE_t})} \tag{3}$$

where $P(j)$ is the choice probability of j, which is calculated with V_t s.

2.2. Random parameter logit model

The RPML model was used in this study to incorporate the individual heterogeneity in the mode choice behaviors. The advantage of the RPML model is that it allows the better estimation result to reflect individual preferences incorporating the respondents' systematic and random distribution components of each choice alternative in their choice sets (Merkert and Beck, 2017). The assumption of constant marginal utilities across all respondents is relaxed by accommodating the spread of preferences within the assumed distribution represented to Normal distribution. Here, there are the variation parameters that reflect the individual preferences for the given attributes in alternative j. The parameters of the given attributes are shown in Eq. (4).

$$\beta_{nkt} = \overline{\beta_{kt}} + \eta_{tk} z_{nkt} \tag{4}$$

where β_{nkt} are the parameters of given attributes that incorporate the variations of individuals; $\overline{\beta_{kt}}$ is the mean marginal utility of a given attribute, k s, of alternative t; η_{tk} is the deviation from holding the mean marginal utility by respondent n for the attribute k in the alternative t; z_{nkt} is a random draw from pre-assumed distributions.

The probability of the chosen alternative mode is changed to the other form considering the specified distribution for the given attributes. Since the Normal distribution is the commonly used distribution form (McFadden and Train, 2000), this study applies the Normal distribution for the unobserved heterogeneity in the choice model. Eq. (5) shows the choice probability of the RPML model incorporating respondents' heterogeneity.

$$P_{nkj} = \int \left(\frac{\exp\left(\alpha_{nkj} + \beta_{nkj} X_{nkj}\right)}{\sum_t \exp(\alpha_{nkt} + \beta_{nkt} X_{nkt})} \right) f(\beta_{nk}|\theta) d\beta_{nk} \tag{5}$$

where P_{nkj} is a probability of alternative, j, given attribute k for choosing an alternative by individual n, consisting of travel attributes and socio-demographic variables. The heterogeneous travel behaviors are captured by the form of $f(\beta_{nk}|\theta)$, where θ is represented to the hyper-parameters with a mean and a standard deviation from the assumed Normal distribution.

The utility function is solved using the log-likelihood estimation process from the 'mlogit' R package program, the most commonly used solving program referenced from Kenneth Train's work (Croissant, 2020). The program calculates the parameters of explanatory variables from the logit-based mode choice model, which have their metrics determined by the input variables.

2.3. Calculating the travel demand and vehicle-Km-traveled

This study employs the EMME/4 program, which is widely used to obtain optimal traffic volume using the link-based traffic assignment method (Wang et al., 2020), including calculating the modal share using the estimated parameters. Since a simulation program includes a macroscopic model with a slight fluctuation in travel demand and matches the analysis method with the Korea Transport DataBase (KTDB, 2019), it is appropriate to analyze a large-scale transport network that generates many trips. The output of the results comprising the travel speed and volumes on each link is calculated to obtain the travel demand and vehicle-km-traveled (VKT). Since the multinomial logit model for modal share varies with the utility function using the estimated parameters for the introduction of emerging transport technology and has the problem of zero probability (Delle Site et al., 2019), in this study, we used the additive logit model to calculate the modal share for UAM. Even though the previous studies have been conducted to calculate the travel demand driven by the differences in utilities among the travel modes without the traffic assignment process (Balac et al., 2019; Bulusu et al., 2021; Rimjha et al., 2021), in this study, the travel time and cost between the origin and destination (OD) pairs are calculated by the traffic volume, and the travel speed for each link via the ground trip assignment, and those attributes are used to calculate the modal share before and after the introduction of UAM. The travel demand of UAM after the introduction is predicted by multiplying the probability of the UAM with total travel demand. Eq. (6) reveals the equation of the additive logit model for the newly introduced travel mode, and the travel demand of UAM is shown in Eq. (7).

$$P^*_{UAM} = P_{UAM} + \frac{exp\left(V^*_{UAM}\right)}{\sum_t exp\left(V^*_t\right)} - \frac{exp(V_{UAM})}{\sum_t exp(V_t)} \tag{6}$$

$$V_{UAM} = V_{Total} \times P^*_{UAM} \tag{7}$$

where P^*_{UAM} is the predicted probability of UAM after the introduction; P_{UAM} is the observed probability of UAM before the introduction, here this value is zero; V_t is the observed utility for each travel mode t before the introduction of UAM; V^*_t is the predicted observed utility for each travel mode t after the introduction of UAM; V_{Total} is the total travel demand for all types of travel modes.

The VKT for each type of vehicle is calculated by the travel speed and volume on each link to obtain the GHG emission. The method of calculating the GHG emission is dealt with in the next section.

2.4. Calculation of GHG emission reduction

Since reducing traffic emissions slows down climate change and improves air quality, researchers have studied the various factors of the environmental impacts from transportation. Studies have focused on the reduction of CO_2 emissions, which is considered the vital measure among the emissions from transportation (Canals Casals et al., 2016; Mudumba et al., 2021). In addition, among the air pollutants stipulated in the Clean Air Conservation Act (Ministry of Environment, 2017), CO_2, which is known to be a major GHG emitted by the transportation sector, has been set as a performance measure for environmental impact. In this study, we have predicted the travel demand after the introduction of UAM, and we have estimated the reduction of emissions based on relieving the congestion of ground traffic following the modal shift. The amount of the reduction of emissions was estimated by comparing the amount of CO_2 emissions generated by the assigned traffic volume before the introduction of UAM with the amount generated by the assigned traffic volume after the introduction of UAM.

In order to estimate GHG emissions according to the assigned traffic volume on the transportation network, it is necessary to apply the emission factor for each type of vehicle to utilize the distribution of the traffic volume by KTDB (KTDB, 2019). CO_2-based GHG emissions were estimated using the emission factors calculated from KDI (KDI, 2017), and they were calculated using the mileage and emissions by type of vehicle and presented according to Korea's emissions using a Computer Program to calculate Emissions from Road Traffic (COPERT) according to the formula used by the European Environment Agency (EEA, 2009). In this study, CO_2-based GHG emission coefficients by the type of vehicle were used to generate the polynomial functions based on average travel speed on the traffic links for each type of vehicle, as shown in Fig. 2.

