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Potential short- to long-term impacts of on-demand urban air mobility on transportation demand in North America

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A R T I C L E I N F O

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A B S T R A C T

This study applies an agent-based approach to investigate the potential individual-level demand for and system-wide impacts of Urban Air Mobility (UAM) in the short- to long-term, in two real U.S. metropolitan areas. The UAM service we envision in this research provides mobility to on-demand requests from one vertiport to another. The investigations consider the existing electric vertical take-off and landing (eVTOL) aircraft models (assuming they are piloted) and vertiport designs, while accounting for the uncertainties in (i) service attributes (e.g., time saving and service price), and (ii) demand characteristics (e.g., perceived waiting time in various conditions). Towards this goal, the state-of-the-art agent-based simulation platform SimMobility is expanded in this research with new modules required for realistic simulation of the demand, supply, and demand–supply interactions. The expanded platform adopts a high-fidelity model system with: (i) a behaviorally sound demand model to mimic the switching behavior from current non-UAM mode to UAM and to capture the individuals' willingness to pay and plan-action dynamics in decision-making; (ii) a detailed operation model to account for not only the integration of ground and aerial transportation but also fleet rebalancing and the intra-vertiport state dynamics such as charging, gate availability, taxiing, pre-landing hovering (as a result of capacity limitations), etc.; (iii) a demand-driven vertiport placement and capacity generation module. The results show that the UAM market is expected to start narrow (0.187 % to 0.197 % of all trips) and remain niche in the long term (1.45 % to 1.81 % of all trips) for both cities. In addition, the service is expected to increase mobility inequality, even in the long term. The potential UAM users turned out to be primarily high-income in all scenarios (e.g., 46.9 % to 59.2 % in the long term). Moreover, car-oriented individuals are identified as the main users – not only are most UAM trips expected to emerge from drive-alone trips (84.7 % to 92.8 % at launch), but also drive-alone is expected to be the most preferred access/egress mode (78.4 % to 83.6 % share among all UAM trips at launch). Notably, short-range UAM trips (i.e., flight distance below 40 km) constitute the majority of the UAM potential demand (94.6 % in the long-term scenario).

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1. Introduction

Advancements in automation, electrification, and communication technologies have brought new opportunities to the transportation sector in recent years, transforming the city landscape and individuals' behaviors. Emerging transportation modes such as Mobility on Demand (MOD) have been investigated in numerous studies. Recently, the industry and researchers have begun to look beyond the ground with the concept of on-demand Urban Air Mobility (UAM), or the so-called "air taxi", to provide service in between vertiports using electric vertical take-off and landing (eVTOL) aircraft.

The concept of UAM may be traced back to around 1917 when the first "flying car", Curtiss Autoplane, was invented by Glenn Curtiss (Cohen et al., 2021; King, 2021). Despite the interests of both the industry (e.g., Ford) and the government ever since, this concept has not achieved commercial viability until recent years, mainly due to various practical (e.g., regulatory) and technical barriers (e.g., vehicle stability and safety) (Cohen et al., 2021). An early form of UAM emerged in the 1950 s to 1980 s when several companies provided scheduled helicopter services in major U.S. cities (Cohen et al., 2021). For instance, New York Airways provided passenger services in New York City, with which a trip from Manhattan to John F. Kennedy International Airport would take only seven minutes and cost $56 in today's price after adjusting for inflation (Beresnevicius, 2019). However, these early UAM businesses eventually ceased operations due to various obstacles: e.g., noise, fuel cost, maintenance issues, and safety (Beresnevicius, 2019).

In recent years, solutions to long-standing technological difficulties have been proposed due to recent advancements in electric propulsion, automation, and sensing (Cohen et al., 2021). Various models of the eVTOL aircraft have been introduced by the industry, including Joby Aviation, Lilium, and EHang. As summarized by Cohen et al. (2021), by March 2020, twelve UAM services are operational, growing from two services in 2014. Various use cases of UAM have been investigated, including air metro, air taxi, airport shuttle, and air ambulance (Hasan, 2018; Goyal et al., 2018). In particular, Goyal et al. (2021) estimated an annual market of 2.5 billion USD in the U.S. for the airport shuttle and air taxi services under a conservative scenario, and a market of 500 billion USD under the most unconstrained scenario.

Despite the rising interests in UAM, the range of its impacts on transportation demand remains understudied, especially in North American metropolitan areas. This study contributes to the literature by addressing the following questions. What range of the market size can be expected in the short- to long-term for UAM, under various uncertainties in the demand- and supply-side parameters? What is the profile of the UAM users in the short- to long-term? How do different supply configurations (e.g., accessibility and service price) affect the UAM market? Providing realistic answers to these questions holds significant value, as it allows policymakers and the industry to make informed decisions regarding UAM implementation. This, however, calls for a comprehensive modeling system that accounts for not only the multi-dimensionally complex nature of human behavior (e.g., the distinction between plans and actions) and UAM service operation, but also the underlying uncertainty in both demand and supply. Existing studies have offered valuable insights into the market size of UAM, but the market composition and the impacts of supply remain unaddressed. Furthermore, several critical details have been overlooked in existing modeling approaches, including the intra-vertiport activities such as charging and vertiport capacity. Finally, the lack of consideration of uncertainties limits the robustness and generalizability of results.

Hence, in this study, we proposed an agent-based simulation framework to comprehensively model UAM by combining demand, supply, and their interactions at fine spatial and temporal levels. Our contribution is twofold. First, we analyzed the potential market size and market composition for UAM under various supply configurations, while considering the uncertainties in both demand and supply-side parameters. Second, we developed a model that enables us to simulate realistic scenarios with: (i) a behaviorally sound demand model that explicitly captures the switching behavior from current modes to UAM, along with the plan-action dynamics in the decision-making process; (ii) a detailed service operation model, including UAM fleet rebalancing and intra-vertiport activities, allowing us to capture the realistic movement of the fleet as well as the constraints of aircraft battery and vertiport capacity; (iii) a realistic demand-driven vertiport placement module that mimics the site selection and capacity generation process by suppliers. The framework has been implemented in the state-of-the-art simulation platform, SimMobility. Two real U.S. metropolitan areas have been simulated and compared.

The remainder of this paper is organized in the following way. The underlying literature is reviewed in Section 2. Afterward, the simulation framework adopted in this research is presented in Section 3, followed by an outline of the simulation experiments in Section 4. The results are presented in Section 5. Finally, policy implications are discussed in Section 6, and the article concludes in Section 7 by providing a summary of the key research findings as well as directions for future studies.

2. Literature review

Researching the future of urban ecosystems incorporating UAM calls for proper consideration of both the demand-side and supply-side factors, their interplay, and the corresponding uncertainties. This section summarizes the existing literature on these factors.

2.1. Supply

On the supply side, the existing studies can be classified into three groups. One group of studies focused on the infrastructure, including vertiport placement and layout designs. The layout designs consider the placement of vertiport facilities, including Final Approach and Take-Off (FATO) zones and gates, under space constraints (Courtin et al., 2018; Preis, 2021; Vascik, 2020; Zelinski, 2020). On the other hand, various vertiport placement approaches have been proposed and can be summarized into the following four categories: (i) heuristic approaches, based on regulation, operational requirements, and experts workshops (Antcliff et al., 2016;

Ploetner et al., 2020; Pukhova et al., 2019; Pukhova et al., 2021); (ii) systematic demand-based and Geographic Information System (GIS)-based approaches (e.g., k-means clustering algorithm) (Arellano, 2020; Fadhil, 2018; Lim & Hwang, 2019; Syed et al., 2017); (iii) optimization methods that maximize benefits of either the operator or the traveler (Daskilewicz et al., 2018; Rath & Chow, 2022; Wang et al., 2020; Wu & Zhang, 2021); (iv) iterative approach that adjusts vertiport locations to the demand subject to the constraint on the desired number of vertiports (Rimjha et al., 2021).

The second group consists of efforts on the development of eVTOL aircraft. Existing models have a total number of seats between 2 and 7, a range between 35 km to 300 km, and a cruise speed between 110 km/h to 322 km/h (ACS Aviation, 2018; Airbus, 2022; Lilium, 2022; EHang, 2022; Volocopter, 2022; Wisk, 2022; Joby Aviation, 2021; Electric VTOL News, 2020; Electric VTOL News, 2022a; Electric VTOL News, 2022b). These aircraft achieve fast charging: e.g., Lilium claims to be able to charge from zero to full battery in 30 min (Young, 2021).

The third group of studies investigated various operational aspects. Charging has been recognized as an important component in operational efficiency with respect to both economic and environmental considerations (Yang et al., 2021; Young, 2021; Reichmann, 2021; UberAir, xxxx). The expected prices reported in academic publications and industry reports range from \$0.273/seat-km to \$6.84/seat-km (Cao, 2021; Dickey, 2018; Klenske, 2021; Goyal et al., 2018). The value of \$0.273/seat-km was reported by Uber Elevate as the long-term price, which is comparable to the average driving cost reported by the American Automobile Association (i.e., \$0.339/km to \$0.511/km) (Dickey, 2018; American Automobile Association, 2020). In addition to price, other operation characteristics (e.g., fleet composition, dispatching algorithm, and routing) have been widely studied, and algorithms for efficient operations have been proposed (Ale-Ahmad et al., 2020; Alvarez et al., 2021; Bennaceur et al., 2022; Kim, 2020; Kohlman et al., 2019; Li et al., 2020; Postorino & Sarné, 2020). Lastly, emissions have been examined, and existing studies suggest that UAM is only greener than internal combustion engine vehicles above a certain distance, and one of the major sources of energy consumption is hovering (Bulusu & Sengupta, 2020; Kasliwal et al., 2019).

2.2. Demand

On the demand side, studies have been conducted to analyze the characteristics and size of the potential UAM demand. In this section, the UAM demand literature is summarized through two lenses: (i) UAM demand characteristics; (ii) UAM market size.

While there exist several major obstacles to UAM implementation, including community backlash, visual and noise pollution, safety, privacy, and equity concerns, empirical studies have revealed interest in UAM among various individuals (Cohen et al., 2021; Goyal et al., 2018; Desai et al., 2021; Al Haddad et al., 2020; Castle et al., 2017; Yedavalli and Mooberry, xxxx; Sánchez, 2021). Income, age, and education have been identified as important predictors of UAM demand (Al Haddad et al., 2020; Boddupalli, 2019; Fu et al., 2019; Garrow et al., 2018). Song et al. (2019) found that variety-seekers (characterized by higher income and having experienced delay(s) in the past) are more likely to switch to UAM. The literature also characterizes the potential UAM trips. Unlike the users' socio-demographic profiles, the literature on the profile of trip purpose reports inconsistent findings. While Fu et al. (2019) and Garrow et al. (2018) found that UAM is most likely to be used for business purposes, Goyal et al. (2018) found that long-distance recreation and airport access/egress are the most likely purposes for using UAM. While some studies found that UAM is attractive for long-distance commute trips, evidence also exists that the market among commuters could be limited (Garrow et al., 2018; Kreimeier et al., 2017; Fu et al., 2020). Lastly, for UAM access/egress trips, riding or driving a personal vehicle, MOD service, and public transit are found to be the most preferred modes (Wu & Zhang, 2021; Goyal et al., 2018; Pukhova et al., 2021; Rothfeld et al., 2018a).

The potential UAM market penetration has also been analyzed. One group of studies analyzed UAM demand using non-UAM data sources such as existing travel survey data and developed models with assumptions on the Value of Time (VOT) of travelers (Syed et al., 2017; Kreimeier et al., 2017; Rothfeld et al., 2018a; Pu et al., 2014; Mayakonda et al., 2020; Balać et al., 2019a; Balać et al., 2019b). These studies reported a penetration rate between nearly zero (0.001 %) and 19 %, showing great uncertainty (Syed et al., 2017; Kreimeier et al., 2017; Rothfeld et al., 2018a; Pu et al., 2014; Mayakonda et al., 2020; Balać et al., 2019a; Balać et al., 2019b).

Another group of studies analyzed the potential UAM market based on UAM Stated Preference (SP) data. The data were used to construct discrete choice models, whose estimated parameters were then used to extend existing simulation models that do not include the UAM travel mode (Ploetner et al., 2020; Pukhova et al., 2019; Pukhova et al., 2021; Rimjha et al., 2021). Vertiport locations were selected using a heuristic approach (i) or the iterative process (iv) as described in Section 2.1 (Ploetner et al., 2020; Pukhova et al., 2019; Pukhova et al., 2021; Rimjha et al., 2021). Vertiport capacities based on the real geographical space were not considered (Ploetner et al., 2020; Pukhova et al., 2019; Pukhova et al., 2021; Rimjha et al., 2021). Among these studies, Pukhova et al. (2019) and Rimjha et al. (2021) did not model fleet operations. On the other hand, Ploetner et al. (2020) and Pukhova et al. (2021) used the agent-based simulation platform MATSim with the UAM extension developed by Rothfeld et al. (2018b), which allows the modeling of fleet operation. These studies reported a potential UAM market size of less than 1 % (Ploetner et al., 2020; Pukhova et al., 2021).

