A66 Develop Methodologies to Inform the Integration of Advanced Air Mobility (AAM) into the NAS

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TABLE OF CONTENTS

TABLE OF ACRONYMS

AAM	Advanced Air Mobility
ASSURE	Alliance of System Safety for UAS through Research Excellence
ATP	Airline Transport Pilot
CBD	Central Business District
CFR	Code of Federal Regulations
CSA	Combined Statistical Areas
eVTOL	electric Vertical Take-off and Landing
FAA	Federal Aviation Administration
GDP	Gross Domestic Product
GRP	Gross Region Product
I28	Innovate28
MSA	Metropolitan Statistical Area
NAS	National Airspace System
O&D	Origin-Destination
OEM	Original Equipment Manufacturer
OpSpecs	Operational Specifications
SMART	Simple Multi-Attribute Rating Technique
TAF	Terminal Area Forecast
TAF-L	Terminal Area Forecast – Legacy
TAF-M	Terminal Area Forecast – Modernized
TAF-M2	Terminal Area Forecast – Modernized 2
TTI	Travel Time Index
UAM	Urban Air Mobility

EXECUTIVE SUMMARY

This report presents the development and implementation of a reproducible modeling framework to forecast the integration of Advanced Air Mobility (AAM) into the National Airspace System (NAS). Building on prior work, the project refined the ASSURE A36 metropolitan ranking methodology by updating datasets and incorporating new variables to identify the most suitable Combined Statistical Areas (CSAs) for AAM/Urban Air Mobility (UAM) deployment prior to developing a methodology assessing the potential impact of Part 135 AAM/UAM transportation on enplanement shifts within metropolitan areas. In developing a methodology to assess how Part 135 AAM/UAM transportation integration would influence potential enplanement shifts within metropolitan areas, a three-phase approach was used to develop a Terminal Area Forecast – Modernized 2 (TAF-M2) model: 1) establish baseline enplanement forecasts; 2) model enplanement shifts due to AAM/UAM using a nested logit framework; and 3) produce revised 25-year forecasts through a forward induction method. The methodology was operationalized using Python scripts to process data, estimate parameters, and forecast annual enplanements across six CSAs. The result is a flexible data-driven toolset for assessing the future impact of AAM/UAM services on airport demand and supporting informed planning and policy decisions.

INTRODUCTION

This final report summarizes the key deliverables from critical subtasks of the A66 FAA project, which aims to develop and integrate a comprehensive Advanced Air Mobility (AAM) and Urban Air Mobility (UAM) Transportation Integration Forecast Methodology into a Terminal Area Forecast -Modernized 2 (TAF-M2) model.

The first step of the project involved reviewing the existing literature and data sources to identify components suitable for an AAM/UAM metropolitan ranking methodology, then proposing an algorithm for AAM/UAM metropolitan ranking. As a result, the project team produced a list of target CSAs for potential analyses in the later process. The second step involved developing the A66 AAM/UAM Transportation Integration Forecast Methodology capable of estimating how AAM/UAM integration might affect Part 121 commercial enplanement shifts within metropolitan areas. This included producing conceptual data flows, equations and assumptions. The third step involved creating Python scripts to implement the full A66 AAM/UAM Transportation Integration Forecast Methodology for the selected CSAs, generating transportation mode utility parameters, airport utility coefficients, and heterogeneity parameters for the proposed TAF-M2 model. The final step included executing the TAF-M2 model with utility parameters and additional data files to produce a 25-year forecast of enplanements in each airport within the six selected CSAs.

REVIEW AND EXPANSION OF A36 METROPOLITAN RANKING METHODOLOGY

2.1 Literature and Data Review

AAM and UAM represent transformative advancements in metropolitan transportation, offering a promising solution to the pressing challenges of urban congestion, pollution, and systemic inefficiencies of existing urban transport systems (Goyal, 2018). By integrating sophisticated air-based transport solutions - such as drones, air taxis, and other electric Vertical Take-Off and Landing (eVTOL) vehicles - into existing transportation frameworks, Part 135 AAM/UAM transportation services aim to redefine urban and regional transportation landscapes (Garrow, 2022; Goyal, 2021).

As urbanization intensifies globally, metropolitan areas face escalating transportation challenges. Traditional ground transportation systems are increasingly strained under the weight of rising populations, leading to traffic congestion and environmental degradation (Lu et al., 2021). Part 135 AAM/UAM transportation services offer innovative solutions to these issues by utilizing vertical airspace, reducing ground traffic congestion and enhancing the sustainability of urban and regional transport systems. The adoption of these technologies promises to improve urban mobility, reduce travel times, and decrease pollution levels, enhancing the overall quality of urban life (Haritos et al., 2023; Mahmassani et al., 2024).

However, an appropriately developed site suitability analysis is critical to the successful implementation of AAM/UAM technologies. Not all urban areas are equally prepared for implementation of Part 135 AAM/UAM transportation services in terms of existing infrastructure, regulatory frameworks, and public acceptance (Haan et al., 2021; Long et al., 2023). The existing infrastructure, economic environment, and regulator landscape of a metropolitan area significantly impacts the feasibility of deploying Part 135 AAM/UAM transportation services. Furthermore, environmental considerations, such as air quality improvement and noise pollution reduction, play a pivotal role in determining suitable locations for implementing these technologies (Thomas, 2023; Reiche et al. 2018).

This literature review explores existing methodologies used to rank metropolitan areas based on potential for implementation and expansion of Part 135 AAM/UAM transportation services. Such ranking methodologies provide crucial information to stakeholders (e.g., city planners, policymakers, private sector leaders) seeking to identify suitable locations for feasible deployment of these technologies (Asmer et al., 2024; Goyal et al., 2021). By examining the various frameworks, models, and factors previously used to assess viable implementation of Part 135 AAM/UAM transportation services across different urban and regional contexts, this review notes the state of contemporary research, highlighting key site suitability characteristics such as urban structure, economic scale, ground traffic congestion levels, travel time indicators, market readiness, existing short-haul markets, and social acceptance of AAM/UAM technologies (, 2023; Haritos et al., 2023; Olivares et al., 2022). In doing so, this review offers valuable insights pertaining to the strengths and limitations of each methodology, as well as feasible inclusion of specific site suitability characteristics. This process guided the selection of appropriate strategies for the A66 project.

2.1.1 AAM/UAM Overview

Ground traffic congestion is a growing problem in the United States. In 2022, total travel delays amounted to 8.5 billion hours, costing approximately $224 billion in lost revenue and wasted fuel consumption – an increase of approximately 4.7 times the amount of the total travel delay from 1982 (Texas A&M Transportation Institute, 2023). Moreover, congestion-related delays have increased to seven times the 1982 levels in urban areas with populations under 500,000 individuals (Texas A&M Transportation Institute, 2023). According to the INRIX 2023 Global Traffic Report, the US contains four of the top ten cities in the world with the highest amount of traffic delays: a) New York City; b) Chicago; c) Los Angeles; and d) Boston (INRIX, 2023). In response to the challenges associated with ever increasing ground traffic congestion, AAM/UAM technologies are being proposed as the optimized solution to enhance urban and regional mobility to and from nearby airports, thereby reducing the ground traffic congestion caused by airport related transportation. As part of the broader aerospace and transportation industries, innovations in AAM/UAM technology have been driven by the ambition to revolutionize transportation of people and goods across diverse landscapes (Pak et al., 2024). While UAM primarily focuses on intra-city travel utilizing eVTOL vehicles, AAM seeks to expand this scope to include intra-regional travel, potentially connecting adjacent cities and rural areas (FAA, 2023b).

2.1.1.1 Regulatory Framework for AAM/UAM Operations

To facilitate the integration of AAM/UAM technologies into the National Airspace System (NAS), the FAA has developed the Innovate28 (I28) initiative which aims to establish integrated AAM operations with Original Equipment Manufacturers (OEMs) and/or operators flying between multiple origin and destination locations by 2028 (FAA, 2023a). This detailed implementation plan outlines a replicable methodology which will be updated periodically to reflect the continued plans and progress of AAM integration as work continues to advance towards the mature state vision of AAM operations across the NAS. The near-term I28 initiative addresses key site operations, workstreams, an integrated master schedule, and an AAM evolution framework. In doing so, the FAA details the regulatory and operational milestones that must be achieved to safely and efficiently integrate AAM into the NAS. To date, the FAA regulates AAM/UAM services in accordance with Title 14 Code of Federal Regulations (CFR) Part 135, Part 141, and Part 145.

2.1.1.2 Title 14 CFR Part 135 Air Carrier and Operator Certification

Title 14 CFR Part 135 Air Carrier and Operator Certification regulations provide an in-depth guide for operators seeking certification to conduct on-demand and scheduled air services. The certification process is divided into five phases: pre-application, formal application, document compliance, demonstration, and inspection. Each phase ensures that operators meet the FAA's strict safety, maintenance, and operational standards (FAA, 2024b).

The Part 135 certification process is crucial for operators who wish to conduct on-demand or scheduled air services. Applicants must determine the type, kind, and scope of operations before starting the certification process, familiarizing themselves with the necessary equipment, facilities, personnel, manuals, and programs required for compliance. Part 135 certificates come in various types, including Air Carrier and Operating certificates, each with specific operational limitations based on aircraft size, passenger capacity, and the scope of operations, such as single-pilot or single pilot-in-command operations (FAA, 2023c).

There are different operational authorities within Part 135 certification, like On-demand and Commuter operations, each with its own restrictions on the number of passenger seats, aircraft size, and geographical areas of operation. The scope of operations is further defined by the FAA through Operations Specifications (OpSpecs). Applicants must develop and maintain manuals, training programs, and designate management positions, though some deviations are allowed for smaller operators. Certification requires thorough preparation and understanding of FAA regulations, as ongoing compliance is essential for maintaining operational authority (FAA, 2023c).

Operators can choose from different levels of certification depending on the complexity of their operations, ranging from Single Pilot and Single Pilot in Command to Basic and Standard Part 135 operators. These levels determine the size of the fleet, the number of pilots, and the geographical reach of operations. Each level has specific limitations and requirements, and as the business grows, operators can apply to expand their scope through an abbreviated certification process. Ongoing communication with the FAA and compliance with regulatory standards is critical for maintaining certification (FAA, 2023c).

To obtain a Part 135 certificate, applicants must meet several general requirements, including US citizenship, establishing a principal base of operations, and having exclusive use of at least one aircraft that meets specific regulatory criteria. Maintenance for Part 135 operations is more stringent than for Part 91, with varying requirements based on the aircraft's seating capacity. Applicants must also obtain economic authority from the Department of Transportation and provide evidence of insurance coverage (FAA, 2024d).

Most eVTOLs are expected to operate within Part 135 regulations, which include recently updated regulations incorporating "powered-lift" operations into the broader commercial aviation framework. The FAA is currently in the process of developing special conditions and additional airworthiness criteria specific to AAM/UAM aircraft (FAA, 2024a).

2.1.1.3 Title 14 CFR Part 141 Pilot School Certification

Title 14 CFR Part 141 Pilot School Certification regulations, established January 24, 2024, aim to streamline application processing and improve applicant readiness. This certification process is structured into five phases: Pre-application, Formal Application, Document Compliance, Demonstration and Inspection, and Certification. Part 141 pilot schools, which differ from Part 61 schools by requiring structured training programs and dedicated facilities, must meet stringent FAA standards throughout these phases, including thorough documentation and facility inspections. Successful completion of these phases results in the issuance of an Air Agency Certificate and training specifications (FAA, 2024e).

Part 141 pilot schools can offer a range of courses, including recreational and private pilot training, instrument ratings, commercial pilot training, and specialized courses such as airline transport pilot (ATP) certification and flight instructor refresher courses. During the certification process, the FAA reviews and approves the school's training curricula, facilities, equipment, and personnel to ensure they meet all regulatory requirements. The new certification process also emphasizes the importance of continuous interaction between the applicant and the FAA to ensure all standards are met, ultimately leading to the issuance of the Air Agency Certificate that allows the school to operate under Part 141 regulations (FAA, 2024e).

2.1.1.4 Title 14 CFR Part 145 Air Agency Certification

Title 14 CFR Part 145 Air Agency Certification regulations are essential for repair stations that perform maintenance, preventive maintenance, or alterations on aircraft and related components. The certification process is detailed and involves multiple phases, including pre-application, formal application, document compliance, demonstration and inspection, and certification. Each phase ensures that repair stations meet strict FAA standards for safety, personnel qualifications, and operational procedures (FAA, 2024f).

Repair stations seeking certification must comply with the FAA's stringent requirements, which include having qualified personnel, appropriate facilities, and approved manuals. The certification process also involves a thorough review and inspection by the FAA to ensure the station's compliance with regulatory standards. The certification process is supported by various resources provided by the FAA, including advisory circulars, orders, and guidelines that outline the requirements and steps for obtaining and maintaining certification. These resources help applicants understand the regulatory framework and ensure they meet all necessary criteria for successful certification (FAA, 2024g).

2.1.2 Ranking U.S. Metropolitan Areas for Potential AAM/UAM Transportation Service Integration

As AAM/UAM technologies transition from conceptual frameworks to operational technologies, the need for a strategic evaluation and systematic ranking of US metropolitan areas based on potential for implementation and expansion of Part 135 AAM/UAM transportation services becomes critical. Not only do such assessments pinpoint US metropolitan areas equipped with the necessary existing infrastructure to implement Part 135 AAM/UAM transportation services but also identify those characterized by the supportive urban structures, dynamic economic conditions, and market readiness to integrate and scale such air mobility solutions (Haan et al., 2021; Haritos et al., 2023; Olivares et al., 2022; Reiche et al., 2018). Such evaluations enable policymakers, urban planners, and private stakeholders to prioritize investments, adjust regulations, and initiate pilot projects in strategically chosen locations. This approach enables AAM/UAM deployment to be finely tuned to the unique characteristics of each US metropolitan area, maximizing the benefits of aerial mobility while seamlessly integrating into the existing urban fabric and minimizing potential disruptions. This proactive approach to strategic planning aims to reduce ground traffic congestion issues related to airport transit effectively and sustainably by transforming urban transportation into a more manageable and efficient system for the future (Haan et al., 2021; Haritos et al., 2023; Olivares et al., 2022).