To calculate the total daily emissions of ground traffic, the traffic network is assigned to each type of vehicle, and the CO_2-based GHG emission functions for each vehicle type are applied to the VKT on the links. Eq. (8) shows the method used to calculate the CO_2-based GHG emissions on the transport network.

$$Emissions = \sum_{l}\sum_{k=1}^{5}(D_{lk} \times VE_{lk}) \tag{8}$$

where *Emissions* is the GHG emissions for daily trips; l is the link of traffic network; k is the types of vehicles, e.g., auto, bus, small truck, medium truck, and large truck; D_{lk} is the vehicle-km for each link with the type of vehicle k; VE_{lk} is the CO_2-based GHG emissions for a given travel speed of the link l with the type of vehicle k.

In order to compare the results of the traffic assignment before and after the introduction of UAM, various transport network scenarios were constructed for the introduction. In this study, mode-specified trips are divided into auto, bus, railway, and UAM, and the scenarios were constructed by considering fleet size and travel cost constraints. The mode specified trips are assigned to transport networks for each configured scenario, and the total CO_2-based GHG emissions before and after introduction were calculated, as shown in Eq. (9) below.

$$Emissions_{Total} = \rho\left(Emissions_{Before} - Emissions_{After}\right) \tag{9}$$

where $Emissions_{Total}$ is the total reduction of GHG emissions for daily trips; ρ is the scale parameter corresponding to the travel demand of UAM for each scenario.

3. Data

3.1. Study area

The Seoul metropolitan area was the study area of this study, given its potential installation of UAM for long-distance trips. The Seoul metropolitan area is the fourth largest population within a metropolitan area in the world, and it has about 25 million residents (Wikipedia, 2021). The Seoul metropolitan area is a public transit-oriented city with 375 railway stations built on 13 railway lines and 12,437 bus stops on 351 bus lines. It has a relatively high ratio of modes of public transit compared to that of cars by building public transportation infrastructure. The government has presented the mode share of each travel mode in the Seoul metropolitan area, i.e., 23.7% of walking, 31.1% of auto, 22.5% of bus, 13.9% of the railway (including the subway and train service), 5.3% of taxis, and 3.7% of others (KTDB, 2019). The mode share of public transit is about 36%, which means the city has a higher mode share than other metropolitan cities due to a well-constructed public transit network.

Nevertheless, the Seoul metropolitan area is one of the most crowded cities, and a high proportion of GHG emissions is emitted from the transport sector. The atmospheric environment is expected to be improved with the introduction of UAM, an eco-friendly on-demand travel service. Even though the most considerable potential for GHG emission reduction is the replacement of trucks with the UAM for transporting goods, we focus on the transport of people instead of goods because the weights of goods using the UAM are expected to be less than 50 kg (KAIA, 2021), and the large trucks are prohibited from entering the city of Seoul by the metropolitan government ordinance.

This study presents two types of surveys: airport travel and urban

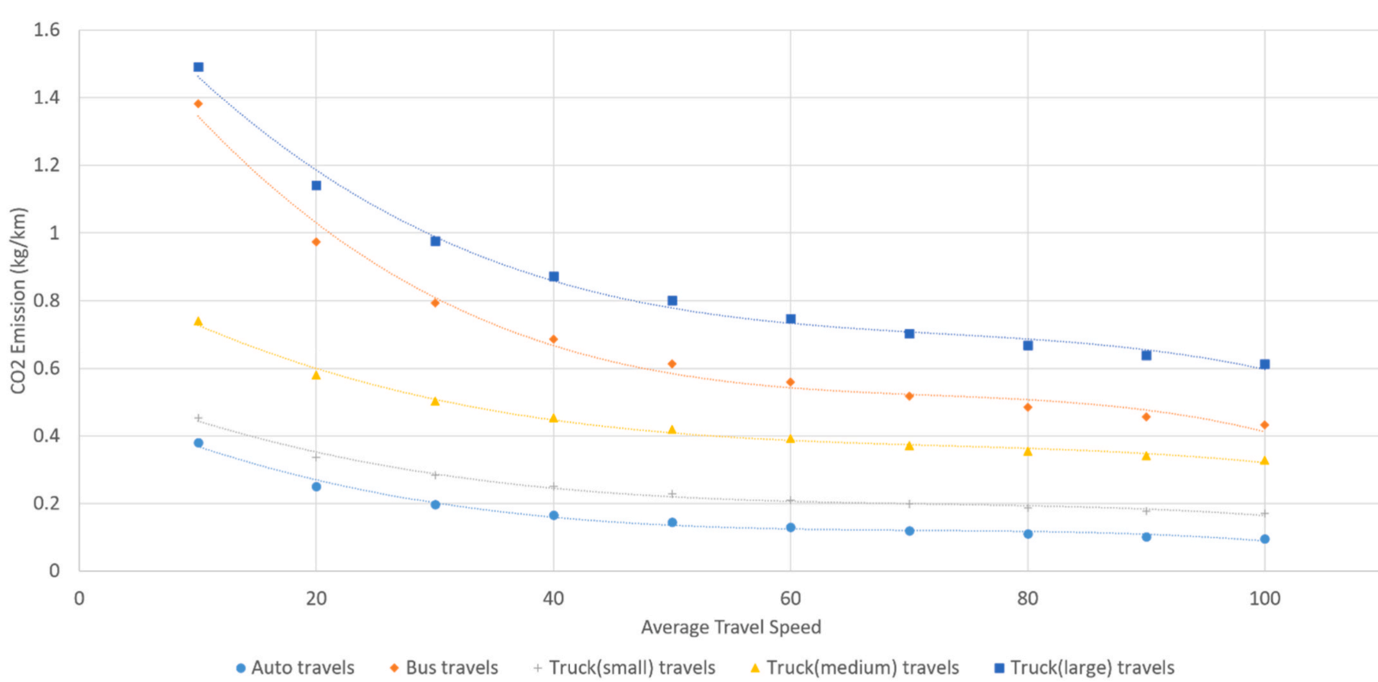


Fig. 2. Functions of CO_2 emissions for each type of vehicle.

travel because it is assumed that the travel behaviors to the airport and urban area are significantly different due to the travel purpose. Fig. 3 depicts two airports and 11 vertiport candidates in the network of the Seoul metropolitan area, and the 11 vertiport candidates are configured so that one vertiport is allocated for every 1–2 million people (e.g., since the city of Seoul has a population of about 9 million people, four vertiports were installed). There are two other travel modes, i.e., auto and public transit, alternated to UAM in the Seoul metropolitan area. Thus, the analysis is divided into airport travel to Incheon International Airport, having about 71 million travels per year before the COVID-19 pandemic in 2019, and urban travel to major places in the urban area, including Gimpo International Airport, having about 25 million of travels per year before the COVID-19 pandemic in 2019 (Korea Airport Corporation, 2022).