2.3. Contribution

Despite the growing body of the UAM literature, major gaps still exist in the state of the knowledge on the system-wide impacts of UAM on transportation demand. While the existing studies on UAM demand have shed light on various demand characteristics, the specific market compositions (by types of trip and user) and the impacts of supply configurations have not been systematically studied yet. Unveiling such impacts requires agent-based simulations to support the various details in modeling. Although agent-based simulations have been performed by Ploetner et al. (2020) and Pukhova et al. (2021), using the MATSim with UAM extension, the market compositions of UAM users/trips have not been analyzed. Furthermore, uncertainties have been overlooked in existing studies, which are critical for understanding the robustness and generalization of results. In addition, while existing agent-based simulations comprehensively capture demand, supply, and demand–supply interactions, they lack essential details for realistic modeling. Modeling of vertiport capacity, intra-vertiport activities such as aircraft charging, and fleet rebalancing are not included in the fleet operation model. However, these details are critical to accurately model UAM service attributes, including waiting time, charging time, and hovering time. Bridging these gaps will benefit both the UAM industry leaders and the urban regulators by enabling a more informed planning approach toward their respective missions.

Towards this goal, we adopted an agent-based simulation framework that combines demand, supply, and their interactions at fine spatial and temporal levels. We extended the state-of-the-art agent-based simulation platform, SimMobility, with this framework. We utilized the extended platform to simulate and compare two metropolitan areas in the United States under diverse scenarios considering varying supply configurations, along with the uncertainties in both demand and supply. Our research contributes to the UAM literature in two ways:

First, our detailed simulation-based approach enables a comprehensive analysis of the potential market size and composition across a host of scenarios with varying supply configurations, while also considering uncertainties in both demand- and supply-side parameters. Second, our approach considers several behavioral dimensions for *users*, *operators*, and *planners* of the system, synergistically, for the first time in the literature. These dimensions include:

(i) We designed and implemented a behaviorally robust demand model that captures the switching behavior from non-UAM modes to UAM and the plan-action dynamics. The final actions people take may or may not be the same as their initial plans. Therefore, it is very critical to capture the dynamics of moving from plans to actions for each individual.
(ii) We implemented an intricate operation model that incorporates UAM fleet rebalancing and intra-vertiport activities, enabling realistic movement of the fleet while accounting for constraints related to aircraft battery and vertiport capacity.
(iii) We adopted a demand-driven approach to the placement and capacity generation of simulated vertiports, that can more realistically emulate the decision-making process of suppliers. Section 3, as follows, summarizes the modeling approach.

3. Simulation laboratory

SimMobility is a high-fidelity, integrated agent- and activity-based simulation laboratory to assess the wide range of systemic- to individual-level impacts of various mobility scenarios. As shown in Fig. 1, SimMobility consists of three main components: (i) the Short-Term component performs a microscopic traffic simulation; (ii) the Mid-Term component simulates the activity and travel patterns for an average day; and (iii) the Long-Term component simulates longer-term decisions such as car ownership, work location, and residential location and its relation to the housing market dynamics (Azevedo et al., 2016).

In this study, the SimMobility Mid-Term component has been used to simulate a typical weekday with the existence of UAM, which

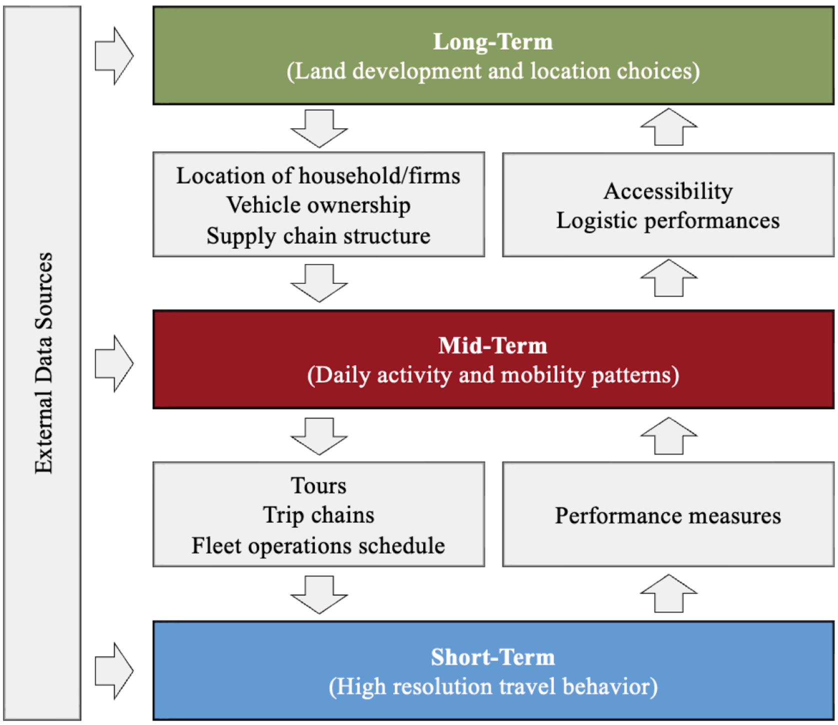

Fig. 1. SimMobility Framework (Azevedo et al., 2016).

brings about various dynamics associated with both supply and demand. Fig. 2 shows the structure of SimMobility Mid-Term, which in turn integrates three major modules: (i) the Pre-day module is an Activity-Based Model (ABM) system that simulates agents' decisions on daily activity and travel plans; (ii) the Within-day module simulates how the agents translate their plans into actions in real-time; and (iii) the Supply module is a multimodal mesoscopic traffic simulator that simulates the movement of agents across the network. The Day-to-day Learning loop ensures that the simulated agents have a robust understanding of the network conditions when planning for their day (Oh et al., 2020). The UAM extension with respect to Pre-day, Within-day, Supply, and the Day-to-day Learning loop is presented in what follows.

3.1. Demand

Both the Pre-day and Within-day modules have been expanded to model UAM demand with a behaviorally sound approach for modeling (i) access/egress modes to/from the vertiports and (ii) possible destination changes with the presence of UAM.

3.1.1. Pre-day

SimMobility Pre-day simulates the Day Activity Schedules (DAS) for agents, based on an ABM system with hierarchical choice models as shown in Fig. 3. Lower-level decisions are conditioned on higher-level decisions (solid arrows), and higher-level models include inclusive values from lower-level models (dashed arrows). There are three major levels: (i) the Day Pattern Level constructs the sequence of tours, as well as availability and purposes of intermediate stops; (ii) the Tour Level models choices of tour travel mode, destination, and time of day; (iii) the Intermediate Stop Level generates the sequence of the stops for tours, and simulates the decisions regarding travel mode, destination, and travel time of these stops. Two types of mode choice models are incorporated: type (A) only models the mode choice and is used in cases where the destination is known a priori (e.g., for fixed-location work activities), while type (B) jointly models the mode and destination choices (Oh et al., 2020).

Both type A and B models in the original SimMobility framework (henceforth, *Baseline Choice Models*) have been expanded to also simulate the decisions pertaining to UAM, by incorporating two new models: (i) a *Consideration Model* and (ii) a *Switching Model*. This framework is shown in Fig. 4. The expanded type (A) model mimics the choice among the following four UAM alternatives: Park & Fly, Kiss & Fly, MOD & Fly, as well as Public Transit (PT)/Walk & Fly. These four alternatives represent choices among various access/egress modes with UAM, respectively drive-alone, carpool, MOD, and PT/walk. The type (B) model further combines these alternatives with different destination zones and thus considers a larger choice set than type (A).

The *Consideration Model* simulates agents' decisions on whether to consider a UAM alternative or not in two sequential steps: (i) the Heuristic availability check, and the (ii) Willingness-to-pay-based consideration. With the Heuristic availability check, an initial filtering is performed for the UAM alternatives, based on the chosen alternative from the *Baseline Choice Model*. The heuristics consider

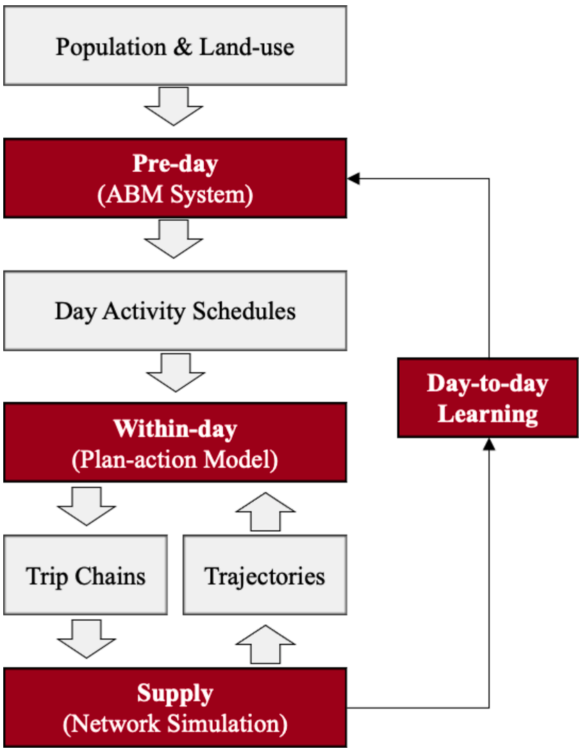

Fig. 2. SimMobility Mid-Term Simulation Flowchart (Oh et al., 2020).

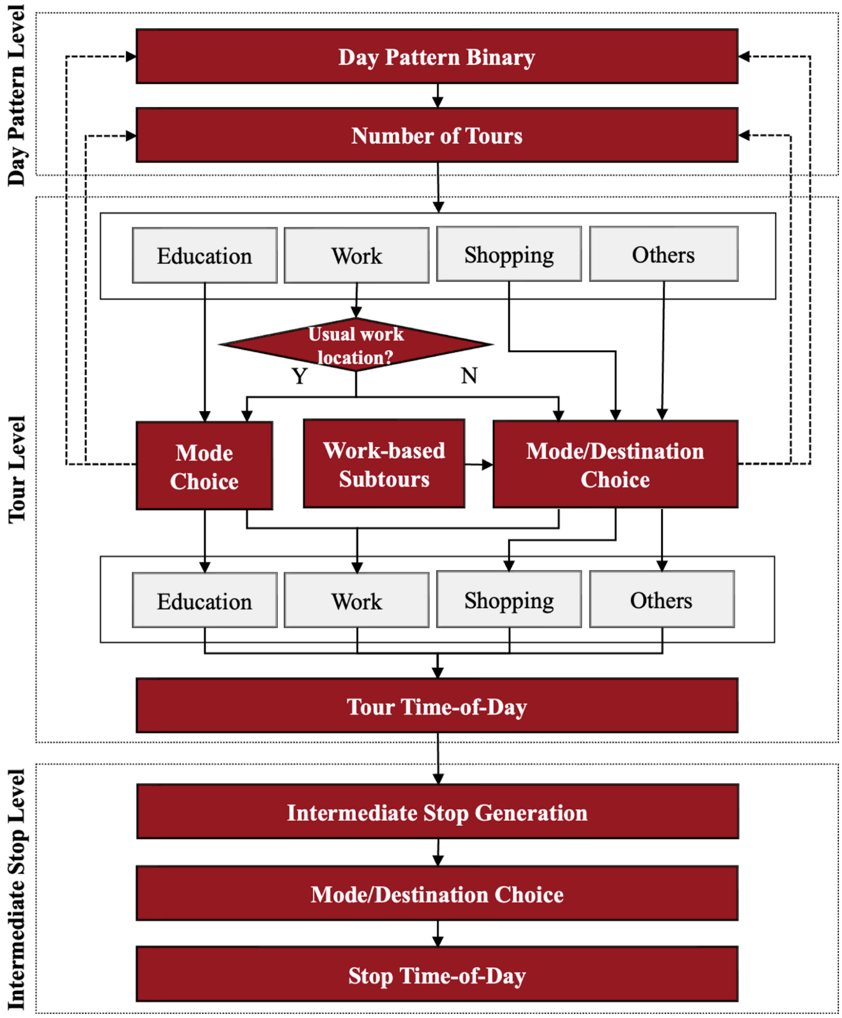

Fig. 3. SimMobility Pre-day Model System (Oh et al., 2020).

the following factors: chosen baseline mode, trip purpose, distance, location attractiveness indices (e.g., employment for shopping activities), and availability of both UAM and the access/egress mode (e.g., Park & Fly is not considered if car is not available). More details may be found in Chen (2022). The *Consideration Model* is capable of handling the reconsideration of locations by evaluation of the location attraction indices, and only locations that are more attractive are considered.

