Journal of Air Transport Management 112 (2023) 102436

Contents lists available at ScienceDirect

Journal of Air Transport Management

journal homepage: www.elsevier.com/locate/jairtraman

Demand analysis in urban air mobility: A literature review

Qi Long [a], Jun Ma [a,*], Feifeng Jiang [b], Christopher John Webster [b,c]

[a] Department of Urban Planning and Design, The University of Hong Kong, Hong Kong
[b] Faculty of Architecture, The University of Hong Kong, Hong Kong
[c] Institute of Data Science, The University of Hong Kong, Hong Kong

ARTICLE INFO

Keywords:
Urban air mobility (UAM)
Electric vertical take-off and landing (eVTOL)
Air taxi
Demand analysis
Urban air mobility life cycle
Literature review

ABSTRACT

Urban air mobility (UAM) is a novel concept that is revolutionizing urban transportation. This transformation is largely due to the development of electric vertical take-off and landing (eVTOL) vehicles, which have made UAM a reality in the urban region. The success of this emerging mode of transportation is largely dependent on market demand. However, there is a lack of systematic reviews on demand analysis for UAM. To address this gap, we conducted a comprehensive review of the recently published literature on demand analysis for UAM. We firstly identified the demand for UAM in various types of on-demand applications, including passenger services, cargo services, and other services. Secondly, we discussed and identified the factors that influence the market demand in UAM, such as time, cost, distance, congestion, safety, privacy, and noise. Additionally, we examined the existing qualitative and quantitative methods for demand analysis in UAM. We found that the most common techniques include stated-preference surveys, discrete choice models, and clustering algorithms. We further discussed the role of market demand in the UAM life cycle, highlighting the potential impacts of demand on the development, implementation, and regulation of UAM systems. Finally, we concluded our review by highlighting several opportunities for future research related to demand analysis for UAM, and these include feasibility of air shuttle services, potential cargo applications, public acceptance, infrastructure placement, integration with existing transportation, and novel demand estimation methods, while addressing various aspects of UAM life cycle, including vehicle technology, infrastructure, airspace, and operation management.

1. Introduction

As a novel concept, urban air mobility (UAM) is recently trending in urban transportation considering the increasingly serious traffic congestion problems worldwide. Driven by major revolutions in vertical take-off and landing (VTOL) technologies including battery, distributed electric propulsion, autonomy technologies, etc. (Cohen et al., 2021), a new type of aircraft namely electric vertical take-off and landing (eVTOL) has been developed (Gipson, 2019). Advanced Air Mobility (AAM) is a general concept originally proposed by the U.S. National Aeronautics and Space Administration (NASA) and the U.S. Federal Aviation Administration (FAA) to describe several kinds of innovative on-demand aviation services on different regional scales including urban, suburban, and rural areas (Cohen et al., 2021). Compared with the typical VTOL aircraft such as traditional helicopters, the novel eVTOL aircraft with less emission of noise and pollution is believed to be safer, easier, and cheaper to operate and maintain in AAM. Yet considering the limitation of the battery capacity as well as the market potential to date, most academic research, and industrial attempts focus on the UAM, an intra-city scale subset of AAM (Cohen et al., 2021).

To further comprehend the concept of UAM, a historical overview of its development, alongside that of VTOL technology, is crucial. The evolution of UAM can be delineated as a progression from traditional helicopter services to contemporary on-demand electric VTOL (eVTOL) aircraft services. The genesis of UAM services employing helicopters can be traced back to the 1940s. Los Angeles Airways utilized helicopters for the transportation of passengers and mail within the Los Angeles area from 1947 to 1971. One notable route connected Disneyland with the Los Angeles International Airport (LAX). However, operations were suspended following two accidents attributed to mechanical failures in 1968 (Garrow et al., 2021; Harrison, 2017). In a parallel development, helicopters were utilized to facilitate passenger services between Manhattan and three primary airports in New York City, namely Newark Liberty International Airport (EWR), LaGuardia Airport (LGA), and John F. Kennedy International Airport (JFK). New York Airways operated these services from 1953 to 1979. Unfortunately, this venture was

* Corresponding author.
E-mail address: junma@hku.hk (J. Ma).

https://doi.org/10.1016/j.jairtraman.2023.102436
Received 13 October 2022; Received in revised form 29 March 2023; Accepted 24 May 2023
Available online 19 June 2023

plagued by multiple accidents resulting from mechanical failures (Cohen et al., 2021; Witken, 1979). Consequently, operations were halted due to the heightened safety concerns. In the 1980s, however, helicopter services experienced a temporary resurgence in Manhattan. Trump Air employed Sikorsky S-61 helicopters to provide scheduled services between Wall Street and LGA, which connected to Trump Shuttle flights. This service was ultimately discontinued in the early 1990s following the acquisition of Trump Shuttle by US Airways (Carlson, 2019; Cohen et al., 2021). Presently, several helicopter operators offer on-demand UAM services for passengers. For instance, BLADE (2021) operates flights connecting various locations in Manhattan with the principal airports in New York City (JFK, LGA, and EWR).

Based on traditional urban helicopter services, the brand-new urban transportation concept with eVTOLs opens up a potential market. Several eVTOL aircraft have been designed and manufactured by the industry. Some of the eVTOL vehicles are under trial operation for UAM by commercial companies. For example, Lilium has completed over 25 trial flights in 2021, initiated the construction of the first US vertiport network in Florida, and has set a target to launch air service in 2024 (*Lilium Air Mobility*, 2021). Joby Aviation, an electric aerial ridesharing company in the US, has finished around 1,000 test flights over the past decade. In anticipation of commercial operations commencing in 2024, the company has established a world-class manufacturing facility in Marina, California (Joby *Aviation, 2021*).

In recent years, the pursuit of UAM has garnered significant interest from both commercial entities and academic circles alike (Straubinger et al., 2020). While various commercial companies continue to compete in the development of novel eVTOL prototypes, academic research has also seen an exponential increase in related literature, including review articles. For example, Straubinger et al. (2020) have made significant contributions to this field by providing a strategic overview of various research directions in UAM. Additionally, Cohen et al. (2021) have reviewed the history, on-demand air mobility ecosystem, market development, and challenges associated with UAM. Despite these efforts, several gaps remain that necessitate a review of UAM from several specific perspectives in order to establish a comprehensive and systematic knowledge system in this field.

The industry consensus accounts that the most potential application scene of UAM currently is to serve as a kind of on-demand service (ODS). Therefore, research on demand analysis for UAM is imperative. The results of demand analysis for UAM provide the reference and guidance for system development, infrastructure construction, regulation establishment, and market operation. More and more researchers begin to discuss the demand for the UAM. For example, a comparative analysis of the on-demand modeling in the context of both UAM and the electric/autonomous vehicle (EV/AV) sectors has been conducted by Garrow et al. (2021). Besides, Sun et al. (2021) reviewed the operational aspect of on-demand air mobility (ODAM), encompassing demand estimation methodologies, infrastructure and vertiport design, as well as operational planning. However, the demand analysis of UAM remains an area of research that is yet to be fully organized. The extant review papers pertaining to demand are largely unsystematic in nature. Therefore, this article endeavors to systematically review the demand for UAM in order to bridge this research gap.

The remainder of this paper is organized into six sections. Section 2 presents the methodology of the review. Section 3 to 6 present the demand analysis for UAM based on the structure shown in Fig. 1. Specifically, Section 3 explores the various on-demand services, including passenger and cargo services, that are affecting the UAM landscape. Section 4 identifies and discusses the factors that impact market demand, which include time, cost, distance, surface traffic congestion, safety and security, privacy, and noise. Section 5 covers the qualitative and quantitative methods used for demand estimation in UAM and provide a comparison of demand analysis approaches between UAM and traditional urban transportation. Section 6 discusses the role of demand in the UAM life cycle, including design, construction, operation, and regulation, and how market demand may influence the development of UAM. Finally, the paper concludes with a discussion of the opportunities and limitations of the review.

2. Methodology

To collect relevant publications on the demand analysis for UAM, we designed our search term as “demand” AND ((“UAM” OR “urban air mobility”) OR (“air taxi” OR “air shuttle” OR “air cargo”) OR (“eVTOL” OR “helicopter”)). “helicopter” is considered here because it is currently the most widely used UAM vehicle. The covered databases include ScienceDirect, IEEE Xplore, AIAA publication database, ASCE Library, Taylor & Francis Online, and Wiley Online Library. Some important conferences in air transportation were also considered, including USA/Europe ATM R&D Seminar (ATM seminar), International Conference on Research in Air Transportation (ICRAT), and SESAR Innovation Days (SIDs).

The searches were conducted in January 2023, and was restricted to literature published in the last six years, which is from 2017 to 2022. The article type was set to articles, conference papers, or book chapters both published and in press. As a result, 74 publications were found from ScienceDirect, 73 IEEE Xplore, and 64 the AIAA publication database. 3 papers from ICRAT and 1 paper from SIDs were also collected. As shown in Fig. 2, the number of publications related to UAM demand has been

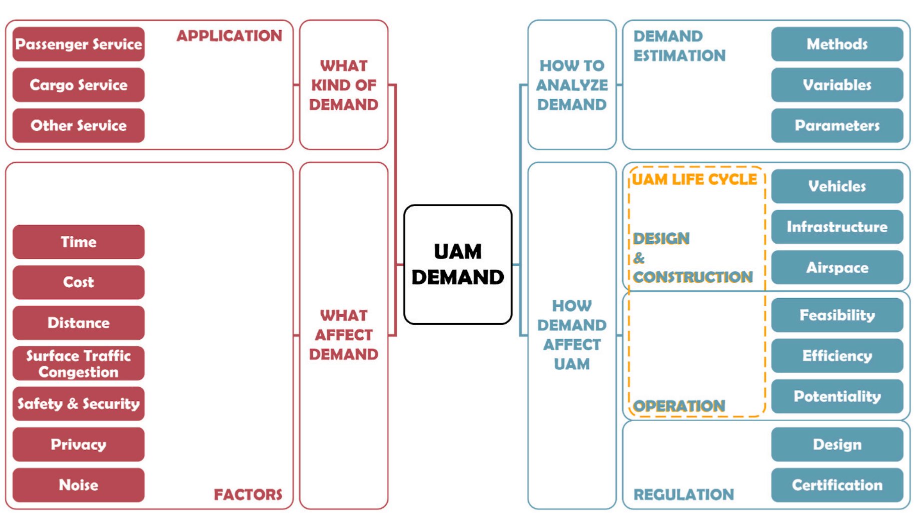

Fig. 1. The review structure of demand for UAM.

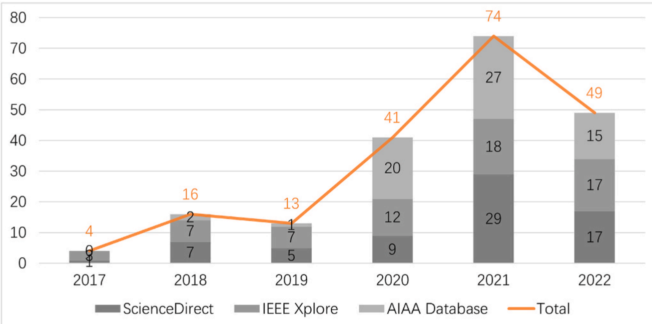

Fig. 2. The number publications related to UAM in recent years.

increasing in the past years. A significant growth happened in 2020, and the number nearly doubled in 2021. The publication sources of the 211 collected papers are summarized in Table 1. It is worth noting that over half of the publications are conference papers from IEEE conferences and AIAA forums.

Since the concept of UAM is often defined as a kind of "on-demand service", the term "demand" is often used as an expository verb in research elaboration. So that after collecting the publications, we further reviewed the titles, abstracts, and content to identify whether they are discussing the market demand for UAM. As shown in Table 2, final number of papers we identified includes 32 from the ScienceDirect, 21 from the IEEE Xplore, and 33 from the AIAA publication database, while no publications were found from the ASCE Library, Taylor & Francis Online, and Wiley Online Library.

3. On-demand application in UAM

To comprehensively analyze the demand for UAM, we first summarized different types of on-demand services in UAM. According to the difference between service objectives and application prospects, the on-demand applications in UAM are categorized into passenger services, cargo services, and other services. Fig. 3 shows the structure of this section. Based on the classification of UAM applications, the difference in operational steps between public transport and point-to-point transport is compared. The detailed segmentation of other services is also listed in Fig. 3. Finally, different market demand raised by these applications is identified and categorized.

Table 1
The sources of the publications reviewed in this study.

	Number of publications	Sources
118 conferences in total	34	AIAA AVIATION FORUM
	24	AIAA SciTech Forum
	17	IEEE/AIAA Digital Avionics Systems Conference (DASC)
	11	Integrated Communications, Navigation, Surveillance Conference (ICNS)
	2	IEEE Intelligent Transportation Systems Conference (ITSC)
		IEEE Aerospace Conference (AERO)
	21	Other conferences
93 journals in total	7	Transportation Research Part C: Emerging Technologies
		IEEE Transactions on Intelligent Transportation Systems
		Journal of Air Transportation
	6	Journal of Air Transport Management
	4	Transportation Research Part A: Policy and Practice
		Transportation Research Part E: Logistics and Transportation Review
		International Encyclopedia of Transportation
	3	Journal of Aerospace Information Systems
		Air Medical Journal
		Aerospace Science and Technology
	2	The American Journal of Emergency Medicine
		Engineering
		Energy
		Chinese Journal of Aeronautics
	37	Other journals

Table 2
Summary of the collected and identified articles.

	ScienceDirect	IEEE Xplore	AIAA Database	Total
Collected	74	73	65	211
Identified	32	21	33	86

Classification of passenger services in UAM was reviewed by Cohen et al. (2021) as a means of reflecting the various evolutionary stages of UAM. A taxonomy is raised in response to the "on-demand" level and passenger capacity (Patterson et al., 2018). From the "most on-demand" to the "least on-demand", passenger services in UAM are classified into private service, air taxi, air pooling, semi-scheduled commuter, and scheduled commuter within this taxonomy (Cohen et al., 2021). In this review, passenger services for UAM are categorized into air shuttle service and air taxi service according to their extent of "on-demand" characteristics. These two types of passenger services show distinct responsiveness to specific passenger demands.

The initial category of urban air mobility (UAM) service is the air shuttle model, which involves regular and predetermined round-trip operations along specific air corridors during the early stages of implementation. The most common mode is the rapid passenger transfer between the airport and downtown defined as the airport shuttle. This kind of single-route shuttle is defined as a "corridor service" in some articles (Bauranov and Rakas, 2021; Cohen et al., 2021). Along with the demand growth and facilities improvement, the air shuttle service can be developed into "hub and spoke" operations providing multiple flights between a hub and numerous vertiports throughout an urban area (Cohen et al., 2021).

Current air shuttle services predominantly employ conventional helicopters as their primary mode of transportation. For example, Heliservices in Hong Kong is operating a flight connecting The Peninsula Hotel Hong Kong (rooftop) and the Hong Kong International Airport (HKG), with a one-way VIP transfer service costing HK$35,700 (Heliservices, 2021). The first shuttle flight in mainland China connecting domestic civil aviation using helicopter transport was also launched in Shenzhen, in 2021. The shuttle flight transporting passengers between the Shenzhen International Airport (SZX) and CBD in Futian costs around CNY5000, operated by the Airbus-135 twin-engine helicopter (Transport Bureau of Shenzhen, 2021).

In recent years, the development of eVTOL vehicles has gained traction as a potential solution for UAM services. This has prompted several modern tech companies to explore the possibility of launching air shuttle services using eVTOLs. For instance, Volocopter plans to launch its air shuttle service in Singapore between 2021 and 2026 (*Volocopter*, 2021); Vertical Aerospace intends to do so in London in 2022; and Lilium has announced plans to launch air shuttle services in Munich, Orlando, and other cities worldwide by 2024–2025 (*Lilium Air Mobility*, 2021); BLADE is also planning to use eVTOLs to replace their existing helicopter shuttle flights operating from airports such as JFK, LGA, and EWR in New York City (BLADE, 2021). Despite some challenges, such as airspace access, route availability, and high costs, air shuttle services using eVTOLs have shown considerable potential and applicability in the short term for passenger service in UAM.

Air taxi service is another kind of passenger service in UAM. Similar to the traditional on-demand taxi services like Uber and Lyft, this kind of service provides more on-demand point-to-point service. Considering

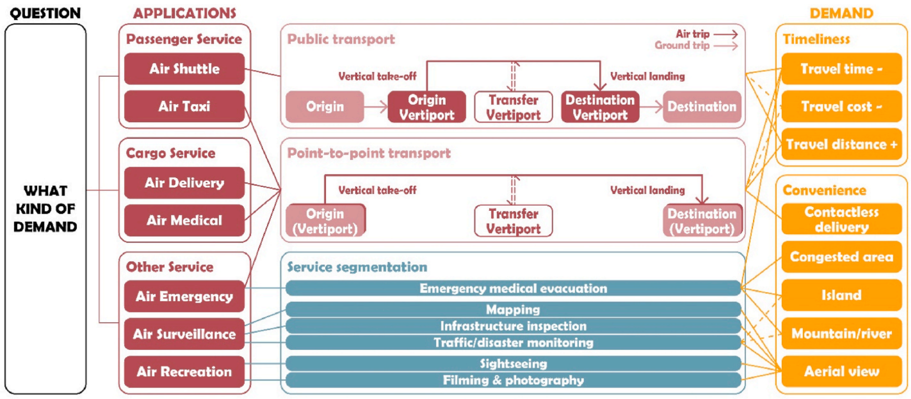

Fig. 3. Different kinds of demand - on-demand applications of UAM.

the potential large market demand, air taxi service is regarded as an advanced stage of UAM. A typical air taxi trip contains mainly three sections: 1) ground transportation from the starting location to the initial vertiport; 2) air transportation between initial and destination vertiports; and 3) ground transportation from the destination vertiport to the destination location (Rajendran and Srinivas, 2020). This form of air taxi service is comparable to the air shuttle as depicted in Fig. 3. However, the point-to-point air taxi on-demand service faces significant challenges in terms of infrastructure limitations, urban airspace and concerns regarding public acceptance. As such, it may not be widely promoted in the near future.

Cargo service in UAM primarily employs unmanned aerial vehicles (UAVs) for the transportation of consumer goods and medical supplies, including medicine, medical equipment, and testing samples. The rapid speed and convenience of UAVs provide a significant advantage for cargo delivery in UAM systems, particularly in challenging terrain conditions such as islands and mountains. Several companies, including Wing, Flirtey, Flytrex, DHL, EHang, Amazon, and Uber Eats, are currently planning and conducting trial runs for consumer goods delivery using UAVs in the United States (Cohen et al., 2021). The Federal Aviation Administration (FAA) has also established the Integration Pilot Program (IPP) to explore the safe integration of drones (FAA, 2019). For medical transport, UAVs have been proposed as effective clinical delivery vehicles for microbiological and laboratory samples, pharmaceuticals, vaccinations, emergency medical equipment, and even patient transportation (Ozkan and Atli, 2021). For example, blood test samples for tuberculosis testing have been transported by UAVs in Ghana, while Zipline International has employed drones to deliver vaccinations and medications in Rwanda (Cohen et al., 2021). Additionally, face masks have been delivered to remote islands in Korea, and laboratory samples have been transported using UAVs by Matternet and Swiss Post in Switzerland (Cohen et al., 2021; Fuel Cells Bulletin, 2020). Despite these advances, concerns persist regarding the application of cargo services in UAM. For example, the escalating market demand and traffic volumes may potentially disrupt other airspace users and compromise the stability of the drone ecosystem itself (Cohen et al., 2021).

Other services in UAM include air emergency, air surveillance, and air recreation. Air emergency services are typically used for emergency medical evacuations from remote or inaccessible locations. On the other hand, potential air surveillance services include mapping, infrastructure inspection, traffic monitoring, and disaster monitoring, such as fire detection. UAM systems also offer air recreation services, such as sightseeing, filming, and photography, which have gained considerable popularity in recent years. At present, the general trend in UAM applications is the replacement of traditional helicopters with electric vertical take-off and landing aircraft (eVTOLs) for these applications. This transition is motivated by the significant advantages offered by eVTOLs, such as reduced noise pollution, lower operating costs, and improved safety features. However, the successful integration of eVTOLs into UAM systems requires addressing several challenges, including infrastructure development, regulatory frameworks, and societal acceptance. Hence, further research is necessary to explore the feasibility and effectiveness of eVTOLs in UAM applications.

4. Factors that affect the demand for UAM

After categorizing the services and applications related to UAM demand, it is important to discuss and identify different factors that may affect the demand for UAM. A stated-preference survey was conducted by Al Haddad et al. (2020) to collect people's perceptions of the UAM adoption time horizon and its factors. The result of the survey was analyzed by several tools including acceptance models, exploratory factor analyses, and discrete choice models to identify and measure the impact of such factors on the adoption and application of UAM. The analysis results suggest that safety and trust, affinity to automation, data concerns, social attitude, and socio-demographics are the important factors of UAM user adoption. Drawing upon a synthesis of previous research, we present a framework of factors that are likely to influence the demand for UAM as depicted in Fig. 4. The identified factors can be broadly classified into three categories, namely trip-related factors (e.g., travel time, cost, and distance), surface traffic congestion as a motivating factor to UAM, and acceptance-related factors (e.g., safety and security, privacy, and noise). This paper delves into the impacts of these factors on different dimensions of UAM travel and acceptance. It is important to note that these impacts are likely to affect the adoption of UAM by users and the general public, which in turn, could significantly influence the market demand for UAM.