3.2. SP survey design

Since respondents unfamiliar with the UAM, which is currently under development and preparing for commercialization in Seoul metropolitan area, do not recognize the attributes of UAM choice, it is necessary to review the previous studies on how they experiment with choice behaviors. In previous studies, the survey-based research method has been employed for the third-highest ranked to identify electrified vehicle adoption (Kumar and Alok, 2020). In such a situation, the choice experiment method based on the SP survey is structured so that people who respond to the survey can respond appropriately to the hypothetical situation by explaining the functional specification before taking the survey (Fu et al., 2019).

The questionnaire consists of three components to understand basic information about the survey respondents and the characteristics of mode choice, i.e., 1) Socio-demographic questionnaires; 2) Questionnaires related to travel behavior; and 3) SP mode choice questionnaires. The questionnaire components were used as an explanatory variable in the mode choice model to interpret behavioral differences. First, questionnaires corresponding to gender, age, occupation, income, and the number of cars owned were surveyed to understand respondents' attributes. Researchers established the mode choice model to identify the mode choice behaviors that incorporate the information of individual characteristics (Fu et al., 2019; Al Haddad et al., 2020; Ahmed et al., 2021). These questionnaires were composed of essential items to identify individual behavioral differences in the SP survey, and the influence on mode choice behaviors can be interpreted from the estimated parameters. In order to protect privacy, multiple-choice questionnaires were used to identify the individual characteristics, i.e., occupation and income level. Second, questionnaires were constructed related to the survey respondents' travel behaviors (detailed in Appendix 1.).

The survey has conducted to estimate the travel demand and environmental impacts after the introduction of UAM in the Seoul metropolitan area at the request of the Korea Transport Institute for the research funded by the Ministry of Land, Infrastructure, and Transport of the Korean government. The choice experiment data were collected for the two types of surveys, i.e., airport and urban travel surveys, via a field and internet-based survey in the Seoul metropolitan area. Airport travel using UAM consists of travel from the airport to the final destination after using the airport or vice versa. Urban travel using UAM is expected to have a functional role as a new mode of transportation in urban areas when it connects specific points within the metropolitan areas. The UAM travels connecting the sub-cities in metropolitan areas are expected to impute the ground traffic and generate emissions; therefore, it reduces the environmental impact by shifting to the UAM travel from the conventional travel modes. It is noteworthy that the introduction of UAM is

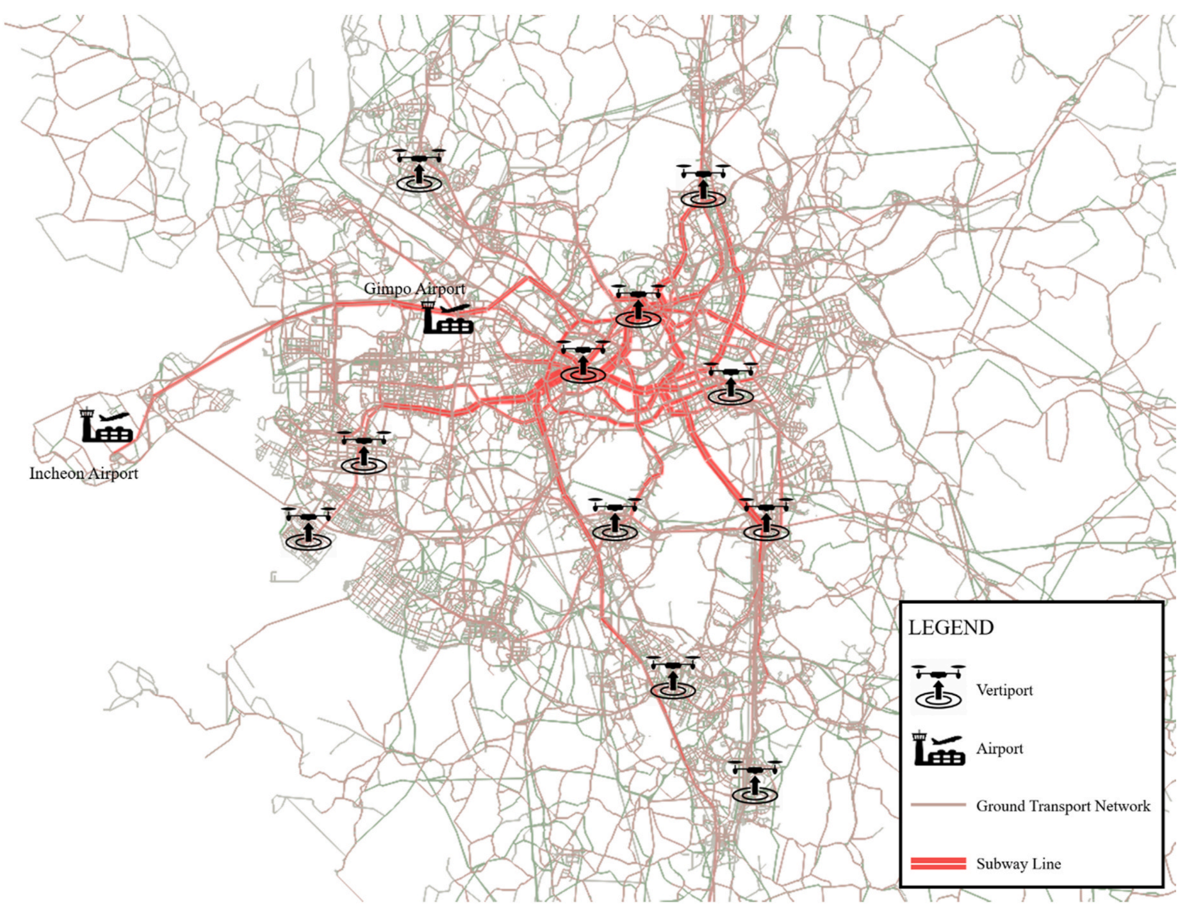


Fig. 3. Transport network in the Seoul metropolitan area.

required for long-distance travel to generate the travel demand compared to ground traffic (Grandl et al., 2018). In this study, the respondents were recruited from the travelers who have traveled for more than 1 h within the Seoul metropolitan area in the last week from the survey, owing to UAM not being an available transportation mode for short trips of less than 1 h.