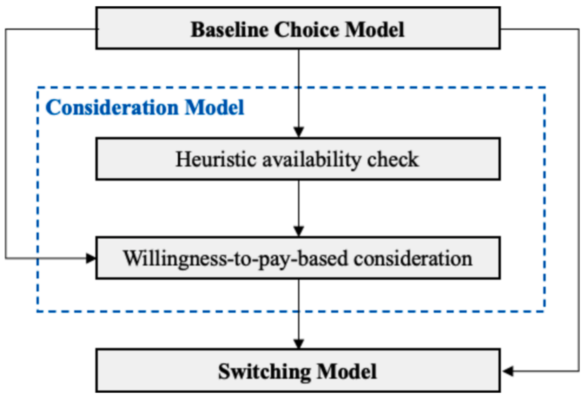

Fig. 4. UAM Pre-day Demand Model.

The Willingness-to-pay-based consideration computes the willingness to pay (WTP) for UAM alternatives against the chosen baseline alternative, based on travel time saving, extra cost, and other socio-demographics. For the extra cost, the total UAM cost considers all legs: access, in-flight, and egress. For perceived time saving, the total UAM travel time is computed as a summation of scaled access, egress, waiting, and in-flight times. The scales are respectively 1.26, 1.64, 1.87, and 1.00, adopted from Song et al. (2019) and Fan et al. (2016). The Willingness-to-pay-based consideration model is presented in Eq. (1) and the parameters are estimated from a Chicago choice experiment study. Table 1 summarizes the estimated parameters. UAM alternatives that passed the Heuristic availability check and have nonnegative WTP are considered available in the *Switching Model*.

$$\begin{aligned}\mathrm{WTP}_{i,n} &= \beta_0 + \beta_{male}D_n^{male} + \beta_{age\_between\_40\_65}D_n^{age\_between\_40\_65} + \beta_{age>65}D_n^{age>65} + \alpha_n \\ &\quad - \mathrm{ExtraCost}_{i,n} + \beta_n^{TS} \times \frac{\mathrm{Income}_n^{\lambda_{inc}} - 1}{\lambda_{inc}} \times \frac{\mathrm{EducYears}_n^{\lambda_{edu}} - 1}{\lambda_{edu}} \times \mathrm{TimeSaving}_{i,n}\end{aligned} \tag{1}$$

Where,

$\mathrm{WTP}_{i,n}$: WTP of individual n for UAM alternative i (USD)
β_0: constant
β_k: coefficient for socio-demographic k
$\alpha_n \sim N(0, \sigma_{AE}^2)$: agent effect for individual n
$\beta_n^{TS} \sim \mathrm{Lognormal}(\mu_{WTP}, \sigma_{WTP}^2)$: WTP for time saving coefficient for individual n
λ_{inc}: box-cox transformation parameter for income
λ_{edu}: box-cox transformation parameter for education
D_n^k: dummy variable of socio-demographic k for individual n (1 if k is true; 0 otherwise)
Income_n: annual household income of individual n (1 K USD)
$\mathrm{EduYears}_n$: years of education of individual n
$\mathrm{ExtraCost}_{i,n}$: extra cost of UAM alternative i for individual n, as compared to the chosen baseline alternative (USD)
$\mathrm{TimeSaving}_{i,n}$: perceived time saving of UAM alternative i for individual n, as compared to chosen baseline alternative (minute)

Lastly, the *Switching Model* is applied to model agents' decisions on changing from their baseline alternative to UAM. This model has two stages. Stage 1 is a multinomial logit model that selects the best option among all UAM alternatives. Eq. (2) presents the money metric utility of UAM alternative i for individual n. Stage 2 is a binary logit model that mimics the switching decision – i.e., whether to switch to the best UAM alternative determined in Stage 1 or to stick to the baseline alternative chosen in the *Baseline Choice Model*. The utility for not-switching is normalized to 0. The switching utility is specified to incorporate the extra cost and perceived time saving, in addition to the socio-demographics, lagged variables on the chosen baseline mode, and a constant. The coefficients of these variables are adopted from Fu et al. (2019) and are all transformed into money-metric to ensure compatibility of the scales. Table 1 summarizes the parameter values.

$$\begin{aligned}U_{i,n} &= -\mathrm{ExtraCost}_{i,n} + \mathrm{VOT}_n \times \mathrm{TimeSaving}_{i,n} + \gamma_0 \\ &\quad + \gamma_{age\_between\_46\_55}D_n^{age\_between\_46\_55} + \gamma_{age\_between\_56\_65}D_n^{age\_between\_56\_65} \\ &\quad + \gamma_{age>65}D_n^{age>65} \\ &\quad + \gamma_{curr\_mode\_PT/carpool}D_n^{curr\_mode\_PT/carpool} + \gamma_{curr\_mode\_walk/bike}D_n^{curr\_mode\_walk/bike} \\ &\quad + \gamma_{monthly\_household\_income>\$8262}D_n^{monthly\_household\_income>\$8262} + \epsilon_{i,n}\end{aligned} \tag{2}$$

Table 1
Willingness-to-pay-based consideration step and Switching Model parameters.

Willingness-to-pay-based consideration step		Switching Model	
Parameter	**Value**	**Parameter**	**Value**
β_0	−82.0	γ_0	−6.21
β_{male}	37.3	$\gamma_{age\_between\_46\_55}$	−2.38
$\beta_{age\_between\_40\_65}$	−51.7	$\gamma_{age\_between\_56\_65}$	−2.38
$\beta_{age>65}$	−91.3	$\gamma_{age>65}$	−3.70
σ_{AE}	25.2	$\gamma_{curr\_mode\_PT/carpool}$	−3.19
μ_{WTP}	0.200	$\gamma_{curr\_mode\_walk/bike}$	−4.23
σ_{WTP}	1.12	$\gamma_{monthly\_household\_income>\$8262}$	1.68
λ_{inc}	−0.0793		
λ_{edu}	−0.262		

Where,
VOT_n: VOT of individual n (USD/min)
γ_0: constant
γ_k: coefficient of socio-demographic variables and lagged variables on chosen baseline mode
D_n^k: dummy variable of socio-demographic variables and lagged variables on chosen baseline mode for individual n (1 if k is true; 0 otherwise)
$\epsilon_{i,n}$: error term of the utility of UAM alternative i for individual n

3.1.2. Within-day

The UAM extension of SimMobility Within-day accounts for the UAM users' decisions on routes and access/egress modes. The UAM and ground networks are integrated as shown in Fig. 5. A UAM node in this model represents a small area that can contain one or several vertiports located in each other's vicinity. For a certain UAM trip, the origin and destination are ground nodes, and each edge can have either of the three types: ground access (i.e., connecting the ground node at the origin to a UAM node), aerial (i.e., connecting two UAM nodes), and ground egress (i.e., connecting the destination UAM node to the destination ground node). A UAM path consists of ground access, aerial, and ground egress edges. The shortest paths that traverse the origin/destination pairs among the ground nodes are computed based on the integrated network and are used for the SimMobility route choice model.

For UAM access/egress modes, agents decide a high-level preference in Pre-day and determine the specific modes in Within-day. If the chosen access/egress mode from Pre-day is feasible during Within-day, the plan is executed without any modifications. However, if the chosen mode is infeasible, the agent attempts to use the next preferred mode based on a pre-determined preference order. For instance, for an agent attempting to drive alone for the egress trip, if the car is not parked nearby the destination vertiport, the agent will use MOD instead. This approach mimics a realistic decision-making process, where travel plans are subject to changes during execution.

3.2. Supply

The modeling of UAM supply considers vertiport infrastructure, eVOTL aircraft, and operations. The methods of vertiport placement and aircraft modeling are summarized in Section 3.2.1, while the resulting design profile may be found in Section 4.3. The UAM controller for operation controls is described in Section 3.2.2.

3.2.1. Vertiport and eVTOL aircraft

For each simulation scenario, vertiports are selected based on real geography, subject to an accessibility constraint. Accessibility is quantified as follows: the percentage of the population who can reach a nearby vertiport in 15 min by driving (hereafter, *accessibility measure*). Driving time estimates are provided by Openrouteservice (Heidelberg Institute for Geoinformation Technology, xxxx). The *accessibility measure* is scenario-specific and may be found in Section 4. The following procedure is applied to iteratively select the vertiport locations, which follows a hierarchy from potential high-demand area to UAM node and to vertiport, as shown in Fig. 6:

1. Select potential high-demand areas based on income and commute (home to work) time data.
2. Select UAM nodes inside the potential high-demand areas.
3. Within the UAM nodes, select the exact vertiport(s) from the buildings, open space, commercial centers, distribution centers, and existing airports.
4. Run SimMobility to find the passenger trip demand of each UAM node. Generate 15-minute isochrones (driving) around selected vertiports and compute the *accessibility measure*.
5. Compare the *accessibility measure* against the value pre-determined for the scenario:

a). If lower than the scenario value, add additional UAM node(s) and, if necessary, select additional potential high-demand area(s).
b). If higher than the scenario value, remove UAM node(s) with low demand.

6. Repeat step 3 to step 5 until the *accessibility measure* is matched.

Capacity, measured as the number of gates and FATOs, is generated for the selected vertiports. The designs shown in Fig. 7, proposed by Vascik (2020), are used. Based on the actual space, either 500 ft x 200 ft or 300 ft x 300 ft design is used. Furthermore, the selection between the satellite and the linear topologies is adjusted to adapt to facility needs. For example, for vertiports that have a

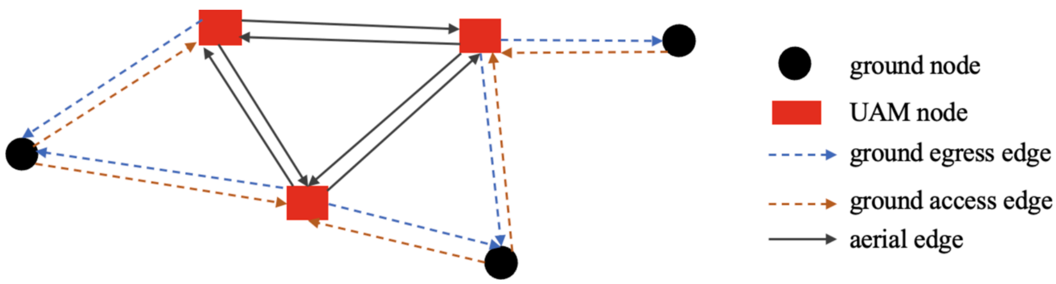

Fig. 5. Integration of Ground Network with UAM Vertiports.

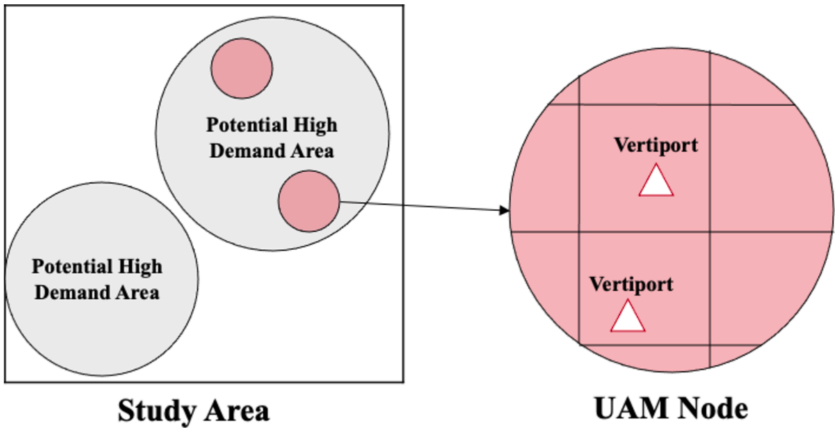

Fig. 6. UAM Vertiport Selection Hierarchy.

high average aircraft waiting time for gates, the layout with a higher number of gates is used. Thus, vertiport capacities are adjusted to the generated demand and UAM traffic. Simulations with SimMobility are necessary for vertiport site selection and capacity generation purposes but are distinct from the Day-to-day Learning loop. The UAM expansion with Day-to-day Learning is summarized in Section 3.3, with which passengers and UAM controller iteratively update their knowledge about the network. However, infrastructure remains unchanged throughout the Day-to-day Learning process.