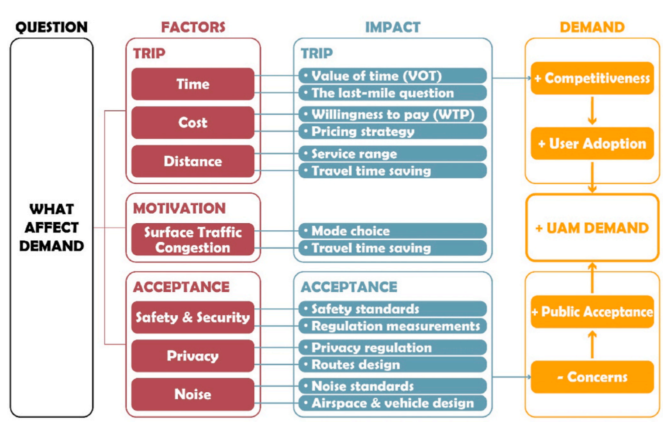

Fig. 4. Different kinds of factors that affect the demand in UAM.

4.1. Trip-related factors

The time factor plays a crucial role in determining the demand for Urban Air Mobility (UAM), as it is a promising solution to alleviate ground traffic congestion issues. In particular, travel time is a critical consideration due to the potential time savings UAM can offer compared to traditional modes of transportation. The discussion of UAM travel time can encompass several facets, including an assessment of the temporal benefits of UAM and the "last-mile problem" that characterizes UAM travel.

In order to assess the time benefits of passenger services in UAM, Ilahi et al. (2021) conduct a survey on the existing literature exploring customers' willingness to pay (WTP) compared with other travel modes including on-demand transport. The WTP can be treated as a typical question in transport demand analysis called the value of time (VOT) problem. Surveys on WTP were conducted by researchers separately in Greater Jakarta in Indonesia as well as in Atlanta, Boston, and Dallas-Ft. Worth, San Francisco, and Los Angeles in the US. Some other articles (Binder et al., 2018; Boddupalli, 2019; Garrow et al., 2019) have designed surveys to assess customers' perceptions and attitudes on factors (including travel time) that influence their particular demand for the use of air taxis. A discrete choice model is usually used in these survey-based research to process the survey datasets. The time benefits of other UAM services such as emergency rescue was also discussed and even adopted in some cases (Rajendran and Srinivas, 2020). For instance, the use of electric vertical takeoff and landing (eVTOL) aircraft in disaster situations, such as evacuating the injured and transporting emergency supplies when roads and bridges are damaged, was deemed advantageous and full of potential.

The "last-mile problem" is a prevalent issue in UAM, whereby the first and last legs of the trip may not be covered by the UAM service, necessitating additional modes of ground transportation. To address this problem, several studies have examined the first- and last-mile aspects of UAM trips to ensure seamless door-to-door service for customers. One proposed solution is a joint scheduling approach that coordinates UAM and last-mile transportation, which can be considered a variation of the Dynamic Dial-a-Ride Problem with Transfers (DARPT) (Masson et al., 2014; Rajendran and Srinivas, 2020). Despite these efforts, there is still a lack of research on the last-mile transport mode of UAM, which is crucial in ensuring the time advantage of UAM passenger services, a critical factor in UAM adoption (Rajendran and Srinivas, 2020). In addition, UAM cargo services, which serve as a form of last-mile delivery, have been discussed for their potential cost- and time-effectiveness effectiveness (Kirschstein, 2020; Rajendran and Srinivas, 2020; Salama and Srinivas, 2020). The insights gained from these studies on the travel time of UAM can be valuable for decision-making during the launch phase, aircraft design, and technology development, enabling the target customer and city to make informed choices.

The cost of UAM services is a significant factor that impacts the demand for this mode of transportation in addition to time. A point worth noting is that the price of services in UAM is much higher than in other alternative traffic modes. The willingness to pay (WTP) problem is the focal point of academia. In practical application, BLADE offers a variety of annual packages ranging from $ 295 to $ 795 US, which includes a per-flight discount for the primary passenger and a guest. The discount ranges depend on the package (BLADE, 2021). Although BLADE currently operates traditional helicopters instead of electric Vertical Take-Off and Landing (eVTOL) aircraft, the practical cost of the service can be used to inform future applications of UAM passenger services. The WTP and VOT from survey studies and operational costs from existing helicopter UAM services help to formulate the pricing strategies for UAM services as the cost directly impacts supply-demand equilibrium and revenue.

Distance is also a critical factor in UAM as it directly affects travel time. Research shows that as distance decreases, access times from/to the port become increasingly important (Garrow et al., 2021; Kleinbekman et al., 2018). Air taxi trips need to be at least 15–25 km (about 9–16 miles) to provide travel time savings over existing modes (Al Haddad et al., 2020). The analysis of distance results in a minimum profitable distance for UAM operation compared with other traffic modes. The profitable distance range may also impact the cruising range in eVTOL vehicle design.

4.2. Motivating factor

Except for the three trip-related factors above, surface traffic congestion represents an immediate motivating factor influencing real-time UAM demand. As an emerging mode of air transportation, UAM has the potential to bypass ground congestion and reduce commute durations (Pons-Prats et al., 2022). UAM is considered the most effective solution for addressing ground traffic congestion in urban areas suggested by some of the researcher (Al Haddad et al., 2020). For example, Antcliff et al. (2016) considered UAM to be competitive in the area with congestion causing two or more hours of commuting every day. The author proposed Silicon Valley as an ideal region for the early introduction of UAM. However, due to the limitation of current three-section air taxi, the first and last mile of a UAM trip still relies on ground transportation (Rajendran and Srinivas, 2020). Therefore, Rothfeld et al. (2020) argue that the induce additional ground transportation demand may resulting in increased traffic congestion (Krull and Muhammad, 2022). In addition, the capacity of vehicles to supply adequate transportation is a crucial factor in evaluating the extent to which UAM can address congestion problems. The trade-off between the cost of providing UAM service and the improvement of transport efficiency necessitates comprehensive analysis, taking into account infrastructure costs, operational costs, capacity, and demand (Pons-Prats et al., 2022).

4.3. Acceptance-related factors

Instead of enhancing the competitiveness of UAM to raise its adoption, an alternative approach to improve market demand for UAM involves fostering public acceptance by addressing people's concerns about the technology. As safety was the main concern for the adoption of UAM concluded by Al Haddad et al. (2020), ensuring comprehensive safety and security in all aspects of UAM is crucial for maintaining public confidence (Ilahi et al., 2021). As illustrated in Table 3, the current literature has further categorized the safety issue in UAM into personal safety, environment safety, operational safety, physical security, and cybersecurity. More specifically, researchers have primarily focused on safety concerns arising from eVTOLs in comparison with traditional helicopters. An integrated framework was designed by Pant et al. (2021) for autonomous drone safety (FADS). The potential threat posed by unauthorized UAVs in airspace is also a topic of ongoing discussion (Du et al., 2021). In many countries, UAV operational restrictions have been

Table 3
Classification of safety & security in UAM.

Classification	Safety & Security
Personal safety	- Passenger: Passenger interference (disruptions, hijacking, sabotage, etc.) - People on the ground
Environment safety	- Weather risk - Wind gusts (especially in high-density urban areas) - Avian/Bird strike risk
Operational safety	- Risk of insiders: Air and ground crew human factors (loss of situational awareness, task saturation, etc.)
Physical security	- Sabotage: Critical system failure (degraded or loss of command and control, GPS; engine failure; etc.) - Terrorism
Cybersecurity of all the enabling IT systems	- Ticketing/Booking - Air traffic management, communications, navigation, surveillance - Autonomous aircraft systems

implemented to ensure safe airspace, encompassing flight purpose, UAV weight, minimum distance from people, minimum distance from buildings or structures, and altitude limits (J. Cho and Yoon, 2018). Regulation plays an important role in guaranteeing the safety and security of UAM. Existing aviation safety regulations, supported by a comprehensive policy and regulatory environment governing aircraft and airworthiness, operations (including crew requirements), and access to airspace, can provide guidance for UAM regulation (Cohen et al., 2021; Graydon et al., 2020). Current civil aviation authorities possess several tools, such as certification, operational approvals, airspace access, and others, to promote safety, which can be extended to UAM regulation (Cohen et al., 2021). For example, concepts in geofencing, such as vehicle operational requirements (keep-in) and protection of surrounding environments (keep-out), have been proposed for UAV airspace access and operation, and can be referenced for UAM (J. Cho and Yoon, 2018).

Addressing privacy implications in the context of limited large-scale implementation of manned aviation, insights can be drawn from the impact of unmanned aerial vehicles (UAVs) on urban environments to inform future strategies and policies. The current evaluation of privacy concerns surrounding UAVs remains relatively nascent (Straubinger et al., 2020). As depicted in Table 4, existing literature on urban air mobility (UAM) privacy encompasses both passenger and urban resident considerations. Lidynia et al. (2017) conducted a study examining public acceptance and perceived barriers to the utilization of civilian drones, suggesting that laypersons exhibit heightened sensitivity to potential privacy infringements. Moreover, negative public perceptions of UAM privacy may pose challenges to its successful implementation (Cohen et al., 2021). In the context of future pooled ride-hailing services for UAM, privacy remains a central concern. The primary source of privacy issues in UAM is attributable to the multitude of sensors integrated into the aircraft. These sensors, while necessary for collecting environmental data to ensure safe flight, present complications in aircraft design. In summary, deliberations on privacy concerns in UAM encompass various factors, including flying altitude, operational periods, route design, and regulatory frameworks.

In relation to noise, the success of the UAM concept is significantly influenced by the demand for low noise emissions, as public acceptance is closely tied to this factor. Preliminary proposals for maximum noise levels have been put forth in various countries and regions, informed by public surveys or existing standards within the aviation industry. For instance, research conducted by NASA suggests that the high-frequency sound produced by vertical take-off and landing (VTOL) vehicles may result in greater annoyance compared to noise from other common transportation methods (Wolfe et al., 2016). Given the difficulty in eliminating high-frequency noise, the Federal Aviation Administration (FAA) has proposed more stringent standards to mitigate the negative impact of UAM on public acceptance. In addition to the United States, the European Union Aviation Safety Agency (EASA) has also conducted a questionnaire on noise acceptance in Europe (Goyal et al., 2018). Both NASA/FAA and EASA have established 65 dB(A) as the acceptable noise level in comparison to urban background noise levels ranging from 55 to 95 dBA (McAlexander et al., 2015), as illustrated in Table 5. The demand for low noise emissions necessitates advancements in vehicle design to minimize noise at its source. Furthermore, the design of airspace and vehicle routing play a critical role in influencing noise transmission.

Table 4
Types of privacies in UAM.

Category	Privacy
Privacy of passenger	- Privacy of communication - Privacy of UAM user's data: · financial · location · trip
Privacy of urban resident	- Privacy of behavior and action - Privacy of data and images (from sensors on aircraft): · collection · storage · management · usage

5. Demand estimation for UAM

In this section, we examine and assess the influence of various factors on market demand for UAM through a review of demand estimation approaches. Numerous methodologies have been developed to analyze UAM market demand with the intent of enhancing its feasibility, efficiency, and potential. Based on distinctions in data sources and methodologies, we categorize existing demand estimation techniques into two primary classes: survey-based demand estimation, which primarily employs qualitative methods, and data-based estimation modeling, which primarily utilizes quantitative methods. Specifically, these approaches can be further subdivided into five categories, corresponding to the five subsections in this section. Fig. 5 presents an overview and classification of demand estimation methods for UAM, with detailed descriptions provided below.

The primary method of analyzing market demand is through the use of survey-based demand estimation. This approach entails collecting subjective and evolving statements from respondents via questionnaires, which is often classified as a qualitative method. In certain cases, qualitative surveys may incorporate quantitative and numeric characteristics to achieve a more precise description and categorization of survey outcomes (Profillidis and Botzoris, 2019). In the field of transport demand analysis, researchers usually assess the thinking, perceptions, acceptances, and mode choices of travelers by conducting surveys. There are two kinds of surveys regarding the statements of interviewees: revealed-preference (RP) and stated-preference (SP) (Fink, 2002; Profillidis and Botzoris, 2019). As Profillidis and Botzoris (2019) elaborated, the stated-preference surveys were designed to ask potential travelers which transportation modes they would take under hypothetical situations, while the revealed-preference surveys refer to changes in existing transport characteristics and services.

In contrast to qualitative approaches, quantitative methodologies employed in market demand estimation for UAM primarily rely on data-based estimation modeling. Based on the time horizon of research objectives, outcomes, and impacts, these methods can be classified into long-term and short-term demand estimation categories. Long-term demand estimation serves as a crucial initial phase for identifying the most promising areas at varying scales to facilitate a more effective launch of UAM market operations. The outcomes of these estimations can also inform ongoing adjustments to operational strategies during long-term market operations. In the context of UAM, long-term demand estimation encompasses evaluations for potential cities/regions and infrastructure placement considerations. Diverging from long-term demand estimation, short-term demand estimation seeks to discern the spatiotemporal distribution patterns of market demand to optimize UAM operational efficiency. Estimation results contribute to the provision of expedited urban aviation services and the reduction of UAM travel costs. This review examines two types of short-term demand estimation methods, focusing on market operation decisions and operational planning challenges, respectively.

Table 5
Noise Metrics of acceptance & measurement. DNL is the acronym for Day-Night Average Sound Level and dBA (A-weighted sound levels) is a weighted measurement of dB.

	NASA & FAA	EASA	City background noise
Max. Noise	DNL 65 dB	65 dBA	55-95 dBA

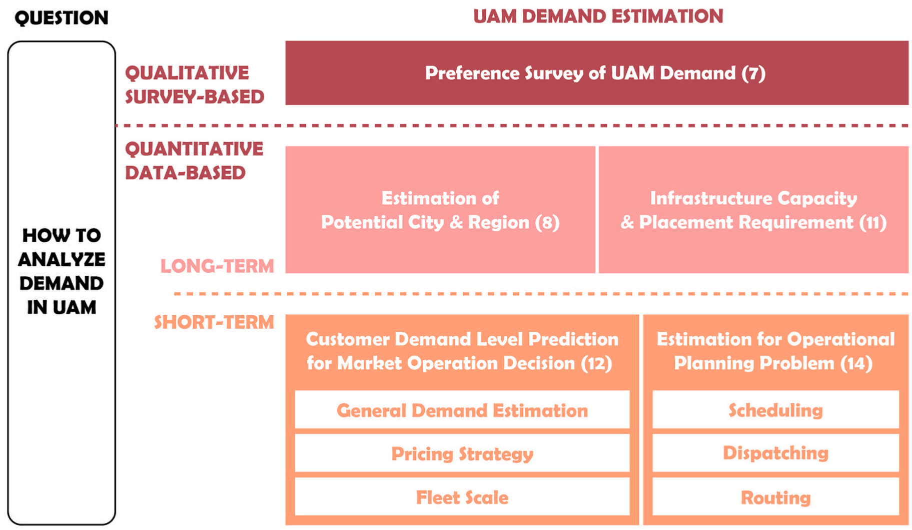

Fig. 5. Demand estimation for UAM (with the number of literatures covered).

5.1. *Preference survey of the market demand for UAM*

As UAM is a nascent concept, the absence of historical data presents a significant challenge in estimating market demand. Stated-preference surveys emerge as a more suitable and efficacious means of gathering data on travel demand and public perceptions of UAM. Consequently, insights gleaned from these surveys can aid in the identification of potential early adopters and inform the development of targeted marketing strategies.

Numerous surveys have been conducted by researchers, consulting firms, and vehicle manufacturers to gauge public willingness to adopt urban air mobility (UAM) services. For instance, the European Union Aviation Safety Agency (EASA) carried out a web-based survey involving 3,690 citizens across six European cities to assess social acceptance of UAM in Europe, as presented in Table 6 (EASA, 2021). The study revealed that Europeans exhibited greater interest in drone delivery services (approximately 64%) compared to air taxi services (49%). Furthermore, over 70% of respondents expressed interest in using at least one service, suggesting a potential UAM market in Europe. Another stated-preference survey conducted in Germany aimed to identify and quantify factors influencing UAM adoption (Al Haddad et al., 2020). This survey also examined participants' perceptions of UAM adoption timelines, providing valuable insights for market planning and UAM implementation. In the United States, surveys have been conducted to gather data for demand modeling utilizing discrete choice models. According to the survey results, high-income households are assumed to be early adopters of electric vertical take-off and landing (eVTOL) aircraft, given their ability to afford the higher value of time (Binder et al., 2018; Boddupalli, 2019). Furthermore, Binder et al. (2018) identified airport transfers, end-to-end city transfers, and daily commuters as the top three market segments for UAM in six metropolitan areas, including Atlanta, Boston, Dallas-Ft. Worth, San Francisco, and Los Angeles. In Korea, the market demand for two types of UAM passenger services: airport travel and urban travel was estimated based on two corresponding stated-preference (SP) surveys conducted in the Seoul metropolitan area (S.-H. Cho and Kim, 2022). A mode choice model was developed using parameters derived from the surveys, and the results were employed to evaluate potential emission reductions upon the introduction of clean energy UAM.

Table 6
Public's interest in UAM applications by EASA.

interest	%
drone delivery	64
an air taxi	49
both	43
at least one service	71

The aforementioned studies primarily focus on developed countries and regions, while research in developing countries is only beginning to emerge. People's willingness to pay for air taxis was modeled by Ilahi et al. (2021) combining SP survey data with RP datasets in Greater Jakarta, Indonesia. Ahmed et al. (2021) collected global data from an online SP survey concerning private and shared passenger services in UAM, which was then modeled using a correlated grouped random parameters bivariate probit framework. This approach aimed to derive a general conclusion regarding people's willingness to pay for UAM services.

Several common aspects in survey design can be discerned from the abovementioned studies, such as measurement and deployment methodologies. Stated choice and stated ranking represent two distinct approaches in stated-preference (SP) surveys, depending on the type of statements employed (Profillidis and Botzoris, 2019). In SP surveys addressing UAM demand with stated ranking, half utilize nonmetric analysis, while the remainder employ a response metric known as the Likert-type scale, as depicted in in Table 7 (Likert, 1932). Consistently, a five-point scale is used across these surveys. Implementing scales facilitates more efficient and objective evaluation of respondent perspectives. Various survey deployment methods encompass paper-and-pencil, mail, telephone, internet, personal interviews, and more. As indicated in Table 7, the majority of surveys examining UAM market demand are conducted online, with one instance combining an online survey with a personal interview. Only one UAM survey employed the paper-and-pencil method. Online surveys offer several advantages, including larger sample sizes, ample time for respondents to provide detailed answers to open-ended questions, and a range of visualization options.

Table 8 summarizes the characteristics of respondents in existing UAM surveys. A significant proportion of respondents in these surveys were under the age of 34, with half of the respondents in an Indonesian survey being under 24. This trend may be attributed to younger individuals exhibiting greater interest in and receptiveness to emerging technologies. Most surveys encompassed all income segments, which could be due to the limitations of the online questionnaire format. Considering that high-income individuals are the potential target demographic for UAM, future surveys should focus on this group. Moreover, a review of the questions in current surveys, as shown in Table 9, highlights topics that could be emphasized in future questionnaires.

Table 7
Review of literature in preference survey of UAM demand.

Literature (Ref.)	Region	Scale (UAM/RAM) or vehicle types	Time frame	Survey Interviewees	Survey method	Survey deployment methods	Attributes	Measurement scale and unit	Survey result analysis method	Summary
EASA (2021)	Six European cities (Hamburg, Paris, Barcelona, Milano, Budapest, and the Oresund region), Europe	UAM	November 2020 to April 2021	3,690 citizens across six European cities	Stated preference survey in both stated choice & stated ranking	online (web-based quantitative survey), personal interview	perceived benefits, concerns, factors of societal acceptance ranking of use cases	nonmetric analysis	Conjoint analysis, a statistical technique that models the behavior of survey participants' choice/trade-off situations	The survey uncovers the public's initial attitude, expected benefits, and concerns toward UAM The result shows that medical and/or emergency transport is the most valuable application of UAM
Ilahi et al. (2021)	Greater Jakarta, Indonesia	On-Demand Transport (ODT) including UAM	April to May 2019	5,143 respondents	Combining both revealed preference and stated preference	paper-and-pencil survey	willingness to pay (WTP)	nonmetric analysis	Multinomial logit model (MNL) & mixed logit model (MXL)	The first survey on a whole metropolitan area population to uncover the WTP of UAM
Ahmed et al. (2021)	worldwide	Air taxi	March 2017	692 respondents	Stated preference survey	online using SurveyMonkey	factors that may affect an individual's willingness to hire and pay for flying taxis and shared flying car services	nonmetric analysis	Correlated grouped random parameters bivariate probit models	An online survey statistically investigating the public willingness to hire and pay for flying taxis and shared flying car services
Al Haddad et al. (2020)	Munich, Germany	Air taxi (eVTOL)	July to September 2018	221 respondents	Stated preference survey	online using Limesurvey Pro	the most influential factors in UAM's adoption time horizon	A five-point Likert-type scale agreement statements	Exploratory factor analyses & discrete choice models (multinomial logit models (MNLs) & ordered logit models (OLMs))	A survey assessing user perceptions based on the timeframe of UAM adoption
Binder et al. (2018)	Atlanta, Boston, Dallas-Ft. Worth, San Francisco, Los Angeles, US	eVTOL	April to June 2018	2500 high-income workers with average one-way commutes of 45 min or more	Stated preference survey	online	factors of WTP	A five-point Likert-type scale agreement statements	/	A survey estimating high-income commuters' WTP for eVTOL flights in urban areas in the US
Boddupalli (2019)	Atlanta, Boston, Dallas-Ft. Worth, San Francisco, Los Angeles, US	Air taxi (eVTOL)	April to June 2019	2500 high-income workers with average one-way commutes of 45 min or more	Stated preference survey	online using Qualtrics Research Suite	influence of several constructs (lifestyle, personality, perceptual, attitudinal, socio-demographic)	A five-point Likert-type scale agreement statements	Multinomial logit models (MNL) and a latent class model	A discrete choice model analyzing the result of 2,500 commuters' preference
(S.-H. Cho and Kim, 2022)	Seoul, Korea	UAM	airport travel: October to November 2020, urban travel: April to May 2020	699 airport users and 1011 travelers who have traveled for more than 1 h within the Seoul metropolitan area in the last week	Stated preference survey	field and online survey	factors of travel behavior and willingness to choose UAM	A seven-point Likert-type scale agreement statements	multinomial logit (MNL) model and random parameter multinomial logit (RPML) model	Two surveys estimating travel demand and environmental impact of two types of UAM passenger services: airport travel and urban travel

Table 8
Characteristics of respondents.