Various methodologies have been developed to estimate the demand for AAM/UAM transportation services worldwide to identify cities and regions with the highest potential for AAM/UAM transportation integration (Haan et al., 2021; Haritos et al., 2023; Long et al., 2023; Mayakonda et al., 2020; Olivares et al., 2022; Reiche et al., 2018). Such methodologies can be categorized as either: a) top-down methodologies; or b) bottom-up methodologies. Top-down methodologies begin with a broad, macroscopic perspective, assessing general trends and overarching regulatory frameworks to anticipate how such mechanisms might influence smaller, more specific aspects of urban mobility (Böhringer et al., 2008). Such an approach is useful for understanding the widespread impacts of market readiness and large-scale economic shifts on urban development and urban mobility trends; however, top-down methodologies may overlook local nuances, which, in some cases, may slow the adaptation to economic, urban mobility, and technological advancement trends. In contrast, bottom-up methodologies take a more granular approach, opting to begin at the micro-level with specific local data points (e.g., individual traveler behavior, specific operational challenges) and building upwards to create a detailed picture of potential scenarios (Böhringer et al., 2009). Such an approach is particularly adept at addressing the practical realities and localized needs of implementing Part 135 AAM/UAM transportation systems; however, bottom-up methodologies are resource-intensive due to the micro-level data required, potentially challenging to scale, and complex to coordinate across larger regions.

2.1.2.1 Top-Down Methodologies

2.1.2.1.1 SMART Model

As part of a broader research effort to estimate AAM passenger market demand, the ASSURE A36 team adopted a top-down methodology focusing on providing a comprehensive analysis of urban and regional metrics to assess and prioritize US metropolitan areas with potential for implementation of Part 135 AAM/UAM transportation services (Olivares et al., 2022). Utilizing the Simple Multi-Attribute Rating Technique (SMART), the ASSURE A36 team developed site suitability scores for the Top 100 Most Populous US Metropolitan Statistical Areas (MSAs) by incorporating a blend of urban structure, economic scale, congestion and travel time, and market readiness variables (Olivares et al., 2022). Through this approach, each MSA was assigned a final score using the weighted average of standardized market condition attributes. Under the SMART model, such weights reflect the relative importance of each variable to the decision-maker (Olivares et al., 2022). The ASSURE A36 research team calibrated these weights by emphasizing the market conditions of UAM launch cities.

To evaluate the ranked result, the A36 team employed psychometric techniques to validate the factors influencing site suitability and segment potential for US MSAs. Statistical analyses for psychometric validation, such as Principal Component Analysis (PCA), were used to assess the reliability and validity of the measurement constructs. Following validation, the A36 team grouped potential sites into categories based upon suitability score. This segmentation helped identify which US metropolitan areas were most likely to success as early adopters of Part 135 AAM/UAM technologies (Olivares et al., 2022). Upon finalizing the MSA rankings, a Bass diffusion model was applied to each MSA to estimate Part 135 AAM/UAM market penetration (Bass, 1969; Olivares et al., 2022).

In subsequent research, the ASSURE A41 team leveraged the results of the ASSURE A36 site suitability analysis detailing the Top 30 Most Populous US MSAs to derive AAM passenger revenue, VTOL aircraft needs/associated capital/operational expenditures, and vertiport infrastructure needs/associated capital/operational expenditures for subsequent input into an economic impact model (Haritos et al., 2023).

The primary advantage of the SMART Model is its thorough approach in combining multiple factors influencing site suitability for Part 135 AAM/UAM transportation services, offering a detailed and nuanced understanding of each potential site based upon a composite of metrics. This comprehensive analysis aids stakeholders in making informed decisions based upon a multitude of intersecting factors, thereby increasing the likelihood of successful Part 135 AAM/UAM transportation services deployment in chosen locations. Furthermore, the psychometric validation aspect ensures reliability and validity of the metrics used in assessing site suitability. However, one notable disadvantage of the SMART Model is the complexity and resource intensiveness required by this approach, as gathering, validating, and analyzing such a broad range of data can be costly and time-consuming.

2.1.2.1.2 Willingness-to-Pay Model

To forecast UAM demand globally, Mayakonda et al. (2020) utilized a willingness-to-pay model. In utilizing this model, Mayakonda et al. (2020) defined the scope of UAM operations as the percentage of total ground-based passenger traffic within a metropolitan area. Their research sought to calculate the share of passenger-kilometers which could potentially be addressed through UAM transportation services. To this end, the willingness-to-pay model was implemented to estimate the percentage of the population that might choose UAM transportation services over traditional ground transportation modes based on the value of travel time savings versus the associated costs of alternative modes of transportation.

The primary advantage of the willingness-to-pay model lies in its ability to leverage extensive datasets for wide-ranging analyses, which can be highly effective for strategic planning at a global scale, allowing for an assessment of overarching trends and the potential impact of regulatory changes across different regions. The primary disadvantages of the willingness-to-pay model include its potential for overlooking local specificities and nuances that might influence UAM viability (e.g., features of a metropolitan area are assumed to be identical to other metropolitan areas). Furthermore, it is underscored by the inability to adapt to rapid or localized changes (e.g., improvements to existing public ground transportation systems, increased/decreased AAM/UAM investments), as well as the potential inability to accurately assess unique operational challenges or community readiness at the micro-level.

2.1.2.1.3 Gravity Model

Becker et al. (2018) developed a global gravity model to forecast interurban air passenger demand and identify potential markets for UAM from 2018 through 2042, assessing 4,435 settlements worldwide. The gravity model predicts the interaction between two entities (e.g., cities) based upon attractiveness and distance between them. In the context of UAM, the model utilizes socioeconomic variables such as metropolitan population size and Gross Domestic Product (GDP), alongside additional variables such as distance, travel costs, and flight frequency, to forecast UAM passenger demand. This model serves as a quantitative instrument to analyze potential UAM markets by estimating the volume of air passenger traffic between city pairs, thereby facilitating strategic planning and investment decisions in the aviation sector. The study provides a comprehensive understanding of the feasibility of UAM implementations based on projected air travel demands, rendering it an invaluable resource for urban planners and UAM providers aiming to exploit emerging urban transport opportunities.

The advantages of this model include its extensive analytical scope, versatile framework applicable across various domains, and robust predictive capabilities for market trends. However, the model's limitations involve the potential oversimplification of complex factors influencing air travel demand, the requirement for extensive and precise multi-variable data, and high sensitivity to specific assumptions and parameters, necessitating meticulous calibration and validation to ensure accuracy and reliability in its predictions (Alexander et al. 2020; Aydin et al. 2022).

2.1.2.2 Bottom-Up Methodologies

2.1.2.2.1 Mode Choice Model

Haan et al. (2023) utilized a mode choice model calibrated to a stated preference survey, alongside contextual socioeconomic census data and cell phone data pinpointing regular commuters' home and work locations, to estimate potential air taxi demand for commuters in the Top 40 Most Populous US CSAs. The mode choice model incorporates individual preferences for various transportation modes influenced by attributes such as travel cost, time savings, and available infrastructure. This bottom-up approach allows for nuanced predictions of UAM demand, focusing on individual-level data and preferences to construct a comprehensive picture of potential market penetration at the metropolitan level.

The primary advantage of this model is its high granularity, enabling precise identification of commuter patterns and socio-economic contexts. This detailed approach allows for accurate demand forecasting and the tailoring of solutions to specific urban needs. However, notable disadvantages include the complexity and resource intensity of data collection and analysis. The reliance on extensive data poses challenges in terms of data privacy, integration, and the requirement for sophisticated analytical tools and expertise. Additionally, despite its high detail, this bottom-up approach may be less scalable across larger regions without significant investment in data infrastructure and processing capabilities.

2.1.2.2.2 Demand Side Model

Reiche et al. (2018) utilized a first-principles model to calculate market size and value, focusing specifically on the airport shuttle and air taxi markets. This comprehensive approach involves a five-step process: Trip Generation, Scoping, Trip Distribution, Mode Choice, and the application of Constraints. The sequence commences with trip generation, where trips are categorized into mandatory and discretionary types based on extensive data sets such as those from the US Department of Transportation. These trips are then scoped by the urban areas and distributed using models like the gravity model to estimate the number of trips switching from ground to air transport. The mode choice step employs the value of time savings to understand consumer preferences, influencing the final market size and viability assessment by incorporating constraints such as infrastructure and regulatory limitations.

The advantages of this methodology include its comprehensive and systematic approach, ensuring that all relevant factors are considered. It utilizes detailed data sources and sophisticated modeling techniques to provide robust and realistic estimates of market size and value. However, its disadvantages include its complexity and resource intensity, requiring extensive data and advanced analytical capabilities. Additionally, reliance on current data may limit the ability to accurately predict future changes and trends; however, it is the most accurate option currently available to predict changes and trends in the future. The methodology is also constrained by the assumptions made, which may not fully capture the dynamic and evolving nature of the UAM market.

2.1.3 Key Factors Influencing Metropolitan Ranking

The previous section outlines several models which have been used to address the inherent complexities of assessing the potential of US metropolitan areas to implement and expand Part 135 AAM/UAM transportation services. Such models have ranged from gravity models, which predict passenger flows based on urban characteristics such as population size and distance, to more sophisticated models which integrate behavioral data to determine passenger preferences. The efficacy and accuracy of these models largely depends on the specification of the appropriate variables. Drawing upon prior research by the ASSURE A36 team, the A66 research team identified six critical categories for evaluating the potential of US metropolitan areas to implement and expand Part 135 AAM/UAM transportation services: a) urban structure; b) economic scale; c) congestion and travel time; d) market readiness; e) existing short-haul markets; and f) social factors. Each of these categories plays a crucial role in ranking US metropolitan areas based on potential for Part 135 AAM/UAM implementation and expansion, influencing strategic decisions regarding where best to implement these innovative mobility solutions.

2.1.3.1 Urban Structure

The urban structure of a metropolitan area plays a fundamental role in determining the sustainability of Part 135 AAM/UAM transportation services deployment in US metropolitan areas by assessing how the physical and organizational layout of a US metropolitan may support AAM/UAM solutions. Prior research has demonstrated population density and polycentrism are critical for understanding traffic patterns, transportation demand, and the feasibility of integrating new technologies into existing urban environments (Arribas-Bel et al., 2024; Gerarudas et al., 2024; Goyal et al., 2018; Olivares et al., 2022).

2.1.3.1.1 Population Density

High population density is often correlated with increased demand for transportation services due to the sheer number of people needing to move within a limited geographic area. In dense urban environments, traditional ground-based transportation can become highly congested, resulting in longer travel times and decreased transportation efficiency. Part 135 AAM/UAM transportation services offer an innovative solution to alleviate ground traffic congestion by leveraging vertical airspace (Gerardus et al., 2024; Olivares et al., 2022). By providing an alternative aerial transportation route, Part 135 AAM/UAM transportation services can significantly reduce the travel time of daily commuters and enhance overall mobility efficiency in densely populated areas.

2.1.3.1.2 Polycentrism

Polycentrism refers to the presence of multiple employment centers within a metropolitan area (Arribas-Bel et al., 2024). Research suggests regions characterized by multiple urban centers can significantly bolster Part 135 AAM/UAM transportation service demand due to inherent bidirectional traffic patterns (Arribas-Bel et al., 2014). Such patterns not only maximize aircraft occupancy by reducing the number of "deadhead" flights, which operate without paying passengers, but also enhance overall operational efficiency (Goyal et al., 2018). This efficiency can, in turn, lower travel costs for users, fostering a positive feedback loop that potentially increases demand. These dynamics underscore how polycentric urban forms could be crucial in the early stages of Part 135 AAM/UAM transportation service deployment, enhancing both the economic viability and the sustainability of operations.

2.1.3.2 Economic Scale

The economic scale of a metropolitan area significantly impacts its capacity to adopt and sustain Part 135 AAM/UAM transportation services. Elements such as the presence of Fortune 1000 companies, Gross Regional Product (GRP) per capita, and personal income levels provide insights regarding the economic vitality and market potential for Part 135 AAM/UAM transportation services (Csomós et al., 2014; Garrow et al., 2018; Godfrey et al., 1999; Goyal et al., 2021; Haan et al., 2023; Kloss & Riedel, 2021; Panek et al., 2007; Pertz et al., 2023; Reiche et al., 2018). Robust economic indicators correlate with a higher likelihood of successful Part 135 AAM/UAM transportation service implementation, reflecting the ability of a US metropolitan area to support new technological infrastructures and services.

2.1.3.2.1 Fortune 1000 Presence

The total number of Fortune 1000 company headquarters within a US metropolitan area serves as a reflection of economic activity and business opportunities. In this regard, US metropolitan areas with more Fortune 1000 company headquarters reflect higher levels of economic activity, which in turn can drive demand for premium transportation services. The presence of Fortune 1000 company headquarters captures the economic vibrancy and business travel demand potential of a US metropolitan area, which are crucial for successful implementation of Part 135 AAM/UAM transportation services (Csomós et al., 2014; Godfrey et al., 1999).