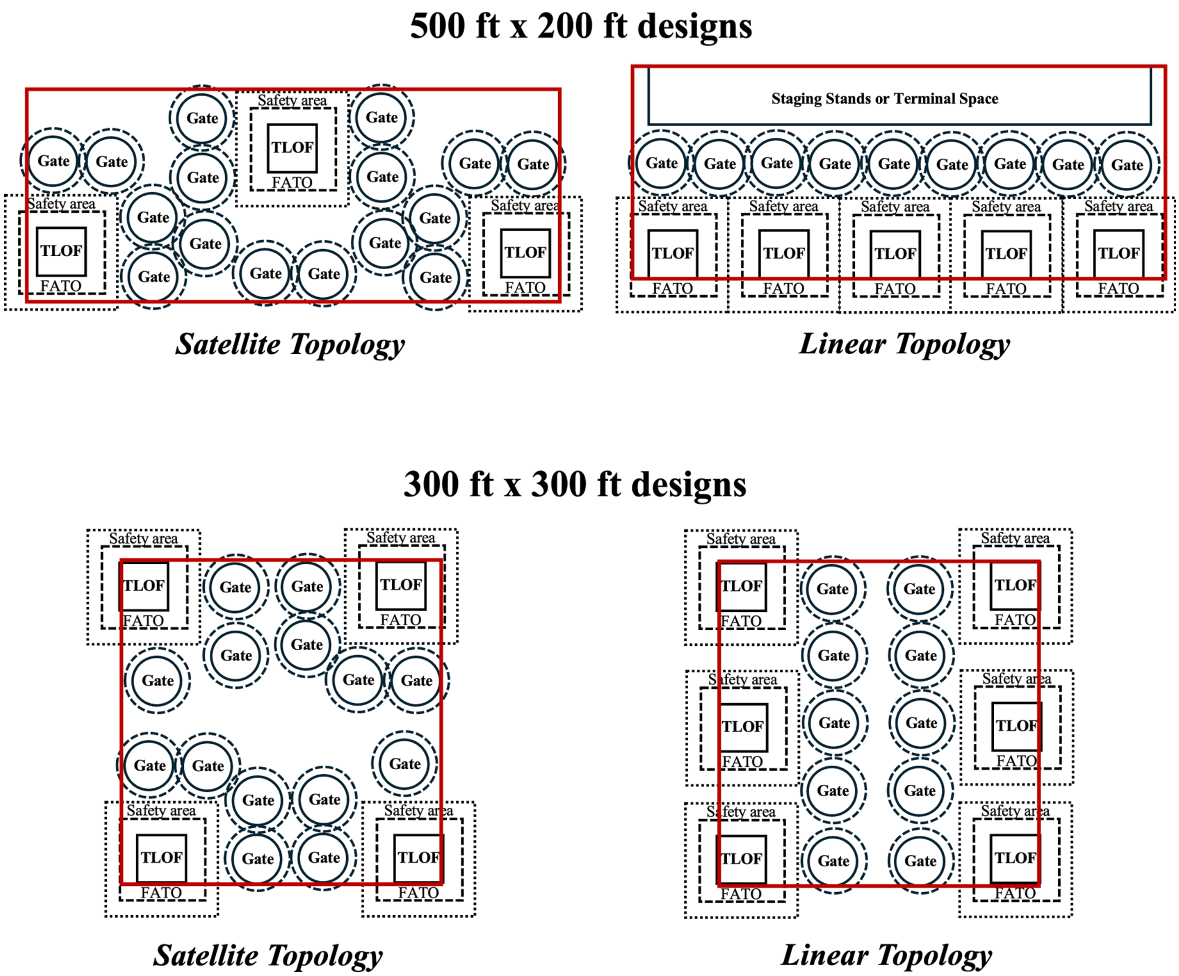

Fig. 7. Vertiport Design (Vascik, 2020).

Aircraft's charging states are modeled for realistic simulation, for which a charging profile is developed. Firstly, based on existing reports, data points regarding the relationship between ranges charged (distance current charging level may support before complete depletion) and charging time are extracted. Next, a function is fitted over the extracted data points to form the charging profile. We assumed that aircraft may charge at the gates.

Fleet size is determined using extensive random local searches during the simulation. For each iteration of the Day-to-day Learning loop, various fleet sizes are experimented for a generated demand, and the best one is selected in step of the Day-to-day Learning process, based on average total passenger waiting time and aircraft hovering time. The total passenger waiting time is defined as the total time spent after arriving at the gate for boarding and before deboarding at the destination, except for the flight duration. Therefore, the time spent in the aircraft waiting for take-off is also included.

3.2.2. UAM controller

A UAM service controller has been developed to represent the operation logic, as depicted in Fig. 8. The controller is capable of modeling detailed aircraft movements and tracking resources at vertiports. Therefore, it can capture various attributes including hovering, charging, and passenger/aircraft waiting times, which are critical for realistic simulations.

Upon a user's request, the controller attempts to match the user with available aircraft at the origin vertiport. Unmatched requests remain in a queue and the users' waiting times are tracked. The trips may be either solo or pooled. Meanwhile, the controller schedules the aircraft's missions and tracks their state dynamics (including the charging levels and seat capacity) through time. In addition to assigning aircraft for take-off/landing, flying, and taxiing missions, the controller explicitly models the intra-vertiport transitions between gates and FATOs (refer to Yoo (2022) for details). It tracks available FATOs/gates at vertiports, along with the aircraft's waiting time for FATOs/gates, e.g., the hovering time. This captures the capacity constraint at the vertiports. Lastly, rebalancing has been implemented to proactively serve demand. More details can be found in Yoo (2022).

3.3. Day-to-day Learning

The Day-to-day Learning module captures agents' iterative learning process of making daily decisions. Under the UAM extension, both passengers and the UAM controller for modeling operations learn through Day-to-day Learning.

The passenger agents learn two UAM service attributes in addition to learning about travel time and cost of non-UAM modes. Firstly, UAM trips' total passenger waiting time is learned as an aggregate zone-to-zone attribute and is used in Pre-day planning. In addition, the time that the passengers expect to submit their requests in advance to avoid waiting at the vertiports is learned as a

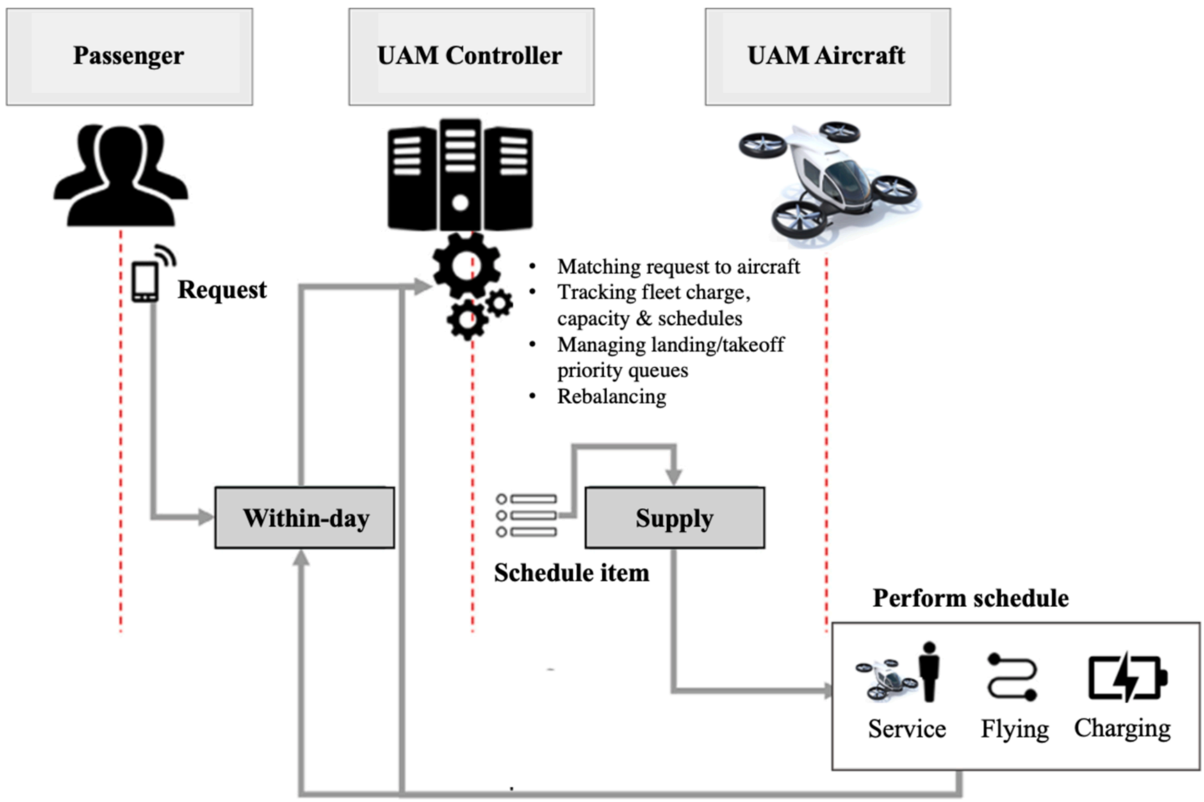

Fig. 8. UAM Service Controller.

vertiport-specific attribute and is used for the Within-day decisions.

The service provider learns the following operational parameters to improve the level of service. Firstly, the vertiport-specific expected hovering time is learned for charging and scheduling purposes. This time is the expected waiting time for an arriving aircraft to be assigned to an available FATO for landing, and it is critical to track for safety. In addition, the time that aircraft with matched trips spend waiting for passengers to arrive is also learned as a vertiport-specific attribute to avoid unnecessary resource consumption at the vertiports – i.e., the aircraft that are waiting for passengers occupy the gate, while the facility may be used for other purposes (e.g., for other aircraft whose passengers have arrived to load passengers and prepare for taking off).

4. Simulation experiments

The simulation laboratory has been applied to study the potential UAM demand in two real North American cities. For both cities, three UAM scenarios are simulated to analyze the effects of supply on demand. The supply configurations vary in capacity, accessibility, and pricing. Uncertainty analyses are performed for all scenarios. The scenario design and study area are described in the following section. The design profiles of vertiport locations and aircraft are detailed as well.

4.1. Scenario design

Three scenarios are studied: at-launch, near-term, and long-term. Uncertainty analyses are performed as sub-scenarios. Table 2 summarizes scenario and sub-scenario designs.

Across all scenarios, it is assumed that the aircraft have a 200 km/h speed and 250 km range, the same as AutoFlight V1500 (Electric VTOL News, 2022b). The aircraft are assumed to be piloted with 3 passenger seats (Goyal et al., 2018; Electric VTOL News, 2022b). Based on Goyal et al. (2018), the price is assumed to be $4.52/seat-km at launch and is reduced by 60 % in the long term. Three supply constraints vary across the three scenarios: accessibility, capacity, and pricing.

Uncertainties of demand model parameters are based on reported standard errors from Fu et al. (2019) and Song et al. (2019). Confidence intervals of 90 % have been computed, whose higher and lower bounds are used for sub-scenarios. For perceived UAM times scales for the access, egress, waiting, and in-flight times adopted from Song et al. (2019), the lower and higher bounds of the 90 % confidence intervals are respectively used for the upper and lower bound sub-scenarios. For the other constants and characteristics parameters adopted from Fu et al. (2019), the higher and lower bounds of the 90 % confidence intervals have been used respectively for the upper and lower bound sub-scenarios.

With respect to the uncertainties in supply, the aircraft model and price are varied. The upper bound sub-scenario assumes fast aircraft with 322 km/h speed, 241 km range and 4 passenger seats, based on Joby Aviation (2021), with a unit price of $3.88/seat-km estimated by Goyal et al. (2018). The lower bound assumes a slow aircraft with 120 km/h speed, 80 km range and 3 passenger seats, based on CityAirbus NextGen (Airbus, 2022). Lastly, as Goyal et al. (2018) reported 50 % uncertainty in the price, the upper bound price is reduced by 50 % and the lower bound price is increased by 50 % for the corresponding aircraft type.

4.2. Study area

Oke et al. (2019) clustered major cities worldwide into 12 typologies based on economic, demographic, urban form, mobility, and environmental indicators. Fig. 9 shows the spider plots of the typology profiles across nine factors (Oke et al., 2019). By profiling and clustering cities worldwide based on multi-dimensional indicators, findings from one city can inform similar research on other cities of the same typology. In this study, we explored the impacts of UAM in two real North American metropolitan areas that belong to distinct typologies: Auto Innovative (AI) and Auto Sprawl (AS). Both types of cities are highly industrialized and car-oriented, but AI cities have more extensive transit systems. Boston, Toronto, and Chicago are examples of the AI cities, while Baltimore, Indianapolis, and St. Louis are notable examples of AS cities (Oke et al., 2019). While we use real city data for input data synthesis and model validation, due to confidentiality concerns of the sponsor, in this article, we refer to the selected real cities by their prototypical names, AI and AS.