Literature (Ref.)	Survey Interviewees	The development level of the region	Age	Gender	Family type	Education	Employment status	Income	Household
EASA (2021)	3,690 citizens across six European cities (Hamburg, Paris, Barcelona, Milano, Budapest, and the Oresund region)	developed countries	18-24, 16% 25-34, 17% 35-44, 18% 45-54, 18% 55-64, 17% 65-75, 14%	Male, 49% Female, 51%	Singles, 21% Couples, 46% Families, 33%	Low (< higher schooling), 37% Medium (< finished college or university), 44% High (>post-graduates), 19%	Full-time (30+ h) incl. self-employed, 53% Part-time or student, 19% Not working, retired and other, 29%	Low (<20k EUR), 21% Medium (20k - 60k EUR), 45% High (>60k EUR), 23% Prefer not to say, 11%	/
Ilahi et al. (2021)	5,143 respondents	developing country	<24, 46.9% 24-29, 11.3% 29-34, 6.3% 34-39, 8.3% 39-44, 8.8% 44-49, 9.2% 49-54, 5.3% >54, 3.9%	Male, 57.3% Female, 42.7%	/	University degree, 31.7%	Full-time, 32.5% Half-time (30 h), 11.6% Half-time (20 h), 13.4% Student, 29.2% Non-worker, 13.2%	/	Owned house, 92.4% Single-family house, 97.2%
Ahmed et al. (2021)	692 respondents	both developed and developing countries	The average age is 30.4	Male, 59.6% Female, 40.4%	/	College degree or higher, 72%	/	< $30k, 22.3% $30k - 50k, 13% > $50k, 64.7%	/
Al Haddad et al. (2020)	221 respondents	developed region	0-17, 0.5% 18-24, 19.5% 25-34, 45.7% 35-44, 19% 45-54, 9.5% 55-64, 5% 65+, 0.9%	Male, 56.1% Female, 43.0%	/	High School, 8.6% Apprenticeship, 2.7% Bachelor, 26.7% Master, 47.5% Doctorate, 13.1%	Full-time employed, 57.9% Part-time employed, 9.1% Student, 28.1% Unemployed, 0.5% Self-employed, 2.3% Retired, 0.9%	<500 €, 7.2% 500–1000 €, 8.6% 1000–2000 €, 11.3% 2000–3000 €, 14.0% 3000–4000 €, 10.9% 4000–5000 €, 10.9% 5000–6000 €, 4.9% 6000–7000 €, 5.4% >7000 €, 6.3%	/
(Binder et al., 2018; Boddupalli, 2019)	2500 respondents	developed country	/	/	/	/	Full-time workers	Annual personal (versus household) income > $150K	/
(S.-H. Cho and Kim, 2022)	699 respondents from airport users	developed country	<29, 38.3% 30-39, 29.6% 40-49, 17.3% 50-59, 11.6% >59, 3.2%	Male, 47.4% Female, 52.6%	/	/	/	<1 million ₩, 5.0% 1–2 million ₩, 10.3% 2–3 million ₩, 25.2% 3–5 million ₩, 26.6% 5–10 million ₩, 18.4% >10 million ₩, 6.9% No Income, 7.6%	/
	1011 respondents from urban travelers	developed country	<29, 16.1% 30-39,	Male, 74.0%	/	/	/	<1 million ₩, 3.4% 1–2 million ₩,	/

(continued on next page)

Table 8 (*continued*)

Literature (Ref.)	Survey Interviewees	The development level of the region	Age	Gender	Family type	Education	Employment status	Income	Household
			36.3% 40-49, 22.4% 50-59, 15.9% >59, 9.3%	Female, 26.0%				6.5% 2–3 million ₩, 20.0% 3–5 million ₩, 29.9% 5–10 million ₩, 33.1% >10 million ₩, 6.5% No Income, 0.6%	

Among the surveys in Table 9, EASA's comprehensive survey covering a majority of UAM-related attributes may serve as an ideal reference for assessing public acceptance and adoption in other regions with UAM potential. Surveys focusing on specific UAM applications, such as cargo services, are needed to acquire targeted data, as most existing surveys only pose questions related to the general UAM concept.

After the deployment of surveys, the data collected are usually further analyzed to estimate the market demand for UAM. In current research, discrete choice models are most adopted to describe, explain, and predict passenger's choice of travel mode between two or more alternatives (e.g., UAM, car, taxi, public transit). The specific models used are the multinomial logit model (MNL), mixed logit model (MXL), random parameter multinomial logit model (RPML), and ordered logit models (OLMs) (Al Haddad et al., 2020; Boddupalli, 2019; S.-H. Cho and Kim, 2022; Ilahi et al., 2021) and the input, output, model difference, and advantages of these models are reviewed in Table 10. The MXL model which considers the standard deviation of alternative specific constants (ASCs) is convinced better than the MNL model in BIC and rho square. And the RPML model considers the respondents' individual heterogeneity in multiple-choice situations to obtain better performance compared with the MNL model. The OLMs are built with a dependent variable (adoption time horizon) to respond to time changes.

The stated-preference (SP) survey, a typical survey method in transportation demand, is currently the most widely utilized qualitative approach for demand estimation in UAM. It can be summarized as follows:

- Numerous SP surveys in UAM primarily employ nonmetric analysis as the measurement scale in state ranking surveys. However, the efficacy of this method has been called into question. A response metric using scales (typically a five-point Likert scale in UAM) may offer a more efficient and objective evaluation of the views expressed by survey respondents.
- Travel time and travel cost are crucial factors for the profitability of ODAM operations, which contribute to UAM's competitiveness compared to other transportation methods.
- To analyze the relationship between travel time, travel cost, and market demand for UAM, discrete choice models are commonly employed to assess data obtained from preference surveys. Various models cater to different requirements, taking specific variables into consideration.
- Lastly, the majority of surveys have been conducted in developed countries and regions, resulting in a lack of relevant studies in developing countries.

5.2. *Demand estimation for potential city and region*

Once preference surveys are conducted, the general market demand for UAM can be estimated based on the respondents' willingness to take UAM and their concerns. The next step is to determine where to apply UAM services. To identify potential cities and regions for initial operation, various methods have been developed to estimate the demand for UAM across cities worldwide. Table 11 provides an overview of the current literature on market demand estimation for potential cities/regions. For instance, a gravity model describing the strength of the relationship between two bodies was used to predict the passenger demand for UAM in different scenarios (Global Environment Outlook (GEO-4) Scenarios of the United Nations Environment Programme) in 2042 based on various socioeconomic factors (Becker et al., 2018; Ortúzar and Willumsen, 2011). An alternative list consisting of 40 cities considering the population and population density was built by researchers in the US. A normalization technique that was relative to the minimum and maximum value of the metric to reorganize the data structure is used to select 10 final cities based on qualitative criteria including ground transportation congestion, weather, existing infrastructure, and ground transportation patterns (Goyal et al., 2018). In a recent study, another set of qualitative criteria were used to identify potential cities in the US for short-distance taking-off and landing (STOL) system. The criteria include the city's level of sprawl, density, presence of water, number of airports, population wealth, presence of high-tech industries, ground transportation congestion and patterns, and weather conditions (Robinson et al., 2018). Similarly, Haan et al. (2021) used cell phone data with commuter behaviors and census data with household income characteristics to predict the number of commuters who would use an air taxi in the 40 populous combined statistical areas (CSAs) in the US. A mode choice model calibrated by data from an SP survey was employed to estimate the air taxi demand, and potential air-taxi commuter routes were identified based on the result of the model. In another study in Singapore, a preliminary feasibility study was conducted to determine which districts have the most demand for UAM and how tourists could benefit from taking a flying taxi using a fare-distance-time comparison that covered various modes of passenger transport (Wai et al., 2021). The study aimed to identify the feasibility of a UAM service and assess the potential market demand for it.

In addition to academic institutions, several commercial organizations have been developing predictive models to identify potential urban areas suitable for urban air mobility (UAM) applications. For instance, NEXA Advisers (2019) devised a model to forecast the demand for various UAM applications such as airport shuttle services, corporate campus shuttles, on-demand air taxi services, medical and emergency services, and regional air transport services. This model employs ArcGIS as its foundation and incorporates multiple input parameters, including population size and density, per capita gross domestic product (GDP), age distribution, existing commercial and business aviation activities, and the presence of Fortune 1000 companies (Garrow et al., 2021; NEXA Advisers, 2019). However, the model's specific details remain undisclosed. Another notable consulting firm, KPMG, has developed a demand prediction model that integrates input factors such as city GDP and GDP growth, city population and population growth, city population density, projected changes in income distribution through 2050,

Table 9
Classification of survey questions.

Literature (Ref.)	Overview of Attributes	Question number	The general attitude towards UAM	UAM applications		Beneficial factors			Public acceptance			Regulation	Mode choice	Others
				passenger services	cargo services	time	cost	Distance/ destination	safety & security	environment (e.g., noise)	privacy & visual pollution			
EASA (2021)	perceived benefits, concerns, factors of societal acceptance, ranking of use cases	36	✓	✓	✓	✓	✓		✓	✓	✓	✓		socio-demographic
Ilahi et al. (2021)	factors & elasticity for all mode choice alternatives					✓	✓	✓					✓	socio-demographic, frequency & type of activity
Ahmed et al. (2021)	factors of peoples' willingness to hire and pay for (shared) air taxis	31	✓	✓			✓	✓	✓	✓		✓		socio-demographic
Al Haddad et al. (2020)	the most influential factors in UAM's adoption time horizon			✓		✓	✓		✓		✓			respondents' travel behavior and socio-demographics, factors ranking
(Binder et al., 2018; Boddupalli, 2019)	factors that influence high-income people's willingness to pay for UAM commuting	80				✓	✓		✓	✓	✓		✓	socio-demographic, individual's current commute, personality, and lifestyle characteristics
(S.-H. Cho and Kim, 2022)	factors of travel behavior and willingness to choose UAM	30	✓	✓		✓	✓		✓				✓	socio-demographic, purpose of travel

Table 10
Discrete choice models used in the UAM survey.

Discrete choice models	Input	Major Feature	Output	Advantages
multinomial logit model (MNL)	- Travel distance - Generic travel costs	Typical model	Mode choice tendency, WTP for each mode	widely used for policy analysis
mixed logit model (MXL)	- Travel time - Travel mode - Socio-demographic attributes, such as household income, age, gender, and education	Considered standard deviation of alternative specific constants (ASCs) compared with the MNL model		better than MNL in BIC and rho-square
random parameter multinomial logit model (RPML)	- Travel costs - Travel time - Travel mode - Socio-demographic attributes - Individual preferences	The variation parameters that reflect the individual preferences for the given attributes are added to the utility function of the MNL model	Mode choice	the respondents' individual heterogeneity in multiple-choice situations is considered to allow better estimation results
ordered logit models (OLMs)	- Affinity to automation - Cost of taxi - Data and ethical concerns - Employment	Attributes are ranked according to patterns in the MNL	The adoption time horizon of UAM and its relevance to those parameters	built with adoption time horizon as a dependent variable

wealth concentration, and data on existing ground services (Mayor and Anderson, 2019). Researchers Anand et al. (2021) and Mayakonda et al. (2020) subsequently utilized the list of potential cities identified in the KPMG report to estimate the UAM share of total passenger kilometers traveled. This estimation is contingent upon factors such as UAM ticket costs, travel time savings, and vertiport density.

Upon reviewing the demand estimation methodologies for potential cities and regions in the context of urban air mobility (UAM), several key observations can be made:

- The parameters employed in the existing research are diverse and, in some instances, incomplete (see Table 12). Current studies primarily focus on factors such as population, population density, and GDP, while potentially overlooking crucial aspects such as surface traffic congestion, regulatory constraints, and public acceptance (e.g., noise, privacy, and visual pollution).
- Consequently, the establishment of a comprehensive and uniform set of parameters may prove beneficial in generating a more persuasive list of potential cities for UAM adoption. These standardized parameters could also serve as a reference for future demand estimation studies in the UAM domain.
- The methodologies utilized in the reviewed literature encompass a range of approaches, including the gravity model for inter-city air mobility, Pugh Matrix, mode choice models (combined with origin-destination matrices), and straightforward comparison methods for intra-city air mobility. However, the incorporation of innovative techniques such as deep gravity models and agent-based models may offer improved responsiveness to additional parameters like points of interest (POI) and urban form, thus enhancing the robustness of demand estimation for UAM applications.

5.3. Demand estimation for infrastructure capacity and placement

After identifying the potential cities and/or regions for UAM implementation, a more detailed analysis of market demand distribution for UAM is required to determine vertiport capacity and placement. Several demand estimation methods supporting infrastructure placement for UAM were discussed by researchers. As a popular clustering method, the k-means algorithm, along with its upgraded algorithms (e.g. k-means++), is widely employed in current station location planning problems in UAM (Arthur and Vassilvitskii, 2007). For example, Bulusu et al. (2021) devised a method for analyzing traffic demand to estimate the maximum number of individuals who could benefit from UAM in the Greater San Francisco Bay Area. As part of this method, feasible combinations of vertiports and the anticipated distribution of a group of 36 vertiports were determined using a k-means++ algorithm (Bulusu et al., 2021). The k-means method was based on an incapacitated facility location problems (FLP) formulation, addressing vertiport location and demand distribution. Another k-means++ algorithm was employed by L. Wei et al. (2020) to initialize a continuous and discrete p-median model. This model sought to minimize the demand-weighted distance of customers to each UAM infrastructure, emphasizing the importance of optimizing infrastructure location to ensure efficient capital utilization (L. Wei et al., 2020). Moreover, research conducted in Northern California utilized a k-means clustering algorithm to identify potential landing sites that minimized the distance between vertiports and the weighted population tract centroids of high-income individuals (Tarafdar et al., 2019). In contrast to the aforementioned studies, this research incorporated the Zillow dataset, which contains information on all available land, as a secondary filter to determine feasible vertiport deployment locations.

To improve the performance of clustering methods and optimize resulting vertiport locations, several researchers have attempted to combine k-means algorithms with other techniques, taking into account operational and demand-related factors. For example, the multi-criteria warm start (MCWS) technique was integrated to an iterative k-means clustering algorithm to build a two-phase location planning model that considered the socio-economic factors of potential UAM passenger (Sinha and Rajendran, 2021). This model, which employed MCWS, demonstrated superior performance in various metrics, such as the Davies Bouldin index, number of clusters, and multi-criteria attributes, when compared to the previous k-means method. A multi-modal UAM simulation using MANTA was conducted by Peng et al. (2022) to design a vertiport network considering dynamic transfer time. A hierarchical method was proposed to minimize the transfer time including both the passenger consolidation time and the aircraft allocation time. In this hierarchical method, a k-median algorithm was utilized to partition the San Francisco Bay Area into main sectors, and passengers within these sectors were further divided into groups. Ultimately, an integer programming (IP) model was employed to assign routes for vertiport network validation. Building on the findings from clustering methods, calibrated mode choice model was used by another researcher in the same region to evaluate UAM's daily demand sensitivity to the number of vertiports and the cost per passenger mile (Rimjha et al., 2021a). To estimate passenger demand for ground trips accessing airports under airspace restrictions, a fuzzy c-means clustering approach was incorporated into the mode choice model, allowing for the estimation of near-optimal vertiport locations within the Dallas-Fort Worth region (Rimjha et al., 2021c).

The heuristic clustering methods employed in research above primarily focused on the spatial and operational requirements for UAM infrastructure placement. In contrast, several optimization algorithms have been utilized for vertiport location optimization. For instance, Rath and Chow (2022) introduced a skyport location problem that responds

Table 11
Review of literature in the estimation of potential city & region.

Literature (Ref.)	Region	Time Frame	Parameters	Data Source	Methods	Summary
Becker et al. (2018)	Worldwide (4435 cities)	2042	socioeconomic Factors	Forecast based on ADI 2012	A gravity model	A gravity model forecasting inter-urban air passenger demand for 2042 and generating a list of potential UAM markets
(NEXA Advisers, 2019)	Worldwide (84 cities)		population and density, gross domestic product (GDP) per capita, age distribution, current commercial and business aviation activity, presence of Fortune 1000 companies	ArcGIS	Interactive city data sets	Modeling demand for UAM for different use cases by interactive city data sets using ArcGIS
Mayor and Anderson (2019)	Worldwide	2050	city GDP and GDP growth, city population and population growth, city population density, city change in income distribution through 2050, wealth concentration, information about existing ground services	cell phone data		A model understanding how UAM demand could grow based on the economics and travel time constraints anticipated to evolve in cities worldwide
(Anand et al., 2021; Mayakonda et al., 2020)	Worldwide (31 cities)	2035	passenger demand, flight hours, fleet size	1. WorldData.info, 2. Demographia World Urban Areas (2019), 3. ITF Transport Outlook (2019)	A top-down methodology	A top-down methodology estimating the demand for UAM transportation worldwide by estimating the WTP for UAM services and by estimating the potential volume of UAM traffic
Goyal et al. (2018)	US		population, population density, ground transportation congestion, weather, existing infrastructure, ground transportation patterns	1. United States Census Bureau (2010), 2. Bureau of Transportation Statistics (BTS) DB1B, 3. Federal Aviation Administration's Aviation Environment Design Tool (AEDT) database	A normalization technique that was relative to the minimum and maximum value of the metric to reorganize the data structure	A qualitative methodology selecting the most potential and representative urban areas for initial UAM analysis
Robinson et al. (2018)	US		wide sprawl, appropriate density, water bodies, population wealth, high-tech industry, congestion, pre-existing airports, weather	1. FAA Obstacle Data Team's database, 2. Uber Elevate	Qualitative Method - a Pugh matrix	A qualitative method identifying suitable candidate cities for the STOL system
Haan et al. (2021)	US		the overall number of commuters (market size), how many of these commuters will choose an air taxi (market share)	1. cell phone data to identify regular commuters in cities, 2. census data to associate household income characteristics with commuters, 3. stated preference survey data	1. Mode choice model, 2. Census track OD matrix of commuters where air-taxi is an option	Identifying potential air taxi commuter routes in 40 U.S. cities, with a set of interactive maps allows readers to visualize the location of potential air taxi 9 commuter routes for the 40 cities
Wai et al. (2021)	Singapore		cost, travel time, and the travel distance	1. data obtained from Grab, 2. Free access or paid access based on the Singapore Tourism Board (STB)	Fare-distance-time comparison covered various modes of passenger transport	A preliminary feasibility study aims to determine which districts had the most in-demand and how tourists could benefit by taking a flying taxi

to elastic demand, determining the optimal placement of vertiports. They proposed a solution framework using hub location problem (HLP) structure in conjunction with a mode choice model, facilitating choice-constrained optimization for UAM infrastructure placement while considering the trade-offs between travel distance, time, and cost. Similarly, Wu and Zhang (2021) developed a network design model to identify and optimize potential vertiport locations by combining the modeling structure of traditional hub-and-spoke problems with mode choice. They employed a deterministic integer programming (IP) model to optimize candidate locations, derived from filter layers on a 3D map in GIS, based on land use restrictions and operational requirements for UAM.

In addition to vertiport location planning for electric vertical takeoff and landing (eVTOL) vehicles, Robinson et al. (2018) proposed a methodology for conducting a parametric analysis of geo-density, specifically tailored to short takeoff and landing operations for on-demand air mobility (ODAM) in Miami, US. The researchers utilized an algorithm designed to determine the maximum length of the longest

Table 12
Input (parameters) & Output of demand estimation for potential city & region.

Literature (Ref.)	Input (Parameters)										Model/Method	Output		
	geo-economic factors					service-related factors					Inter-city mobility/ Intra-city mobility	number of passengers	size of market/WTP	list/rank of potential cities
	population	GDP	economics	surface traffic congestion	others	time	cost	distance/ destination	regulation	others				
Becker et al. (2018)	✓	✓	✓		Language, Capital, Tourism-attraction intercontinental		✓	✓			Gravity model	The number of air passengers between two cities		
(NEXA Advisers, 2019)	✓	✓	✓	✓	Livability, Business Aviation Activity			✓		Existing Heliports and Fleets	Model details not disclosed, visualized by ArcGIS		Expected UAM market size, Minimum investment	
Mayor and Anderson (2019)	✓	✓	✓			✓				Information about existing ground services	Model details not disclosed	The number of passengers		
(Anand et al., 2021; Mayakonda et al., 2020)			✓			✓	✓	✓			A binary model comparing the WTP of travelers for UAM trips with the cost of a UAM trip		Travelers' WTP for UAM services	
			✓					✓		Trip purpose, Alternative mode	A top-down methodology	The potential volume of UAM traffic		
Goyal et al. (2018)	✓			✓	Weather Impacts, Demand sizing of premium airline passengers in an urban area				✓	Existing infrastructure, Existing transportation	Selecting methodology based on qualitative criteria			List of 10 potential urban areas for initial analysis
Robinson et al. (2018)			✓	✓	Wide sprawl, Appropriate building density, Water bodies, The high-tech industry, Weather					Pre-existing airports	Pugh matrix			A qualitative list of 9 cities
Haan et al. (2021)	✓		✓		Existing vertiport locations	✓	✓	✓		AV ownership, Ride guarantee, eVTOL parameters	Mode choice model (the multinomial logit (MNL) model)	Expected number of eVTOL aircraft commuters	Potential air taxi commuter routes	Rank according to the number of commuters in each city
	✓				Zip codes						OD (Origin-Destination) Matrix	Total number of commuters	Market size estimates	
Wai et al. (2021)						✓	✓	✓			Fare-distance-time comparison			The most in-demand districts

rectangle with a specified width within a polygon. This algorithm was employed to identify restriction areas that would impede airport deployment based on the geo-density constraints. A comprehensive summary of the existing literature discussed earlier is presented in Table 13. This overview encompasses various aspects of the studies, including the region of focus, vehicle types, problem size, data sources, model input and output parameters, and a brief synopsis of each research project.