2.1.3.2.2 Gross Regional Product (GRP) per Capita

GRP per capita measures the economic output of a region, serving as a key indicator of its overall economic health and productivity (Panek et al., 2007). A higher GRP per capita suggests a robust economic environment that can support the adoption of innovative technologies and services, including Part 135 AAM/UAM transportation services (Goyal et al., 2021; Reiche et al., 2018). Regions with high GRP per capita are typically characterized by a dynamic mix of industries, substantial investment in technology, and a skilled workforce in high-tech sectors, making these regions prime candidates for Part 135 AAM/UAM transportation services deployment. These areas often have the financial resources and the business need for efficient, rapid transportation solutions that Part 135 AAM/UAM transportation services can provide, such as reducing travel time for busy professionals or quickly connecting key economic hubs. Furthermore, a strong GRP per capita indicates consumer purchasing power and a business climate that may be more receptive to premium-priced mobility solutions. In this context, Part 135 AAM/UAM transportation service providers can find a ready market for their services, not only in commuter transport but also in applications such as urgent medical transport, high-speed logistical support, and exclusive recreational travel. Ultimately, a high GRP per capita can be a precursor to a thriving Part 135 AAM/UAM transportation ecosystem, fostering a culture of innovation and making the region a leader in next-generation urban mobility solutions.

2.1.3.2.3 Personal Income

Higher real personal income generally indicates greater disposable income, which can increase the likelihood that residents and businesses will adopt new, and potentially more expensive, technologies like Part 135 AAM/UAM transportation services (Haan et al., 2023; Kloss & Riedel, 2021; Pertz et al., 2023). Prior research indicates higher income groups are more likely to support Part 135 AAM/UAM transportation aircraft additions to transportation nodes (Garrow et al., 2018; Kloss & Riedel, 2021; Yedavalli & Moodberry, 2019). As such, US metropolitan areas with higher average income levels should be more receptive to these services, providing a robust customer base necessary to sustain operations. At the individual level, higher real personal income can influence an individual's willingness to pay for premium services, which is directly applicable to the potential for Part 135 AAM/UAM transportation services implementation and expansion as it has direct implications for market size, service pricing strategies, and the ultimate profitability of Part 135 AAM/UAM transportation service providers (Garrow et al., 2018; Yedavalli et al., 2019).

2.1.3.3 Congestion and Travel Time

Congestion and travel time are critical indicators of the need for alternative transportations solutions such as Part 135 AAM/UAM transportation services. Elevated congestion levels and prolonged travel times not only deteriorate quality of life but also hinder economic productivity. Prior research has often relied on indicators such as the Travel Time Index (TTI), average commute time to work, and average drive time from an airport to the Central Business District (CBD) to gauge the severity and impact of congestion within urban areas (Haan et al., 2021; Long et al., 2023; Mahmassani et al., 2024; Rimjha et al., 2021; Sarkar et al., 2023; Zhang et al., 2023). Furthermore, such indicators typically identify metropolitan areas which could significantly benefit from the time savings and relative travel efficiency offered by Part 135 AAM/UAM transportation services.

2.1.3.3.1 Travel Time Index

The TTI assesses how peak travel times compare to free-flow conditions, serving as an essential tool for assessing traffic congestion severity during the busiest travel periods (Texas A&M Transportation Institute, 2023). By providing a quantitative assessment of how much longer trips take during peak hours relative to light traffic conditions, the TTI highlights the periods of greatest inefficiency within urban transport networks. The TTI is instrumental for evaluating the potential impact of Part 135 AAM/UAM transportation services, identifying the travel times and locations in which these services could offer the most significant time savings to commuters. In areas with higher TTI values, Part 135 AAM/UAM transportation services could significantly reduce travel times, offering a compelling alternative to traditional ground transportation. As such, the TTI is a crucial variable to consider within a site suitability analysis for Part 135 AAM/UAM transportation service deployment, guiding stakeholders by identifying the optimal urban areas for infrastructure development and service implementation (Long et al., 2023; Sarkar et al., 2023).

2.1.3.3.2 Average Time to Work

Average commute time serves as a critical indicator of congestion and inefficiency within urban transportation networks (Zhang et al., 2023). Longer average commuting times often signal congested ground transportation networks, which can make faster, aerial alternatives more attractive to commuters. Metropolitan areas with extensive average commute times may therefore exhibit a higher demand for Part 135 AAM/UAM transportation services, as residents seek more efficient travel options to reduce their daily transit durations. This metric is especially relevant to densely populated or geographically expansive cities where ground traffic significantly extends daily commutes (Long et al., 2023; Rimjha et al., 2021). In such environments, the introduction of Part 135 AAM/UAM transportation services could dramatically improve the quality of life by providing quicker, less stressful travel alternatives. Furthermore, these environments can benefit economically from the introduction of Part 135 AAM/UAM transportation services, as reduced transit times allow for increased labor productivity, enhanced business operational efficiency, and greater attractiveness to potential new residents and investors.

2.1.3.3.3 Airport to CBD Drive Time

The drive time from each airport to the CBDs in a US metropolitan area reflects the accessibility and efficiency of existing ground transportation options for essential business and travel routes. As faster travel times between airports and CBDs are crucial for business travelers, this indicator serves to highlight areas where Part 135 AAM/UAM services can offer considerable time savings (Haan et al., 2021; Mahmassani et al., 2024). Longer drive times due to congested roads or distant airport locations can significantly impede the efficiency of business travel and logistics, making faster, more direct Part 135 AAM/UAM transportation services increasingly attractive. In metropolitan areas where the airport-to-CBD commute are notoriously lengthy or prone to unpredictable delays, Part 135 AAM/UAM transportation services can offer a compelling value proposition by drastically reducing travel times and enhancing predictability and comfort. This not only improves individual traveler experience but also boosts overall business productivity. Consequently, metropolitan areas with longer airport-CBD drive times present prime opportunities for Part 135 AAM/UAM transportation service implementation that can capitalize on the demand for quicker, more efficient travel options. This in turn can lead to early adoption and robust market growth in regions where traditional transport infrastructures are less capable of meeting the time-sensitive needs of modern commuters and businesses.

2.1.3.4 Market Readiness

Market readiness assesses the preparation of a metropolitan area to integrate and support Part 135 AAM/UAM transportation services based on existing infrastructure and regulatory environments. Prior research has relied upon indicators such as heliports and airports per capita, regional airport presence, Class B airspace presence, Class G airspace congestion, existing investments in related technologies in determining the readiness of a region to implement advanced air mobility solutions (Anticliff et al., 2021; Bauranov et al., 2021; Haan et al., 2021; Mahmassani et al., 2024; Olivares et al., 2021; Reiche et al., 2018; Schuh et al., 2021).

2.1.3.5 Heliports per Capita

A higher density of heliports per capita can significantly enhance the operational readiness and accessibility of Part 135 AAM/UAM transportation services, providing numerous convenient points of departure and arrival. This infrastructure is crucial for the quick adoption and integration of Part 135 AAM/UAM transportation services into urban landscapes (Mahmassani et al., 2024; Olivares et al., 2021). Metropolitan areas with a greater number of heliports per capita indicate a pre-existing familiarity and acceptance of aerial transport among the population and businesses, potentially easing regulatory and societal hurdles. Additionally, these regions may have more developed logistical and maintenance frameworks to support aerial operations, facilitating smoother and more efficient service implementations. Therefore, evaluating the heliport density relative to the population gives a clear insight into which cities might rapidly leverage Part 135 AAM/UAM transportation services to enhance their transportation networks, thereby improving connectivity and reducing travel times for their residents and workforce. However, there is a limitation to the data for heliports per capita, as the heliports primarily used for medical purposes cannot be distinguished from other heliports.

2.1.3.6 Airports per Capita

A higher number of airports suggest enhanced accessibility and convenience, key factors that could accelerate the adoption of Part 135 AAM/UAM transportation services (Reiche et al., 2018; Haan et al., 2021). Cities with more airports per capita are likely to have better-developed aviation infrastructure, including established routes, maintenance facilities, and a population that is more accustomed to air travel as a regular mode of transportation. This infrastructure not only supports the immediate operational needs of Part 135 AAM/UAM transportation services but also provides a foundation for scaling operations as demand grows. Additionally, a greater airport density may indicate a higher tolerance and demand for travel options that bypass ground traffic, making these metropolitan areas prime targets for Part 135 AAM/UAM transportation service providers looking to introduce innovative air mobility solutions. Such environments could significantly benefit from reduced travel times and increased connectivity between airports and urban centers, enhancing overall economic productivity and quality of life.

2.1.3.7 Class B Airspace

Class B airspace is typically found around the busiest airports, characterized by strict air traffic control due to the high volume of commercial airline traffic. For Part 135 AAM/UAM transportation service operations, navigating through or near Class B airspace requires sophisticated coordination and compliance with stringent regulatory requirements to ensure safety and minimize disruptions to existing air traffic (Bauranov et al., 2021; Mahmassani et al., 2024; Olivares et al., 2022). The integration of Part 135 AAM/UAM transportation service operations within these busy airspaces can signal advanced technological capability and operational sophistication, which are key for the safe and efficient integration of these services into the national airspace. However, the complexity of operations in Class B airspace also poses challenges, potentially requiring more robust technological solutions and higher operational standards. Metropolitan areas encompassing or adjacent to Class B airspace may thus offer both significant opportunities and unique challenges for Part 135 AAM/UAM transportation service providers. Successfully operating in these areas could pave the way for widespread acceptance and integration of Part 135 AAM/UAM transportation service technologies, particularly in regions where the demand for quick, efficient transport is high due to dense population and significant economic activity.

2.1.3.8 Class G Airspace Congestion

Class G airspace represents uncontrolled airspace where air traffic control does not provide service, typically existing below 1,200 feet outside of controlled airspace zones. The congestion level in Class G airspace is an essential metric for assessing the potential for Part 135 AAM/UAM transportation services in metropolitan areas. Less congested Class G airspace allows for easier entry and operational flexibility for Part 135 AAM/UAM transportation services vehicles, making it an attractive feature for cities considering these technologies (Bauranov et al., 2021; Olivares et al., 2022). Metropolitan areas with low Class G airspace congestion may provide a more conducive environment for piloting and scaling Part 135 AAM/UAM transportation service operations, as such areas face fewer barriers to routine flights and less potential for conflicts with other airspace users. On the other hand, low Class G airspace congestion may also mean less economic attractiveness. This ease of access can accelerate the adoption and integration of Part 135 AAM/UAM transportation services, enhancing urban connectivity and reducing travel times. Conversely, higher Class G airspace congestion could complicate operations due to increased navigational challenges and the need for more stringent deconfliction measures, potentially slowing the rollout and increasing the costs of Part 135 AAM/UAM transportation services. Therefore, understanding Class G airspace congestion levels is essential for metropolitan ranking and strategic planning in the deployment of Part 135 AAM/UAM transportation solutions.

2.1.3.9 Existing Investment

Existing investments in Part 135 AAM/UAM transportation service infrastructure and technology within a metropolitan area are critical indicators for assessing potential for Part 135 AAM/UAM transportation services integration and expansion. Cities that have already committed significant resources to the development of aviation-related infrastructure, such as vertiports, maintenance facilities, electricity power supply, air traffic management tools, operational principles and air traffic control technologies, are likely better prepared to support the complexities of Part 135 AAM/UAM transportation service operations (FAA, 2023b; Schuh et al., 2021; Olivares et al., 2022). Such investments not only demonstrate a proactive approach to embracing new mobility solutions but also indicate a readiness to integrate these systems into the existing transportation network. Moreover, prior investments can lead to quicker regulatory approvals, community acceptance, and faster implementation and scaling of services. For metropolitan ranking, areas with substantial existing investments in relevant technologies and facilities suggest a higher potential for successful Part 135 AAM/UAM transportation service deployment, as they already have both interest and financial means to use these types of vehicles. These regions are likely to attract further investments and partnerships, driving innovation and growth in advanced air mobility. This makes them prime candidates for early adoption and market leadership in the Part 135 AAM/UAM transportation services sector.

2.1.4 Existing Short-Haul Markets

The existing short-haul market within metropolitan areas plays a vital role in determining the potential success and utility of Part 135 AAM/UAM transportation services, emphasizing the existing demand for quick, efficient transportation options for distances under 150 miles, a range well within the ideal parameters of Part 135 AAM/UAM transportation service operations. By assessing the volume and stability of these existing markets, one can predict where Part 135 AAM/UAM transportation services could supplement or replace existing transportation modalities by offering a faster and more convenient alternative.

2.1.4.1 Airport Short-Haul Market Stability <150 miles

The number of flight origins and destinations within 150 miles is a critical indicator of the demand for short-haul travel, which serves as a key market for Part 135 AAM/UAM transportation services (Olivares et al., 2022). This metric effectively captures existing demand for short-distance air travel, highlighting routes that Part 135 AAM/UAM transportation services could connect more efficiently. Metropolitan areas with a high volume of short-haul connections demonstrate a substantial need for rapid, convenient transportation options that bypass the complexities and delays often associated with traditional air and ground transportation. By focusing on such areas, Part 135 AAM/UAM transportation services can tap into an established market, providing faster direct flights that reduce travel times and enhance passenger convenience. This not only makes Part 135 AAM/UAM transportation services highly attractive to regular travelers utilizing these routes but also provides the case for economic investment in Part 135 AAM/UAM transportation services by directly addressing a clear, existing demand for improved short-distance travel options.

2.1.5 Social Factors

Social factors such as public acceptance, perceived safety, and concerns about noise and visual pollution can significantly influence the feasibility of implementing Part 135 AAM/UAM transportation services in metropolitan areas. Prior research indicates these elements reflect community members openness to and comfort with new technologies, which has the potential to accelerate or hinder adoption of Part 135 AAM/UAM transportation services (Goyal et al., 2021; Thomas, 2023; Haritos et al., 2023; Hill et al., 2023; Olivares et al., 2022; Reiche et al., 2018; Vascik et al., 2017).