3.3. Descriptive statistics

The respondents sampled were airport users in the airport travel survey, and the survey of urban travel recruited respondents who had traveled in the Seoul metropolitan area within a week. The survey was conducted for two periods, i.e., an urban travel survey was conducted from April 16 to May 07 in 2020, and an airport travel survey was collected from October 22 to November 06 in 2020. Although the surveys were conducted during the chaos caused by the COVID-19 pandemic, the respondents were asked to answer the questionnaires, and the screening process was implemented to remove any inappropriate responses. The final samples for estimating parameters were 699 responses for airport travel and 1011 responses in the urban area. The quota for collecting samples has been placed considering each age group, similar to the census of the Seoul metropolitan area.

The descriptive statistics of the two types of travel surveys in the dataset are summarized in Table 1. A screening questionnaire about the interest in emerging transport technology has been added to obtain meaningful survey results with the sample interested in introducing emerging transport technology. The respondents were questioned about their knowledge of the UAM during the first screening process, which causes the limitations to collect the female sample from the online survey, meaning that the male is more likely interested in emerging transport technology. Even though we have requested the sample considering the ratio of age group in the Seoul metropolitan area, as seen in Table 1, the quotes (e.g., gender and age group) of the sample were not matched with the Seoul metropolitan area census. Since the two surveys were conducted by different methods, the descriptive statistics showed different characteristics concerning the socio-demographic aspects. The age group data showed different characteristics, i.e., in the airport travel survey, many respondents were young travelers with ages ranging from 20 to 39, whereas, in the urban travel survey, there was a high ratio of respondents whose ages were 30–49 and who are the economically active population. To overcome the sampling imbalance, we calculated the sampling weights using iterative proportional fitting techniques, frequently used in environmental economics for all variables, at least in terms of gender and age groups (Soto et al., 2018).

On the other hand, the travel purposes in the two travel surveys were quite different. There was a high ratio of leisure trips in the airport travel survey, whereas a high ratio of commuting trips in the urban travel survey. More than 20% of the respondents have traveled in helicopters before, and about 4–7% of the respondents had flown in helicopters for military duty.

Table 1
Descriptive statistics of travel surveys.

Variable	Statistics				
	Airport travel survey		Urban travel survey		Seoul Metropolitan Area Census
	Frequency	Share	Frequency	Share	
Individuals	699	–	1011	–	–
Samples	14,679	–	21,231	–	–
Socioeconomic Characteristics					
Gender					
Male	331	47.4%	748	74.0%	49.9%
Female	368	52.6%	263	26.0%	50.1%
Age					
Younger than 29 years old	268	38.3%	163	16.1%	14.3%
30–39 years old	207	29.6%	367	36.3%	15.3%
40–49 years old	121	17.3%	226	22.4%	16.6%
50–59 years old	81	11.6%	161	15.9%	16.5%
60 and older than 60 years old	22	3.2%	94	9.3%	21.2%
Income (Monthly)					
Less than 1 million won	35	5.0%	34	3.4%	8.6%
1–2 million won	72	10.3%	66	6.5%	13.8%
2–3 million won	176	25.2%	202	20.0%	16.0%
3–5 million won	186	26.6%	302	29.9%	26.8%
5–10 million won	129	18.4%	335	33.1%	35.8%
More than 10 million won	48	6.9%	66	6.5%	
No Income	53	7.6%	6	0.6%	–
Purpose					
Commuting	13	1.9%	474	46.9%	45.8%
Business	137	19.6%	112	11.1%	14.3%
Leisure	416	59.5%	128	12.6%	20.4%
Visiting Relatives	111	15.9%	104	10.3%	–
Others	22	3.1%	193	19.1%	19.4%
Possession of Auto					
No auto	133	19.0%	120	11.9%	–
One auto	357	51.1%	707	69.9%	–
Two and more than two autos	209	29.9%	184	18.2%	–
Experience of taking a helicopter					
For leisure	93	13.3%	192	19.0%	–
For military duty	32	4.6%	75	7.4%	–
For business	14	2.0%	51	5.0%	–
For emergency	3	0.4%	20	1.9%	–
No experience	557	79.7%	725	71.7%	–
Transportation Mode Used					
Auto (Driving Alone)	165	23.6%	531	52.5%	–
Car-sharing	11	1.6%	8	0.8%	–
Public Transit	461	66.0%	441	43.6%	–
Taxi	45	6.4%	24	2.4%	–
Others	17	2.4%	7	0.7%	–

4. Results and discussions

4.1. Estimation results of mode choice model

There are two types of estimated results for airport travel and urban travel surveys incorporating the level of service, socioeconomic, and experience variables. In this study, two types of estimation methods were used, i.e., 1) the MNL model, which is applicable for a modal split among travel modes in the transport network, and 2) the RPML model, which provides a better understanding of behavioral realism considering travelers' heterogeneity. The parameters of the RPML model were estimated for the two types of travel using 100 Holton draws to generate the choice probability from the assumed Normal distribution.

Table 2 shows the final results of estimating the airport and urban travel mode choice models from multiple estimation trials by including and excluding some variables to obtain the most efficient model. The total observations generated by the two travel surveys were 14,679 and 21,231, and they are multiplied by the number of respondents, i.e., 21 choice cases. In the mode choice model, the pseudo-R^2 (corresponding to ρ^2) is employed to evaluate the appropriacy of the estimated model as the goodness-of-fit index, of which is compared to R^2 in the regression model. The goodness-of-fit indexes (ρ^2) are promising results for all types of models, which is expected to have a value greater than 0.2 (If

Table 2
Estimation Results of Airport and Urban Travel Scenarios for UAM: multinomial and random parameter logit models with the level of service, socioeconomic, and experience variables.