A detailed examination of the input parameters, output, and methodologies employed in the papers discussed is provided in Table 14. In terms of modeling parameters that influence infrastructure placement based on demand, most researchers have considered geo-economic factors such as population or population density. However, economic factors, including household income and urban land use, have not been extensively incorporated. Given the high costs associated with UAM options for travelers, it is crucial to account for income factors in demand-based modeling. Moreover, aligning land use with predicted vertiport locations is essential for feasible implementation. Additionally, analyzing service-related factors, such as time, cost, and distance, is necessary, as they directly impact UAM demand and the subsequent planning of vertiports. In summary:

- As indicated in Table 15, the k-means algorithm and its enhanced variants are the most prevalent clustering methods for determining optimal vertiport locations. However, these approaches often yield ideal results that may lack practical implementation capabilities.
- Addressing the implementation limitations identified in the reviewed literature, it is recommended to integrate models with available land use data (e.g., vacant land) to pinpoint feasible landing site locations.
- Despite the incorporation of several enhancement methods into clustering algorithms to account for socio-economic factors, demand, and transfer time, as shown in Table 15, the responsiveness to passenger demand and urban building environments remains insufficient in previous infrastructure placement research.
- In the existing literature, the infrastructure placement problem for UAM is occasionally approached as a component of a mode choice model, which is extensively applied to customer-level demand prediction. As a result, vertiport locations are often determined by assuming a fixed number of locations based on the centroids of population census units. However, comprehensive and systematic methods for location planning remain an area of ongoing exploration and development.

5.4. Demand estimation for general market operation

Following the selection of operational cities and vertiport placement, accurately predicting customer demand levels is a crucial and necessary step for making informed market operation decisions prior to the implementation of UAM services. As a type of on-demand service, UAM operation efficiency is intrinsically linked to the spatiotemporal distribution of customer demand (Davis et al., 2018; Luo et al., 2021; Rajendran and Srinivas, 2020). More specifically, accurate demand forecasting can enhance system efficiency, thereby reducing total travel time, travel costs, and energy consumption for UAM trips. A decrease in energy consumption can, in turn, lower operational costs while increasing travel distances, ultimately boosting UAM's competitiveness. To achieve these objectives, analytical approaches employed by existing on-demand mobility (ODM) services can be adapted to on-demand services within the UAM context. It is worth noting that the majority of prior research on on-demand services in UAM has primarily focused on air taxi services (ATS).

In the initial stage of demand prediction modeling, it is crucial to identify factors affecting air taxi services (ATS) to ensure the validity and accuracy of the model. Researchers have dedicated efforts to discern the critical factors that influence demand modeling. As an example, predictors of willingness to fly in autonomous air taxis were identified by Winter et al. (2020) through valid statistical models based on data from an SP survey. These six significant predictors, accounting for over 76% of the variance in UAM adoption willingness, include familiarity, value, fun factor, wariness of new technology, fear, and happiness. Upon reviewing existing models, the predictors for ATS demand prediction modeling have been compiled, categorized, and presented in Table 16 as a reference for future research. These predictors encompass categories such as airspace, population, surface traffic congestion, location, environment, and time-related factors. Considering the identified factors, customer demands for UAM can be estimated using specific models, which can elucidate the relationships between these predictors and demand, consequently enhancing the operation and management of UAM services. The on-demand literature (Jiang et al., 2019; Moreira-Matias et al., 2013) predominantly focused on predicting the number of short-term customer requests (5–60 min) using time-series or machine learning approaches. Most demand modeling methods in previous ATS studies have been adapted from ODM services.

Numerous studies have developed various frameworks and models for general demand prediction in air taxi services (ATS), as outlined in Table 17. These tables provide an overview of the fundamental information of these studies, including region, vehicle types, problem researched, data source, model input and output, and a summary. Key findings include the following: Straubinger et al. (2021) proposed a scenario-based estimation framework for assessing aircraft demand across different scenarios on a global scale. Bulusu et al. (2021) developed a traffic demand analysis method using an incapacitated facility location problem (FLP) formulation to address the vertiport location and demand distribution problem, estimating the maximum number of individuals who could benefit from UAM. Researchers have also constructed various mode choice models, which are widely used in transportation demand modeling, to estimate ATS demand at the customer level. For example, Haan et al. (2021) developed a calibrated mode choice model to predict the number of potential commuters using ATS in the 40 most populous combined statistical areas (CSAs) in the US, creating census tract origin-destination (OD) matrices of potential commuters using a combined dataset based on cell phone data and census data as input for the calibrated mode choice model. Lastly, to forecast total demand for long-distance air travel in 2040, Justin et al. (2021) calibrated a mode choice model based on the generalized cost of travel, utilizing historical trip distribution datasets from the literature.

The mode choice model, widely employed in urban air mobility (UAM) research, is a component of the four-step model, a well-established demand estimation framework in the transportation field (Weiner, 1997). The four steps of this framework are illustrated in Fig. 6. Only a limited number of studies in the UAM domain have addressed trip generation and trip distribution steps, which may be attributed to the scarcity of historical UAM data. The majority of existing research estimating market demand for UAM focuses primarily on the mode choice step, drawing from stated preference (SP) surveys, commute data, and census data. Furthermore, research on the final step of trip assignment in UAM remains limited. Fig. 6 also summarizes the typical methods and models employed at each step, serving as a reference for future systematic demand estimation in the UAM field.

In addition to trip-based models such as the mode choice model, activity-based models like agent-based models have emerged in recent years. For instance, Balac et al. (2019) presented an agent-based framework using Eqasim in a case study conducted in Zurich, Switzerland, to explore UAM demand in the region, demonstrating demand sensitivity to various technological and operational parameters. Eqasim is a novel extension that enables users to convert survey data into the widely recognized agent-based transport simulation framework, MATSim, simplifying the design of scenarios for agent-based models. More significantly, the extension offers an option to utilize SP survey data to overcome the challenge of obtaining historical data on UAM travel. A comparison between Eqasim and MATSim is provided in

Table 13
Review of literature on infrastructure capacity & placement requirement.

Literature (Ref.)	Region	Vehicle types	Problem Size	Data Source	Input	Model/Method	Output	Summary
Bulusu et al. (2021)	SF Bay Area, US	VTOL	36 vertiports	A subset of commuter data for the San Francisco Bay Area, procured by the Mobiliti team at Berkeley Lab from the SFCTA Champ 6 model	Daily commuters in a metropolitan region	An incapacitated FLP formulation of the vertiport location and demand distribution problem, A k-means approach (k-means++)	Number of commuters benefiting from UAM	Identifying the maximum number of commuters that can benefit from UAM based on the feasible combinations of vertiports predicted
(L. Wei et al., 2020)	South Florida, US	STOL	10, 50 vertiports	Demand point locations and candidate facility points extracted using QGIS 3.4.4-Madeira as ESRI Shapefiles and read in using the Geopandas v0.4.0 library	Demand point locations and candidate facility points	Continuous & discrete p-median model initialized with k-means++	Final optimal locations	A model minimizing the demand-weighted distance of customers to each supporting facility
Rimjha et al. (2021a)	Northern California, US	VTOL	50 - 400 vertiports	1. National Household Travel Survey-2017 Add-on Data 2. Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics 3. American Community Survey-2017	Number of vertiports, UAM CPM value, Start placement of vertiports	A mode choice model (mixed conditional logit model)	A final set of vertiports, Placement maximizes UAM demand	A calibrated mode choice model evaluating the daily UAM demand sensitivity to the number of vertiports
Tarafdar et al. (2019)	Northern California, US	VTOL	200, 300, 400 vertiports	1. The National Household Travel Survey database (NHTS), 2. The Origin-Destination Employment Statistics (LODES, 2015), 3. The American Community Survey (ACS, 2017)	The ACS and LODES data are mapped on each other to determine the number of commuters belonging to each income bracket	A k-means clustering algorithm to figure out the potential landing site	Landing sites without considering topography, obstruction, land compatibility, and the price of land	Landing sites were selected using the k-means clustering algorithm to minimize the distance between weighted population tract centroids of the high-income population and the landing sites
				4. Zillow data	Land price, topography, classification, acreage, and other factors available from the Zillow	A secondary filter to k-cluster and population centroids	The best possible location for the landing sites	Analysis of how Zillow acts as a complementary dataset to filter out potential locations for a landing site
Rimjha et al. (2021c)	Dallas-Fort Worth region, US	VTOL	50 vertiports	The 2015 originating passenger survey conducted by UNISON consulting at DFW and DAL on behalf of the North Central Texas Council of Governments (NCTCOG)	Data points for clustering are developed from a random selection of census blocks centroids of a census block group weighted by its UAM potential	A demand-driven clustering approach using the fuzzy C-means clustering method which has a similar objective function as hard k-means	A vertiport location set	A vertiport placement method utilizing the mode choice model to estimate the near-optimal location of vertiports, which are further used to estimate the final UAM demand for a given number of vertiports
Robinson et al. (2018)	Miami, US	STOL	15,666 potential park locations	FAA Obstacle Data Team's database	Data (height above ground level alongside exact GPS coordinates) for all significant obstacles	A Methodology for parametric analysis of STOL airpark geo-density (an algorithm finding the maximum length of the approximate longest rectangle of width w in a polygon P)	Potential airpark locations, The maximum runway length for the primary airpark concept	Estimated the geo-density of airparks suitable for short takeoff and landing ODAM operations
Rath and Chow (2022)	NYC, US	VTOL	149 taxi zones + 3 airports	NYC taxi and limousine commission FHV (for-hire-vehicles) trip record data from	OD trips from NYV taxi data, taxi zones, fare structures	A hub location problem (HLP) structure (RDR model (maximize ridership) & REV model (maximize	Optimal vertiport locations	A skyport location problem with method framework responding to elastic demand to determine optimal choices of vertiports

(continued on next page)

Table 13 (*continued*)

Literature (Ref.)	Region	Vehicle types	Problem Size	Data Source	Input	Model/Method	Output	Summary
				2019 (July to December)		revenue) using Gurobi optimization tool) with a mode choice model (binary logit model)		
Peng et al. (2022)	SF Bay Area, US	VTOL	6 - 116 vertiports	Trips in 2040 based on census and household travel survey data generated by the Bay Area Metropolitan Transportation Commission (MTC)	OD trips, Aerial time & dynamic transfer time	A multi-modal UAM simulation using MANTA, a k-median algorithm, an Integer Programming (IP) model	A hierarchical vertiport network	A hierarchical vertiport network design method using a multi-modal UAM simulation based on a k-median algorithm and an integer programming (IP) model
Sinha and Rajendran (2021)	NYC, US	VTOL	18 vertiports	Data established by a prior study on air taxi network design (Rajendran and Zack, 2019)	OD trips, socio-economic factors	An iterative k-means clustering algorithm, multi-criteria warm start (MCWS) technique	Recommended location of the vertiports	A unique two-phase location analytics model integrating the multi-criteria warm start (MCWS) technique with an iterative k-means clustering algorithm
Wu and Zhang (2021)	Tampa Bay area, US	VTOL	30 vertiports	1. Elevation from lidar data, land use, and regulation policies 2. travel demand data from the Tampa Bay Regional Planning Model (TBRPM) 3. socio-demographic information	Lidar, land use, and regulation, travel demand data, socio-demographics	3D map from lidar and filter layers in GIS	Optimal vertiport locations, UAM demand, user allocation and mode choices	A network design model based on GIS to identify potential locations based on existing land use restrictions and aircraft operational requirements, and a modeling structure of a p-median hub-and-spoke network problem (integer programming (IP) model) for optimization

Table 19, outlining the differences between the two models, their respective inputs and outputs, as well as the advantages and limitations of each model.

Diverging from studies relying on survey and census data, several researchers have sought to utilize ground taxi trajectory data due to the similarities between traditional ground taxis and air taxis. Rajendran and Zack (2019) filtered a subset of regular taxi customers as potential air taxi users to estimate ATS demand. They established a procedure to identify potential ATS demand from taxi trajectory data based on parameters such as commute distance and duration. This approach's feasibility was evaluated using millions of New York City taxi trips. Building on the same trajectory dataset, Rajendran et al. (2021) compared four popular machine learning algorithms (MLAs), including logistic regression, artificial neural networks, random forests, and gradient boosting, to predict customer demand levels for ATS during different daily periods across various geographic regions. The predictive results indicated that the gradient boosting algorithm was the top-performing model.

Several studies have investigated demand estimation for ATS pricing strategies. Tarafdar et al. (2019) proposed a life cycle cost (LCC) model to estimate the operational costs and fare structure of urban air mobility (UAM). This model employed systems dynamics methodology using rate and differential equations. Rimjha et al. (2021c) conducted sensitivity analyses of UAM demand relative to cost per passenger mile (CPM) in the Dallas-Fort Worth region using a mode choice model with airport ground access. In Los Angeles, another mixed conditional mode choice model was constructed by Rimjha et al. (2021b) to analyze the impact of UAM's CPM. These findings contribute to feasibility analyses in subsequent research processes. Previous studies have also addressed demand estimation for fleet scale planning. For example, Rajendran and Shulman (2020) suggested a discrete-event systems simulation approach integrated with the Define, Measure, Analyze, Design, and Verify (DMADV) framework to determine the number of air taxis required to match potential UAM demand in New York City.

In this section, three primary methods have been employed for estimating customer-level demand in urban air mobility (UAM), including mode choice models, agent-based models, and machine learning algorithms. Although the input, output, and objectives of these methods differ, a meaningful comparison can be made to highlight their advantages and appropriate scenarios, as summarized in Table 20. Additionally, a detailed categorization of input parameters and output for the methods adopted in the reviewed articles can be found in Table 18, serving as a reference for future demand estimation modeling in UAM.

In conclusion, several gaps and opportunities can be identified within this section:

- The absence of historical data poses a significant challenge at this stage, necessitating the development of standardized UAM datasets in the future, if possible. To address this data scarcity, some researchers have attempted to analyze air taxi travel patterns using filtered regular taxi datasets. However, this method relies on percentage filters and assumptions, which may be unconvincing.
- Calibrated mode choice models and agent-based models, based on stated preference surveys, are the predominant methods for UAM demand estimation. By incorporating regional characteristics in survey data, these models can be adapted for cities and regions worldwide.

Table 14
Input (parameters & data source) & Output of demand estimation for infrastructure.

Literature (Ref.)	Input (Parameters & Data Source)							Model/Method	Output
	geo-economic factors			service-related factors					
	population	economics	land use	time	cost	distance/ destination	regulation		
Bulusu et al. (2021)						Distance to vertiport from a trip origin/ destination		An incapacitated FLP formulation of the vertiport location and demand distribution problem, A k-means approach (k-means++)	Distribution of the vertiport clusters
(L. Wei et al., 2020)	Number of commuters					Demand-weighted distance of customers to each supporting facility		Continuous & discrete p-median model initialized with k-means++	Optimal vertiport locations
Rimjha et al. (2021a)	A vertiport at each block-group centroid in the region (LEHD Origin-Destination Employment Statistics (LODES, 2015))			Travel time	Travel cost	Travel distance		A mode choice model (mixed conditional logit model)	A final set of vertiports, placement maximizes UAM demand
Tarafdar et al. (2019)	LEHD Origin-Destination Employment Statistics (LODES, 2015)	Information on the different income brackets for the passengers (from ACS, 2017)		Trip time	Trip pricing	Trip distance		A k-means clustering algorithm to figure out the potential landing site	Landing sites without considering topography, obstruction, land compatibility, and the price of land
			Land price, topography, classification, acreage, and other factors available from the Zillow dataset					A secondary filter to k-cluster and population centroids	The best possible location for the landing sites (on available land)
Rimjha et al. (2021c)	Census blocks centroids of a census block group weighted by its UAM potential							A demand-driven clustering approach using the fuzzy C-means clustering method	Set of near-optimal vertiport locations
Robinson et al. (2018)			Obstacle data (height above ground level alongside exact GPS coordinates) for all significant obstacles					A Methodology for parametric analysis of STOL airpark geo-density	Potential airpark locations, The maximum runway length for the primary airpark concept
Rath and Chow (2022)				Ground & aerial trip time	Ground trip fare & 3 air taxi trip price scenarios	Ground trip distance & aerial trip distance		A hub location problem (HLP) structure (RDR model (maximize ridership) & REV model (maximize revenue) using Gurobi optimization tool) with a mode choice model (binary logit model)	Optimal vertiport locations

(continued on next page)

Table 14 (*continued*)

Literature (Ref.)	Input (Parameters & Data Source)							Model/Method	Output
	geo-economic factors			service-related factors					
	population	economics	land use	time	cost	distance/ destination	regulation		
Peng et al. (2022)				Aerial trip time & dynamic transfer time		Trips OD		A multi-modal UAM simulation using MANTA, a k-median algorithm, an integer programming (IP) model	A hierarchical vertiport network
Sinha and Rajendran (2021)	Passenger willingness to fly and demand satisfaction based on socio-economic factors		on-road travel limit	Time savings	Operational cost	Air taxi trips OD		A unique two-phase location analytics model integrating the multi-criteria warm start technique (MCWS) with an iterative k-means clustering algorithm	Recommended location of the vertiports
Wu and Zhang (2021)	Socio-demographic information		Land use, elevation	Travel time		Trips OD	Regulation policies	3D map from lidar and filter layers in GIS, An integer programming (IP) model using Gurobi for optimization	Optimal vertiport locations

Table 15
Clustering algorithms and their enhancement for UAM infrastructure placement.

Clustering algorithms	Description	Enhancement	Input	Output	Features/advantages
k-means	a widely used clustering technique that seeks to minimize the average squared distance between points in the same cluster	/	candidate vertiport locations (trip OD)	vertiport clusters	/
		land use filter	candidate vertiport locations + land use	optimal vertiport locations (on available land)	land use considered
		multi-criteria warm start (MCWS) technique	candidate vertiport locations + socio-economic factors	optimal vertiport locations	socio-economic factors considered
k-means++	the initial clustering centers randomly chosen are weight according to their squared distance squared from the closest center already chosen to achieve better performance	facility location problems (FLP) formulation	candidate vertiport locations + commuting demand		demand distribution considered
		a continuous and discrete p-median model	candidate vertiport locations		demand-weighted distance of customers to each vertiport is minimized
k-median	calculating the median instead of the mean for each cluster to determine its centroid	integer programming (IP) model	candidate vertiport locations	a hierarchical vertiport network	dynamic transfer time considered
fuzzy c-means	the data point belongs to each cluster to some degree specified by a membership grade instead of assigned to a cluster	/	candidate vertiport locations + UAM potential weight	near-optimal vertiport locations	low computational cost, airspace restrictions addressed

- Machine learning algorithms have recently been introduced to UAM as a potential research direction, with newer deep learning algorithms possibly offering improved performance.
- Most existing studies concentrate on estimating potential customer quantities and fleet sizes at a general level. However, it is important to consider more specific user groups, such as high-income travelers, as a potential area of investigation.
- While air taxis are the primary focus of current research, air shuttles and cargo services might represent more feasible short-term UAM applications, given the limitations in infrastructure quantity and distribution. In the long term, point-to-point air taxi services may emerge as a potential application, as they maximize the time advantage of UAM. In this context, first- and last-mile ground trips should be minimized or even replaced by air travel to enable responsive on-demand services.

Table 16
Predictors of ATS demand prediction modeling.

Classification	Predictors
Airspace	- airspace availability
Population	- used population dataset as a way to represent potential demand - density
Surface Traffic Congestion	- travel time index: the ratio of the travel time during the peak period to the time required to make the same trip at free flow speeds - commuter stress index: similar to the travel time index but based only on the peak direction of travel - annual congestion cost: the value of travel delay and extra fuel consumed in traffic congestion
Location-related	- pickup and drop-off locations - distance
Environment-related	- temperature - weather conditions - wind speed - humidity - fog - visibility
Time-related	- month of the year - day of the week - time of the day

5.5. Demand estimation for operational planning problems

Upon the implementation of UAM services, demand estimation for operational planning problems in UAM aims to enhance efficiency during service operations. These problems include minimizing the number of empty air taxis congesting the airspace, designing the most efficient routes, and more. Given that fuel consumption and crew salary costs associated with fleet and crew scheduling typically represent the major expenses for an airline, emphasis is placed on addressing operational planning problems (Sun et al., 2021). Similar to traditional aviation services, operational planning can substantially improve UAM competitiveness by reducing service pricing due to decreased energy consumption and operational costs. This section presents a review of dynamic operational planning problems, categorized into three key areas as illustrated in Table 21: scheduling, dispatching, and routing. An overview of the literature examined in this section is also provided in Table 21, which includes region, vehicle types, problem researched, data source, model input and output, and a summary of each article. Key details from these articles are discussed as follows.

Flight scheduling plays a crucial role in determining the optimal daily schedule of flight operations. Additionally, deciding on a sequence of flight legs for individual aircraft is an important aspect of the scheduling problem. In prior UAM research, the scheduling problem is often converted into an optimization problem. For instance, Rajendran and Harper (2021) employed a simulation algorithm based on three criteria, total delivery time, cost, and emissions to identify the best transportation routes. The authors suggested that same-day package delivery companies could utilize the algorithm to plan the most effective alternatives for serving customers promptly. In a study by Kim (2020), two heuristic algorithms (particle swarm optimization (PSO) and genetic algorithm (GA)) were combined with a greedy algorithm to address the on-demand fleet scheduling problem for UAM. Contrasting with previous research in other transportation fields, a novel formulation enabled scheduling for a heterogeneous fleet, affecting both service quality and operational efficiency.