The input data to SimMobility are synthesized from various data sources for the real AI and AS cities, based on the method developed by Tsogsuren (2018). The road network is synthesized and prepared from those cities' real road network using OpenStreetMap contributors (2020). The public transit network, including the schedule, interchanges, and routes, is synthesized from publicly available General Transit Feed Specification (GTFS) data of the study area AI and AS. Regarding population, microdata samples and aggregate statistics from the U.S. Census are collected, with which the Hierarchical Iterative Proportional Fitting is applied to synthesize the population (Census Bureau, 2020a; Census Bureau, 2020b).

Both AI and AS are real U.S. metropolitan areas that consist of multiple counties. In AI city, there is a central business district in the core and several suburban cities are located in the periphery. In AS, two major cities are located close to each other and are well-connected through highways. This creates more long-distance trip demand compared to AI, as shown in Figure 13. Both AI and AS have a large number of population, with 7 million in AI and 4.5 million in AS. Compared to AS, AI city is composed of a wealthier population, with higher shares of the population belonging to middle-income ($100 k − $250 k annual household income) and high-income households (>$250 k annual household income), as shown in Fig. 20. AS has a higher car mode share as shown in Fig. 10.

The following baseline modes are relevant for both areas: private bus (e.g., shuttle bus), PT, drive-alone, carpooling with two people, carpooling with three or more people, walk, bike, motor, taxi, and MOD. PT has three access/egress modes: walk, drive-alone, and MOD. Four types of activities are included: work, education, shop, and others. The baseline model without UAM is calibrated against travel diary data, with a lognormally distributed VOT. The mode share, activity pattern, trips by time of day, and trip distance

Table 2
Scenario and Sub-scenario Configurations.

Scenario	Sub-scenario	Unit Price ($/seat-km)	Accessibility Measure	Capacity	Aircraft Model	Demand Model	
						Perceived UAM Time Scales	**Constant and Characteristic Parameters**
At-launch	Upper bound	1.94	70 %	1 vertiport/UAM node	Joby	90 % CI lower bound	90 % CI higher bound
	Average case	4.52			AutoFlight V1500	estimate (mean)	
	Lower bound	6.79			CityAirbus NextGen	90 % CI higher bound	90 % CI lower bound
Near-term	Upper bound	1.94		(Assume a sufficient capacity; 2.5′ waiting time)	Joby	90 % CI lower bound	90 % CI higher bound
	Average case	4.52			AutoFlight V1500	estimate (mean)	
	Lower bound	6.79			CityAirbus NextGen	90 % CI higher bound	90 % CI lower bound
Long-term	Upper bound	0.777	90 %		Joby	90 % CI lower bound	90 % CI higher bound
	Average case	1.81			AutoFlight V1500	estimate (mean)	
	Lower bound	2.71			CityAirbus NextGen	90 % CI higher bound	90 % CI lower bound

Footnote:

1. Accessibility measure: the percentage of population who can reach a nearby vertiport in 15 min by driving in car.
2. Aircraft model specifications:
   a. Joby: 322 km/h speed; 241 km range; 4 passenger seats
   b. AutoFlight V1500: 200 km/h speed; 250 km range; 3 passenger seats
   c. CityAirbus NextGen: 120 km/h speed; 80 km range; 3 passenger seats
3. For demand model parameters, 90% confidence intervals (CI) are constructed for the estimates from Fu et al. (2019) and Song et al. (2019). The higher and lower bounds are used for the sub-scenarios.

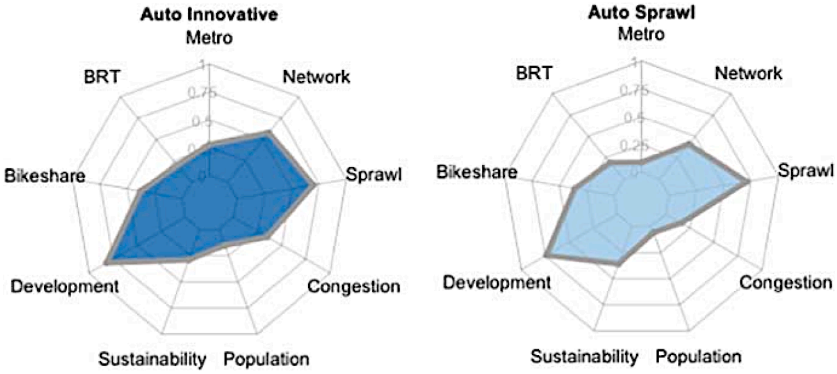

Fig. 9. Typology Profiles (Oke et al., 2019).

have been calibrated. Fig. 10, Fig. 11, Fig. 12, and Figure 13 show the validation results, which suggest that the baseline model reasonably replicates the travel pattern of the two prototype cities.

4.3. *Vertiport and eVTOL aircraft Configuration*

Vertiport locations have been selected based on the method presented in Section 3.2.1. Under the accessibility constraint defined in Table 2, for the at-launch and near-term scenarios, 23 vertiports have been selected for AI and 19 for AS. For the long-term scenario, respectively 61 and 56 vertiports have been selected for AI and AS. Spatially, in AI, the vertiports are densely located nearby the center major city, with some sporadically distributed in the suburban and rural areas. On the contrary, AS has two major cities around which vertiports are concentrated.

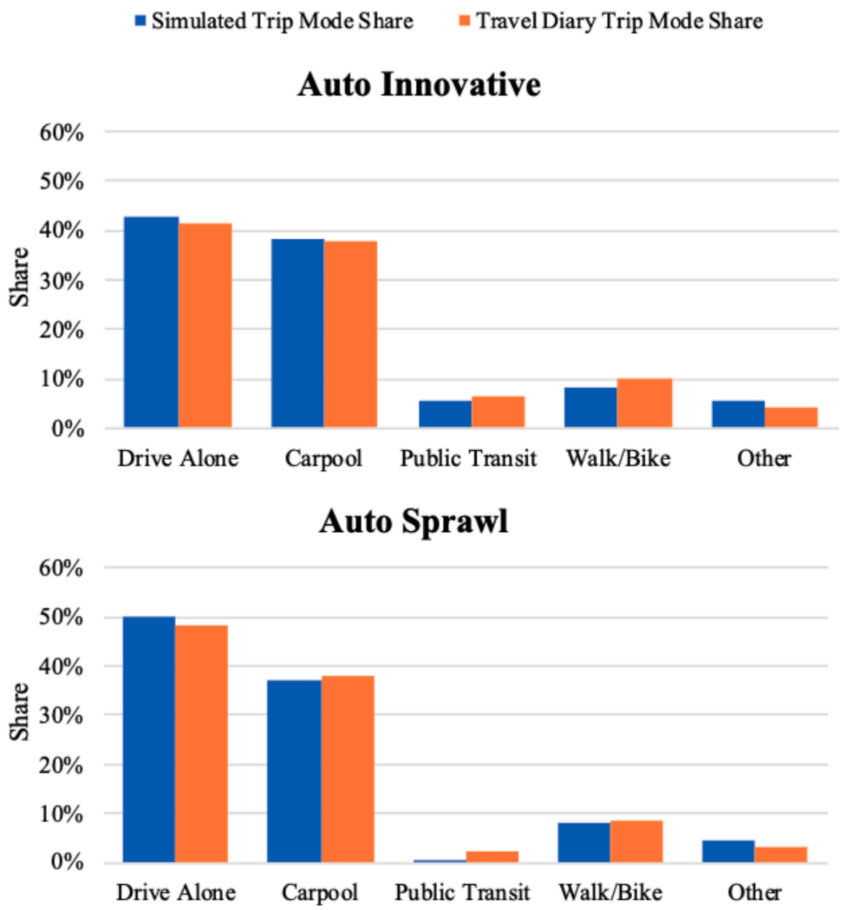

Fig. 10. Trip Mode Share Validation.

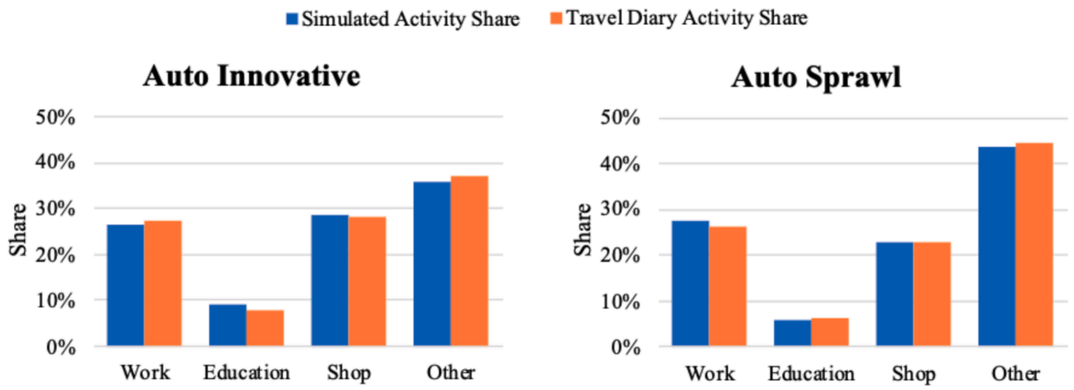

Fig. 11. Trip Activity Pattern Validation.

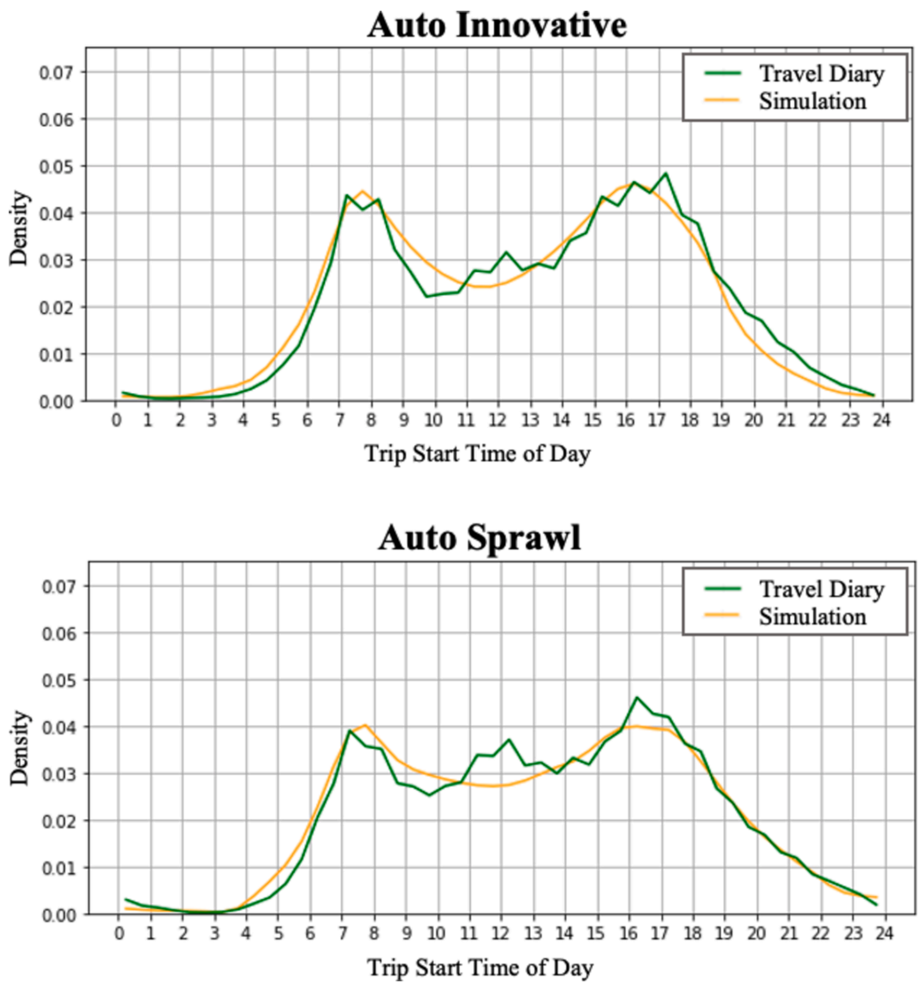

Fig. 12. Trip Time of Day Validation.

Lastly, the charging profile has been developed as described in Section 3.2.1. Lilium reports being able to charge from zero to 80 % in 15 min and to fully charge in 30 min (Young, 2021). The profile fitted from this report is shown in Fig. 14.