Variables		Airport Travel Scenario		Urban Travel Scenario	
		MNL	RPML	MNL	RPML
Alternative Specific Constant (ASC)					
α_{Auto} (Auto)		3.1378*** (15.5)	6.8798*** (16.3)	2.5395*** (21.8)	4.1164*** (24.7)
α_{UAM} (UAM)		5.3206*** (41.4)	15.1362*** (17.5)	4.4956*** (38.1)	11.5623*** (27.5)
$\alpha_{Public\ transit}$ (Public transit)		4.4485*** (30.9)	10.0838*** (39.4)	3.5845*** (28.1)	6.635*** (33.4)
Level of Service Variables					
$\overline{\beta}_{TT}$ (Travel Time)	Auto	−0.0216*** (−6.9)	−0.0512*** (−7.9)	−0.0145*** (−14.7)	−0.0218*** (−25.6)
(Constant)	UAM	−0.0391*** (−16.3)	−0.1164*** (−26.9)	−0.0370*** (−22)	−0.0879*** (−35.3)
	Public transit	−0.0220*** (−11.2)	−0.0559*** (−16.6)	−0.0086*** (−7.7)	−0.0205*** (−12.6)
σ_{TT} (Travel Time)	Auto	–	0.1755*** (38.5)	–	0.1364*** (60.9)
(Standard Deviation)	UAM	–	0.1603*** (42.7)	–	0.1329*** (52.5)
	Public transit	–	0.1553*** (46.2)	–	0.1319*** (56.8)
β_{TC} (Travel Cost)	Auto	−0.0648*** (−19.0)	−0.1206*** (−12.8)	−0.0452*** (−20.5)	−0.0661*** (−14.7)
(Thousand Won)	UAM	−0.0897*** (−51.1)	−0.2094*** (−64.6)	−0.0713*** (−59.2)	−0.1531*** (−76.6)
	Public transit	−0.0539*** (−17.3)	−0.1254*** (−21.9)	−0.1518*** (−15.2)	−0.2258*** (−13.2)
Socioeconomic variables					
Male		–	−0.3511** (−3.3)	–	−0.0144 (−0.3)
Age 10–20		–	0.0848 (1.0)	–	−0.0671 (−1.0)
Age 50–60+		–	0.0248 (0.3)	–	−0.0534 (−1.0)
Low Income		–	−0.8711*** (−9.5)	–	−0.4743*** (−6.9)
High Income		–	−0.3698*** (−4.9)	–	−0.2552*** (−5.2)
Purpose: Commuting		–	−1.2452*** (−3.7)	–	−0.1905*** (−3.3)
Purpose: Business		–	−1.1586*** (−8.1)	–	−0.2825*** (−3.4)
Purpose: Leisure		–	−1.1360*** (−8.9)	–	0.1458* (1.9)
Purpose: Visiting Relatives		–	−1.7169*** (−12.4)	–	−0.4961*** (−7.1)
Experiences variables					
Experience of Helicopter					
For leisure		–	0.5408*** (5.2)	–	0.4024*** (6.8)
For military duty		–	0.5520** (3.1)	–	0.7551*** (5.7)
For business		–	0.8409*** (5.2)	–	0.4429*** (4.5)
For emergency		–	2.9924** (2.6)	–	0.6643** (2.5)
Information about UAM		–	0.4555*** (6.2)	–	0.3720*** (7.4)
Worry for taking UAM					
High cost		–	−1.2475 (−1.5)	–	−1.9955*** (−5.8)
Safety		–	−0.7028 (−0.9)	–	−1.7220*** (−5.1)
Shortage for infrastructure		–	−0.6410 (−0.8)	–	−1.2031*** (−3.4)
Security		–	−0.7808 (−0.9)	–	−1.3454*** (−3.6)
Goodness-of-fit					
Observations		14,679	14,679	21,231	21,231
Respondents		699	699	1011	1011
Number of Parameters		9	30	9	19
LL(0) (Initial Log-Likelihood)		−10,054.00	−10,054.00	−14,709.00	−14,709.00
LL(β) (Log-Likelihood at Convergence)		−7500.30	−4795.00	−11,060.00	−7937.00
Rho-squared w.r.t. Zero at Convergence		0.2540	0.5231	0.2481	0.4604
Adjusted Rho-squared w.r.t. Zero at Convergence		0.2549	0.5261	0.2487	0.4617

Footnote: The scenarios were divided into two types of urban and airport travels incorporating the two types of SP surveys, and the results were come out to show the differences in travel behaviors of the travels. The MNL model was established to estimate the travel demand of UAM from the two scenarios, and the RPML model was developed to identify the travel behaviors considering the socioeconomic and experience variables.

the R^2 has the value of 0.6, pseudo-R^2 is corresponding to the value of 0.3) (Mokhtarian, 2016). The behavioral interpretations are illustrated via the RPML model, which reflects the heterogeneous travel behaviors for behavioral realism, and the MNL model is used to calculate the modal split after the introduction of UAM.

Initially, according to the airport travel, the positive ASCs for all travel modes indicated that traveling by three types of travel modes is preferred to other travel mode uses, and the highest ASC of UAM is referred to the travel mode that had the most preference after the introduction of UAM. As expected, the travel time and cost parameters are negative, but there are significant heterogeneous behaviors in choosing travel time variations (referred from the parameters of standard deviations of travel time), and the travelers are reluctant to spend money for their travels. Even though shorter travel times and lower travel costs are preferred across all types of travel modes, the travel time and cost of UAM have the more significant effect on choosing the travel mode because it has a higher absolute value of parameters than other travel modes.

Addressing urban travel, most ASCs and level of service variables are more petite than airport travel in absolute values except for the parameter of travel cost for public transit. This result reveals the largely intuitive insight that travelers traveling in urban areas are less reluctant to use their travel time and cost, but travelers choosing public transit are more sensitive to travel costs because travelers in urban areas are paying the daily costs. It is noteworthy that, when travelers travel to the airport, they usually take a Limousine bus (which provides a higher level of service in terms of the seat, media service, and any other items to enhance the travelers' comfort), they pay a high public transit fare, and they are less sensitive to higher travel cost than urban travel outcomes due to occasional travel cost. Travelers are less likely to choose the UAM for commuting trips considering the parameter of commuting purpose, whereas they prefer to choose the UAM for leisure trips in urban travel.