In addition to the algorithms above, mixed-integer linear programming (MILP) serves as an alternative method employed by researchers to address UAM scheduling problems. MILP offers a viable solution for tackling scheduling problems within a reasonably short time frame, enabling feasible real-time operational scheduling. Wei et al. (2021) utilized a mixed-integer program to achieve scheduling optimizations across several independent star-branch networks, which were decomposed from an on-demand UAM network with uncertain travel times. The network nodes represent infrastructures with limited landing capacity. Wu and Zhang (2020) formulated a mixed-integer program aimed at minimizing passengers' total waiting time in their eVTOL charging scheduling model, striving to balance eVTOL recharging requirements and passenger service demand. To discover the optimal required arrival time for efficient on-demand UAM arrivals, Kleinbekman et al. (2020) developed a framework using a novel rolling-horizon scheduling algorithm based on MILP with route selection capability. A novel airspace design for the vertiport terminal area was proposed to fit this framework. A multi-commodity network flow framework based on an integer model is presented by Roy et al. (2020) for eVTOLs' optimal arrival scheduling. The implemented framework can identify the fleet size necessary to meet specific user demand.

Like the traditional air traffic management (ATM), demand capacity balancing (DCB) is essential for ensuring safe and efficient UAM operations within urban airspace. The high-density air mobility services in crowded urban low-altitude airspace raise challenge for devising appropriate air traffic scheduling to maintain a balance between demand and limited airspace resources. Current research has begun to address DCB-related issues for UAM. For instance, Xie et al. (2021) present a UAS traffic management (UTM) system framework that incorporates a recurrent neural network (RNN) algorithm and a genetic algorithm (GA) to facilitate DCB services in low-altitude urban airspace. Tabu Search (TS) algorithm and A-star (A*) path planning algorithm based on Four-Dimensional Trajectory (4DT) functionalities was used by Xie et al. (2022) to realize an uncertainty-resilient and flexible DCB in low-altitude urban airspace. A DCB algorithm including Strategic Conflict Management Service (SCMS) and Demand-Capacity imBalance Detection service (DCBD) was developed for NASA's demand capacity imbalance detection and resolution service for UAM (Lee et al., 2022). And a set of system effectiveness measures and metrics was proposed by Moolchandani et al. (2022) for data analysis of X4 simulations using NASA's DCB algorithm. To resolve the DCB issue and separation conflict at the strategic stage, a multi-agent reinforcement learning (MARL) method was developed based on a multi-agent asynchronous advantage actor-critic (MAA3C) framework, utilizing mask recurrent neural networks (RNNs) (Huang et al., 2022). In order to enhance the performance of DCB algorithms, several studies have been conducted to analyze the factors and parameters affecting the DCB problem. P. Wei and Chen (2021) proposed a simulation method that integrated a DCB algorithm and a rule-based tactical deconfliction approach to select DCB parameters for the DCB process and solution. Additionally, a hybrid artificial intelligence (AI) algorithm framework, which combined a Deep Q-Learning Network (DQN) with a genetic algorithm (GA) model based on the Gated Recurrent Unit (GRU) architecture, was developed to investigate the impact of uncertainty factors on UAV trajectory conformance for the DCB process and solution. These studies demonstrate the potential for advanced modeling and simulation techniques to improve the accuracy and effectiveness of DCB algorithms.

Dispatching plays a vital role in enhancing the efficiency and economy of UAM flights. This involves two important aspects: fleet assignment and crew dispatching. Fleet assignment refers to the assignment of an appropriate aircraft type to each flight in the schedule, while crew dispatching involves the pairing of crew resources based on flight schedules. To meet real-time demand in a centralized air taxi network, Rajendran (2021) has developed a hybrid simulation goal programming (HSGP) model. The model integrates both simulation and goal programming techniques to calculate the required number of air taxis. Routing estimation is another crucial aspect that contributes to the design of the most efficient route for a specific flight, particularly in ride-sharing mode. The routing model must take into account trajectory planning and collision avoidance under safety considerations. For instance, Yun et al. (2021) present a method based on distributed QMIX-based multi-agent deep reinforcement learning (MADRL) to compute optimal trajectories for Unmanned Aerial Vehicles (UAVs)

Table 17
Review of literature in ATS demand prediction modeling.

	Literature (Ref.)	Region	Vehicle types	Problem	Data Source	Input	Model/Method	Output	Summary
General demand estimation	Rajendran et al. (2021)	New York City (NYC), US	Air Taxi (eVTOL)	The estimation of passenger demand for ATS across time and space	1. data established by a prior study on air taxi network design (Rajendran and Zack, 2019) 2. the API of a commercial weather service provider	pickup date and time, drop-off date and time, number of passengers transported, latitude and longitude of origin location, latitude and longitude of the destination location	1. K-means clustering algorithm 2. Four popular MLAs: (logistic regression, artificial neural networks, random forests, gradient boosting)	Estimated air taxi demand variation over different days of week and months	Predicting the demand for air taxi UAM services during different times of the day in various geographic regions of NYC using MLAs
	Haan et al. (2021)	US	Air Taxi (eVTOL)	Computing a measure of air taxi demand across multiple U.S. cities	1. cell phone data to identify regular commuters in cities, 2. census data to associate household income characteristics with commuters, 3. stated preference survey data	the overall number of commuters (market size), how many of these commuters will choose an air taxi (or market share)	1. Mode choice model, 2. Census track OD matrix of commuters where air-taxi is an option	The number of these commuter trips for which air-taxi is an available option, the number of eVTOL trips	Identifying potential air taxi commuter routes in 40 U.S. cities, with a set of interactive maps allows readers to visualize the location of potential air taxi 9 commuter routes for the 40 cities
	Rajendran and Zack (2019)	New York City (NYC), US	Air Taxi (eVTOL)	Sub-setting the potential air taxi demand from the regular taxi records	Publicly available NYC Taxi and Limousine Commission data records	air taxi travel time, time savings	A procedure for sub-setting the potential air taxi demand from the regular taxi records, considering specific parameters such as commute distance and duration	A subset of the regular taxi customers	Estimating the demand for air taxi services from a subset of the regular taxi customers
	Justin et al. (2021)	Northeast US	small gauge electrified aircraft	Predicting the demand for AAM	historical datasets from 2008 for airfare	travel time, cost, market preference	Mode choice model	2040 air & auto biz market preference	A demand model based on an empirically calibrated generalized cost of travel combined with an MNL model, which applied to 2040 forecasts of the aggregated demand for long-distance travels
	Straubinger et al. (2021)	Worldwide		A scenario-based estimation of UAM vehicle demand	UN-Urbanization dataset	a set of worldwide cities and agglomerations (population of agglomeration, income, inequality of income, international trade, and commerce)	A method separating the use-cases and applying calculation models, which have taken account of the specific characteristics of each application	Forecasted fleet to cover demand at peak hour per city agglomeration, archetype, scenario, development over time	Estimating vehicle demand over different scenarios and for different time steps
	Balac et al. (2019)	Zurich, Switzerland	eVTOL	Investigating demand for UAM	1. sociodemographic attributes are derived from a detailed census data set, 2. the countrywide HTS (household travel survey), 3. two publications by Zurich Airport	process time, cruising speed, variable cost	1. An agent-based approach (Eqasim based on MATSim), 2. Mode choice model (MNL)	The flow of passengers between vertiports	A methodology investigating demand for UAM using an agent-based approach
	Bulusu et al. (2021)	SF Bay Area, US	VTOL	The maximum number of commuters that can benefit from UAM	A subset of commuter data for the San Francisco Bay Area, procured by the Mobiliti team at Berkeley Lab from the SFCTA Champ 6 model	daily commuters in a metropolitan region	An incapacitated FLP formulation of the vertiports location and demand distribution problem, A k-means approach (k-means++)	Number of commuters benefiting from UAM	Identifying the maximum number of commuters that can benefit from UAM based on the feasible combinations of vertiports predicted
Demand for pricing strategy	Tarafdar et al. (2019)	Northern California, US	VTOL	Fare model analysis	Maintenance cost parameters applicable to advanced General Aviation (GA) aircraft	facilities cost, periodic costs, variable costs, fixed costs, personnel costs, training costs,	A UAM Life-cycle Cost (LCC) model employing the Systems Dynamics to estimate each category of the cost contributing to the overall cost of operating an	UAM operational costs	A life cycle cost (LCC) model to estimate UAM operational costs and estimate a fare structure

(*continued on next page*)

Table 17 (*continued*)

	Literature (Ref.)	Region	Vehicle types	Problem	Data Source	Input	Model/Method	Output	Summary
						capital and amortization costs	eVTOL (using STELLA Author software package)		
	Rimjha et al. (2021c)	Dallas-Fort Worth region, US	VTOL	Daily airport UAM demand sensitivity to UAM CPM	The 2015 originating passenger survey conducted by UNISON consulting at DFW and DAL on behalf of the North Central Texas Council of Governments (NCTCOG)	the UAM alternative was added to the mode choice set after estimating UAM trip characteristics for each OD pair	Mode choice model (an airport ground access model)	daily one-way UAM airport passenger trips	The sensitivity of demand concerning the CPM offered by the UAM operating agency, considering a constant 50 vertiports in the region
	Rimjha et al. (2021b)	Los Angeles, US	VTOL	UAM demand estimation for airport access	1. The 2019 Passenger Survey Los Angeles International Airport 2. T-100 database maintained by the Bureau of Transportation Statistics (BTS)	originating passenger survey data, the daily number of originating passengers at LAX, vertiport Locations in 50, 75, and 100 Vertiport Set	A mixed conditional mode-choice model (mixed conditional logit model)	daily one-way UAM airport passenger trips	Estimating demand for UAM in the airport ground access segment of Los Angeles International Airport (LAX). A feasibility analysis utilizing the developed UAM demand estimation framework to analyze sensitivity concerning UAM passenger cost per mile (CPM) and UAM network size (number of vertiports)
Demand for fleet scale	Rajendran and Shulman (2020)	New York City (NYC), US	Air Taxi (eVTOL)	Understanding the air taxi operations to determine the number of air taxis required to fulfill the demand for urban air mobility in NYC	The approach recommended by (Rajendran and Zack, 2019) to assess the air taxi demand	vertiport/vertistop sites and eligible customer population, the vehicle capacity, number of air taxis in the system, maximum customer wait time	A discrete-event systems simulation approach integrated with the Define, Measure, Analyze, Design, and Verify (DMADV) framework	average vehicle utilization (SE), average time spent by a customer in the system (SE), average waiting time per customer (SE), number of customers availing air taxi service per week (SE)	To examine the air taxi network operations using the discrete event system simulation approach to determine the number of air taxis that are required to fulfill the potential UAM demand in New York City

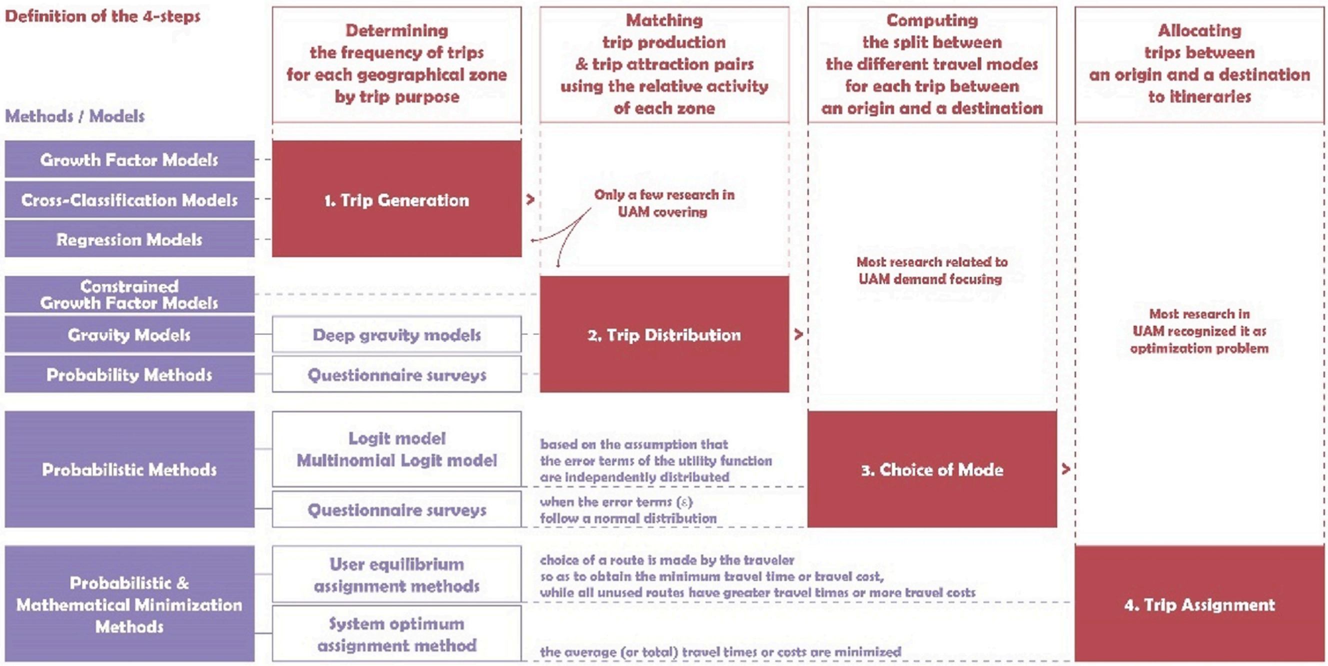

Fig. 6. The 4-step model in UAM.

while considering vehicle collisions, battery status, and passenger behaviors.

Overall, the efficient scheduling, fleet assignment, crew dispatching, and routing estimation contribute significantly to the overall efficiency and economy of UAM operations. An examination of various methodologies utilized for addressing the operational planning problem in UAM is presented in Table 22. This tabulation delineates the key parameters, merits, limitations, and appropriate implementation contexts for each method, thereby facilitating a holistic understanding of their potential application in UAM operations. Eventually, several gaps and opportunities in operational planning for UAM were identified:

- The current limitations of regulation, people's acceptance, and market expectations of UAM commercial companies suggest that manned eVTOL vehicles are suitable for initial implementation of UAM services. However, manned eVTOLs require different airspace management than UAVs under Unmanned Traffic Management (UTM) or helicopters under today's ATM systems. Therefore, current research on UAM operational planning mainly focuses on UTM, which may not be suitable for the potential manned UAM passenger services.
- As the market operation of UAM is limited and the airspace for UAM operation is not clearly defined, detailed research on operational planning for UAM is limited and challenging. In this context, strategic planning may be a future direction for UAM operation in the future scenario. Strategic planning mainly provides pre-flight conflict resolution with coordinated operation plans to avoid collisions.
- In terms of airspace management for UAM, solving the DCB problem in the strategic planning is a fundamental trend to increase safety and reduce airspace congestion. Most current research on the DCB problem focuses on UAVs, but solving the DCB planning for manned eVTOLs may meet the requirements of commercial passenger services in the short term.
- Finally, the arrival and departure planning to and from vertiports is another crucial aspect of operational planning for UAM. Current research relies on previous methods developed based on helicopters and small fixed-wing aircraft. Therefore, future studies on the solution and optimization of arrival and departure planning for eVTOLs are necessary. Overall, these gaps and opportunities in operational planning for UAM require further research to facilitate the successful implementation of UAM services in the future.

To summarize, we present an overview of market demand estimation methodologies for UAM in Fig. 7. Methods for the analysis and forecast of transport demand can be categorized into qualitative methods and quantitative methods. The methods employed for analyzing and forecasting transportation demand can be broadly classified into qualitative and quantitative approaches. To determine the appropriate scenarios for employing these methods within the context of UAM, we have conducted a comparative analysis of the advantages and disadvantages of both qualitative and quantitative techniques, as presented in Table 23. Each method exhibits suitability for specific problem domains, as illustrated by the connections depicted in Fig. 7. These demand estimation problems have been organized in this section according to the market demand estimation process for UAM, progressing from long-term to short-term perspectives and transitioning from a general overview to a more focused analysis.

We examined the qualitative and quantitative methods used in transport demand modeling, which can be categorized into four groups as shown in Fig. 7. Among these methods, survey methods, particularly Stated Preference (SP) Surveys, are the most commonly used and efficient for estimating Urban Air Mobility (UAM) demand. In contrast, quantitative methods in transportation demand, such as time series models, have not been applied to UAM demand estimation due to the lack of historical data. In UAM, discrete choice models, such as multinomial logit models (MNL), are frequently used for predicting general customer demand levels (i.e., mode choice estimation). In addition, agent-based models and the gravity model are used for demand prediction and estimating travel flow between the origin and destination. Moreover, machine learning algorithms (MLAs) are a promising direction for UAM demand estimation. Among the various clustering analysis methods, k-means clustering is the most commonly used in identifying transportation analysis zones (TAZs) and data processing steps in UAM. Overall, this research suggests that both qualitative and quantitative methods can be used for UAM demand estimation, and machine learning algorithms are a promising direction for future research.

Table 18
Input (parameters) & Output of ATS demand prediction modeling.

	Literature (Ref.)	Input (Parameters)										Model/Method	Output	
		geo-economic factors				service-related factors								
		population	economics	congestion	others	time	cost	distance/ destination	environment	regulation	others		number of passengers	size of market/WTP
General demand estimation	Rajendran et al. (2021)	✓				✓		✓	✓			1. K-means clustering algorithm 2. Four popular MLAs: logistic regression, artificial neural networks, random forests, gradient boosting	air taxi demand levels across different periods and locations	
	Haan et al. (2021)	✓		✓	existing vertiports locations	✓	✓	✓			AV ownership, ride guarantee, eVTOL parameters	Mode choice model (MNL)	expected number of eVTOL aircraft commuters	potential air taxi commuter routes
		✓			zip codes							OD (Origin-Destination) Matrix	total number of commuters	market size estimates
	Rajendran and Zack (2019)	✓				✓						A procedure for sub-setting the potential air taxi demand from the regular taxi records	a subset of the regular taxi customers	
	Justin et al. (2021)					✓	✓				air travel market preference	Mode choice model	the probability of choosing an air travel mode in a binary choice setting	
	Straubinger et al. (2021)	✓	✓		UAM market rates						seat capacity	Calculation models taking account of specific characteristics of each application scenarios		trips per day and trips per peak hour of UAM, forecasted fleet amount in different scenarios
	Balac et al. (2019)	✓				✓	✓	✓			eVTOL parameters	1. Eqasim, a novel extension to the widely known agent-based transport simulation framework MATSim	passenger flows, traveler behavior characteristics	
		✓	✓			✓	✓	✓				2. Mode choice model (MNL)		
	Rajendran and Zack (2019)	✓		✓		✓						Time savings over 25%/50% based on corresponding vertiport combinations	commuters benefiting from UAM	
Pricing strategy	Tarafdar et al. (2019)	✓	✓		land-use	✓	✓	✓			eVTOL parameters, life-cycle costs	UAM Life-cycle Cost (LCC) model employing the Systems Dynamics methodology (using STELLA Author software package)		UAM operational costs
	Rimjha et al. (2021c)	✓	✓		number of vertiports, airspace availability	✓	✓	✓				calibrated mode choice model (an airport ground access model)		daily one-way UAM airport passenger trips
	Rimjha et al. (2021b)	✓			number of vertiports	✓	✓	✓				a mixed conditional mode choice model (mixed conditional logit model)		daily one-way UAM airport passenger trips
Demand for fleet scale	Rajendran and Shulman (2020)				Vertiports number & location	✓	✓	✓			air taxi parameters, number of vehicles	a discrete-event systems simulation approach integrated with the Define, Measure, Analyze, Design, and Verify (DMADV) framework	number of customers availing air taxi service per week	average vehicle utilization, time spent, waiting time per customer

Table 19
Agent-based approach (MATSim & Eqasim).

Tool	MATSim	Eqasim
Type	a multi-agent-based large-scale traffic system simulation tool	a novel extension to the MATSim
Difference	applying an evolutionary algorithm to simulate decision-making for transport modes, departure times, or even activity locations	using discrete choice models to specifically investigate the choice of transport mode for travelers. in Eqasim, the re-planning phase of MATSim is replaced by a Discrete Mode Choice model that more heavily emphasizes mode change than on-time departure changes
Input	a scenario requires a large number of datasets, such as census data, the road network, mobility behaviors (e.g., public transport schedules and daily plans)	datasets from survey data
Output	traffic flow and traveler behavior characteristics (typically in a single day)	traffic flow and traveler behavior characteristics (more emphasis on mode choice)
Advantages	designed for large-scale scenarios (movements of large numbers of agents can be simulated at the same time), can be analyzed at road-level and per-second detail. flexibility and the ability to model emergent behavior	allows the user to convert the raw survey data into an agent-based model (i.e., MATSim), simplifying the design of scenarios for agent-based models using open data
Shortcoming	the complexity of these models makes them hard and time-consuming to set up, which is one of their important limitations	Limitation of data source: survey data

In this research paper, we provide an overview of the relationship between Urban Air Mobility (UAM) demand estimation and the input/output of related methods used in current research, as depicted in Fig. 8. Time, cost, and distance are critical service-related parameters that feature in almost all methods. Population and economic elements, such as Gross Domestic Product (GDP) or household income, are also important factors in demand prediction methods, as they help to identify high-demand cities or regions for study. In addition to these parameters, several other factors have an impact on the placement of vertiports, airspace and routing design, urban building environment, public acceptance, and regulation. However, the current methods reviewed in this paper are not effective in covering these factors. Thus, novel methods, models, or frameworks that can effectively address these parameters in the market demand estimation for UAM are potential avenues for future research.

6. Demand in UAM life cycle

Upon reviewing the demand analysis methods for UAM, the impact of demand analysis methods on the UAM industry is discussed in this section. Since market demand is a crucial driver for the development of on-demand services in UAM, it is necessary to clarify the role of demand in the UAM life cycle. This section provides a review of demand estimation methods from the perspective of their application in the UAM life cycle, which can be divided into three stages: design, construction, and operation with management, with regulation running throughout the entire process. Due to the interdependence of design and construction, we reviewed them as a single entity in this paper. Therefore, this section is organized into three subsections: design and construction, operation and management, and regulation. As illustrated in Fig. 9, each subsection/element can be further divided into three components. The impact of demand on each segment of the UAM life cycle is reviewed by discussing current research, identifying gaps and challenges, and outlining future opportunities. Other factors, aside from demand, are also examined and identified to uncover future opportunities. Overall, this section emphasizes the importance of market demand analysis in the UAM industry and highlights the need for further research to fully realize the potential of UAM.