5. Results

This section presents the results from the simulations. With UAM rapidly evolving, the at-launch scenario is first presented in detail to provide insights into the market of UAM in the upcoming years. Next, the near-term and long-term scenario results are

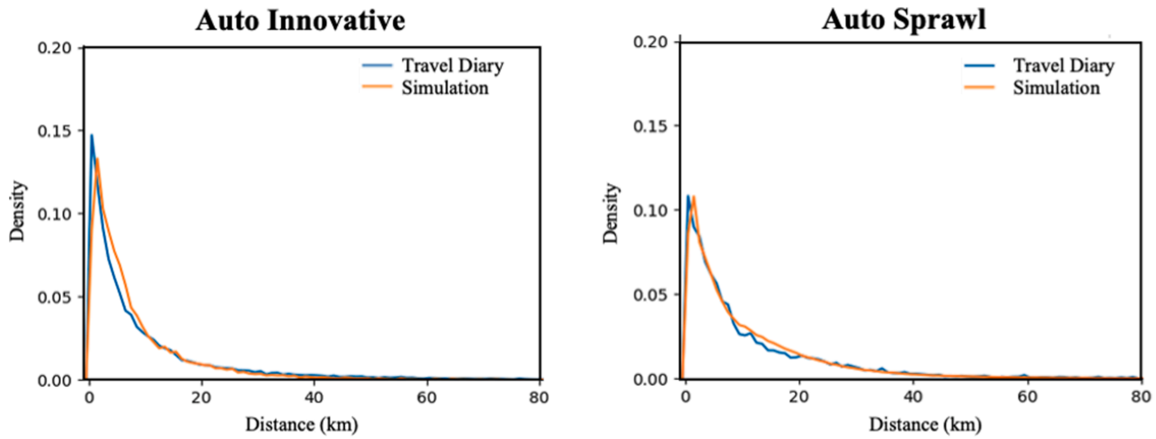

Fig. 13. Trip Distance Distribution Validation.

presented, and all three scenarios are compared, which allows us to observe potential UAM demand changes with varying supply configurations.

5.1. The At-Launch scenario

In this section, the potential market sizes with uncertainties are presented in Section 5.1.1. Section 5.1.2 and Section 5.1.3 present additional results of the average case sub-scenario.

5.1.1. Market size

The potential market size, including penetration rate and the number of daily UAM passenger trips, are shown in Fig. 15, with uncertainties. While the market penetration rates are similar, the number of UAM trips is considerably higher in AI than in AS. This could be explained by the higher population and thus larger addressable market in AI. In addition, the average time saving is 59.2 min in AI and 53.7 min in AS. Thus, the potential demand for AI is higher as UAM saves more time. Lastly, AI individuals have higher income, which indicates higher VOT. The uncertainty is shown to be large in both cities, indicating that variations in price, aircraft type, and unobserved factors, e.g., public perception, play significant roles in determining UAM demand. However, the upper bounds of the penetration rate of both cities are low, indicating that the potential UAM market is niche at launch. The scale of the market size found in our study is similar to the results of existing studies performing agent-based simulation (Ploetner et al., 2020; Pukhova et al., 2021).

5.1.2. Demand characteristics

This section is devoted to the characteristics of the UAM demand in the at-launch average case sub-scenario. Fig. 16 presents the UAM penetration rate by trip purpose and shows that the penetration rate among work trips is higher than non-work trips in both cities. Similar results have been found in existing studies (Fu et al., 2019; Garrow et al., 2018).

Fig. 17 depicts the modal shift, breaking down the UAM trips by the modes from which switching happened. Most of the switching comes from drive-alone trips, but the shares are notably different between AI and AS (92.8 % in AI and 84.7 % in AS), indicating that UAM is more appealing to individual drivers in AI than in AS. One reason could be the higher level of congestion in AI. Carpool is the second major source of switching, though contributing only 3.78 % and 8.97 % in AI and AS, respectively. In both cities, PT has a low

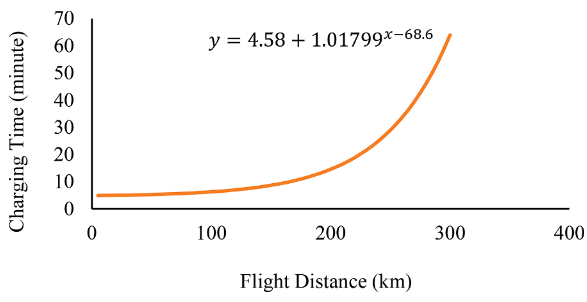

Fig. 14. Charging Profile.

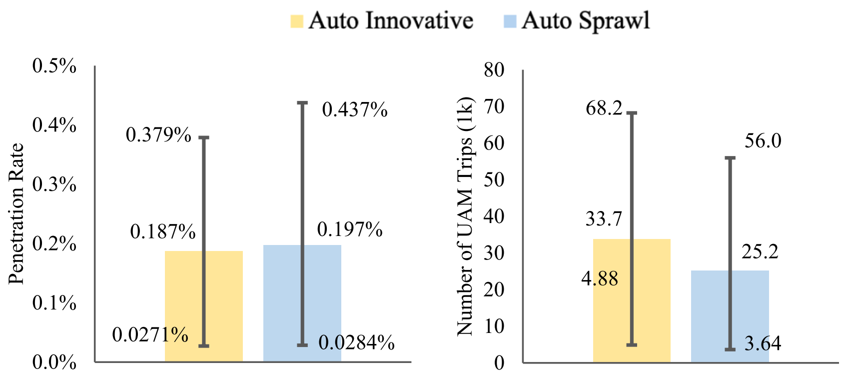

Fig. 15. UAM Demand in At-Launch Scenario.

share of switching to UAM (0.986 % in AI and 0.356 % in AS), which is reasonable as PT users in the context of North American cities are mostly non-choice riders with low VOTs.

The access/egress mode shares of UAM trips are shown in Fig. 18. Most of the trips are Park & Fly. As noted, the majority of the potential UAM trips come from drive-alone, which further highlights that while the potential UAM travelers are mainly car-oriented individuals, they are expected to continue their reliance on personal vehicles after switching. Furthermore, in line with the literature, our results indicate that MOD constitutes the next largest access/egress mode share, with its share being higher in AS than in AI (Wu & Zhang, 2021; Goyal et al., 2018).

5.1.3. Supply

The SimMobility Pre-day attributes are updated throughout the Day-to-day Learning loop by different times of day (AM, OP, and PM). For each of these periods, an hour representative of the demand is selected to perform the simulation. For AM and PM, the hours selected capture the peak demand, while, for OP, the hour captures the lowest demand at midday. For both cities, the selected hours are 7:30 AM to 8:30 AM (AM), 11 AM to 12 PM (OP), and 4 PM to 5 PM (PM).

Fleet size, average hovering time, and average total passenger waiting time are presented in Table 3 for the at-launch average case sub-scenario. The total passenger waiting time at equilibrium is around 14 min for peak hours in AI, but only around 7.5 min for AS. This indicates that individuals in AI are willing to accept a higher waiting time than those in AS, as time saving is also higher in AI. The hovering times are low for both cities in all simulation periods, but OP hovering time is lower than the two other periods due to the lower demand.

The fleet size required for AI is 350, which is lower than the 600 for AS. This is due to the spatial distribution of the vertiports, and the UAM demand generated. Recall that AS has two major cities with a high density of vertiports. A similar pattern of UAM demand has also been observed: it is highly concentrated around the two cities, with only a few intra-city UAM trips. Therefore, to satisfy the demand, the fleet size needs to be large enough to serve both cities separately to avoid having to rebalance between the cities. For AI, which has vertiports densely located near the sole major city at the center of the study area, since a large fleet consumes resources at vertiports and leads to aircraft congestion, the fleet size should be kept small for efficient operations. Hence, AS requires a larger fleet than AI.

5.2. Potential UAM demand in near- to Long-Term scenario

This section compares three scenarios varying in supply configurations, including capacity, accessibility, and pricing. While Section 5.2.1 compares the potential market size with uncertainties, Section 5.2.2, Section 5.2.3, and Section 5.2.4 present results for average case sub-scenarios only.

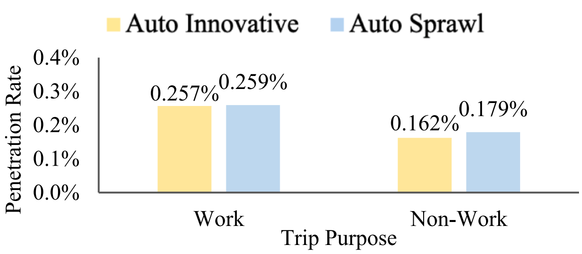

Fig. 16. UAM Penetration Rate by Trip Purpose.

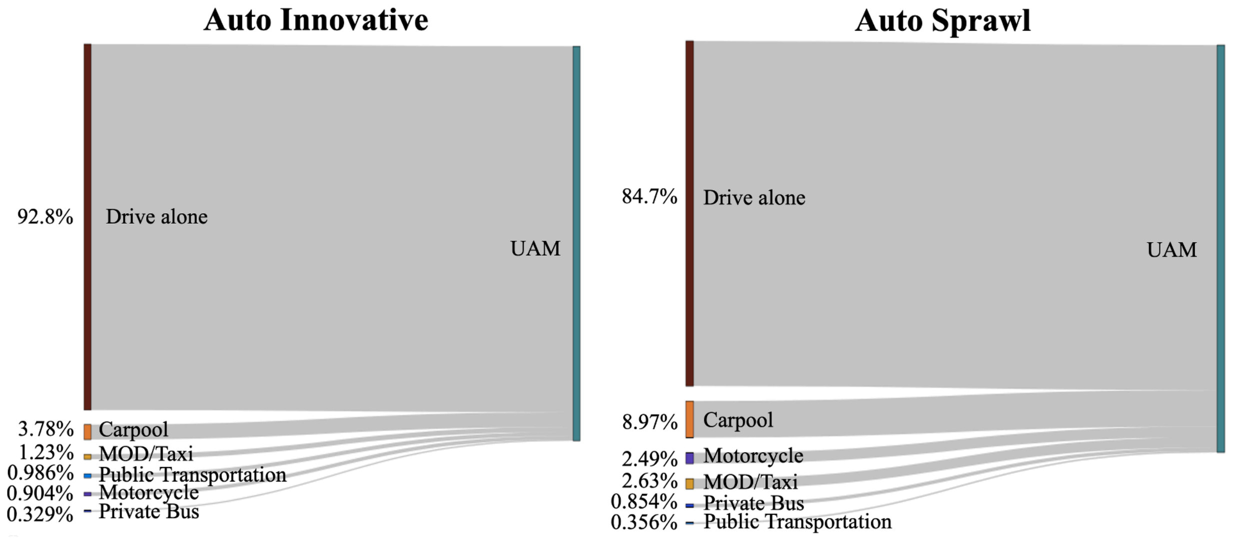

Fig. 17. Modal Shift.

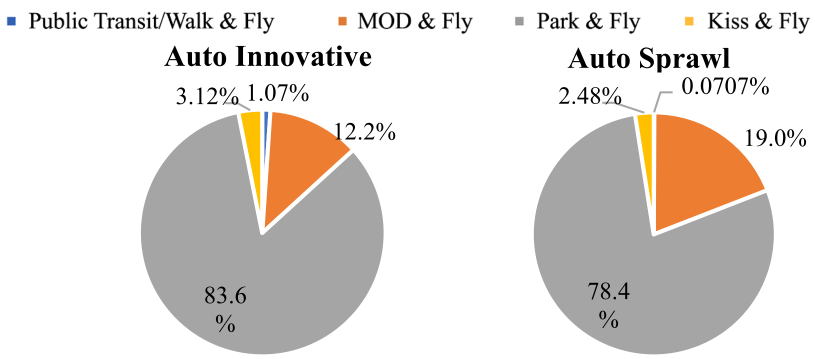

Fig. 18. Access/Egress Mode Share.

Table 3
At-Launch Scenario Average Case Supply Simulation Results.

City	Auto Innovative			Auto Sprawl		
Period	**AM**	**OP**	**PM**	**AM**	**OP**	**PM**
Fleet size	350	300	350	500	500	600
Hovering time (second)	6.84	0.656	11.7	9.90	2.40	9.83
Total passenger waiting time (minute)	13.5	5.66	14.4	7.18	6.41	7.99

5.2.1. Market size

The penetration rates across all scenarios are shown in Fig. 19, along with the associated uncertainties. While the penetration rate of AI is smaller than AS in the at-launch scenario, when supply constraints are lifted, AI has higher penetration than AS. Furthermore, the effects of supply are subject to notable differences across the two cities. In the near-term scenario, for AI, the penetration rate increases by 226 % (from 0.187 % to 0.610 %), and further increases by 196 % in the long-term scenario (from 0.610 % to 1.81 %). For AS, the increases are 102 % and 265 %.