Considering the socioeconomic and experience variables for both types of surveys, several variables concern the choice behaviors for choosing UAM travel mode. The previous research has demonstrated that female and younger travelers are likely to choose UAM (Ahmed et al., 2021); likewise, this study shows that those travelers are willing to choose UAM, and even the age group of 50–60 years old is more likely to choose UAM for airport travel. The parameters of experience of taking a helicopter and having the information about UAM have positive effects on choosing UAM, whereas the worry for taking UAM has a negative effect on the use of UAM. It is noteworthy that the awareness and experience of the air travel modes remove the hesitation concerning travel mode choice considering the estimated parameters of helicopter experience and information about the UAM having positive values, but concerns about taking new types of air mobility reduce the probability of choosing UAM. The worry about high travel costs significantly impacts choosing UAM for both results, so it is necessary to consider the policy implications for relieving the travel cost.

The willingness-to-pays (WTPs) for taking UAM are calculated by comparing the estimated travel time parameters and cost of each travel mode. The estimated results show that the WTPs for the airport and urban travel range from 29,191 (airport travel) to 34,457 (urban travel) won. We estimate the travel demand with the variations of WTPs of the UAM ranged from 24,000 to 36,000 won in airport travel and 28,000 to 42,000 won in urban travel to obtain the results by competing to other travel modes in Seoul metropolitan area.

4.2. Predicting the UAM travel demand

The effect of the introduction of UAM on the entire transport network is analyzed through traffic assignment after the comparison between before and after the installation. A travel demand forecasting for the comparison of before and after the introduction of UAM is required to

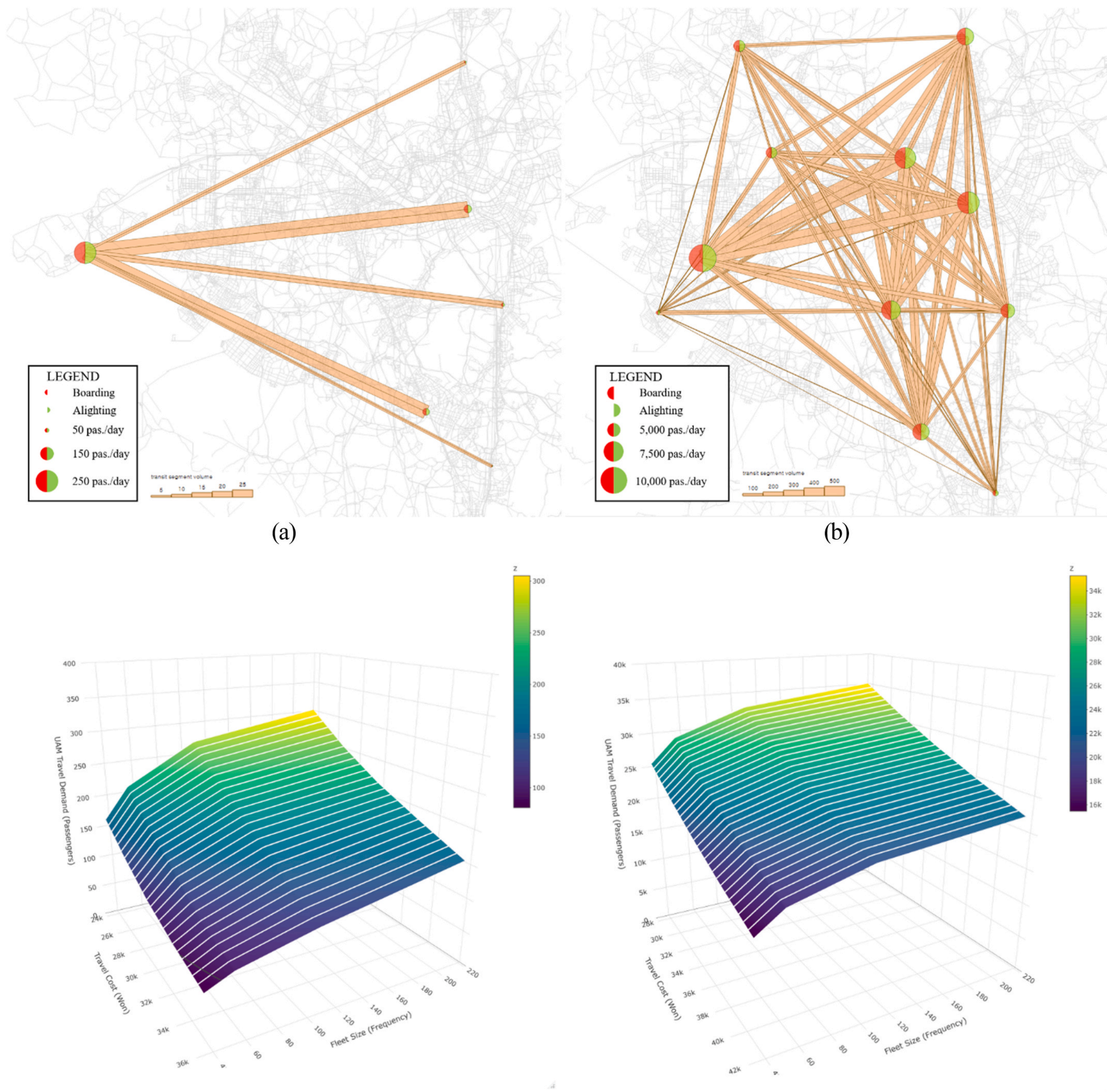


Fig. 4. Predicted Travel Demand of UAM (Color Bar): (a) Airport Travel Demand for each Transit Line (216 fleet size and 24,000 Won); (b) Urban Travel Demand for each Transit Line (216 fleet size and 28,000 Won); (c) Variation of Airport Travel Demand; (d) Variation of Urban Travel Demand.

obtain the CO_2-based GHG emissions for the ground traffic status via user equilibrium (UE) traffic assignment results. Fig. 4 illustrates the UAM travel demand after the introduction of UAM. Fig. 4(a) and (b) present the assigned travel demand of UAM for the optimistic scenarios, which includes the lowest transit fare cost and the 216 fleet size. The former is airport travel connections between the airport and some city centers apart from more than 50 km, and the latter is urban travel that connects 12 vertiports within the Seoul metropolitan area. Fig. 4(c) and (d) depict the variations of UAM travel demand constrained with travel cost and fleet sizes. The UAM travel demands for airport travel varied from 81 to 305 trips, and the UAM travel demand for urban travel ranged from 15,477 to 35,301. The results show that the travel demand affected by the travel cost has a higher variation than that of the demand affected by the size of the fleet, and the travel demand for airport travel is sensitive to those constraints which are the operating strategies because the routes are usually on the highway network that has fewer variations of travel time and cost for other ground travel modes.