2.1.5.1 Social Acceptance

The level of social acceptance towards new technologies significantly influences the feasibility and rapid integration of Part 135 AAM/UAM transportation services into existing urban transportation systems. Metropolitan areas that exhibit higher degrees of social acceptance towards Part 135 AAM/UAM transportation services are likely to experience smoother implementation and more rapid adoption rates (Goyal et al., 2021; Thomas, 2023; Olivares et al., 2022; Reiche et al., 2018; Thipphavong et al., 2018; Vascik et al., 2017). This social acceptance can stem from a variety of sources, such as a community's openness to innovation, environmental conscientiousness, or history of embracing new transportation solutions. Furthermore, positive public perception of Part 135 AAM/UAM transportation services can lead to supportive local policies, facilitating necessary infrastructure developments and regulatory approvals (Dietrich, 2020; Wisk, 2021). For metropolitan ranking, assessing social acceptance helps identify regions where Part 135 AAM/UAM transportation services are more likely success, ensuring investments are placed in strategic markets with the public is prepared to support and utilize these solutions.

The ASSURE A41 team conducted a stated preference survey to investigate public perception of AAM/UAM, as well as how various factors might influence public willingness to utilize such services (Haritos et al., 2023). The ASSURE A41 survey covered a wide range of demographic groups, assessing respondents' comfort flying in an autonomous aircraft, their price sensitivity, and the potential impact of the COVID-19 pandemic on their travel behavior. Results indicated a general interest in Part 135 AAM/UAM transportation services; however, respondent comfort varied significantly based upon how the AAM/UAM aircraft would be piloted (i.e., pilot operator, semi-autonomous, autonomous) and the respondent's prior experience with air travel.

Furthermore, results highlighted how individual-level factors (e.g., household income, primary modes of transportation, average daily commute) shape public attitudes towards Part 135 AAM/UAM transportation service adoption. Overall, the ASSURE A41 results suggest targeted education and a gradual integration of autonomous technologies may be necessary to build public trust and encourage broader social acceptance of Part 135 AAM/UAM transportation services.

2.1.5.2 Perceived Safety

Public perceptions of safety regarding Part 135 AAM/UAM transportation technologies can greatly influence individual willingness to support and utilize Part 135 AAM/UAM transportation services (Fu et al., 2019; Thomas, 2023; Haritos et al., 2023; Hill et al., 2020; Kloss et al., 2021). According to the European Union Aviation Safety Agency (EASA), most pedestrians were reluctant to accept automated UAM services due to the perceived risks such aircraft posed to their individual safety (EASA, 2021). Metropolitan areas with more favorable perceptions pertaining to the safety of Part 135 AAM/UAM transportation services are more likely to exhibit faster integration and expansion. These perceptions can be enhanced through transparent safety records, effective communication of safety protocols, and visible endorsements from trusted regulatory bodies (Hasan, 2019). Furthermore, demonstrations of successful emergency response strategies and robust safety features in Part 135 AAM/UAM transportation technologies can further reassure the public. For metropolitan ranking, assessing public perceptions regarding the safety of Part 135 AAM/UAM transportation services gauges public readiness to embrace and utilize such services. Greater perceptions of safety can accelerate the adoption process by facilitating smoother regulatory approvals and public cooperation, thereby positioning metropolitan areas with higher perceptions of safety as ideal candidates for Part 135 AAM/UAM transportation service operations.

2.1.5.3 Noise and Visual Pollution

The impact of Part 135 AAM/UAM transportation services on the urban environment, particularly in terms of noise generated by aircraft and the visual intrusion of additional flight paths and infrastructure, can significantly influence public acceptance (EASA, 2021; Thomas, 2023; Haritos et al., 2023; Panchal & Egmond, 2023; Reiche et al., 2018). Metropolitan areas that are sensitive to noise disturbances and visual changes, especially densely populated cities with stringent environmental regulations, might face more challenges in adopting Part 135 AAM/UAM transportation services (Hasan, 2019; Thipphavong et al., 2018; Wisk, 2021). Conversely, regions that can mitigate these impacts through technology - such as quieter eVTOL aircraft and well-integrated vertiport designs - have a higher potential for successful Part 135 AAM/UAM transportation service integration. For metropolitan ranking, assessing the existing tolerance and regulatory framework regarding noise and visual pollution is essential. This assessment helps identify areas where Part 135 AAM/UAM transportation services could be deployed with minimal environmental disruption, ensuring a smoother introduction of services and fostering community support by aligning with local environmental values.

The potential of Part 135 AAM/UAM transportation services to transform urban and regional transportation is immense, presenting innovative solutions to the escalating challenges of congestion, pollution, and inefficiencies that accompany global urbanization. This literature review systematically explored methodologies for ranking metropolitan areas based on potential for implementation and expansion of Part 135 AAM/UAM transportation services, underlining the necessity of comprehensive planning to mitigate the complexities of modern urban transport.

In synthesizing insights from various models and assessing factors which influence the viability of Part 135 AAM/UAM transportation services across different urban and regional contexts, this review emphasizes the importance of urban structure, economic scale, congestion, travel time, market readiness, existing short-haul markets, and social acceptance. These factors are important in determining sites suitable for Part 135 AAM/UAM transportation service implementation and expansion.

Subsequent ASSURE A66 efforts necessitate the formal adoption and execution of an appropriate methodology to rank US MSAs based on potential for implementation and expansion of Part 135 AAM/UAM transportation services. The A66 research team chose to adopt the methodologies employed by the ASSURE A36 team. The A36 approach, which combines a series of urban and regional metrics to rank metropolitan areas, has proven both robust and insightful. It also allows for the seamless incorporation of new factors into the model, enhancing its adaptability. The psychometric validation aspect further ensures the reliability and accuracy of the metrics used in assessing site suitability, making this methodology a comprehensive tool for site suitability analysis. Integrating these established techniques into the ASSURE A66 project alongside an expanded set of variables should enhance predictive accuracy, thereby optimizing efforts to identify the most promising regions for the introduction and expansion of AAM and UAM services.

The A66 research team incorporated the comprehensive set of factors outlined within this literature review; however, variables pertaining to social factors were excluded from the ranking methodology due to the lack of data available at the national level. Assessments of social factors which influence the support for, and utilization of Part 135 AAM/UAM transportation services are often derived from local stated preference or omnibus surveys and such data collection efforts are beyond the scope of the ASSURE A66 project. However, inclusion of the expanded set of variables pertaining to the remaining factors (i.e., urban structure; economic scale; congestion and travel time; market readiness; existing short-haul markets) were selected for inclusion to ensure the strategic ranking of US MSAs were thorough and reflective of the multifaceted dynamics which influence Part 135 AAM/UAM transportation service implementation, utilization, and expansion.

2.2 Expansion of A36 Metropolitan Ranking Methodology

Based on the pervious literature review, the Simple Multi-Attribute Rating Technique (SMART), was applied for ranking metropolitan areas with potential for AAM/UAM transportation integration. The metropolitan areas were evaluated at the CSA level, resulting in a CSA suitability ranking for AAM/UAM.

The primary objective of this section was to update the data sources from Team A36, reorganize the metropolitan areas (shifting from MSA to CSA), and add two additional variables to SMART: electrical consumption and local incentives. The final ranking results served as a reference for the targeted CSAs picked up for the following section.

2.2.1 Data Collection

One of the objectives of this section was to update all relevant data based on the ASSURE A36 team’s work. Additionally, the expanded methodology included two new variables. Details on where to download the data can be found in Appendix A. The list of variables is shown in Table 1.

Table 1. CSA Suitability Analysis Variables for AAM/UAM.

Variable	Variable Description
Population Density	Average population per square mile
Polycentrism	Number of employment-subcenters
Fortune 1,000 Presence	Number of Fortune 1000 company headquarters
Gross Regional Product	Gross domestic product of CSA per capita
Average Time to Work	Average one-way commute time, minutes
Travel Time Index	Index of peak period to free-flow conditions
Airport to Central Business District Drive Time	Estimated driving time in free-flow conditions from commercial airports to central business district, weighted by the number of commercial aircraft operations
Heliports Per Capita	Number of heliports per capita
Airports Per Capita	Number of airports per capita
Class B Airspace	Presence (or not) of Class B Airspace in CSA (binary)
Class G Airspace Congestion	Average total hours per square mile in Class G airspace
Electricity Consumption	Number of electricity consumption per capita
Local Incentive	Number of local government incentive
Existing Investment	UAM Launch City (1.0) or Headquarters City (0.5)
Airport Short-Haul Market Stability	Count of flight origins and destinations within CSA for distances shorter than 150 miles

2.2.2 Input Datasets

The input dataset included the following key data sources:

- List of populations in CSAs.
- List of census tract land area in USA.
- List locations of polycentrism in USA.
- List locations of Fortune 1,000 headquarters in USA.
- Average time to work in CSAs.
- Travel time index in each city of USA.
- Average airport to Central Business District (CBD) drive time.
- List locations of heliport and airport in USA.
- List UAM launch cities and headquarters cities in CSAs.
- Electricity consumption in CSAs.
- The local government incentive for AAM/UAM company.
- The data set from A36 team.
- The short-haul flights in CSAs.

The details of those datasets are introduced in Appendix B.

Table 2. The Weight of Each Variable and Variable Category

Category	Category Weight Total	Variable	Variable Weight
Urban Structure	35	Population Density	15.0
		Polycentrism	20.0
Economic Scale	15	Fortune 1000 Presence	5.0
		GDP per Capita	10.0
Congestion	7.5	Average Time to Work	2.5
		Travel Time Index	2.5
		Airport to CBD Drive Time	2.5
Readiness	32.5	Heliports per Capita	5.0
		Airports per Capita	5.0
		Class B Airspace	2.5
		Class G Airspace Congestion	5.0
		Electricity Consumption	5.0
		Local Incentive	5.0
		Public & Private Investment	5.0
Existing Demand	10	Airport Short Haul OD <150 Miles	10.0

2.2.3 Python Scripts

One Python script for this section is saved in the code folder, which serves two purposes:

- Data processing: Processes the downloaded data and outputs the processed datasets for the Terminal Area Forecast – Modernized 2 (TAF-M2) model.
- Ranking model: Applies the SMART to ranking the site suitability for AAM/UAM in each CSA. The weight of each variable is shown in Table 2.

2.2.4 Top 20 CSA Suitability Ranking

After running the Python script, the site suitability score was generated for each CSA. The weight set in Table 2 represents a blended emphasis on urban structure and readiness categories (with a higher weight for these two categories), referred to as the base scenario. Several additional scenarios emphasize different categories. The weight sets for these scenarios are discussed in Appendix C. The top 20 CSAs for the base scenario are shown in Table 3, while the results for the infrastructure readiness scenario are shown in Table 4.

Table 3. Most Suitable CSAs for AAM/UAM Services- Base Scenario

Rank	CSA	Score
1	New York-Newark, NY-NJ-CT-PA	78.53
2	Los Angeles-Long Beach, CA	69.24
3	San Jose-San Francisco-Oakland, CA	68.07
4	Miami-Port St. Lucie-Fort Lauderdale, FL	43.9
5	Chicago-Naperville, IL-IN-WI	40.79
6	Boston-Worcester-Providence, MA-RI-NH	38.38
7	Washington-Baltimore-Arlington, DC-MD-VA-WV-PA	36.59
8	Seattle-Tacoma, WA	35.09
9	Detroit-Warren-Ann Arbor, MI	33.83
10	Atlanta--Athens-Clarke County--Sandy Springs, GA-AL	32.28
11	Houston-Pasadena, TX	31.15
12	Dallas-Fort Worth, TX-OK	30.22
13	Charlotte-Concord, NC-SC	27.56
14	Denver-Aurora-Greeley, CO	26.78
15	Sacramento-Roseville, CA	26.18
16	New Haven-Hartford-Waterbury, CT	25.51
17	Philadelphia-Reading-Camden, PA-NJ-DE-MD	25.24
18	Portland-Vancouver-Salem, OR-WA	24.63
19	Nashville-Davidson--Murfreesboro, TN	24.36
20	Raleigh-Durham-Cary, NC	24.27

Table 4. Most Suitable CSAs for AAM/UAM Services- Infrastructure Readiness Scenario

Rank	CSA	Score	Rank Change from Base Scenario
1	New York-Newark, NY-NJ-CT-PA	79.32	0
3	San Jose-San Francisco-Oakland, CA	75.30	+1
2	Los Angeles-Long Beach, CA	67.73	-1
4	Miami-Port St. Lucie-Fort Lauderdale, FL	49.72	0
6	Boston-Worcester-Providence, MA-RI-NH	42.27	+1
5	Chicago-Naperville, IL-IN-WI	41.90	-1
7	Washington-Baltimore-Arlington, DC-MD-VA-WV-PA	37.87	0
8	Seattle-Tacoma, WA	36.51	0
19	Nashville-Davidson--Murfreesboro, TN	35.49	+10
11	Houston-Pasadena, TX	35.04	+1
15	Sacramento-Roseville, CA	34.46	+4
14	Denver-Aurora-Greeley, CO	33.63	+2
12	Dallas-Fort Worth, TX-OK	33.58	-1
26	Dayton-Springfield-Kettering, OH	33.35	+12
10	Atlanta--Athens-Clarke County--Sandy Springs, GA-AL	32.88	-5
16	New Haven-Hartford-Waterbury, CT	32.54	0
20	Raleigh-Durham-Cary, NC	31.96	+3

THE TERMINAL AREA FORECAST – MODERNIZED 2 (TAF-M2) MODEL FRAMEWORK

Urban transportation is projected to experience a transformative shift with the introduction of AAM and UAM services, as these technologies have the potential to shift how people travel within U.S. CSAs by providing transportation options that differ from those currently available. To project the extent of these changes, the TAF-M2 Model Framework seeks to assess potential shifts in Part 121 enplanements among airports within select U.S. CSA that may result from the integration of AAM/UAM transportation services into existing urban transportation systems. While the existing TAF-M Methodology is first based on the MSA level and then disaggregates to the airport-level, the proposed TAF-M2 methodology is based on the CSA level to account for instances in which multiple MSAs are in close proximity to each other and then disaggregate to the airport-level. This section outlines the three-phase approach utilized to achieve this goal.