6.1. Design & construction

The design and construction phases are critical for the realization of Urban Air Mobility (UAM). In these initial stages, it is essential to understand the role of demand analysis, as the design indicators and construction standards are based on user demand. Since the physical UAM system comprises three parts, namely vehicles, infrastructure, and airspace, the impact of demand on the design and construction of UAM will be reviewed according to this classification. This section will help to identify the necessary design and construction standards that are required to meet the demand of UAM users.

The design and development of appropriate Vertical Takeoff and Landing (VTOL) aircraft constitute a critical component for the successful implementation of an UAM transportation system. As illustrated in Fig. 10, varying demand stemming from diverse UAM applications and operational modes necessitates distinct vehicle parameter requirements. These various demands subsequently influence the fundamental design and production of vehicles, striking a balance between practicality, safety, comfort, and cost-effectiveness. Moreover, Fig. 10 also categorizes other factors impacting vehicle design and manufacturing, encompassing aspects of feasibility, safety, and economic considerations. Several design standards have been proposed by governments and organizations in the United States and Europe, reflecting the requirements of potential UAM users. Nevertheless, the parameters and standards for vehicle design and manufacturing must be further defined to satisfy public demand and enhance the operation of UAM services. Key considerations include:

- Ensuring that the technological requirements of UAM vehicle design offer substantial advantages over traditional helicopters.
- Developing UAM vehicle design standards aimed at fostering public acceptance and facilitating widespread adoption.

In an UAM transport system, the infrastructure serves as a critical component for aircraft take-off and landing, scheduling, and maintenance. Similar to vehicle design and manufacture, various UAM demand types, including passenger, cargo, and other services, require different infrastructure demands, impacting the scale, type, component, and layout of UAM infrastructure, as shown in Table 24. Vertiports/vertistops require different facilities to meet the demand for various operational tasks. Traffic flow demand, including takeoff and landing frequency, maintenance and parking scheduling, and operational time, needs to be estimated to provide references for UAM infrastructure design and planning, such as night takeoff and landing capability. Guerreiro et al. (2020) develop a vertiport scheduling algorithm to calculate the capacity and takeoff-landing capability of various vertiport configurations. Since UAM is highly sensitive to time, the efficient placement of infrastructure to meet user demand is crucial in reducing travel time to and from the vertiports and improving operational efficiency. Fadhil et al. (2019) identify demand-related factors for infrastructure placement and planning, including population density, job density, median income, existing noise, and ground-based transport accessibility.

Many overlooked issues could be summarized in this part. A prominent aspect is the design standard for UAM infrastructure, with a particular emphasis on safety standards. For instance, the European Union Aviation Safety Agency (EASA) has defined guidelines for safety zones, approach slopes, and obstacle clearance in relation to heliports, which can be adapted for UAM vertiports (EASA, 2018). Furthermore, specific design and planning considerations, such as the development

Table 20
Demand estimation methods in ATS demand prediction modeling.

Method/Model		Definition	Description	Input	Output	Advantages	Shortcoming
Mode choice model		a typical method of research on consumer choice behavior,	utility functions used to calculate the probability that an individual selects a particular mode, refer essentially to utility theory techniques	population, income, infrastructure locations, travel preference data (time, cost, distance from state-preference survey), eVTOL parameters (capacity, cruise speed)	number of passengers, potential routes	maximization of utility of individuals at the urban level, a large amount of data can be used	the variable time cannot be account for, and each trip at the urban level is supposes to be independent, an assumption which is contrary to the reality of urban trips interrelated among them, any error at each step is reflected in the successive steps
Agent-based model	MATSim	a multi-agent-based large-scale traffic system simulation tool	a platform applying an evolutionary algorithm to simulate decision-making for transport modes, departure times, or even activity locations	a scenario requires many datasets, such as census data, the road network, mobility behaviors (e.g., public transport schedules and daily plans)	traffic flow and traveler behavior characteristics (typically in a single day)	designed for large-scale scenarios (movements of large numbers of agents can be simulated at the same time), can be analyzed at road-level and per-second detail. flexibility and the ability to model emergent behavior	the complexity of these models makes them hard and time-consuming to set up, which is one of their important limitations
	Eqasim	a novel extension to the MATSim	in Eqasim, the re-planning phase of MATSim is replaced by a Discrete Mode Choice model to specifically investigate the choice of transport mode for travelers, which more heavily emphasizes mode change than on-time departure changes	datasets from survey data	traffic flow and traveler behavior characteristics (more emphasis on mode choice)	allows the user to convert the raw survey data into an agent-based model (i.e., MATSim), simplifies the design of scenarios for agent-based models using open data	limitation of data source: survey data
Machine learning algorithms (with k-means clustering algorithm)		algorithms that can improve automatically through experience and by the use of data	building a model based on training data to make predictions without being explicitly programmed to do so	number of passengers, pickup/drop-off date and time, infrastructure location, environment	air taxi demand levels across different periods and locations	take easily into account great amounts of data, simulate nonlinearities and complex situations	may data present high fluctuations

and adaptation of logistical systems, should be tailored to accommodate the demands of tasks at vertiports for UAM cargo services. In addition to demand, a variety of factors influence infrastructure design and planning, as enumerated in Table 25. These factors encompass safety-related, environmental, social, and operational considerations, each playing a crucial role in the overall development and implementation of UAM infrastructure.

The urban airspace serves as the operational space for Urban Air Mobility (UAM) vehicles. The demand for UAM is a crucial element in UAM airspace design, while other factors are reviewed in Table 26, as identified by Bauranov and Rakas (2021). The application and operation modes of UAM can be classified as intra-city travel (UAM) and inter-city travel (AAM) based on trip distance, or air taxi (on-demand) and air metro (commute) based on travel mode. Special tasks, such as emergency rescue, medical transport, and sightseeing, may require different airspace design requirements. Thus, airspace design must define various airspace classifications or divisions to meet different demands. For instance, Balakrishnan et al. (2018) published their airspace designs, which include basic flight, free route, corridors, and fixed route, as an example of meeting various UAM demands.

Several studies have begun to explore the relationship between UAM demand and airspace design. For example, Murça (2021) developed a data-driven probabilistic traffic model that utilizes historical aircraft trajectory data and meteorological information to predict the distribution of aero-traffic patterns for airspace delimitation in urban areas. A framework with airspace design in the vertiport terminal area based on a novel rolling-horizon scheduling algorithm was introduced by Preis and Hornung (2022) to minimize the vehicle arrival times. Despite these advances, evident gaps persist in addressing airspace-related concerns:

- The definition of UAM airspace remains in its nascent stage; a consensus on the airspace definition is necessary for further progress in the field.
- Research on airspace design from a demand-centric perspective is limited. Consequently, it is essential to identify demand-related factors that can inform urban airspace design and contribute to a more comprehensive understanding of the subject.

6.2. *Operation & management*

The operation and management stage serves as the primary stage in the Urban Air Mobility (UAM) life cycle, where demand needs to be considered during almost the entire process of operation. A typical planning process of an airline involves customer demand prediction, market segmentation, fleet dispatching and scheduling, and crew scheduling (Bazargan, 2010; Sun et al., 2021). Given the characteristic of UAM, which combines traditional aviation, on-demand transport, and public transit, this paper discusses the impact of demand on the entire operation process in the following sequence. To represent each part of UAM operation and management, a keyword is summarized as follows:

- Feasibility (pre-operation) - Operational planning
- Efficiency (intra-operation) - Operational management
- Potentiality (post-operation) - Demand promotion on target user

First, similar to the market segmentation process in the traditional airline industry, the feasibility of UAM operation in a certain region must be assessed to determine whether it can be a potential market for UAM (Sun et al., 2021). The demand level of UAM is recommended to be identified during the operational planning stage using survey-based and long-term data-based estimation methods reviewed in Section 4. Second, the efficiency of UAM operation is a crucial element for the success of UAM market operation. Demand analysis must be conducted to provide a basis for decision-making regarding strategy adjustment and operational scheduling to minimize scheduling and assignment costs of fleets, flights, and crews using short-term data-based estimation

Table 21
Review of literature in estimation for the operational planning problem.

	Literature (Ref.)	Region	Vehicle types	Problem	Input	Model/Method	Output	Summary
on-demand scheduling problem	Rajendran and Harper (2021)	New York City (NYC), US	cargo (aviation vehicle as one of the alternatives)	Courier services explore means to transport packages in a cost- and time-effective way	travel time and cost parameters	The simulation algorithm determines the best alternative to the three criteria: total delivery time, cost, and pounds of emitted	the best performing alternative	A simulation algorithm that assists same-day package delivery companies to serve customers instantly
	Kim (2020)		Heterogeneous fleet	scheduling problem of on-demand mobility with a heterogeneous fleet	nodes (i.e., vertiports), travel time and cost parameters, seating capacity	1. A novel formulation of the scheduling problem for UAM with a heterogeneous fleet, 2. Two heuristic algorithms (PSO and GA) combined with a greedy algorithm	a near-optimal solution for scheduling problems, which maximizes the net profit, while minimizing the final queue size	A novel formulation of the scheduling problem and two heuristic algorithms (PSO and GA) combined with a greedy algorithm are proposed to solve the MoD scheduling problem for UAM
	(Q. Wei et al., 2021)	Atlanta, US	UAVs	scheduling for UAM networks that accounts for uncertainty in travel time and limited landing capacity	travel time range, the route between nodes in a star-branch network, vertiports capacity, number of UAVs	Reasonably decompose a UAM network as several independent star-branch networks, a mixed integer program for obtaining an optimal schedule	schedule that minimizes the gaps between the arrival times and the corresponding deadlines	A mixed-integer program for scheduling problems in UAM networks
	Wu and Zhang (2020)		VTOLs	strategy for recharging & passenger serving scheduling balance	eVTOL battery parameters, time of eVTOL takeoff, land, pick up passengers, and get charged	A mixed integer program modeling the eVTOL charging scheduling process	schedule that minimizes the total waiting time of passengers	A reasonable short-time method for solving the charging and passenger serving scheduling problem, which makes it feasible for real-time operations of UAM service
	Kleinbekman et al. (2020)		eVTOLs	optimal and efficient on-demand eVTOLs arrivals	arrival time, parameters and number of vehicles, the capacity of vertiport	A novel rolling-horizon scheduling algorithm with route selection capability (mixed-integer linear program)	landing time slots (or RTAs) for all arriving eVTOLs to achieve minimum total delay	The optimal required time of arrival for eVTOLs
	Roy et al. (2020)	Atlanta, US	eVTOLs	minimize the total eVTOL arrival delay at the vertiport	trip time, cost, distance, number of vertiports and vehicles	A multi-commodity network flow framework (Integer Model)	identify the fleet size needed to meet a given user demand	The optimal framework with dispatch algorithm & other supporting models helps to identify the fleet-size
	Xie et al. (2021a)		UAVs	demand capacity balancing (DCB)	airspace parameters, UAVs parameters, flight distance & speed	A hybrid algorithm (Recurrent Neural Network (RNN) algorithm + Genetic Algorithm (GA))	DCB solutions	A UTM system framework based on an AI algorithm supporting a resilient and flexible DCB process and solution
	Xie et al. (2022)		UAVs		airspace parameters, UAVs parameters, flight plan & routes	A hybrid algorithm (Tabu Search (TS) algorithm + A-star (A*) path planning algorithm)	DCB solutions	An uncertainty-resilient and flexible DCB process and solution framework
	(Lee et al., 2022; Moolchandani et al., 2022)	Dallas/ Fort Worth urban area, US	eVTOLs		flight plan (origin, destination, desired departure time at origin vertiport, and estimated arrival time at destination), vertiport capacity	A DCB algorithm including Strategic Conflict Management Service (SCMS) and Demand-Capacity imBalance Detection service (DCBD)	DCB solutions	A DCB algorithm developed for NASA's demandcapacity imbalance detection and resolution service for UAM
	Huang et al. (2022)		eVTOLs		airspace parameters, UAVs parameters, flight plan & routes	A multi-agent asynchronous advantage actor-critic (MAA3C) framework based on mask recurrent neural networks (RNNs)	DCB solutions	A multi-agent reinforcement learning (MARL) method addressing the strategic conflict issue (DCB) in low-altitude UAM operations
	(P. Wei and Chen, 2021)	New York City (NYC), US	helicopter	DCB parameters selection	airspace parameters, UAVs parameters, flight plan & routes	A simulation algorithm integrating DCB and a rule-based tactical deconfliction	DCB parameters for solution	A simulation selecting DCB parameters (capacity and window size) to strategically precondition UAM operations for DCB solution

(*continued on next page*)

Table 21 (*continued*)

	Literature (Ref.)	Region	Vehicle types	Problem	Input	Model/Method	Output	Summary
	Xie et al. (2021b)		UAVs	analysis of uncertainty factors affecting UAS trajectory conformance for DCB	state data generated by the system decision (active update) and external feedback state data (feedback update)	A hybrid AI algorithm architecture (a Deep Q-Learning Network (DQN) + GA model based on the Gated Recurrent Unit (GRU) architecture)	DCB solutions	A hybrid AI algorithm architecture for efficient and uncertainty-resilient DCB process and solution
dispatching problem	Rajendran (2021)	New York City (NYC), US	air taxi	Allocating and dispatching air taxis dynamically	number of passengers arriving, travel time, air taxi idle time, passenger waiting time, number of air taxis available, etc.	A hybrid simulation goal programming (HSGP) model that can make real-time decisions (an algorithm integrating simulation and goal programming for making real-time dispatching decisions)	real-time decisions on (i) whether the air taxi must become idle or pick up customers, and (ii) the station to which the air taxi should be dispatched if the air taxi is operational	The number of air taxis required to serve the potential customer
vehicle routing problem	Yun et al. (2021)		eVTOL	compute the optimal passenger transportation routes	passenger behaviors, collisions among eVTOL, and eVTOL battery status	A distributed QMIX-based multi-agent deep reinforcement learning (MADRL)	the optimal passenger transportation routes	Method for computing optimal trajectories for UAVs via deep reinforcement learning (DRL)

modeling in Section 4. Lastly, demand promotion based on the UAM demand analysis is an important way to improve the potentiality of UAM operations. Since the UAM applications are just getting started, two strategies to realize such improvement could be raised: 1) increase the attractiveness of UAM by precise positioning of market demand and increasing operational efficiency, and 2) decrease the negative impact on the public to increase public acceptance. Furthermore, specific operational problems need to be explored regarding the development of UAM. As an example, the maintenance scheduling and the pilot training/scheduling problems can be explored based on operational demand estimation (Cohen et al., 2021). Furthermore, other factors that impact UAM operation and management except demand are identified in Table 27. These factors are categorized into safety, capacity, efficiency, and economy.

6.3. *Regulation*

Another crucial element for the successful introduction of Urban Air Mobility (UAM) is appropriate regulation, which includes regulation design, i.e., standards definition, and certification. UAM demand mainly impacts regulation design. Essentially, the regulation of UAM is associated with demand through the entire process of the UAM life cycle, as shown in Fig. 9. Demand impacts the design, construction, operation, and management of the UAM system. Hence, regulation must be in place to govern the operation of the entire UAM system and be appropriately updated to accommodate the development of UAM in each step. Currently, there are discussions about developing consensus standards for UAM globally. While UAV operational restrictions are in effect in several countries, including Australia, Canada, Hong Kong, Japan, Singapore, South Korea, and the United Kingdom, these restrictions, including flight purpose, UAV weight, minimum distance from people and buildings, and altitude limit, can be adopted as references for airspace design and operation for UAM based on demand (J. Cho and Yoon, 2018). Furthermore, the adaptation of existing helicopter regulations to UAM may be a potential direction to develop appropriate regulation for UAM operations. Future research could focus on identifying the most effective regulation design for UAM that considers the impact of UAM demand on the entire UAM system.

7. Discussion and conclusion

For very good reasons, our review of UAM demand studies contains few references to the context in which the wider demand for an aerial urban future will be realized. Cities are very adept at adapting to transport technology. Major technological advancements fundamentally change how humans organize themselves within and between cities. These advancements reshape urban extents, networks for goods, services, people, and energy flow, as well as the size, shape, density distribution, and spatial spread of social products across national, regional, and global city systems.

Predicting the future effects of new technologies on urban environments is as challenging as foreseeing the innovations themselves. Nevertheless, informed conjectures can be made regarding the impact of UAM demand on cities, how cities might adapt to accommodate UAM demand, and how cities may, in turn, influence demand. In truth, cities and transport technologies always co-evolve.

As the railway revolution matured and culminated in an investment bubble, European cities, exemplified by London, underwent significant restructuring. This transformation began with the construction of inbound railway lines originating from various directions, forming a radial pattern of stations that channeled demand from the city's high-density, horse-drawn technology-created central core. These stations were established around the city's periphery, resulting in a necklace of grand stations. Railway trunk routes subsequently carved their way through the informal suburbs that had emerged around urbanized rural villages and along the nascent trunk horse and carriage roadways. Within a

Table 22
Methods in estimation for the operational planning problem.

types	Method/model		Description	Parameters	Advantages	Shortcomings	Suitable application scenarios
on-demand scheduling problem	the alternative simulation algorithm		simulation algorithm determines the best alternative with regards to the three criteria: total delivery time, cost, and pounds of emitted	time, cost, and sustainability	the variability in travel time and cost parameters are considered to make the algorithm more applicable in real-life	limited parameters	determining the best package delivery alternatives
	heuristic algorithm	particle swarm optimization (PSO)	a population-based optimization algorithm: each particle (i.e., candidate solution) moves through the search space with the knowledge of its own (personal) best location and local/global best location	nodes (i.e., vertiports), travel time and cost parameters, seating capacity	easy to implement, is relatively less sensitive to objective functions, has few design parameters, and converges quickly, with Higher Computational Efficiency	more suitable for optimization problems in continuous space, such as trajectory optimization, lower Solution Quality	efficiently searches for (suboptimal) routes
		genetic algorithm (GA)	an evolutionary algorithm that mimics the natural process of evolution and has been widely used for VRP variants		a population-based evolutionary algorithm with binary (or discrete) coded chromosomes, so it can efficiently handle integer programming, such as routing problems, with Higher Solution Quality	lower computational efficiency	
	greedy algorithm (combined with a heuristic algorithm)		the greedy algorithm can fully load vehicles given demand, queue size, and seating capacity	travel demand, queue size, and seating capacity	yield locally optimal solutions that approximate a globally optimal solution in a reasonable amount of time	does not produce an optimal solution	assigns passengers to vehicles, while preserving the feasibility of solutions
	Mixed-integer linear programming (MILP)		a mathematical optimization or feasibility program in which only some of the variables are constrained to be integers, while other variables are allowed to be non-integers.	trip time, cost, distance, number & capacity of vertiports and vehicles, vehicle parameters	the use of integer variables greatly expands the scope of useful optimization problems that you can define and solve	integer variables make an optimization problem non-convex, and therefore far more difficult to solve. Memory and solution time may rise exponentially as you add more integer variables	service and vehicle scheduling in transportation networks
	Recurrent Neural Network (RNN) algorithm		a feedback neural network dealing with time-varying problems in DCB	state data consisting of time series	integrating input airspace states data from environmental feedback states data and actively update states data within the system to enhance the DCB decision model	time consuming, hard to process long sequences	time-varying problems
dispatching problem	hybrid simulation goal programming (HSGP) model		an algorithm integrating simulation and goal programming for making real-time dispatching decisions	number of passengers arriving, travel time, air taxi idle time, passenger waiting time, number of air taxis available, etc.	a simulation-based approach that can handle large-size problems i.e. millions of decision variables, performs significantly better than the existing nearest neighborhood algorithm concerning measures	takes significantly more time to yield the model outputs, computationally more complex	allocate and dispatch air taxis dynamically
vehicle routing problem	QMIX		a distributed multi-agent deep reinforcement learning (MADRL)	passenger behaviors, collisions among eVTOL, and eVTOL battery status	better absolute performance and learning speed, considerable performance gains on a task with heterogeneous agents (compared with IQL and VDN)	it can fail in environments in which an agent's best action is dependent on the actions the other agents take, i.e., in environments in which agents must coordinate at the same timestep	compute the optimal passenger transportation routes

period of approximately two decades, this single speculative development wave irreversibly altered the geography of urban transport demand, which thereafter evolved under its own dynamics.