4.3. Environmental impacts

This study estimated the environmental impact of changes in CO_2 emissions via road traffic before and after the introduction of UAM. Researchers have explored the GHG emission reduction after the UAM introduction to identify the amount of reduction from the specific trips, not the network-wide evaluation (Afonso et al., 2021; Mudumba et al., 2021). This study showed the environmental impacts from the change in traffic volume according to the modal shift to UAM, which affected the link travel speed and the amount of GHG emission emitted by each type of vehicle. Fig. 5 illustrates the amount of the reduction of CO_2-based GHG emissions.

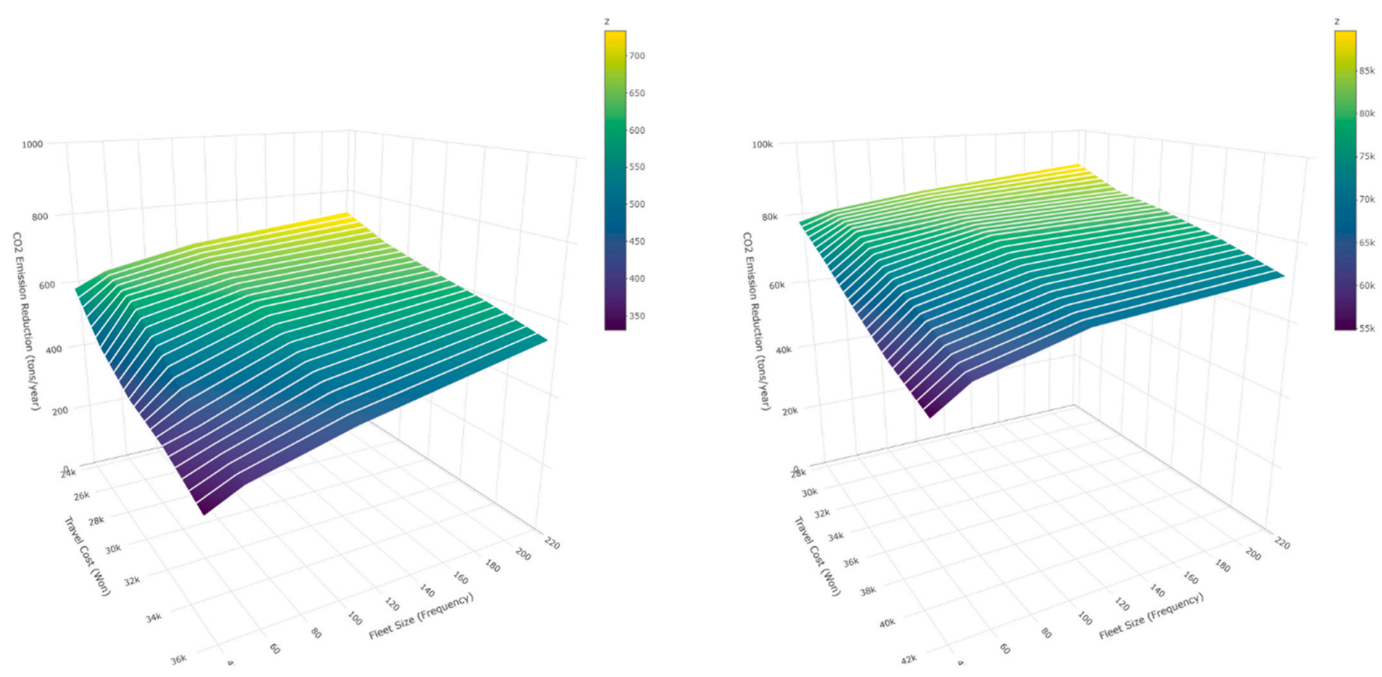
In airport travel, shown in Fig. 5(a), the reductions of CO_2 emissions were relatively low compared to the variation of UAM travel demand due to its low modal shift from ground travels. In other words, since there is a minor variation of traffic volume on the links, there is no considerable amount of change in the emissions of CO_2. Even though the environmental impact is relatively low, it is still highlighted that the reduction of CO_2 emissions were generated by the introduction of UAM.

In urban travel, depicted in Fig. 5(b), the reductions of CO_2 emissions were estimated to be a considerably large amount by the introduction of UAM. UAM travel demand for urban travels resulted in a more significant reduction of CO_2 emissions compared to that for airport travels, i.e., the annual reductions in the amount of CO_2 emissions were about 90 thousand tons per year. It is noting that this was a relatively large amount compared to the total amount of CO_2 emissions in the transportation sector, which is about 101.7 million tons per year (IEA, 2022); in addition, 0.1% of the modal shift from the ground trips, which are about 30 million trips (KTDB, 2019), results in a 0.1% reduction in CO_2 emissions. Since changes in traffic volume reduce the emissions, we need to develop emerging transport technologies focused on environmental impact.

4.4. Policy Responses for the proliferation of UAM

The introduction of a future UAM system in the transport network will be complex and require building consensus for long-term planning. The calculation of the reduction of the CO_2 emissions is politically a multidimensional problem, but we demonstrate the strength and weakness of introduction of the UAM. Based on the research findings, we propose some responsive policy strategies for the proliferation of UAM to improve the multimodal network system and economic feasibility. There are pros and cons introducing the UAM in a transport network compared to conventional ground mobility (e.g., auto and public transport) including (1) No congestion charge for the marginal cost of increasing one more vehicle, but the cost of building the infrastructure, (2) Eco-friendly travel service without any emissions during the operation if we do not consider the manufacturing the process of UAM and source of electricity, (3) On-demand service, and (4) fare and cost issue.