Phase I: TAF-M Part 121 Enplanement Forecasts: Utilizing the existing TAF-M Methodology, 25-Year Forecasts of annual Part 121 enplanement estimates were constructed for each selected U.S. MSA, as well as for each airport within each selected U.S. MSA. These forecasts served as a baseline of annual Part 121 enplanement estimates through 2050 based on the assumption that AAM/UAM airport access services will not be introduced within the selected U.S. MSA during the forecast period.

Phase II: AAM/UAM Transportation Integration Forecasts: Next, the A66 AAM/UAM Transportation Integration Forecast Methodology was applied to determine the extent of potential annual Part 121 enplanement shifts between airports within each selected U.S. metropolitan area due to the introduction of AAM/UAM airport access services into respective metropolitan urban transportation systems. To this end, a nested logit model was utilized to estimate the appropriate weights of annual Part 121 enplanement shifts for each airport within each selected U.S. CSA based on factors which influence discrete passenger choices pertaining to: a) airport access mode; and b) airport preference.

Phase III: TAF-M2 Part 121 Enplanement Forecasts: Finally, TAF-M2 25-Year Forecasts of annual Part 121 enplanement estimates were constructed for each airport within each selected U.S. CSA by utilizing a forward induction approach. Annual airport-level weights developed through the A66 AAM/UAM Transportation Integration Forecast Methodology were iteratively applied to annual MSA-level Part 121 enplanement estimates developed through the TAF-M Methodology. The TAF-M2 forecasts serve as a counterfactual of annual Part 121 enplanement estimates through 2050 based on the assumption AAM/UAM airport access services are introduced in the immediate future within the selected U.S. CSAs.

3.1 Phase I: TAF-M Part 121 Enplanement Forecasts

This section provides a brief overview of the existing TAF-M Methodology utilized to forecast Part 121 enplanements. For the sake of brevity, this section limits its discussion to the simplified TAF-M Origin-Destination (O&D) passenger forecast model presented in the TAF-M Methodology. For more information regarding the coefficient estimation and the dynamic log-log approximation process, please visit https://www.faa.gov/sites/faa.gov/files/data_research/aviation/taf-m_methodology.pdf.

3.1.1 TAF-M Background

The Terminal Area Forecast (TAF) is the official Federal Aviation Administration (FAA) forecast of aviation activity for U.S. airports, consisting of TAF-M (Modernized) and TAF-L (Legacy) forecasts. The TAF-M covers forecasts of Part 121 enplanements and commercial operations for airports with over 100,000 enplanements per year, while the TAF-L covers forecasts for all other U.S. airports. The TAF-M model represents an enhancement to TAF-L by generating segment-level enplanement and commercial operation forecasts. The TAF-M origin and destination model provides insight regarding the flow of passengers from origin point i to destination point j rather than considering passenger counts at a static specific location. The O&D passenger demand forecast at the airport-pair level involves two steps: 1) coefficient estimation; and 2) forecast generation with a dynamic log-log approximation process.

3.1.2 Mathematical Framework

To forecast future O&D passenger counts for U.S. MSA, as well as each airport within U.S. MSA, the TAF-M methodology was applied utilizing the following equation (FAA, 2023):

Equation 1A.

$$Passenger_{i-j,t+1} = Passenger_{i-j,t} * \left(1 + \beta_1 * \left(\frac{Income\ Origin_{i,t+1}}{Income\ Origin_{i,t}} - 1\right) + \beta_2 * \left(\frac{Income\ Dest_{j,t+1}}{Income\ Dest_{j,t}} - 1\right)\right)$$

Where:

- i and j indices represent the origin airport and destination airport.
- t represents quarter.
- β_1 and β_2 are Origin-Income elasticity and Destination-Income elasticity, where the value is positive and stand for the impact of income to the passenger number.

This framework follows assumptions outlined by the original TAF-M methodology (https://www.faa.gov/media/76666). After the forecasted O&D passengers were predicted, it was scaled to T100 segment (Since O&D only captures the 10^{th} coupon's route, it is to be matched by routes (100%) segment followed from T100-Segment). Then the scaled forecasted O&D passengers from each MSA was then assigned to a route (i.e., airport-to-airport). This was accomplished using an assignment algorithm where the number of scaled O&D passengers was distributed across various routes based on historical information available for the same quarter of the previous year (FAA, 2023). The TAF-M origin passenger count for each airport within selected U.S. MSAs was used in conjunction with the A66 AAM/UAM Integration Forecast Methodology (see Phase II) to estimate potential shifts in passenger count for each airport within selected U.S. CSA.

3.2 Phase II: AAM/UAM Transportation Integration Forecasts

This section provides an overview of the A66 AAM/UAM Transportation Integration Forecast Methodology, including a brief overview of modeling decisions, theoretical assumptions, mathematical frameworks, and limitations/future directions. Since there was a lack of ground truth data to fit the proposed methodology, the constrained optimization method detailed in Section 3.3.4.1 was applied to obtain the parameter values in the proposed methodology.

3.2.1 Methodological Overview

To understand the implications of the introduction of Part 135 AAM/UAM commercial services, assumptions regarding vertiport placement must first be made to determine factors which influence the utility (e.g., time and cost) of utilizing Part 135 AAM/UAM commercial services. Based on discussions with the FAA, as well as internal discussions among the performers, the centroid of each census tract within a CSA was used as a proxy for potential vertiport locations which will facilitate Part 135 AAM/UAM commercial services. Additionally, there was an assumption that not all passengers would adopt Part 135 AAM/UAM commercial transportation services at the same time, and the ratio of passengers utilizing these services would be updated annually within the model. For example, in 2024, the AAM/UAM utility will be multiplied by 0, indicating that no passenger will utilize Part 135 AAM/UAM commercial transportation services. This ratio will increase each year and in 2050, the Part 135 AAM/UAM commercial transportation services utility will be used directly, meaning all passengers will be assumed to potentially adopt Part 135 AAM/UAM commercial transportation services.

Next, a nested logit choice model (Pels et al., 2003; Thrane, 2015; Zhao et al., 2020) was utilized to understand passenger behaviors pertaining to transportation access choice and airport choice. Prior research has consistently demonstrated the utility of logit models in estimating probabilities of selecting specific ground transportation access modes (Hess et al., 2011; Pasha et al., 2020), as well as specific airports (Basar & Bhat, 2004; Harvey, 1987; Hess & Polak, 2006a; Pels et al., 2003; Skinner, 1976; Windle & Dresner, 1995), based on the characteristics of options within the choice set. This behavioral perspective is crucial to understand potential shifts in passenger preferences and predict the passenger distribution across airports and transportation access modes after the introduction of Part 135 AAM/UAM commercial services.

Though a variety of logit-based models (i.e., multinomial logit, nested logit, cross-nested logit, probabilistic choice set multinomial logit) have been utilized to assess airport choice, Pels et al. (2003) has noted nested logit choice models are best used to explain joint airport-transportation access mode decisions. The nested logit choice model assumes passengers make decisions based upon which choice provides the maximum utility, a measure of the satisfaction or benefit derived from a particular choice modeled as a function of choice option attributes. As such, the nested logit choice model was applied to estimate the passenger weight at each airport within each selected U.S. CSA through 2050.

To achieve the A66 research objectives, the following steps were implemented:

a) Estimation of Transportation Mode and Airport Utilities
b) Estimation of Passenger Choice Probabilities
c) Estimation of Passenger Counts
d) Estimation of Passenger Weights for Each Airport

Due to a lack of available field data regarding individual-level decisions pertaining to airport choice and ground transportation access mode choice, as well as a lack of available field data pertaining to passenger uptake of Part 135 AAM/UAM commercial services, a constrained optimization process was utilized to calculate model constants and coefficients for selected variables. Regarding model specification, variable selection was guided by extant research on ground transportation mode choice selection and airport selection. To this end, transportation mode utility was specified based upon travel time and travel cost, while airport utility was specified based upon average airfare, flight frequency, average transfers, and on-time flight performance. Travel time estimates for Part 135 AAM/UAM transportation were calculated as the linear distance from the centroid of each census tract to each airport within a selected U.S. CSA multiplied by the average speed of AAM/UAM vehicles, while travel time estimates for ground transportation modes were derived from Apple Maps. Travel cost estimates for Part 135 AAM/UAM transportation were derived from UAM Geomatics, while travel cost estimates for ground transportation modes were derived based on calculations of base cost and mileage. For additional information pertaining to data sources and prior research regarding these variables, see Appendix D.

The passenger weights for each airport were subsequently utilized as inputs for developing the TAF-M2 Part 121 enplanement estimates in Phase III.

3.2.2 Assumptions

Prior to engaging in analytical procedures, the following assumptions must be detailed for this research framework:

a) The centroid of each census tract will be utilized as a proxy for a potential vertiport location.
b) Vertiports are assumed to be capable of handling all Part 135 AAM/UAM commercial transportation services during the prediction period.
c) The number of passengers who may potentially adopt Part 135 AAM/UAM commercial transportation services will increase by up to 2% annually. For analytical purposes, the number of passengers assumed to adopt Part 135 AAM/UAM commercial transportation services in 2024 will be 0%.
d) Each airport is subject to a 10% annual limit on enplanement changes.
e) Each passenger will be assumed to travel from the centroid of their respective census tract to each metropolitan airport by one of four transportation modes: public transportation (i.e., bus, subway), taxi/Uber/Lyft, personal vehicle, or AAM/UAM. The travel time and travel cost will differ for each of the four transportation modes.
f) Each passenger is assumed to be rational, making their transportation mode choice solely based on travel time and travel cost. In other words, each passenger is assumed to select their transportation mode based on which has the maximum utility.
g) Each passenger within a census tract is assumed to make the choice regarding transportation mode and airport selection based on the nested logit choice model probability.
h) The transportation utility model (see Equation 1B below) and the airport utility model (see Equation 2B below) will have fixed coefficients across each CSA, as well as across time.
i) The emergence of Part 135 AAM/UAM commercial services will not impact on the coefficients of the nested logit choice model.
j) The ratio of passengers-to-population is based on household income for each census tract within a single CSA.
k) The μ_d in Equation 3B (see below) is fixed at the airport-level.
l) The model only considers passengers departing from each census tract to the airport, assuming the passenger will make the same transportation mode and airport choices for their return flights.

3.2.3 Mathematical Framework

The mathematical framework of the A66 AAM/UAM Transportation Integration Forecast Methodology is as follows:

3.2.3.1 Estimation of Transportation Mode and Airport Utilities

The utility of transportation mode U_a and utility of airport U_d from an origin census tract to a destination airport *d* with transportation mode *a* was assessed as a linear function of the following attributes:

Equation 1B. Utility of Transportation Mode

$$U_a = \beta_a + \beta_{Time} Time_{a,d} + \beta_{Cost} Cost_{a,d}$$

Equation 2B. Utility of Airport

$$U_d = \beta_d + \beta_{Fare} Fare_d + \beta_{Flights} Flights_d + \beta_{Transfer} Transfer_d + \beta_{Perform} Perform_d$$

where:

- β_a and β_d are the transportation mode-specific constant and airport-specific constant.
- β_{Time}, β_{Cost} , β_{Fare}, $\beta_{Flights}$, $\beta_{Transfer}$, and $\beta_{Perform}$ are coefficients for the variables assessing travel time, cost ticket fare, flights, transfer and airport on-time performance respectively.
- $Time_{a,d}$ and $Cost_{a,d}$ are the travel time and cost associated with transportation mode a for airport d in census tract location.
- $Fare_d, Flights_d, Transfer_d$ and $Perform_d$ are average air ticket fare, average number of flights, average number of transfers and average time delay in airport d.
- The coefficients in this section will be calculated by the constrained optimization process detailed in Section 3.3.4.1.
- Equation 1B is assessed at the census-tract level, while Equation 2B is assessed at the airport-level.

3.2.3.2 Estimation of Passenger Choice Probabilities

The softmax function, which is typically used to transform utilities into probabilities (Ben-Akiva et al., 1985; Bouchard et al., 2007; Pels et al., 2003), was utilized to convert the utility of transportation mode and the utility of airport into probabilities for analysis. These probabilities were calculated as follows:

Equation 3B. Probability of Choosing Transportation Mode Given Specific Airport

$$Pr_{a|d} = \frac{e^{\left[\frac{\beta_a + \beta_{Time} Time_{a,d} + \beta_{Cost} Cost_{a,d}}{\mu_d}\right]}}{\sum_{a \in \mathrm{A}(d)} e^{\left[\frac{\beta_a + \beta_{Time} Time_{a,d} + \beta_{Cost} Cost_{a,d}}{\mu_d}\right]}}$$

Equation 4B. Probability of Choosing Specific Airport

$$Pr_d = \frac{e^{[\beta_d + \beta_{Fare} Fare_d + \beta_{Flights} Flights_d + \beta_{Transfer} Transfer_d + \beta_{Perform} Perform_d + V_1]}}{\sum_{d \in \mathrm{D}} e^{[\beta_d + \beta_{Fare} Fare_d + \beta_{Flights} Flights_d + \beta_{Transfer} Transfer_d + \beta_{Perform} Perform_d + V_1]}}$$

Equation 5B. Maximum Expected Utility

$$V_1 = \mu_d \ln\left\{\sum e^{\left[\frac{\beta_a + \beta_{Time}Time_a + \beta_{Cost}Cost_a}{\mu_d}\right]}\right\}$$

Where:

- $Pr_{a|d}$ is the probability of choosing transportation mode a given airport d.
- Pr_d is the probability of choosing airport d.
- $A(d)$ is transportation mode a in airport d.
- D is all airports within the CSA.
- e is the exponential function.
- μ_d is an inclusive value parameter (heterogeneity parameter) in airport d, where alternatives within a nest become closer substitutes if μ_d gets closer to 0, and the model reduces to the multinomial logit model when $\mu_d = 1$. It will be calculated using the constrained optimization process detailed in Section 3.3.4.1.
- Equations 3B – 5B are assessed at the airport-level using census tract estimates.