How might the narrative of UAM unfold? The literature reviewed thus far offers limited conjectures based on currently observable trends. There are some bigger, speculative thoughts in this literature, but typically captured in the discussion and conclusion to individual papers, as in this one. We end our own review paper on this note to help make

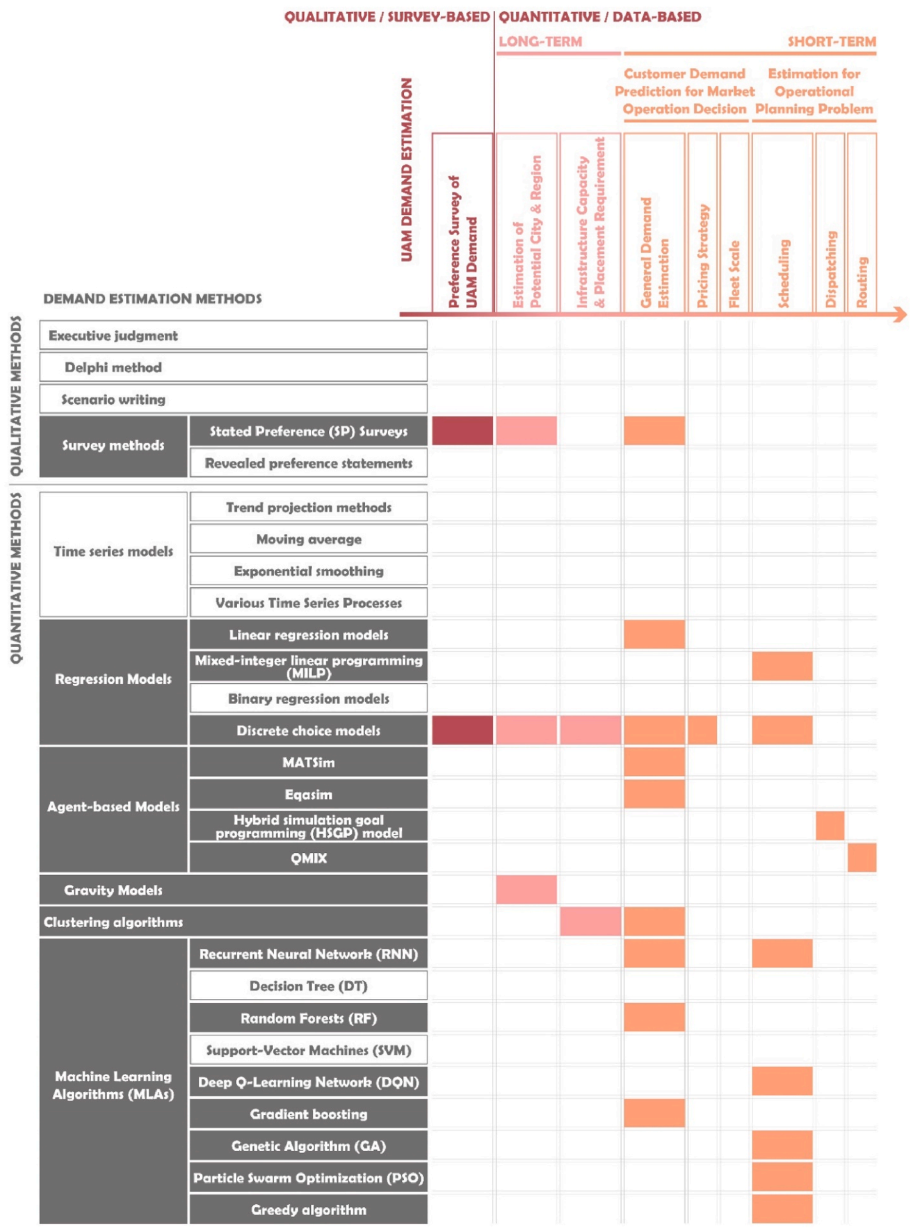

Fig. 7. Qualitative & quantitative methods in UAM demand estimation.

the point that urban transport demand follows technological cycles and sharp discontinuities. UAM will not buck this trend. What may reasonably be predicted in terms of co-evolutionary trends, drawing insights from the papers reviewed?

Similar to trains, buses, and cars, we predict that reserved transportation corridors will play a role in the context of UAM. While they may not be as apparent a solution for UAM as they are for ground-based travel, these corridors can help address various transport externalities associated with urban transportation, such as noise, privacy, safety, demand-supply clearing efficiency, equity, economies of scale, returns to scale, and the spatial organization of jobs and housing. Even if every backyard in a city served as a private UAM station, there would be a need for channeling flight paths to minimize externalities.

Hotelling tells us that clustering of services at central points is a private optimum, while dispersed services are publicly optimal. This dynamic reverses for UAM, as dispersed UAM launch and storage pads are privately optimal as a private transport service. However, they may not be socially optimal in terms of equal access and labor market efficiency. This necessitates local centers, which may or may not coincide with large-scale transport interchange facilities. The optimal private location for such facilities will exhibit clustering, similar to the observed patterns in the 19th-century ring of train stations (e.g., London's Euston and Kings Cross). Consequently, centralized facilities will be more clustered if the market is less regulated, and less clustered if the market is more regulated.

In these ways, we may be able to imagine some of the spatial manifestations of UAM demand in future cities We suggest that there is a rich research agenda at the interface of simulation and speculative thinking about the design and spatial adaptation of future cities to UAM technologies. As we continue to explore the potential of UAM and its implications on urban spaces, it is important to acknowledge the rapid growth in research, industry, and commercial exploration of UAM, alongside the numerous challenges that still hinder safe and stable commercial operation. Several reviews (Bauranov and Rakas, 2021; Cohen et al., 2021; Garrow et al., 2021; Goyal et al., 2021; Polaczyk et al., 2019; Rajendran and Srinivas, 2020; Straubinger et al., 2020; Sun et al., 2021) have provided insights into the fundamental concepts, definitions, and history of UAM, establishing a research framework that

Table 23
Advantages and disadvantages of qualitative & quantitative methods in UAM.

Classification	Advantages	Disadvantages
Qualitative methods	can analyze specific cases	cannot assure a high level of validity and reliability
	can afford an overall examination of complex matters	generalization within a wider context may be dangerous or erroneous
	permit a descriptive approach	the dependence on viewpoints expressed by the analyst and the participants
	frequently used when not much data exists	a long time is usually required
Quantitative methods	accuracy	the complexity of human behavior is difficult to consider
	rationality and eventually causality	not all humans act in the same way
	numerical values	based on the assumption that facts are true and the same for all people all the time
	forecasting ability	may exclude degrees of freedom and choice options
	control at any time of the validity of the relationship between dependent and independent variables	Interference from factors of subjectivity, and depend on the analyst, interpretation techniques, etc.

propels the field forward. Complementing these existing reviews, the present review focuses on the market demand for UAM. It is our hope that this article contributes to the advancement and deepening of UAM understanding, as demand is a crucial factor influencing the field.

In this article, we addressed several questions related to UAM demand, such as the types of demand, factors affecting demand, methods for analyzing demand, and the impact of demand on UAM. To explore these questions, we reviewed UAM applications in Section 3, market demand factors for UAM in Section 4, market demand estimation methods for UAM in Section 5, and the influence of demand on the UAM life cycle in Section 6, respectively. While the design and organization of the review may be considered subjective, it provides a comprehensive overview of UAM demand.

Based on the discussions of issues, gaps, and challenges in the previous sections, several potential research directions in UAM can be identified:

- Air shuttle services may be more feasible in the short term compared to air taxis, which face limitations in infrastructure construction in high-density urban areas. The on-demand characteristics of air taxis can be combined with the shuttle transit characteristics of air metro services to improve efficiency.
- Cargo service is another potential application of UAM, offering advantages such as reduced labor costs and avoiding manned airworthiness certification. However, the potential of UAM cargo service has not been fully explored. Research is needed to investigate the potential applications of unmanned aircraft in cargo service and the advantages and disadvantages of this service compared to traditional cargo transportation modes.
- Public acceptance is a critical factor in the market demand for UAM, and more studies are required to investigate this aspect.
- UAM infrastructure is a research priority, and challenges include infrastructure placement and airspace design in high-density urban areas with complex urban environments that often coincide with high-demand areas. Research is needed to identify the optimal location and design of these facilities to meet the demand for UAM, taking into account factors such as population density, job density, existing noise, and ground-based transport accessibility.
- The integration of UAM with existing transportation modes is crucial for the initial implementation of UAM services. Future research could focus on developing efficient and suitable integrative ways to solve the first and last-mile problem in UAM service.
- Data collection is a significant challenge in UAM demand estimation due to the lack of historical data. Future research could focus on developing novel methods, models, or frameworks that can cover parameters such as urban building environment, public acceptance, and regulation, which are not effectively covered by current methods.

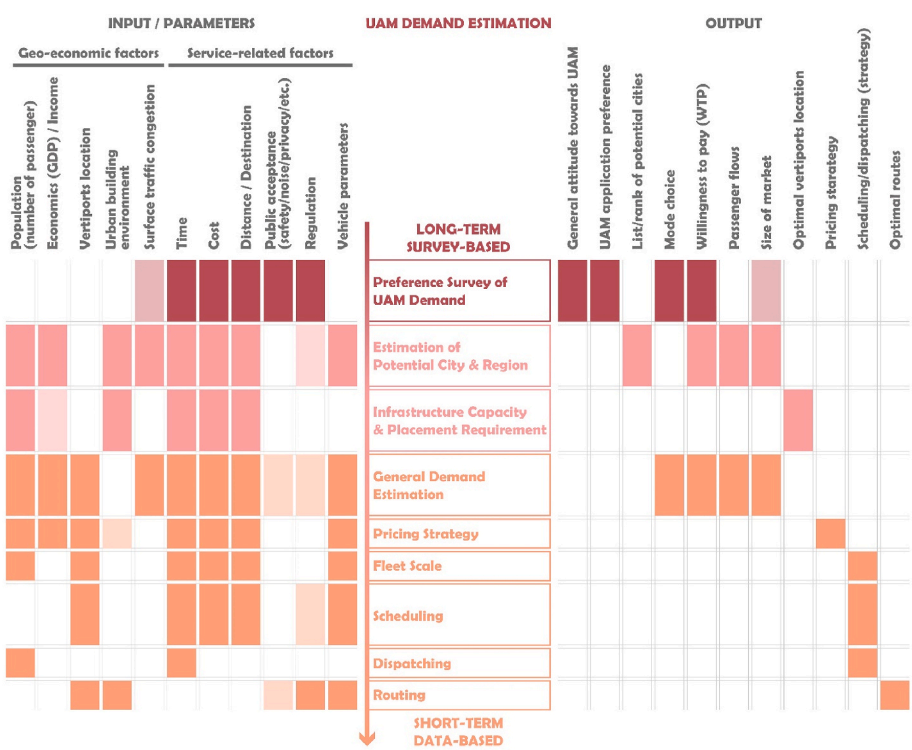

Fig. 8. Input (parameters) & output of UAM demand estimation methods/models.

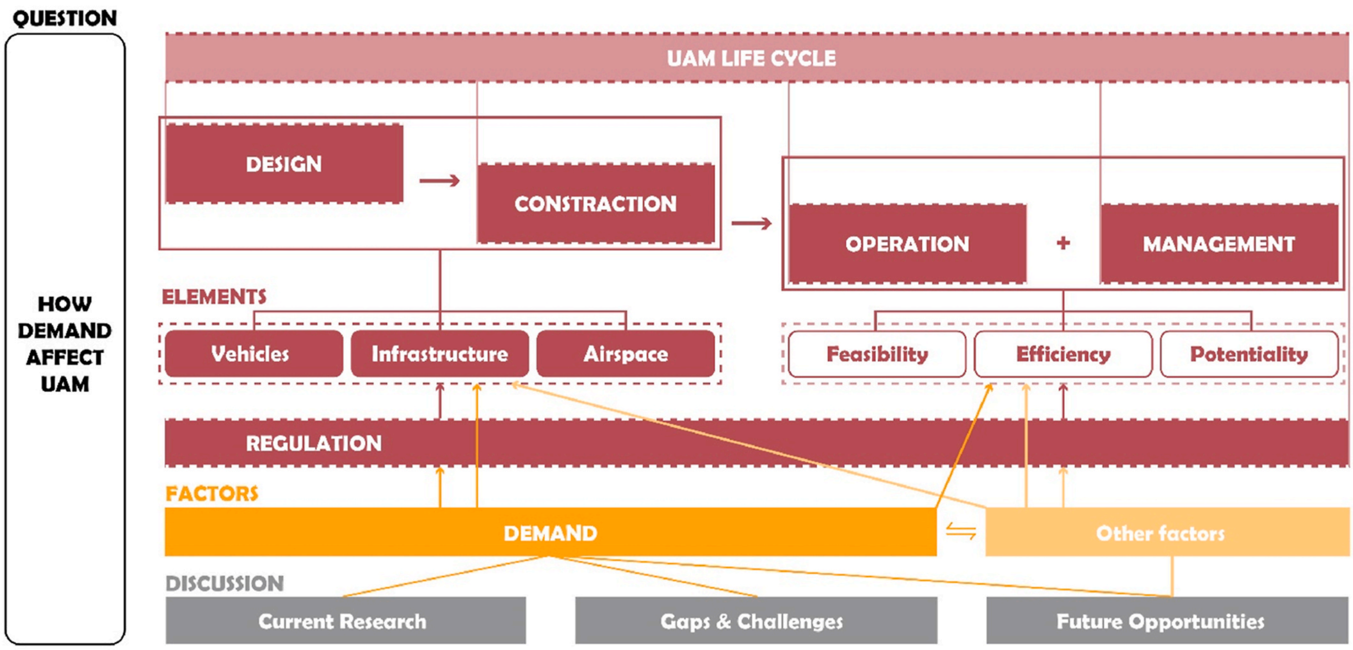

Fig. 9. How demand affects UAM - The life cycle of UAM.

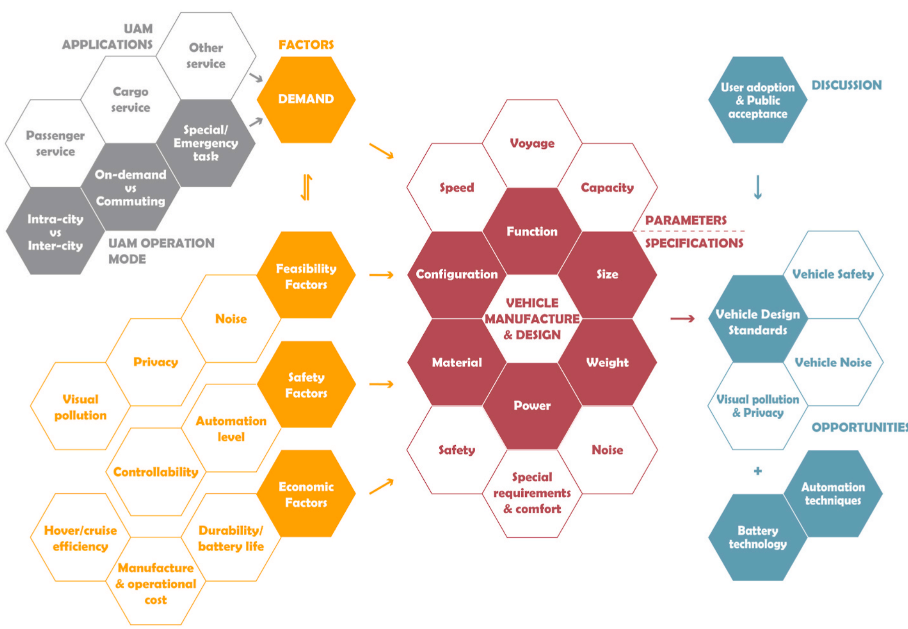

Fig. 10. How demand impacts the UAM vehicles' design and manufacture.

Table 24
Configuration of UAM vertiport/vertistop.

Infrastructure	Configuration
Vertiports	- Vertipads - FATO (Final Approach and Take-Off) - Service facilities: · Parking stands · Terminal · Vehicle maintenance · Communications, navigation, surveillance, and IT infrastructure
Vertistops	- Vertipads - FATO (Final Approach and Take-Off) - Limited-service facilities (optional)

Table 25
Factors impacting UAM infrastructure design and planning (except demand).

Classification	Factors
Environmental factors	- Land availability - Weather condition - Airspace availability - Accessibility
Economic factors	- Land price - Construction cost - Ground handling support convenience
Social factors	- Public acceptance - Noise interval

Table 26
Factors impacting UAM airspace design (except demand).

Classification	Factors
Safety-related factors	- Geofence (impose minimum safety margin of virtual buffer around the obstacle) - Object avoidance - Wind gusts - Weather
Environmental factors	- Noise - Visual pollution
Social factors	- Privacy
Operational factors	- System factors - Vehicles factors

- More research is needed to investigate the potential of machine learning algorithms and agent-based models for UAM demand estimation, as they show great potential in improving the accuracy of demand estimation.

Regarding the issues and challenges identified in the previous sections, this paper presents potential opportunities for future research in UAM across the various stages of the UAM life cycle. In terms of UAM vehicles, several research directions could be pursued, including investigating user adoption and public acceptance of UAM in various urban environments and analyzing the trade-off between vehicle noise and cost of design and manufacture. Additionally, research on vehicle safety, including accident scenario planning, bird strike risk, loss of control, and risk due to wind gusts, is crucial. Furthermore, there is a need for research and discussion about visual pollution and privacy problems, including data usage, rights, anonymization, and de-identification of data collected by aircraft in the urban environment. Finally, developing vehicle technology that fits the demand mentioned above, such as automation techniques and battery technology, is a promising research direction.

Regarding UAM infrastructure, future research could be conducted on various topics, including determining vertiport capacities based on demand analysis, developing models for the vertiport selection problem considering capacity constraints, and infrastructure placement methods considering various demand factors. Additionally, research on the availability of land for large-scale vertiports in high-demand urban areas and multimodal transportation problems is necessary.

In UAM airspace, further research is needed on integrating vehicle to airspace, developing a noise-centered airspace concept design, and studying community input and design, including visual pollution and privacy concerns. Additionally, investigating the impact of ground infrastructure on urban airspace planning, including landing and take-off sites, real estate, zoning, planning issues, inequalities, and air rights, is crucial. Finally, exploring the application of new technologies to airspace management for UAM, such as Sense-and-Avoid or Detect-and-Avoid, is a promising research direction.

In UAM operation and management, future research could be conducted on the feasibility and potentiality of UAM operation modes based on specific demand estimation. Furthermore, investigating the maintenance scheduling problem and the pilot training/scheduling problems based on operational demand estimation is necessary. Finally, developing UAM life cycle operational cost modeling to formulate pricing strategies is a crucial research direction.

Table 27
Factors impacting UAM operation and management (except demand).

Classification	Factors
Safety	
Capacity	- Fleet size - Vehicle configurations - Ride guarantee availability
Efficiency	- Travel time - Access/egress/waiting times - Transfer convenience
Economy	- Travel cost - Operational cost & pricing strategy - Market size

Overall, this paper presents various potential research directions in UAM, which could support the development and implementation of UAM systems in urban environments that meet the demand of users efficiently and sustainably. It is important to acknowledge that most of the literature employed for this review encompasses studies conducted prior to or during the early stages of the COVID-19 pandemic. The pandemic has exerted a profound impact on the transportation sector as a whole. The increasing prevalence of remote work, coupled with a decline in commuting and commercial travel, has introduced considerable uncertainty for the future of air transportation. In conclusion, hopefully, the panorama drawn by this article can help to achieve the ambition of efficient, safe, and stable operation of UAM.

Authorship statement

Conception and design of study: Qi Long, Jun Ma; Drafting the manuscript: Qi Long; revising the manuscript critically for important intellectual content: Qi Long, Jun Ma, Feifeng Jiang, Christopher John Webster. Approval of the version of the manuscript to be published: Qi Long, Jun Ma, Feifeng Jiang, Christopher John Webster.

Declaration of competing interest

No conflict of interest exists in the submission of this manuscript.

Data availability

No data was used for the research described in the article.

Acknowledgements

The authors express their sincere gratitude to the anonymous reviewers for their valuable feedback and constructive criticism that contributed significantly to the improvement of this research work.

References

Advisers, N.E.X.A., 2019. UAM Global Markets Study. NEXA Advisors. https://www.nexaadvisors.com/uam-global-markets-study.

Ahmed, S.S., Fountas, G., Eker, U., Still, S.E., Anastasopoulos, P.C., 2021. An exploratory empirical analysis of willingness to hire and pay for flying taxis and shared flying car services. J. Air Transport. Manag. 90, 101963 https://doi.org/10/gnmtht.

Al Haddad, C., Chaniotakis, E., Straubinger, A., Plötner, K., Antoniou, C., 2020. Factors affecting the adoption and use of urban air mobility. Transport. Res. Pol. Pract. 132, 696–712 https://doi.org/10/ggxp3d.

Anand, A., Kaur, H., Justin, C.Y., Zaidi, T., Mavris, D.N., 2021. A scenario-based evaluation of global urban air mobility demand. In: AIAA Scitech 2021 Forum. American Institute of Aeronautics and Astronautics. https://doi.org/10.2514/6.2021-1516.

Antcliff, K., Moore, M., & Goodrich, K. (2016, June 13). Silicon Valley as an Early Adopter for On-Demand Civil VTOL Operations. https://doi.org/10/ggxp2n.

Arthur, D., Vassilvitskii, S., 2007. k-means++: the Advantages of Careful Seeding, vol. 11.

Aviation, Joby, 2021. Joby Aviation. https://www.jobyaviation.com/.

Balac, M., Rothfeld, R.L., Hörl, S., 2019. The prospects of on-demand urban air mobility in Zurich, Switzerland. In: 2019 *IEEE Intelligent Transportation Systems Conference (ITSC)*, pp. 906–913 https://doi.org/10/gnmth2.

Balakrishnan, K., Polastre, J., Mooberry, J., Golding, R., Sachs, P., 2018. Blueprint for the Sky: the Roadmap for the Safe Integration of Autonomous Aircraft.

Bauranov, A., Rakas, J., 2021. Designing airspace for urban air mobility: a review of concepts and approaches. Prog. Aero. Sci. 125, 100726 https://doi.org/10.1016/j.paerosci.2021.100726.

Bazargan, M., 2010. Airline Operations and Scheduling, second ed. Ashgate.

Becker, K., Terekhov, I., Gollnick, V., 2018. A Global Gravity Model for Air Passenger Demand between City Pairs and Future Interurban Air Mobility Markets Identification. https://doi.org/10.2514/6.2018-2885.

Binder, R., Garrow, L.A., German, B., Mokhtarian, P., Daskilewicz, M., Douthat, T.H., 2018. If you fly it, will commuters come?. In: A Survey to Model Demand for eVTOL Urban Air Trips. In *2018 Aviation Technology, Integration, and Operations Conference*.