First, no congestion charge, since the UAM does not generate the CO_2 emissions for the long-distance travel by connecting to the vertiports on the major nodes, travelers do not have to pay for any parking fee or congestion fee for the marginal cost of one more vehicle increase in the urban area. In contrast, even though there is no congestion cost in terms of ground traffic, we have to consider the support of cost for building infrastructure. It is necessary to compare the scale of congestion



(a) (b)

Fig. 5. Emission reduction (Color bar): (a) Variation of emission reduction by airport travel; (b) variation of emission reduction by urban travel.

reduction and building infrastructure costs to judge whether introducing the UAM is beneficial or not.

Second, eco-friendly travel mode, while UAM is operated with full electric service, operating UAM on the congested traffic network yields the significant 'co-benefits' on air quality by reducing the air pollutants from the carbon combustion engine. As the result of environmental impacts, after the introduction of UAM in the urban area, the small amount of modal shift is expected to the relatively high reduction of CO_2 emissions. But, we have to consider that if cars are also electrified in increasing numbers, the relative eco-friendliness of UAM is decreased as the emissions from other transport modes are reduced.

Third, on-demand service, respondents who have experienced a type of vehicle similar to UAM or had the information about the UAM before tend to choose UAM, but others tend to be reluctant to use UAM due to safety and security issues. From the research finding, an active marketing strategy for the proliferation of UAM is necessary to consider travelers' characteristics to provide the on-demand travel service. If the government offers the promotion for taking the experience of the UAM to mitigate the fear of the UAM and deadheading problem, it would be the promoting method for the emerging travel mode operating the on-demand service. Also, since this service is not a fully on-demand service to connect with the origin and destination, we should think of the proliferation of the UAM to support the flexible operation for the long-term planning.

Lastly, fare and cost issue, the Korean government expects that the UAM fare will be about 100,000 won as an appropriate level (KAIA, 2021); however, as suggested by the results of this study, it was analyzed that the appropriate fare for UAM is considered as about 30,000–38,000 won per hour. Considering the long-term environmental impact rather than the short-term economic benefit of introducing UAM, it is necessary to encourage the emerging transport technology at a lower transit fare as a policy response (Rimjha et al., 2021). In the feasibility evaluation for the introduction of UAM, it is worth noting that the evaluation of the environmental impact for the future introduction of UAM is suggested as the policy response for the crisis of climate change and global warming rather than just judging the quantitative effect of cost-benefit evaluation. Since the UAM system is described as being operated by private companies (e.g., Lilium, Joby Aviation, and Hyundai), the government should support the land infrastructure for the initial setting of the emerging system considering the promoting of implementation, reduction of congestion, increase in job opportunities, and etc.

5. Conclusions

Along with establishing a smart mobility system, emerging transport technologies have been developed to provide passengers with a high level of service. As interest in the environmental impact increases, eco-friendly and energy-efficient travel modes are encouraged actively in the transport network. Urban air mobility is considered an emerging transport technology that replaces ground traffic in urban areas and provides more improved on-demand services. This new travel mode is expected to become an innovative travel mode that provides high-speed and high-level services in urban transport networks in the future, which will increase its market share accordingly. Researchers have studied the introduction effect by developing electrified vertical take-off and landing to minimize the environmental impact, and they have evaluated the environmental impact by modeling greenhouse gas emissions by introducing urban air mobility.

This study has established the mode choice model according to the introduction of urban air mobility and evaluated the environmental impact by the modal shift from ground traffic using the estimated parameters in Seoul metropolitan area. In order to construct a mode choice model for emerging travel modes, the stated preference survey commonly has been applied to estimate the parameters for the new travel modes, so questionnaires using travel attributes have been constructed to explore the travelers' behaviors. Two different questionnaires were constructed to compare the difference between airport and urban travels, and the parameters were estimated based on variations in travel time (20–120 min) and cost (5 thousand to 75 thousand won) for the new travel mode. The macroscopic simulation model, i.e., the EMME 4.0 program, was used to calculate the traffic volume assigned in an entire transport network. The additive logit model was used to model the modal shift behaviors compared to ground travel attributes, resulting in varying travel demands (81–35,301 trips/day) according to the scenarios. The environmental impact of the introduction of urban air mobility was evaluated by estimating the amount of the reduction of CO_2-based greenhouse gas emissions (7 hundred to 90 thousand ton) that could be achieved through changes in the traffic volume on the transport network. The results showed that the introduction of urban air mobility reduces traffic congestion in the complex transport network, so the environmental impact is relatively more considerable compared to the urban air mobility travel demand. Policy responses for the proliferation of urban air mobility have been discussed through the results of analysis on the mode choice behavior and environmental impact to help the future decision-makers prepare for lessening transit fare and minimizing the introduction cost of UAM.

This study conducted the travel demand forecast and environmental impact of introducing urban air mobility in the Seoul metropolitan area. Researchers have mentioned that urban air mobility replaces conventional airport travels with an appropriate distance to maximize the introduction effect (Grandl et al., 2018). It is necessary to survey long-distance (regional) travel, i.e., from 100 to 400 km, to analyze the mode choice behaviors. It is also noteworthy that research is required to maximize the introduction effect of urban air mobility by establishing a multimodal system, i.e., Mobility-as-a-Service (MaaS). In order to estimate the environmental impact of the introduction of urban air mobility more accurately, it will be necessary to consider the cost considering the lifecycle of the vehicle and facility and determine the appropriateness of the introduction effect along with the greenhouse gas emissions generated from electricity production.

CRediT authorship contribution statement

Shin-Hyung Cho: Conceptualization, Methodology, Software, Investigation, Formal analysis, Writing – original draft, Visualization. **Myeonghyeon Kim:** Methodology, Validation, Supervision, Data curation, Writing – review & editing, Funding acquisition.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: This research was supported by the Korea Agency for Infrastructure Technology Advancement (KAIA) grant (21ACTO-B151239-03) funded by the Ministry of Land, Infrastructure and Transport of Korean government.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2022.132139.

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