3.2.3.3 Estimation of Passenger Counts

After the nested logit choice model was implemented to determine transportation mode and airport probabilities, estimates of passengers from each census tract within a U.S. CSA were assessed using the assumption each passenger within the census tract would make the same travel choice (i.e., the airport with the highest probability of selection for a census tract would receive all passengers from the census tract). The total passenger estimate for all census tracts within a metropolitan area were assessed as follows:

Equation 6B. Estimate of Passengers Choosing Specific Airport

$$P_{Count\_d} = \alpha * \sum_{Census\ Tract} \alpha_c Pr_d * P_{census\ tract}$$

Where:

- P_{Count_d} is passenger count for airport d.
- $P_{census\ tract}$ is census tract population.
- α_c is the median household income ratio for each census tract ($\alpha_c = \frac{Median\ Household\ Income\ of\ the\ Census\ Tract}{Median\ Household\ Income\ of\ the\ CSA}$)
- α is the passenger ratio within the CSA ($\alpha = \frac{Total\ Passengers\ of\ the\ CSA}{\sum_{Census\ Tract} \alpha_c P_{census\ tract}}$).
- Equation 6B is assessed at the airport-level using census tract estimates.

3.2.3.4 Estimation of Airport Weights

Finally, after assessing the passenger count for each airport, the passenger weight of each airport within a CSA was assessed as follows:

Equation 7B. Estimate of Passenger Flow Weight for Specific Airport

$$W_d = \frac{P_{Count\_d}}{\sum_D P_{Count\_d}}$$

Where:

- W_d is the passenger weight of airport.

- Equation 7B is estimated at the airport-level.

3.2.4 Constrained Optimization

To calculate airport passenger weights using a nested logit choice mode, the coefficients for Equations 1B, 2B, and 3B (i.e., $\beta_{Time}, \beta_{Cost}, \beta_{Fare}, \beta_{Flights}, \beta_{Transfer}, \beta_{Perform}, \mu_d$) need to be estimated. Due to a lack of field data regarding transportation choice and airport choice, the traditional statistical model fitting process could not be directly applied to this research (Pels et al., 2003; Zhao et al., 2020). As such, a constrained optimization process was proposed to estimate these coefficients.

Constrained optimization is a mathematical technique used to find the optimal solution to a problem subject to certain restrictions or constraints. This can be used to minimize or maximize the objective function while adhering to the constraints. In this research, the objective function was to minimize the difference between the TAF-M generated passenger count and the calculated passenger count for each airport. The constraints were the calculated probability of each transportation mode equal to the observed percentages of each transportation mode arriving at an airport which were sometimes published by local airport authorities, which were published on the airport official website (i.e. LAX). These reports present survey results detailing percentages of passengers which utilized various ground transportation modes to access a specific airport. Throughout the project, the A66 research team identified reports containing the observed percentages for three airports in New York, NY as well as the LAX airport in Los Angelos, CA.

The mathematical formula utilized was:

Equation 8B. Objective Function for Constrained Optimization:

$$minimize\ S(\beta, \mu_d) = \sum_{airport} \left(P_{Count\_t} - P_{Count}(\beta, \mu_d)\right)^2$$

Subject to:

$$P_{a|d} = P_{a|d}(\beta, \mu_d)$$

Where:

- P_{Count_t} is the TAF-M generated passenger count for airport a.
- $P_{Count}(\beta, \mu_n)$ is the calculated passenger count for airport a.
- $P_{a|d}$ is the observed percentage of transportation mode a for airport d.
- $P_{a|d}\ (\beta, \mu_d)$ is the calculated probability of transportation mode a for airport d.

By applying constrained optimization algorithm, the coefficients β_{Time}, β_{Cost}, β_{Fare}, $\beta_{Flights}$, $\beta_{Transfer}$, $\beta_{Perform}$ and μ_d were estimated. Accordingly, the passenger flow weight of passenger counts for each airport within a metropolitan area could be calculated. As the coefficients were assumed to not change when Part 135 AAM/UAM commercial services are introduced, by applying transportation mode utility function and airport utility function for Part 135 AAM/UAM services, the passenger count shifts after Part 135 AAM/UAM services launch could also be derived. The results of this analysis provided valuable insights into the potential impact of Part 135 AAM/UAM commercial services on the passenger distribution among metropolitan airports.

3.3 Phase III: TAF-M2 Part 121 Enplanement Forecasts

This section provides an overview of the TAF-M2 Methodology, which utilized forward induction to iteratively apply the airport weights developed through the A66 AAM/UAM Transportation Integration Forecast Methodology (Phase II) to the 25-Year TAF-M Part 121 enplanement forecast passenger counts (Phase I) to produce a new 25-Year TAF-M2 Part 121 enplanement forecast.

3.3.1 Methodological Overview

Upon completing Phase I and Phase II, TAF-M2 Part 121 enplanement estimates were developed using forward induction to iteratively apply the airport-level passenger weights developed through the A66 AAM/UAM Transportation Integration Forecast Methodology (Phase II) to the MSA-level TAF-M passenger count estimates (Phase I) through 2050.

The forward induction approach, derived from fundamental concepts in game theory, allows for inferences regarding passenger behavior based on the assumption passengers will make rational choices regarding future behavior similar to their observed historical decisions (Catonini & Penta, 2022; Pearce, 1984; Perea, 2010). The rationality assumption of the forward induction approach implies passengers make decisions based upon which option provides the maximum utility, similar to the assumptions of discrete choice modelling (e.g., nested logit choice models) (Perea, 2010). Relative to the backward induction approach which ignores past behavior, the forward induction approach provides a richer strategic framework for decision making by incorporating the theoretical assumption that past behavior can signal future behavior, allowing for more nuanced predictions (Perea, 2010). Relative to the backward induction approach, which is most effective in scenarios of complete and perfect information, the forward induction approach is more adaptable to scenarios involving incomplete and imperfect information (i.e., the forward induction approach is more flexible since it can incorporate additional information as it becomes available) (Perea, 2010).

As such, the forward induction approach was more suitable for use in the TAF-M2 Methodology for the following reasons:

- The TAF-M currently utilizes the forward induction approach to make predictions of Part 121 enplanements based on historical data.
- The A66 AAM/UAM Transportation Integration Forecast Methodology utilizes historical data to make predictions related to passenger choices regarding transportation access mode and airport preference. The historical data provides the total number of passengers, average airfare at each airport, and census tract travel time and cost to the airport in each CSA for the target quarter, which would be used in the proposed TAF-M2 methodology for this project.
- The requisite assumption of the backward induction approach that future passengers would make rational decisions based on complete and perfect information is untenable. In reality, passengers often make decisions based upon incomplete information regarding all possible choice options.
- The backward induction approach requires the assumption of fixed end states (i.e., fixed outcomes) (Alós-Ferrer & Klaus, 2017), which runs counter to the intended purpose of A66 research to develop a flexible-network commercial aviation methodology. As Part 135 AAM/UAM commercial services have yet to be

implemented, it is impossible to account for all possible future network states, as would be necessary when utilizing the backward induction approach.

The analytical steps for applying the forward induction approach were as follows:

1. Airport-level passenger weights were developed through the A66 AAM/UAM Transportation Integration Forecast Methodology (Phase II).
2. The airport-level passenger weights developed through the A66 AAM/UAM Transportation Integration Forecast Methodology (Phase II) were applied to the metropolitan-level TAF-M passenger counts to produce TAF-M2 passenger counts for each airport within selected U.S. CSAs.
3. The adjusted TAF-M2 passenger counts for each airport within selected U.S. CSAs were converted to TAF-M2 Part 121 enplanement estimates.
4. Based on the 100,000 Part 121 enplanement threshold designated by the TAF-M Methodology, airports within the selected U.S. CSAs were reclassified as active TAF-M2 airports or non-TAF-M2 airports.
5. The TAF-M2 route ratios were updated accordingly to inform calculations for the subsequent year.
6. The enplanement numbers in each CSA were updated according to the TAF-M2 CSA passenger numbers, where the updated CSA-level enplanements were used for next year's TAF-M prediction.
7. Step 1 – Step 5 were iteratively repeated for each year until final results were obtained for 2050.

Figure 1 presents a visual illustration of the TAF-M2 process outlined above. Figure 2 shows the data flow between TAF-M and TAF-M2.

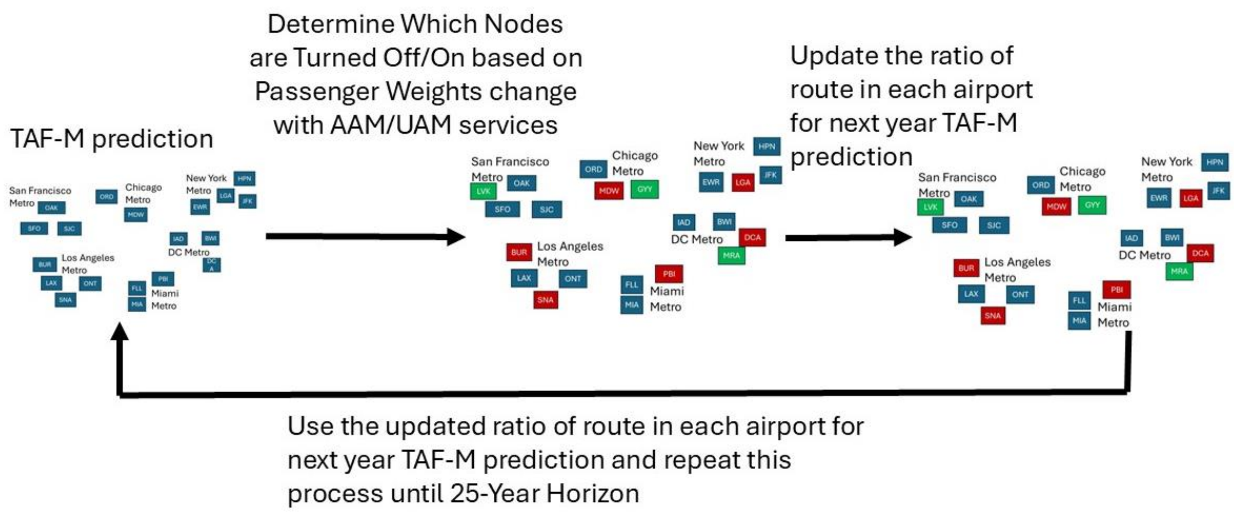

Figure 1. TAF-M2 Application of the Forward Induction Approach

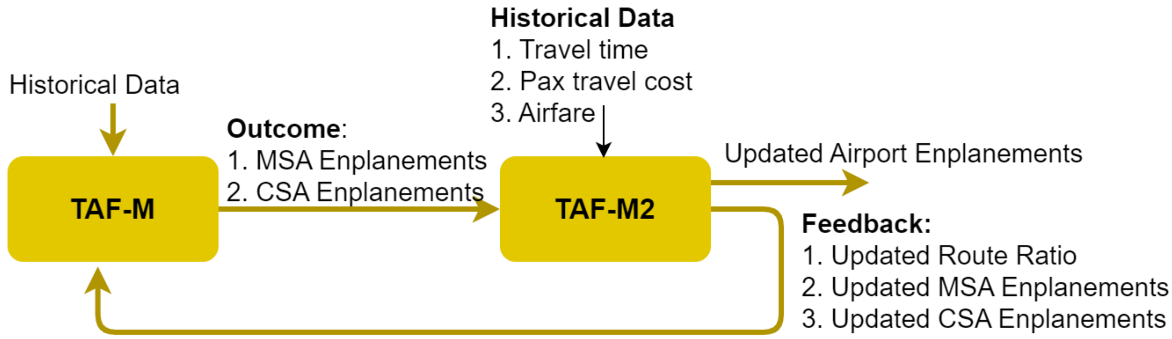

Figure 2. The data flow between TAF-M and TAF-M2.

3.4 Limitations and Potential Adjustments for Future Research

The proposed methodology contained the following limitations:

- The assumption that all census tracts have the same parameters (β_{Time}, β_{Cost}, β_{Fare}, $\beta_{Flights}$, $\beta_{Transfer}$, $\beta_{Perform}$, μ_d) for the nested logit choice model may not be robust enough. This could be improved as in-field data regarding transportation modes to the airport for each census tract is obtained.
- The assumption that the emergence of Part 135 AAM/UAM services will not impact on the coefficients of the nested logit choice model may not be strong enough. It could be updated to accommodate new data on Part 135 AAM/UAM commercial services when available in the future.
- The mathematical model pertaining to passenger decisions utilizes a very simplified formula (Equation 1B and 2B). In reality, passengers often have incomplete information or make irrational choices. Furthermore, personal preference (e.g., the acceptance rate of Part 135 AAM/UAM commercial services) is not considered in this research.

Regarding potential adjustments for future research, the proposed methodology allows for additional variables (e.g., travel purpose, residency status, passenger demographics) to conveniently be considered so long as the appropriate data is available, increasing the flexibility of this model.