The uncertainties grow from at-launch to long-term scenario. While similar in at-launch and near-term scenarios, the uncertainty of AI is smaller than AS in the long-term scenario. One reason could be the price of long-range UAM trip. Let us define the penetration rate of long-range trips as the number of UAM trips with a flight distance greater than 40 km divided by the number of trips that would have a flight distance greater than 40 km as well if using UAM. For the long-term average case sub-scenario, the penetration rates among long-range trips are, respectively, 4.68 % and 2.35 % for AI and AS. However, in the long-term upper bound sub-scenario, the rates increase to 18.5 % and 19.4 % for AI and AS, which are 296 % and 727 % increases from the average case. With a price as low as

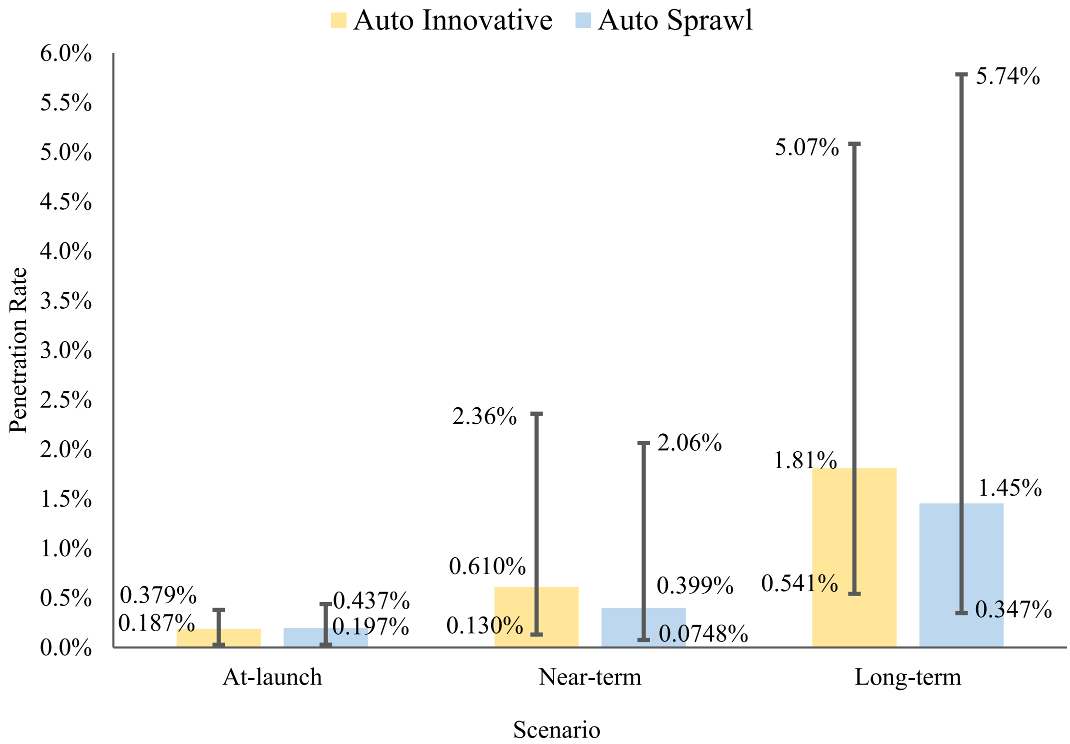

Fig. 19. Penetration Rate Across Scenarios.

$0.777/seat-km in the long-term upper bound sub-scenario, AS is then able to capture significantly more demand. This contributes to the higher uncertainty in AS in the long-term scenario.

5.2.2. Potential user income distribution

Fig. 20 presents the annual household income distribution of the potential UAM users in average case sub-scenarios, compared to the population distribution. The high-income individuals (i.e., annual household income greater than $250 k) constitute 15.9 % and

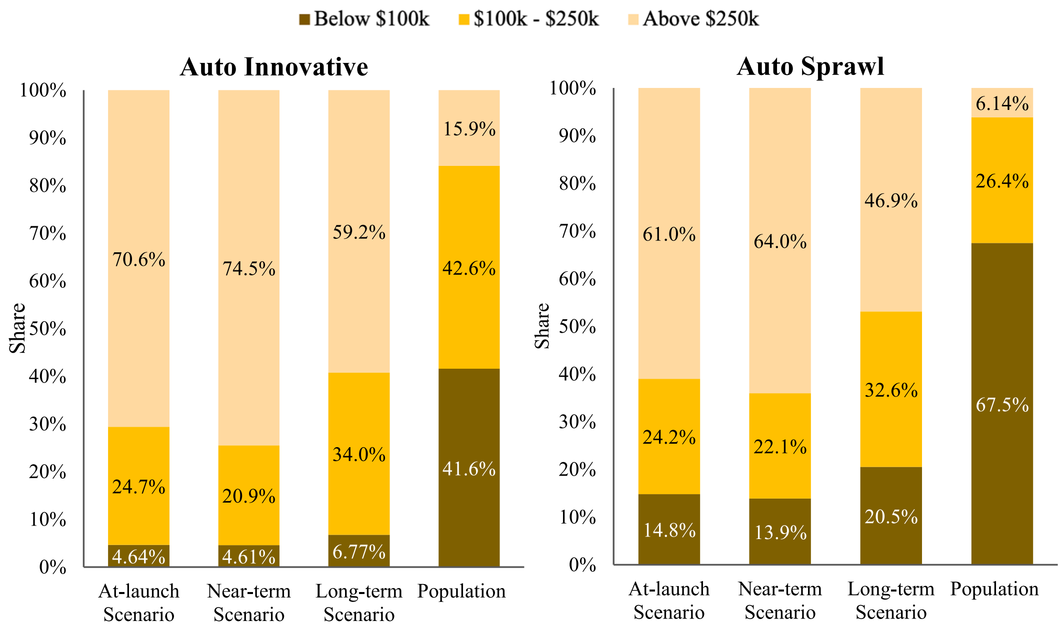

Fig. 20. UAM Users Annual Household Income Distribution.

6.14 % of the total population of AI and AS, respectively. However, they are the majority of the UAM users in all three scenarios in both cities. This indicates the existence of equity issue with UAM. Similarly, it has also been found in the literature that high-income individuals are more likely to be potential users of UAM (Fu et al., 2019; Garrow et al., 2018). Overall, UAM users in AI have a more skewed income distribution than AS. In the at-launch scenario, while 70.6 % of the UAM users in AI belong to the high-income class, a lower percentage of 61.0 % in AS belong to this class.

In the near-term scenario when capacity is increased, in both cities, the shares of high-income individuals among all UAM users increase while shares of middle-income ($100 k − $250 k) decrease. Although the overall penetration rate increases (Fig. 19), UAM is more exclusive for high-income individuals in the near term. In the long-term scenario when the price is reduced and accessibility is increased, even though the equity issue persists, it is alleviated as compared to at-launch and near-term scenarios.

5.2.3. Potential market size by trip type

As observed in Section 5.1.2, work and current drive-alone trips constitute the major UAM demand. Therefore, the market penetration rate changes over a combination of trip purpose and baseline mode are presented in this section, with the following trip types: (A) work and drive-alone, (B) non-work and drive-alone; (C) work and non-drive-alone; (D) non-work and non-drive-alone. Fig. 21 shows the results for the average case sub-scenarios. Overall, penetration rates increase for all types in both cities, and the increases are more significant in the long-term than in the near-term scenario. Across the scenarios, type A and B remain the ones with the highest penetration rate. In the long-term scenario, type C's penetration rate increases significantly in AI but not in AS. Lastly, type D sees significant increases in both cities: while nearly zero in the at-launch scenario, the penetration rates of AI and AS increase to 0.306 % and 0.372 % in the long-term scenario respectively. Overall, the results indicate that, in the long term, the UAM market attracts not only work and drive-alone trips but others as well, bringing in opportunities for various trip types.

5.2.4. Potential market size by flight distance

Fig. 22 shows the flight distance distribution of the simulated UAM demand in at-launch and long-term average case sub-scenarios. Similar to the findings of Fu et al. (2020), our results indicate that the majority of the UAM trips are short-range with a flight distance below 40 km, with a share of over 90 % in both cities and both scenarios. In the long-term scenario, there are fewer short-range UAM trips but still over 90 %. This could be due to the lack of demand to travel long-distance in an urban setting and the higher cost of long-distance UAM trips.

The market penetration rates across different flight leg distances are compared in Fig. 23, across all average case sub-scenarios. For AI, the penetration rate of long-range trips is higher than short-range across all scenarios. The difference is the largest in the long-term scenario. On the contrary, in AS at-launch and near-term scenarios, the penetration rate of short-range trips is larger. One reason could be that long-range trips are not as affordable as short-range trips in these two scenarios, while the price is significantly reduced in the long-term scenario. Since AS has a lower income level, affordability is shown to be the limiting factor to capture the expensive long-range demand in AS.

Lastly, price sensitivity analysis has been performed for the long-term scenario. The penetration rate change by flight distance is shown in Fig. 24, with a price factor of 90 %, 80 %, 70 %, and 60 % (1.63, 1.45, 1.27, 1.09 $/seat-km respectively). Therefore, in the

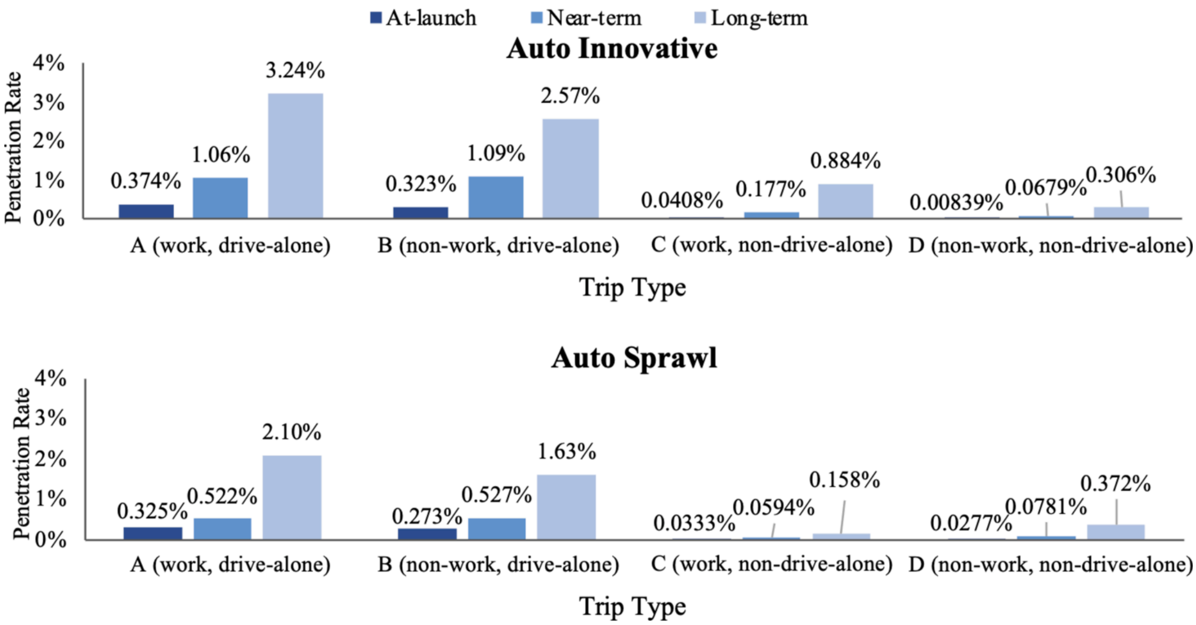

Fig. 21. Market Penetration by Trip Purpose and Baseline Mode.

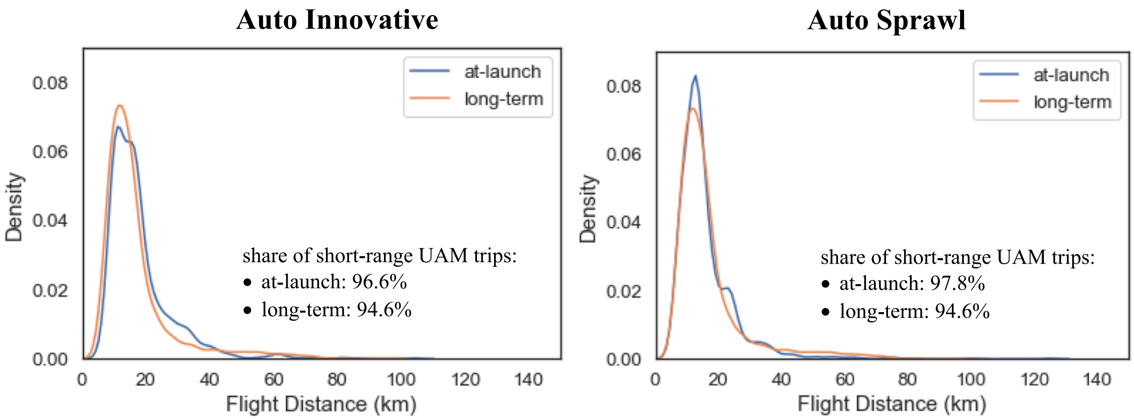

Fig. 22. UAM Flight Distance Distribution.