American Institute of Aeronautics and Astronautics. https://doi.org/10.2514/6.2018-2882.
BLADE, 2021. Fly the Future Today—BLADE. https://www.blade.com/airport.
Boddupalli, S.-S., 2019. *Estimating Demand for an Electric Vertical Landing and Takeoff (eVTOL) Air Taxi Service Using Discrete Choice Modeling* [Thesis. Georgia Institute of Technology. https://smartech.gatech.edu/handle/1853/61811.
Bulusu, V., Onat, E.B., Sengupta, R., Yedavalli, P., Macfarlane, J., 2021. A traffic demand analysis method for urban air mobility. IEEE Trans. Intell. Transport. Syst. 22 (9), 6039–6047 https://doi.org/10/gm8g84.
Carlson, J., 2019. In: 1977 Five Were Killed in Helicopter Accident Atop Midtown's Pan Am Building. https://gothamist.com/news/in-1977-five-were-killed-in-helicopter-accident-atop-midtowns-pan-am-building.
Cho, S.-H., Kim, M., 2022. Assessment of the environmental impact and policy responses for urban air mobility: a case study of Seoul metropolitan area. J. Clean. Prod. 360, 132139 https://doi.org/10.1016/j.jclepro.2022.132139.
Cho, J., Yoon, Y., 2018. How to assess the capacity of urban airspace: a topological approach using keep-in and keep-out geofence. Transport. Res. C Emerg. Technol. 92, 137–149. https://doi.org/10.1016/j.trc.2018.05.001.
Cohen, A.P., Shaheen, S.A., Farrar, E.M., 2021. Urban air mobility: history, ecosystem, market potential, and challenges. IEEE Trans. Intell. Transport. Syst. 22 (9), 6074–6087 https://doi.org/10/gm3qs5.
Davis, N., Raina, G., Jagannathan, K., 2018. Taxi demand forecasting: a HEDGE-based tessellation strategy for improved accuracy. IEEE Trans. Intell. Transport. Syst. 19 (11), 3686–3697. https://doi.org/10.1109/TITS.2018.2860925.
Du, W., Guo, T., Chen, J., Li, B., Zhu, G., Cao, X., 2021. Cooperative pursuit of unauthorized UAVs in urban airspace via Multi-agent reinforcement learning. Transport. Res. C Emerg. Technol. 128, 103122 https://doi.org/10/gjwfxn.
EASA, 2018. Certification Specifications and Guidance Material for the Design of Surface-Level VFR Heliports. *located at aerodromes that fall under the scope of Regulation (EU) 2018/1139*. https://www.easa.europa.eu/downloads/97998/en.
EASA, 2021. Urban Air Mobility (UAM). https://www.easa.europa.eu/domains/urban-air-mobility-uam.
FAA, 2019. *UAS Integration Pilot Program*. UAS Integration Pilot Program. https://www.faa.gov/uas/programs_partnerships/completed/integration_pilot_program/.
Fadhil, D.N., Moeckel, R., Rothfeld, R., 2019. GIS-Based infrastructure requirement analysis for an electric vertical take-off and landing vehicle-based transportation system. Transport. Res. Procedia 41, 101–103. https://doi.org/10.1016/j.trpro.2019.09.020.
Fink, A., 2002. How to Ask Survey Questions. SAGE.
Fuel Cells Bulletin, 2020. DMI fuel cell drone delivers face masks to remote Korean islands. Fuel Cell. Bull. 2020 (5), 5–6. https://doi.org/10.1016/S1464-2859(20)30188-7.
Garrow, L.A., German, B., Mokhtarian, P., Glodek, J., 2019. A survey to model demand for eVTOL urban air trips and competition with autonomous ground vehicles. In: AIAA Aviation 2019 Forum. AIAA Aviation 2019 Forum, Dallas, Texas. https://doi.org/10.2514/6.2019-2871.
Garrow, L.A., German, B.J., Leonard, C.E., 2021. Urban air mobility: a comprehensive review and comparative analysis with autonomous and electric ground transportation for informing future research. Transport. Res. C Emerg. Technol. 132, 103377 https://doi.org/10/gnb5h9.
Gipson, L., 2019. *Advanced Air Mobility (AAM)* [Text]. NASA. http://www.nasa.gov/aam.
Goyal, R., Reiche, C., Fernando, C., Serrao, J., Kimmel, S., Cohen, A., Shaheen, S., 2018. *Urban Air Mobility (UAM) Market Study* (HQ-E-DAA-TN65181). https://ntrs.nasa.gov/citations/20190001472.
Goyal, R., Reiche, C., Fernando, C., Cohen, A., 2021. Advanced air mobility: demand analysis and market potential of the airport shuttle and air taxi markets. Sustainability 13 (13). Article 13, https://doi.org/10/gnhqwh.
Graydon, M., Neogi, N.A., Wasson, K., 2020. Guidance for designing safety into urban air mobility: hazard analysis techniques. In: AIAA Scitech 2020 Forum. AIAA Scitech 2020 Forum, Orlando, FL. https://doi.org/10.2514/6.2020-2099.
Guerreiro, N.M., Hagen, G.E., Maddalon, J.M., Butler, R.W., 2020. Capacity and throughput of urban air mobility vertiports with a first-come, first-served vertiport scheduling algorithm. In: AIAA AVIATION 2020 FORUM. American Institute of Aeronautics and Astronautics. https://doi.org/10.2514/6.2020-2903.
Haan, J., Garrow, L.A., Marzuoli, A., Roy, S., Bierlaire, M., 2021. Are commuter air taxis coming to your city? A ranking of 40 cities in the United States. Transport. Res. C Emerg. Technol. 132, 103392 https://doi.org/10/gnmthp.
Harrison, S., 2017. Los Angeles Airways Helicopter Overturns. The Los Angeles Times. March 10. https://www.latimes.com/visuals/photography/la-me-fw-archives-airways-helicopter-overturn-20170221-story.html.
Heliservices, 2021. Customized Flight. Heliservices HK Ltd. http://heliservices.com.hk/en/customised/.
Huang, C., Petrunin, I., Tsourdos, A., 2022. Strategic conflict management for performance-based urban air mobility operations with multi-agent reinforcement learning. In: 2022 International Conference on Unmanned Aircraft Systems (ICUAS), pp. 442–451. https://doi.org/10.1109/ICUAS54217.2022.9836139.
Ilahi, A., Belgiawan, P.F., Balac, M., Axhausen, K.W., 2021. Understanding travel and mode choice with emerging modes; a pooled SP and RP model in Greater Jakarta, Indonesia. Transport. Res. Pol. Pract. 150, 398–422 https://doi.org/10/gnmthj.
Jiang, S., Chen, W., Li, Z., Yu, H., 2019. Short-term demand prediction method for online car-hailing services based on a least squares support vector machine. IEEE Access 7, 11882–11891. https://doi.org/10.1109/ACCESS.2019.2891825.
Justin, C., Payan, A., Mavris, D., 2021. Demand Modeling and Operations Optimization for Advanced Regional Air Mobility https://doi.org/10/gnz7q2.
Kim, S.H., 2020. Receding horizon scheduling of on-demand urban air mobility with heterogeneous fleet. IEEE Trans. Aero. Electron. Syst. 56 (4), 2751–2761 https://doi.org/10/ghdk38.
Kirschstein, T., 2020. Comparison of energy demands of drone-based and ground-based parcel delivery services. Transport. Res. Transport Environ. 78, 102209 https://doi.org/10.1016/j.trd.2019.102209.
Kleinbekman, I.C., Mitici, M.A., Wei, P., 2018. EVTOL arrival sequencing and scheduling for on-demand urban air mobility. In: 2018 *IEEE/AIAA 37th Digital Avionics Systems Conference (DASC)*, pp. 1–7 https://doi.org/10/gnmthw.
Kleinbekman, I.C., Mitici, M., Wei, P., 2020. Rolling-horizon electric vertical takeoff and landing arrival scheduling for on-demand urban air mobility. J. Aero. Inf. Syst. 17 (3), 150–159 https://doi.org/10/gm6f5t.
Krull, L.F., Muhammad, B., 2022. Urban Air Mobility: Insights into Potentials and Challenges. *2022 25th International Symposium On Wireless Personal Multimedia Communications*. WPMC), pp. 267–272. https://doi.org/10.1109/WPMC55625.2022.10014836.
Lee, H., Moolchandani, K.A., Arneson, H., 2022. Demand capacity balancing at vertiports for initial strategic conflict management of urban air mobility operations. In: 2022 *IEEE/AIAA 41st Digital Avionics Systems Conference (DASC)*, pp. 1–10. https://doi.org/10.1109/DASC55683.2022.9925753.
Lidynia, C., Philipsen, R., Ziefle, M., 2017. Droning on about drones—acceptance of and perceived barriers to drones in civil usage contexts. In: Savage-Knepshield, P., Chen, J. (Eds.), Advances in Human Factors in Robots and Unmanned Systems. Springer International Publishing, pp. 317–329. https://doi.org/10.1007/978-3-319-41959-6_26.
Likert, R., 1932. A technique for the measurement of attitudes. Arch. Psychol. 22 140, 55–55.
Lilium Air Mobility, 2021. Lilium Air Mobility - Lilium. https://lilium.com/.
Luo, H., Cai, J., Zhang, K., Xie, R., Zheng, L., 2021. A multi-task deep learning model for short-term taxi demand forecasting considering spatiotemporal dependences. J. Traffic Transport. Eng. 8 (1), 83–94. https://doi.org/10.1016/j.jtte.2019.07.002.
Masson, R., Lehuédé, F., Péton, O., 2014. The dial-A-ride problem with transfers. Comput. Oper. Res. 41, 12–23. https://doi.org/10.1016/j.cor.2013.07.020.
Mayakonda, M., Justin, C.Y., Anand, A., Weit, C.J., Wen, J., Zaidi, T., Mavris, D., 2020. A top-down methodology for global urban air mobility demand estimation. In: AIAA AVIATION 2020 FORUM. American Institute of Aeronautics and Astronautics. https://doi.org/10.2514/6.2020-3255.
Mayor, T., Anderson, J., 2019. Urban Air Mobility, vol. 12.
McAlexander, T.P., Gershon, R.R., Neitzel, R.L., 2015. Street-level noise in an urban setting: assessment and contribution to personal exposure. Environ. Health 14 (1), 18. https://doi.org/10.1186/s12940-015-0006-y.
Moolchandani, K.A., Lee, H., Arneson, H., Cheng, A., 2022. A data analysis approach for simulations of urban air mobility operations. In: 2022 *IEEE/AIAA 41st Digital Avionics Systems Conference (DASC)*, pp. 1–7. https://doi.org/10.1109/DASC55683.2022.9925864.
Moreira-Matias, L., Gama, J., Ferreira, M., Mendes-Moreira, J., Damas, L., 2013. Predicting taxi–passenger demand using streaming data. IEEE Trans. Intell. Transport. Syst. 14 (3), 1393–1402. https://doi.org/10.1109/TITS.2013.2262376.
Murça, M.C.R., 2021. Identification and prediction of urban airspace availability for emerging air mobility operations. Transport. Res. C Emerg. Technol. 131, 103274 https://doi.org/10/gnmthm.
Ortúzar, J. de D., Willumsen, L.G., 2011. Modelling Transport, fourth ed. Wiley. 4th Edition. https://www.wiley.com/en-us/Modelling+Transport%2C+4th+Edition-p-9780470760390.
Ozkan, O., Atli, O., 2021. Transporting COVID-19 testing specimens by routing unmanned aerial vehicles with range and payload constraints: the case of Istanbul. Transportation Letters 13 (5–6), 482–491. https://doi.org/10.1080/19427867.2021.1896063.
Pant, Y.V., Li, M.Z., Rodionova, A., Quaye, R.A., Abbas, H., Ryerson, M.S., Mangharam, R., 2021. FADS: a framework for autonomous drone safety using temporal logic-based trajectory planning. Transport. Res. C Emerg. Technol. 130, 103275 https://doi.org/10/gnmthr.
Patterson, M.D., Antcliff, K.R., Kohlman, L.W., 2018. A Proposed Approach to Studying Urban Air Mobility Missions Including an Initial Exploration of Mission Requirements, vol. 19.
Peng, X., Bulusu, V., Sengupta, R., 2022. Hierarchical vertiport network design for on-demand multi-modal urban air mobility. In: 2022 *IEEE/AIAA 41st Digital Avionics Systems Conference (DASC)*, pp. 1–8. https://doi.org/10.1109/DASC55683.2022.9925782.
Polaczyk, N., Trombino, E., Wei, P., Mitici, M.A., 2019. A Review of Current Technology and Research in Urban On-Demand Air Mobility Applications. *8th Biennial Autonomous VTOL Technical Meeting and 6th Annual Electric VTOL Symposium 2019*. https://repository.tudelft.nl/islandora/object/uuid%3A10d1c68a-dfb9-4419-a912-26e6c1742853.
Pons-Prats, J., Živojinović, T., Kuljanin, J., 2022. On the understanding of the current status of urban air mobility development and its future prospects: commuting in a flying vehicle as a new paradigm. Transport. Res. E Logist. Transport. Rev. 166, 102868 https://doi.org/10.1016/j.tre.2022.102868.
Preis, L., Hornung, M., 2022. *Identification of driving Processes for vertiport operations using agent-based simulation | AIAA SCITECH 2022 forum* (world). In: AIAA SciTech Forum. https://doi.org/10.2514/6.2022-0215.
Profillidis, V.A., Botzoris, G.N., 2019. Chapter 4—executive judgment, delphi, scenario writing, and survey methods. In: Profillidis, V.A., Botzoris, G.N. (Eds.), Modeling of Transport Demand. Elsevier, pp. 125–161. https://doi.org/10.1016/B978-0-12-811513-8.00004-2.

Rajendran, S., 2021. Real-time dispatching of air taxis in metropolitan cities using a hybrid simulation goal programming algorithm. Expert Syst. Appl. 178, 115056 https://doi.org/10/gnmthn.

Rajendran, S., Harper, A., 2021. Simulation-based algorithm for determining best package delivery alternatives under three criteria: time, cost and sustainability. Transp. Res. Interdiscip. Perspect. 12, 100484 https://doi.org/10/gnpqx3.

Rajendran, S., Shulman, J., 2020. Study of emerging air taxi network operation using discrete-event systems simulation approach. J. Air Transport. Manag. 87, 101857 https://doi.org/10/gnmthk.

Rajendran, S., Srinivas, S., 2020. Air taxi service for urban mobility: a critical review of recent developments, future challenges, and opportunities. Transport. Res. E Logist. Transport. Rev. 143, 102090 https://doi.org/10/gmt955.

Rajendran, S., Zack, J., 2019. Insights on strategic air taxi network infrastructure locations using an iterative constrained clustering approach. Transport. Res. E Logist. Transport. Rev. 128, 470–505 https://doi.org/10/gm6fs5.

Rajendran, S., Srinivas, S., Grimshaw, T., 2021. Predicting demand for air taxi urban aviation services using machine learning algorithms. J. Air Transport. Manag. 92, 102043 https://doi.org/10/gmw5s8.

Rath, S., Chow, J.Y.J., 2022. Air taxi skyport location problem with single-allocation choice-constrained elastic demand for airport access. J. Air Transport. Manag. 105, 102294 https://doi.org/10.1016/j.jairtraman.2022.102294.

Rimjha, M., Hotle, S., Trani, A., Hinze, N., 2021a. Commuter demand estimation and feasibility assessment for urban air mobility in northern California. Transport. Res. Pol. Pract. 148, 506–524 https://doi.org/10/gjwgk3.

Rimjha, M., Hotle, S., Trani, A., Hinze, N., Smith, J.C., 2021b. Urban Air Mobility Demand Estimation for Airport Access: A Los Angeles International Airport Case Study. *2021 Integrated Communications Navigation And Surveillance Conference (ICNS)*, 1–15 https://doi.org/10/gkrg6g.

Rimjha, M., Hotle, S., Trani, A., Hinze, N., Smith, J., Dollyhigh, S., 2021c. Urban Air Mobility: Airport Ground Access Demand Estimation. AIAA AVIATION 2021 FORUM. https://doi.org/10.2514/6.2021-3209.

Robinson, J.N., Sokollek, M.-D., Justin, C.Y., Mavris, D.N., 2018. Development of a Methodology for Parametric Analysis of STOL Airpark Geo-Density. https://smartech.gatech.edu/handle/1853/61916.

Rothfeld, R., Straubinger, A., Fu, M., Al Haddad, C., Antoniou, C., 2020. Chapter 13—urban air mobility. In: Antoniou, C., Efthymiou, D., Chaniotakis, E. (Eds.), Demand for Emerging Transportation Systems. Elsevier, pp. 267–284. https://doi.org/10.1016/B978-0-12-815018-4.00013-9.

Roy, S., Herniczek Kotwicz, M.T., Leonard, C., Jha, A., Wang, N., German, B., Garrow, L., 2020. A multi-commodity network flow approach for optimal flight schedules for an airport shuttle air taxi service. In: AIAA Scitech 2020 Forum. American Institute of Aeronautics and Astronautics. https://doi.org/10.2514/6.2020-0975.

Salama, M., Srinivas, S., 2020. Joint optimization of customer location clustering and drone-based routing for last-mile deliveries. Transport. Res. C Emerg. Technol. 114, 620–642. https://doi.org/10.1016/j.trc.2020.01.019.

Sinha, A.A., Rajendran, S., 2021. A novel two-phase location analytics model for determining operating station locations of emerging air taxi services. Decision Anal. J., 100013 https://doi.org/10/gnmthh.

Straubinger, A., Rothfeld, R., Shamiyeh, M., Büchter, K.-D., Kaiser, J., Plötner, K.O., 2020. An overview of current research and developments in urban air mobility – setting the scene for UAM introduction. J. Air Transport. Manag. 87, 101852 https://doi.org/10/gmvfv9.

Straubinger, A., Helmchen, F., Ploetner, K.O., Kaiser, J., 2021. Proposing a scenario-based estimation of global urban air mobility demand. In: AIAA AVIATION 2021 FORUM. American Institute of Aeronautics and Astronautics. https://doi.org/10.2514/6.2021-3207.

Sun, X., Wandelt, S., Husemann, M., Stumpf, E., 2021. Operational considerations regarding on-demand air mobility: a literature review and research challenges. J. Adv. Transport. 2021, e3591034 https://doi.org/10/gngftn.

Tarafdar, S., Rimjha, M., Hinze, N., Hotle, S., Trani, A.A., 2019. Urban Air Mobility Regional Landing Site Feasibility and Fare Model Analysis in the Greater Northern California Region. *2019 Integrated Communications, Navigation And Surveillance Conference (ICNS)*, 1–11 https://doi.org/10/gnmth4.

Transport Bureau of Shenzhen, 2021. 深圳开通国内首条民航客运与直升机运输接驳航线. http://jtys.sz.gov.cn/jtzx/wycx/fjcx/cxtx/content/post_8639137.html.

Volocopter, 2021. Volocopter. https://www.volocopter.com/.

Wai, C.W., Tan, K., Low, K.H., 2021. Preliminary study of transport pattern and demand in Singapore for future urban air mobility. In: AIAA Scitech 2021 Forum. American Institute of Aeronautics and Astronautics. https://doi.org/10.2514/6.2021-1633.

Wei, P., Chen, S., 2021. Estimating airspace resource capacity for advanced air mobility operations. In: AIAA AVIATION Forum. https://arc-aiaa-org.eproxy.lib.hku.hk/doi/10.2514/6.2022-3317.

Wei, L., Justin, C.Y., Mavris, D.N., 2020. Optimal placement of airparks for STOL urban and suburban air mobility. In: AIAA Scitech 2020 Forum. American Institute of Aeronautics and Astronautics. https://doi.org/10.2514/6.2020-0976.

Wei, Q., Nilsson, G., Coogan, S., 2021. Scheduling of Urban Air Mobility Services with Limited Landing Capacity and Uncertain Travel Times. *2021 American Control Conference (ACC)*, 1681–1686 https://doi.org/10/gnmthv.

Weiner, E., 1997. Urban Transportation Planning in the United States: an Historical Overview. U.S. Department of Transportation.

Winter, S.R., Rice, S., Lamb, T.L., 2020. A prediction model of Consumer's willingness to fly in autonomous air taxis. J. Air Transport. Manag. 89, 101926 https://doi.org/10/gnb3sz.

Witken, R., 1979. New York Airways Acts to File for Bankruptcy. The New York Times. https://www.nytimes.com/1979/05/16/archives/new-york-airways-acts-to-file-for-bankruptcy-suing-sikorsky.html.

Wolfe, P.J., Malina, R., Barrett, S.R.H., Waitz, I.A., 2016. Costs and benefits of US aviation noise land-use policies. Transport. Res. Transport Environ. 44, 147–156. https://doi.org/10.1016/j.trd.2016.02.010.

Wu, Z., Zhang, Y., 2020. Optimal eVTOL charging and passenger serving scheduling for on-demand urban air mobility. In: AIAA AVIATION 2020 FORUM. American Institute of Aeronautics and Astronautics. https://doi.org/10.2514/6.2020-3253.

Wu, Z., Zhang, Y., 2021. Integrated network design and demand forecast for on-demand urban air mobility. Engineering 7 (4), 473–487 https://doi.org/10/gmvf26.

Xie, Y., Gardi, A.G., Sabatini, R., 2021a. Hybrid AI-based demand-capacity balancing for UAS traffic management and urban air mobility. In: AIAA AVIATION 2021 FORUM. https://doi.org/10.2514/6.2021-2325.

Xie, Y., Gardi, A., Sabatini, R., 2021b. Reinforcement learning-based flow management techniques for urban air mobility and dense low-altitude air traffic operations. In: 2021 *IEEE/AIAA 40th Digital Avionics Systems Conference (DASC)*, pp. 1–10. https://doi.org/10.1109/DASC52595.2021.9594384.

Xie, Y., Gardi, A., Sabatini, R., Liang, M., 2022. Hybrid AI-based dynamic Re-routing method for dense low-altitude air traffic operations. In: 2022 *IEEE/AIAA 41st Digital Avionics Systems Conference (DASC)*, pp. 1–9. https://doi.org/10.1109/DASC55683.2022.9925777.

Yun, W.J., Jung, S., Kim, J., Kim, J.-H., 2021. Distributed deep reinforcement learning for autonomous aerial eVTOL mobility in drone taxi applications. ICT Expr. 7 (1), 1–4 https://doi.org/10/gnpqx4.