Furthermore, if additional field data pertaining to the variables listed in Equations 1B – 8B are available, the model can be improved through the incorporation of this additional field data or by imposing additional constraints so model calibration can be enhanced. The methodology to refine the model based on ground truth data is included in Appendix G.

Additionally, this framework allows for future research to nest airports by various characteristic categories (e.g., passenger count, airlines present), allowing different sets of coefficients to be considered by airport category.

METRO-SPECIFIC PARAMETERS FOR AAM FORECAST METHODOLOGY

In this section, the A66 performers focused on refining and operationalizing the A66 AAM/UAM Transportation Integration Forecast Methodology by incorporating metro-specific parameters for selected CSAs and developing the corresponding Python scripts to produce the required parameters. This process included defining and enumerating internal geographic areas within each targeted MSA, data collection, and development of Python scripts for the methodology that guided by insights and constraints gathered in prior sections.

Following the delineation of these targeted CSAs, the team implemented the full A66 AAM/UAM Transportation Integration Forecast Methodology using Python, building upon earlier algorithmic development. The resulting system was then used to generate metro-specific input parameters necessary for the final implementation of the TAF-M2 model in the following section. This included leveraging the metropolitan ranking framework and the developed modeling and simulation outputs.

4.1 Data Collection

One of the objectives of this section is to document the sources of all relevant data for the targeted CSAs that informed the A66 AAM/UAM Transportation Integration Methodology within the TAF-M2 model. Based on the ranking result in section 2, six CSAs were selected as the target CSA for the following process, which were New York, Los Angles, San Francisco, Chicago, Miami and Washington DC. Details on where to download the data can be found in Appendix D. Instructions on how to download and pre-process the datasets are included in Appendix F.

4.2 Input Datasets

The input dataset included the following key data sources:

- List of airports in the CSA.
- List of census tracts in the CSA.
- Travel time and cost from each census tract to the airport in CSA.
- Population data for each census tract.
- Airfare for flights departing from each airport.
- Average transfer ratio for each airport.
- On-time performance data for each airport.
- Annual operations and enplanement number for each airport.
- Ground transportation statistics.
- The median household income for each census tract.
- The median household income.

Since the datasets for on-time performance and average transfer ratios from DB1B are large, the downloaded files were not included in the uploaded dataset folder; instructions for download were provided in Appendix D.

4.3 Python Scripts

Two Python scripts were created for this section, which serve distinct purposes:

- **Data processing:** Processes the downloaded data and outputs the processed datasets for the TAF-M2 model.
- **Constrained Optimization:** Estimates parameters for the nested logit choice model (described in Section 3). The output includes parameters for use in the TAF-M2 model.
- **TAF-M2:** Fully documented scripts for proposed TAF-M2 model in Section 3.

4.4 Dataset Introduction

- **Airport List:** A complete list of airports in the CSAs with at least 10 annual operations in 2023, which include the name of the airport and their corresponding latitudes and longitudes.
- **Census Tract List:** A comprehensive list of census tracts within the CSA, including location and population information.
- **Median Household Income:** Census tract-level median household income data and the average median household income for the CSA.
- **Travel Time and Cost to Airport:** Using Apple Map API to retrieve travel time and distance from each census tract to each airport, this included both ground transportation and any potential Part 135 AAM/UAM commercial transportation options. Then, American Automobile Association (AAA) data was used to calculate private car cost to the airport based on distance, and City Cab rates for taxi and ride-share options. Finally, UAM Geomatics provided Part 135 AAM/UAM commercial transportation service ticket price predictions, which was used to estimate travel mode utility.
- **Airfare:** Average airfare data is collected from the Bureau of Transportation Statistics.
- **Airport Transfer:** Data on the transfer ratios from each airport from the BTS website, which was used to estimate airport utility.
- **On-Time Performance:** Data on delays and cancellations sourced from the BTS website.
- **Annual Operations and Enplanements Number:** FAA data regarding annual operations and enplanement numbers.
- **Annual Passenger Transportation Mode:** Airport public data of 2023 for transportation mode utility calculations.

4.5 Parameter Generation

- Use available transportation and aviation datasets to generate transportation mode utility parameters.
- Utilize TAF-M predicted enplanements at metropolitan airports to derive airport utility parameters.

25-YEARS FORECASTS WITH TAF-M2 MODEL

In this section, the proposed TAF-M2 methodology in section 3 will be implemented with Python scripts for all CSAs and produce annual forecasts over a 25-year planning horizon (2025–2050). These forecasts include the predicted enplanements number and the location (latitude and longitude) of each airport.

5.1 Deliverables

- **Datasets:** Incorporates key variables for the six chosen CSAs, including airports, census tracts, travel time/cost, population, airfare, median household income, transfer rates, on-time performance, and passenger numbers. The details of those datasets are included in Appendix E.
- **Python Scripts:** Fully documented scripts for TAF-M2 model, including data pre-processing, data-processing, constrained optimization and TAF-M2. Two accompanying Microsoft Word documents are provided which introduce a road map of the Python scripts and a ReadMe file.
- **Parameters:** The transportation parameters, airport parameters and airport heterogeneity parameters in the six chosen CSAs.
- **25-Years Prediction:** The enplanement prediction from 2025 to 2050 for each airport and corresponding airport latitude and longitude.

CONCLUSION

The efforts undertaken in this project established a robust and reproducible framework to evaluate the potential impact of Part 135 AAM/UAM commercial transportation integration within the NAS. By expanding metropolitan ranking methodologies and embedding a behavioral passenger choice model into the TAF-M2 forecasting process, the project delivers a scalable and flexible approach to forecasting the redistribution of air travel demand resulting from Part 135 AAM/UAM services.

The developed methodology not only highlights the CSAs most ready for early Part 135 AAM/UAM adoption but also quantifies the dynamic enplanement impacts such services could have over a 25-year planning horizon. While current limitations—such as the absence of nationwide behavioral data—necessitated the use of constrained optimization for parameter estimation, the framework is designed to accommodate future enhancements as empirical data becomes available.

Overall, this project equips FAA and stakeholders with the data infrastructure, modeling tools, and analytical insight necessary to guide Part 135 AAM/UAM integration strategies, investment decisions, and regulatory planning in a rapidly evolving transportation landscape.

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APPENDIX A: VIABLE DATA SOURCES FOR A66 METROPOLITAN RANKING METHODOLOGY

Table 1 details viable data sources pertaining to variables discussed throughout the literature review for potential utilization in the proposed A66 Metropolitan Ranking Methodology. As discussed in this literature review, it is important to note that social factors will be excluded from the proposed methodology due to the lack of requisite data to conduct a nationwide assessment. As previously stated, such data collection efforts are beyond the scope of the ASSURE A66 project.

Table A.1. Data Sources for the A66 Metropolitan Ranking Methodology.

Category	Variable	Definition	Data Source	Reference
Urban Structure	Population Density	The number of people living per square mile.	US Census Bureau	Gerardus et al., 2024 Olivares et al., 2022
	Polycentrism	The number of distinct employment centers within a metropolitan area.	Arribas-Bel and Sanz-Gracia (2014) https://www.tandfonline.com/doi/full/10.1080/02723638.2014.940693#d1e140	Arribas-Bel et al.,2024 Goyal et al., 2018
Economic Scale	Fortune 1000 Presence	The number of Fortune 1000 company headquarters is located within a metropolitan area.	Fortune	Godfrey et al., 1999 Csomós et al., 2014
	Gross Regional Product (GRP)	The total economic output of a region, like GDP but at a metropolitan level.	Bureau of Economic Analysis https://www.bea.gov/data/gdp/gdp-county-metro-and-other-areas	Panek et al., 2007 Goyal et al., 2021 Reiche et al., 2018
	Personal Income	The average income of individuals within a metropolitan area.	S&P Global	Haan et al., 2023 Kloss et al., 2021 Pertz et al., 2023 Garrow et al., 2018 Yedavalli et al., 2019
Congestion and Travel Time	Average Time to Work	The average duration it takes for commuters to travel from home to work.	US Census Bureau	Rimjha et al., 2021 Long et al., 2023 Zhang et al., 2023
	Travel Time Index	A measure that compares peak travel times to free flow conditions indicates the severity of traffic congestion during peak periods.	Texas A&M Transportation Institute https://mobility.tamu.edu/umr/	Long et al., 2023 Sarkar et al., 2023 Texas A&M Transportation Institute, 2023
	Airport to CBD Drive Time	The average driving time from airports to the CBD in metropolitan.	Google Map	Haan et al., 2021 Mahmassani et al., 2024

Table A.1. Data Sources for the A66 Metropolitan Ranking Methodology (Cont.).

Category	Variable	Definition	Data Source	Reference
Market Readiness	Heliports Per Capita	The number of heliports is relative to the population in a metropolitan area.	FAA	Mahmassani et al., 2024 Olivares et al., 2021
	Airports Per Capita	The number of airports relative to the population in a metropolitan area.	FAA	Reiche et al., 2018 Haan et al., 2021
	Regional Airport	The number of regional airports in a metropolitan area.	FAA	Antcliff et al., 2021 Olivares et al., 2022
	Class B Airspace	Presence (or not) of Class B Airspace in MSA (binary).	FAA	Bauranov et al., 2021 Mahmassani et al., 2024 Olivares et al., 2022
	Class G Airspace Congestion	Average total aircraft operation hours per square mile in Class G airspace.	FAA	Bauranov et al., 2021 Olivares et al., 2022
	Existing Investment	UAM launch city or UAM headquarters city locations.	UAM Geomatics	Schuh et al., 2021 Olivares et al., 2022
Existing Short-Haul Market	Airport Short-Haul Market Stability (<150 miles)	The volume of flight arrival and departure points within MSA for total flight distances of less than 150 miles.	The Airline Origin and Destination Survey (DB1B) https://www.transtats.bts.gov/DatabaseInfo.asp?QO_VQ=EFI&Yv0x=D	Olivares et al., 2022

APPENDIX B: INTRODUCTION OF RANKING DATASET

Population (Population.xlsx):

- **CSA (string):** The name of the CSA
- **Population (int):** The total population of the CSA

Area of Land (US_2023_CensusTract_Centroid_GCS_WGS1984_LAT_LONG.csv):

- **TRACTCE (string):** Census tract code
- **STATEFP (int)**: State FIPS code
- **COUNTYFP (int)**: County FIPS code
- **ALAND (float):** The total land area

GDP (GDP.csv):

- **GEOName (string):** The name of the CSA
- **2022 (int):** The total GDP in 2022

AAM Launch City (AAM_CITY.xlsx):

- **City (string):** The name of the CSA
- **number (int):** The count number for city

AAM Company Headquarter (AAM_Company.xlsx):

- **Headquarters (string):** The name of the CSA for headquarters
- **number (int):** The count number for headquarters

Polycentrism (Checked_Poly.csv):

- **MSA (string):** The name of the MSA
- **Poly (int):** The recorded polycentrism in 2010
- **CSA (string):** The name of CSA

Fortune 1000 Company (fortune1000_2023.csv):

- **Company (string):** The company's name
- **HeadquartersCity (string):** The city where the company is headquartered.
- **HeadquartersState (string):** The state where the company is headquartered.

GDP (Census_Tract_Population_2020.xlsx):

- **GEO_ID (string)**: The census tract ID
- **NAME (string)**: The census tract name.
- **Total_Population (int)**: The total population of the census tract.

Average Time to Work (Travel_time.xlsx):

- **CSA (string):** The name of the CSA
- **travel_time (float):** The average commuting time (minutes)

Travel Time Index (Travel_time_index.xlsx):

- **Urban Area (string):** The name of the city

- **Year (int):** The year of travel time index measurement
- **Travel_Time_Index (float):** The travel time index value

A36 Team Dataset (SSA_data.xlsx):

- **MSA (string):** The name of the MSA
- **Class_B (int):** Presence of Class B airspace
- **Class_G (float):** Average total hours per square mile in Class G airspace

Airport and Heliport (all-airport-data.xlsx):

- **Facility Type (string)**: The type of facility.
- **Loc Id (string)**: The ID of the facility.
- **State Name (string)**: The latitude of the census tract.
- **City (string)**: The name of the city
- **County (string):** The name of the county

Local Incentive (Incentive_CSA.csv):

- **CSA (string):** The name of the CSA
- **State (string):** The state in which the CSA is located
- **Incentive (float):** The monetary or policy incentive value associated with the CSA

Existing Investment (AAM_in_CSA.cxlsx):

- **CSA (string):** The name of the CSA
- **Launched (float):** The number of AAM locations that plan to launch in CSA
- **Headquarters (float):** The number of AAM headquarters located in CSA

Electrical Consumption (Electrical.xlsx):

- **CSA (string):** The name of the CSA
- **Consumption MMBtu (float):** The commercial energy consumption measured in MMBtu

Electrical Consumption in County Level
(energy_consumption_expenditure_business_as_usual_county.csv):

- **County Name (string):** The name of the County
- **State Name (string):** The name of the State
- **Year (int):** Year
- **Consumption MMBtu (float):** The commercial energy consumption measured in MMBtu

Airport Short-Haul Market (Shor_flight.csv):

- **Airport (string)**: The airport ID.
- **LONGITUDE (float)**: The longitude of the airport.
- **LATITUDE (float)**: The latitude of the airport.