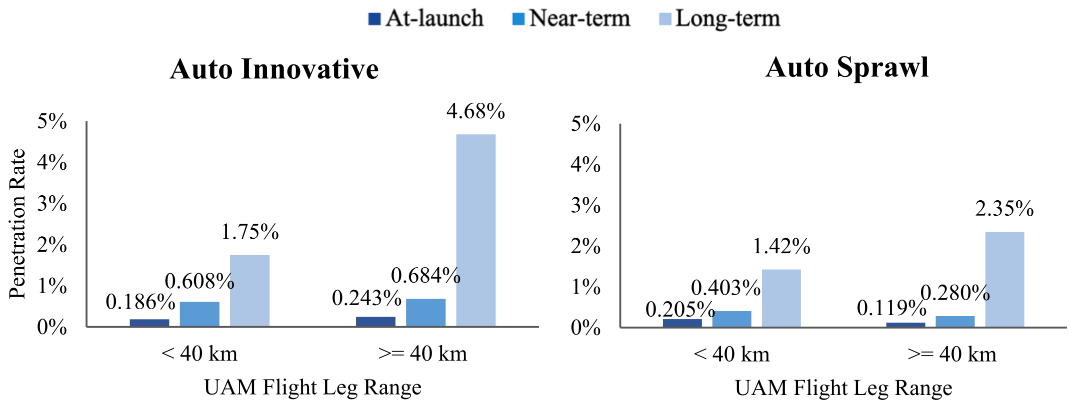

Fig. 23. Market Penetration by Flight Distance.

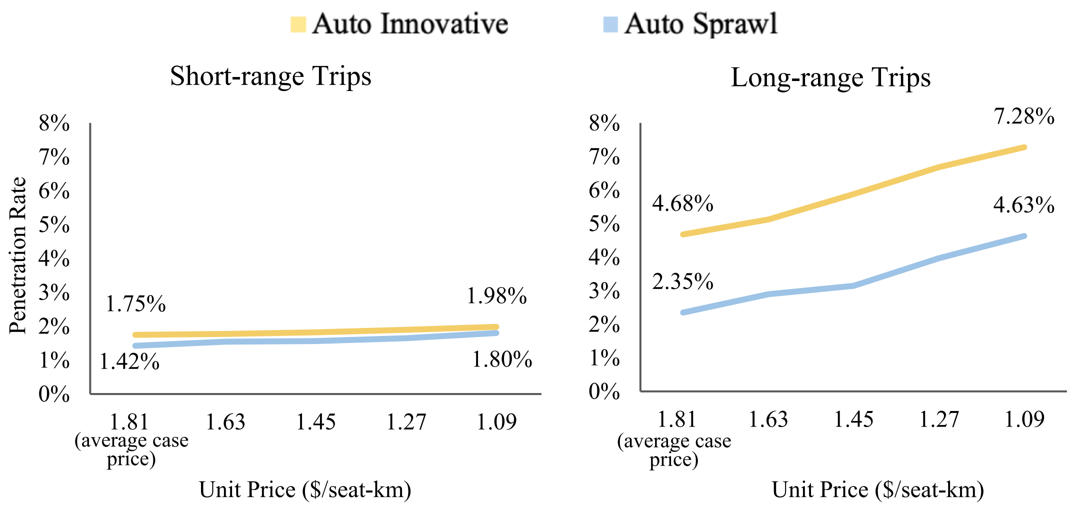

Fig. 24. Long-term Scenario Price Sensitivity Analysis by Flight Distance.

long-term scenario, the change in penetration rate among short-range trips is small. For the long-range trips, however, even though the price is low already in the average case sub-scenario with $1.81/seat-km, the change in penetration rate is still significant as the price decreases. Price is the limiting factor to capture long-range demand as a change in unit price is magnified significantly by distance and is reflected in the total price.

6. Policy implications

In this study, we have carefully analyzed the UAM demand market under various scenarios, along with uncertainties in both demand and supply. By simulating the at-launch, near-term and long-term scenarios that vary in supply configurations, four major themes emerge from our results.

The first theme that emerges from our results pertains to the niche but significantly uncertain potential UAM market. The potential penetration rate of UAM at launch was found to be less than 0.2 % in both AI and AS and increased to 1.81 % and 1.45 % in AI and AS, respectively, in the long-term scenario. However, there are high uncertainties in both cities, with the uncertainties growing from the at-launch scenario to the long-term scenario. Thus, despite the envisioned benefits of UAM in alleviating congestion, it may not have substantial impacts due to the niche market. Moreover, the large uncertainties highlight the need for robust analyses to understand the effects of UAM on congestion and emissions for informed policymaking.

The second theme is associated with equity issues concerning income disparity. Our results have shown that the majority of the UAM users are high-income individuals with an annual household income above $250 k, constituting around half of the UAM users in the long term. On the other hand, these individuals only constitute around 6 % to 16 % of the total population in the two cities studied. Increased capacity would exacerbate the issue in the near term. However, in the long term, with increased accessibility and reduced pricing, the issue, though persisting, could be alleviated. Thus, regulators should be aware of this issue and design policies to mitigate it. For instance, UAM may be used to complement PT. Furthermore, methods to improve accessibility for underdeveloped areas may be investigated in future studies.

The third theme relates to the necessity of proper parking infrastructure management. It has been observed in this study that the majority of UAM users are car oriented. While they switch to UAM, drive-alone remains to be their most preferred mode for access/egress to/from the vertiports. Thus, the infrastructure around the vertiports should be properly managed to support the parking demand. Evidence from the literature suggests that improper management could lead to increased driving time searching for parking and thus exacerbate the traffic condition near the vertiports (Arnott & Rowse, 2009). Future research should evaluate the impacts of the UAM vertiport parking demand and compare the performance of different solutions. Policymakers may encourage the operators to cooperate with the Transportation Network Companies (TNCs) to provide package services of UAM that include discounted access/egress trips with MOD. Shuttle services may be also deployed.

The fourth theme highlights the significance of UAM emission analysis by trip range. From the at-launch to the long-term scenario, our results have indicated that around 94.6 % of the UAM demand is expected to be for trips with a flight distance shorter than 40 km. At the same time, the literature shows that short-range UAM trips may be less energy-efficient than long-range trips, and thereby, less environmentally friendly (Kasliwal et al., 2019). Therefore, the impacts of UAM on the energy ecosystem and the environment must be carefully evaluated by trip distance. Proper regulations could be introduced to avoid energy-inefficient short-range trips. Strategies to promote pooled UAM trips to increase occupancy could be implemented, possibly through incentivizing users. Additionally, the imposition of taxes on emissions could be considered as a measure to encourage environmentally friendly practices of the suppliers. Further investigation should be performed to carefully evaluate the system-wide impacts of UAM on the emission under various scenarios forming around different regulatory policies.

7. Summary and Conclusion

This study meticulously evaluates the system-wide impacts of UAM on transportation demand. The state-of-the-art simulation platform, SimMobility, has been expanded to model UAM demand, supply, and demand–supply interactions at fine spatial and temporal levels. Our contribution to the UAM literature is twofold. First, under various supply configurations, we investigated the potential market size and market composition for UAM, considering the uncertainties in: (i) service attributes (aircraft specifications and service price); (ii) demand characteristics (unobserved factors such as perception). Second, we developed a realistic simulation model that features: (i) a behaviorally sound demand model to mimic the switching behavior from the current non-UAM mode to UAM and to capture the plan-action dynamics; (ii) an elaborate model for service operation that incorporates UAM fleet rebalancing and intra-vertiport activities, which thus realistically captures the fleet movement and the constraints in aircraft battery and vertiport capacity; (iii) a demand-driven vertiport placement and capacity generation model to emulate supplier decisions. Two real U.S. metropolitan areas have been simulated and compared.

Several policy implications emerged from this research. First, the UAM market is niche but with great uncertainties. The penetration rate is less than 0.2 % at launch and grows to 1.45 % and 1.81 % in the long-term scenario respectively for AS and AI, but with increasing uncertainty as well. Second, the potential equity issue exists – most of the potential users are high-income, even under the long-term scenario. Third, the results indicate the importance of proper parking infrastructure management near vertiports. In this study, it has been shown that the majority of potential users are car oriented, who still prefer drive-alone for access/egress to/from the vertiport. Fourth, we observe the necessity to study the impacts of UAM on emission by trip distance. Across the simulations, while long-range trips greater than 40 km flight distance have a higher penetration rate in the long term, short-range trips still constitute the majority of the potential UAM demand.

There are several limitations of this study that call for further study. Firstly, future studies may account for the induced demand in the demand model. As UAM increases transport supply, new trips may be generated due to factors such as reduced travel time and improved connectivity. Second, in this study, work trips do not distinguish between the regular commute and business trips. However, business and commute trips have distinct characteristics, which may result in different sizes of demand switching to UAM. While existing studies have separately discussed the attractiveness of UAM to commute and business trips, the potential UAM demand from the commute and business trips has not been compared yet to the best of the authors' knowledge. Thirdly, the UAM controller developed in this study could be further improved by designing more efficient operation algorithms and incorporating an energy model, which would enable the analysis of environmental impacts. Similarly, while vertiport capacity has been incorporated, it has been implicitly assumed that there will be space available at the vertiports for aircraft waiting for available gates after landing, while this may not be the case given real-world space constraints. Finally, the impacts of sociological factors have not been modeled in this study but may significantly influence the diffusion of transport innovations. For instance, user experience, word of mouth, and marketing can affect the willingness to consider and adopt innovative transport solutions (Struben & Sterman, 2008). While the simulation laboratory used in this study models individual decision-making processes, it does not incorporate agent interactions or marketing impacts. As Struben and Sterman (2008) suggest, however, these factors significantly influence adoption: direct word of mouth and effective marketing facilitate diffusion, under which scenario potentially leads to higher market penetration of UAM. Conversely, the absence of these factors might result in lower-than-expected adoption rates. Future work will be needed to incorporate sociological factors into the agent-based model.

In the broader literature of demand analyses of emerging transport modes, we observed a series of papers that designed stated preference (SP) surveys to understand individuals' choice behavior under the presence of innovations such as electric vehicles or autonomous cars, as reviewed by Guan et al. (2024), Harb et al. (2021), Liao et al. (2016) and Hardman et al. (2018). Experimental design-based SP surveys could capture individuals' preferences during hypothetical scenarios by keeping the bias minimum. Although this method is very popular, it could only capture limited facets of travel decisions. Specifically, the majority of the studies that analyze daily travel demand focus on single-trip based mode choice behavior. However, many other critical components such as location choice, activity type choice, and departure time choice are absent in such analysis. Moreover, the activity-based or tour-based analysis is absent in those stand-alone stated preference-based studies. To address this limitation, we investigated how the UAM integration reshapes individuals' daily activity and travel behavior. Our contribution lies in developing a simulator which is based on a system of random utility maximization-based behavioral models. Using this simulator, we can understand individuals' activity type, mode, location, departure time, and traveling distance choices due to the emergence of the UAM. We adopted parameters from existing studies, assuming behavioral similarities between our study areas and the studies we referenced. For future research, we plan to collect stated preference-based survey data to understand how the emergence of the UAM will impact individuals' activity type, mode, location, departure time, and traveling distance in the context of trip-based and tour-based travel behavior. SimMobility will be updated based on the new dataset and models. However, it has not been empirically established or found that this approach will generate results different from the current one.

CRediT authorship contribution statement

Kexin Chen: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Ali Shamshiripour:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Software, Visualization, Writing – review & editing. **Ravi Seshadri:** Conceptualization, Funding acquisition, Methodology, Project administration, Writing – review & editing. **Md Sami Hasnine:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Methodology, Project administration. **Lisa Yoo:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization. **Jinping Guan:** Conceptualization, Funding acquisition, Methodology. **Andre Romano Alho:** Conceptualization, Project administration. **Daniel Feldman:** Data curation, Formal analysis. **Moshe Ben-Akiva:** Conceptualization, Formal analysis, Funding acquisition, Methodology, Project administration, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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