City to County Cross-table (place_to_county.xlsx):

- **NAME (string):** The name of the city
- **STATEFP (int)**: State FIPS code

- **COUNTYFP (int)**: County FIPS code

CSA to MSA Cross-table (CSA.xlsx):

- **CBSA Code (string):** The MSA ID
- **CBSA Title (string)**: The name of MSA
- **CSA Title (string)**: The name of CSA
- **FIPS State Code (int)**: State FIPS code
- **FIPS County Code (int)**: County FIPS code

Connecticut New and Old County Cross-table (ct_cou_to_cousub_crosswalk.xlsx):

- **STATEFP (int)**: State FIPS code
- **NEW_COUNTYFP (int)**: County FIPS code
- **COUSUB_NAMELSAD (string):** The new name of county

State FIPS Code (state_code.csv):

- **STATEFP (int)**: State FIPS code
- **STATE (string)**: The name of state

APPENDIX C: SITE SUITABILITY SCENARIOS

The five categories are assigned weights of 45%, 10%, 15%, and 5% based on the work from Team A36. For different scenarios, the emphasis on each category will vary. For example, in the urban structure scenario, urban structure is the most important category and has the highest weight. The variable weighting for each scenario is shown in Table 1. The Top 20 CSA rankings for these scenarios are shown in Tables 2 and 3 (the result of infrastructure readiness is shown in 3.1).

Table C.1. Variable Weighting for Other Scenarios.

		Urban Structure		Economic Scale		Cong & Com Stress		Infr. Readiness		Exist. Short Haul	
Category	**Variable**	**Category**	**Variable**	**Category**	**Variable**	**Category**	**Variable**	**Category**	**Variable**	**Category**	**Variable**
Urban Structure	Population Density	45.0	22.5	10.0	5.0	15.0	7.5	15.0	7.5	10.0	5.0
	Polycentrism		22.5		5.0		7.5		7.5		5.0
Economic Scale	Fortune 1000 Presence	10.0	5.0	45.0	22.5	10.0	5.0	10.0	5.0	25.0	12.5
	GDP per Capita		5.0		22.5		5.0		5.0		12.5
Congestion	Average Time to Work	15.0	5.0	15.0	5.0	45.0	15.0	25.0	8.3	5.0	1.7
	Travel Time Index		5.0		5.0		15.0		8.3		1.7
	Airport to CBD Drive Time		5.0		5.0		15.0		8.3		1.7
Readiness	Heliports per Capita	25.0	3.0	25.0	3.0	25.0	3.0	45.0	5.0	15.0	1.0
	Airports per Capita		3.0		3.0		3.0		5.0		1.0
	Class B Airspace		3.0		3.0		3.0		5.0		1.0
	Class G Airspace Congestion		3.0		3.0		3.0		5.0		1.0
	Electrical Consumption		5.0		5.0		5.0		10.0		5.0
	Local Incentive		5.0		5.0		5.0		10.0		5.0
	Public & Private Investment		3.0		3.0		3.0		5.0		1.0
Existing Demand	Airport Short Haul OD <150 Miles	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	45.0	45.0

Table C.2. The Top 20 Suitable CSAs - Urban Structure and Economic Scale Scenario

Rank	Urban Structure Scenario	Economic Scale Scenario
1	New York-Newark, NY-NJ-CT-PA	New York-Newark, NY-NJ-CT-PA
2	Los Angeles-Long Beach, CA	San Jose-San Francisco-Oakland, CA
3	San Jose-San Francisco-Oakland, CA	Los Angeles-Long Beach, CA
4	Miami-Port St. Lucie-Fort Lauderdale, FL	Chicago-Naperville, IL-IN-WI
5	Boston-Worcester-Providence, MA-RI-NH	Boston-Worcester-Providence, MA-RI-NH
6	Chicago-Naperville, IL-IN-WI	Miami-Port St. Lucie-Fort Lauderdale, FL
7	Washington-Baltimore-Arlington, DC-MD-VA-WV-PA	Washington-Baltimore-Arlington, DC-MD-VA-WV-PA
8	Detroit-Warren-Ann Arbor, MI	Seattle-Tacoma, WA
9	Seattle-Tacoma, WA	Dallas-Fort Worth, TX-OK
10	Houston-Pasadena, TX	Houston-Pasadena, TX
11	Dallas-Fort Worth, TX-OK	Denver-Aurora-Greeley, CO
12	Atlanta--Athens-Clarke County--Sandy Springs, GA-AL	Atlanta--Athens-Clarke County--Sandy Springs, GA-AL
13	Philadelphia-Reading-Camden, PA-NJ-DE-MD	Nashville-Davidson--Murfreesboro, TN
14	New Haven-Hartford-Waterbury, CT	Salisbury-Ocean Pines, MD
15	Denver-Aurora-Greeley, CO	Charlotte-Concord, NC-SC
16	Nashville-Davidson--Murfreesboro, TN	Minneapolis-St. Paul, MN-WI
17	Orlando-Lakeland-Deltona, FL	Philadelphia-Reading-Camden, PA-NJ-DE-MD
18	Cleveland-Akron-Canton, OH	Raleigh-Durham-Cary, NC
19	Raleigh-Durham-Cary, NC	Phoenix-Mesa, AZ
20	Allentown-Bethlehem-East Stroudsburg, PA-NJ	Detroit-Warren-Ann Arbor, MI

Table C.3. The Top 20 Suitable CSAs – Congestion Stress and Short Haul Scenario

Rank	Congestion Stress Scenario	Short Haul Scenario
1	New York-Newark, NY-NJ-CT-PA	New York-Newark, NY-NJ-CT-PA
2	San Jose-San Francisco-Oakland, CA	Chicago-Naperville, IL-IN-WI
3	Los Angeles-Long Beach, CA	Los Angeles-Long Beach, CA
4	Miami-Port St. Lucie-Fort Lauderdale, FL	San Jose-San Francisco-Oakland, CA
5	Chicago-Naperville, IL-IN-WI	Seattle-Tacoma, WA
6	Seattle-Tacoma, WA	Atlanta--Athens-Clarke County--Sandy Springs, GA-AL
7	Washington-Baltimore-Arlington, DC-MD-VA-WV-PA	Charlotte-Concord, NC-SC
8	Denver-Aurora-Greeley, CO	Houston-Pasadena, TX
9	Houston-Pasadena, TX	Dallas-Fort Worth, TX-OK
10	Nashville-Davidson--Murfreesboro, TN	Washington-Baltimore-Arlington, DC-MD-VA-WV-PA
11	Boston-Worcester-Providence, MA-RI-NH	Boston-Worcester-Providence, MA-RI-NH
12	Dallas-Fort Worth, TX-OK	Detroit-Warren-Ann Arbor, MI
13	Atlanta--Athens-Clarke County--Sandy Springs, GA-AL	Denver-Aurora-Greeley, CO
14	Sacramento-Roseville, CA	Phoenix-Mesa, AZ
15	San Antonio-New Braunfels-Kerrville, TX	Portland-Vancouver-Salem, OR-WA
16	Raleigh-Durham-Cary, NC	Philadelphia-Reading-Camden, PA-NJ-DE-MD
17	New Orleans-Metairie-Slidell, LA-MS	Miami-Port St. Lucie-Fort Lauderdale, FL
18	Allentown-Bethlehem-East Stroudsburg, PA-NJ	Minneapolis-St. Paul, MN-WI
19	Las Vegas-Henderson, NV	Raleigh-Durham-Cary, NC
20	Orlando-Lakeland-Deltona, FL	Las Vegas-Henderson, NV

APPENDIX D: DATA SOURCES FOR TAF-M2 METHODOLOGY

Table D.1. Details of the data sources for TAF-M2 Methodology.

Dataset Name	Data Source	Link
Airport List	FAA TAF-M FAA Class D Airport	https://www.faa.gov/data_research/aviation/taf
Census Tract List	U.S. Census Bureau	https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.2023.html#list-tab-790442341(3.1.0)
Average Airfare	Bureau of Transportation Statistics	https://www.transtats.bts.gov/averagefare/
Annual Operations	FAA TAF-M	https://www.faa.gov/data_research/aviation/taf
Annual Enplanements	FAA TAF-M	https://www.faa.gov/data_research/aviation/taf
Average Airport Transfer Ratio	Airline Origin and Destination Survey (DB1B-Market)	https://www.transtats.bts.gov/DatabaseInfo.asp?QO_VQ=EFI&Yv0x=D
Transportation Mode	LAX and JFK Ground Transportation Traffic Statistics	https://www.lawa.org/lawa-investor-relations/statistics-for-lax/ground-transportation-traffic-statistics https://www.panynj.gov/airports/en/statistics-general-info.html
Average On-Time Flight Performance	Bureau of Transportation Statistics	https://www.transtats.bts.gov/DL_SelectFields.aspx?gnoyr_VQ=FGK&QO_fu146_anzr=b0-gvzr
Travel Time and Distance by Transportation Access Mode	Apple Map API*	https://developer.apple.com/documentation/applemapsserverapi/
Travel Cost by Transportation Access Mode	UAM Geomatics AAA City Cab Metro	https://www.uamgeo.com/ https://exchange.aaa.com/automotive/aaas-your-driving-costs/ https://lacitycab.com/rates/ https://www.metro.net/riding/fares/
Population in Census Tract	U.S. Census Bureau	https://data.census.gov/table/DECENNIALPL2020.P1?q=Population%20Total&g=010XX00US$1400000
Median Household Income	U.S. Census Bureau	https://data.census.gov/table/ACSST5Y2022.S1901?q=median%20income&g=010XX00US$1400000 https://data.census.gov/table/ACSST5Y2022.S1901?q=median%20income&g=010XX00US$3300000

*The Apple Maps API provides automobile and transit (public transportation) information from one location to another. If public transportation is unavailable, the time and distance values will be marked as missing. According to the Apple Maps API website, it includes all types of public transportation and accounts for all transfers to the destination. If no public transportation is available, the proposed model will exclude the public transportation mode. (https://www.transtats.bts.gov/averagefare/)

APPENDIX E: INTRODUCTION OF TAF-M2 DATASET

In this section, we list the variables included in the final datasets that are uploaded as attachments (XX stands for the name of the CSA).

Apple Map API (Apple_ API_XX.csv):

- **census (string)**: The census tract ID
- **Airport (string)**: The airport ID
- **Type (string)**: Transportation mode type
- **Distance (int)**: The travel distance (meters) for each transportation mode.
- **Time (int)**: The travel time (seconds) for each transportation mode.
- **Static_Time (int)**: The travel time (seconds) for driving without traffic.
- **Time_zone (string)**: The depart time in Coordinated Universal (UTC) time.

Census tract location (Census_tract_Long_Lat_XX.csv):

- **GEOIDFQ (string):** The census tract ID
- **Longitude (float):** The longitude of the census tract.
- **Latitude (float):** The latitude of the census tract.

Airport location (Airport_Long_Lat_XX.csv):

- **IDENT (string):** The airport ID
- **LONGITUDE (string):** The longitude of the airport.
- **LATITUDE (string):** The latitude of the airport.

Airport features (Airport_features_XX.csv):

- **Airport (string)**: The airport ID
- **Delay (float)**: The ratio of delayed enplanements at CSA airports.
- **Cancel (float)**: The ratio of cancelled enplanements at CSA airports.
- **Result**: The ratio of enplanements not on time at CSA airports (scaled to the range [0,1]).
- **Fare (float)**: The average airfare at CSA airports (scaled to the range [0,1]).
- **Frequency (float)**: The airport annual operations at CSA airports (scaled to the range [0,1]).
- **Enplanements (int)**: The airport annual enplanements at CSA airports (scaled to the range [0,1]).
- **Weight (float)**: The weight of enplanement number for each CSA airport inside the CSA metropolitan.
- **Connect_rate (float)**: The transfer ratio at CSA airports (scaled to the range [0,1]).

Census tract travel features (census_tract_feature_XX.csv):

- **census (string):** The census tract ID
- **Airport (string):** The airport ID
- **Type (string):** Transportation mode type
- **Distance (float):** The travel distance (meters) for each transportation mode.
- **Time (float):** The travel time (seconds) for each transportation mode.

- **Static_Time (float):** The travel time (seconds) for driving without traffic.
- **Population (int):** The population inside the census tract.
- **Fly_distance (float):** The flying distance from census tract to airport.
- **Fly_time (float):** The flying time from census tract to airport.
- **Cost_private_car (float):** The cost of the travel with private car from census tract to airport.
- **Cost_shared_car (float):** The cost of the travel with shared car from census tract to airport.
- **Cost_transit (float):** The cost of the travel with public transportation from census tract to airport.

Census Tract Population (Census_Tract_Population_2020.xlsx):

- **GEO_ID (string)**: The census tract ID
- **NAME (string)**: The census tract name.
- **Total_Population (int)**: The total population of the census tract.

Airports and CSA cross-table (airports_within_CSA.xlsx):

- **IDENT (string):** The airport ID.
- **CSA (string):** The name of the CSA.

Airfare (Consumer_Airfare_Report_Airport_Pair_Markets.csv):

- **Year (int):** The data collected year.
- **quarter (int):** The data collected quarter.
- **airport_1 (string)**: The original airport ID.
- **airport_2 (string)**: The destination airport ID.
- **fare (float)**: The flight airfare.

Airfare Result (XX_Airfare.csv):

- **Airport (string)**: The airport ID.
- **Airfare (float)**: The annual average airfare.

On Time Performance (Ontime_XX.csv):

- **Airport (string)**: The airport ID.
- **Delay (float)**: The ratio of delay enplanements at LA airports.
- **Cancel (float)**: The ratio of cancelled enplanements at LA airports.
- **Result (float)**: The total delay and cancellation rate at LA airports.

Transfer in Airport (Airport_Connect_XX.csv):

- **Airport (string)**: The airport ID.
- **Depart (int)**: The depart number of the airport.
- **Connect (int)**: The connection number of the airport.
- **Connect_rate (float)**: The connect rate in the airport (Connect_rate = Connect/Depart).

TAF-M Operations (AirportsOperations.xlsx):

- **locid (string):** The airport ID.

- **ayear (int):** The year.
- **itn_Ac (int):** The air carrier operations.

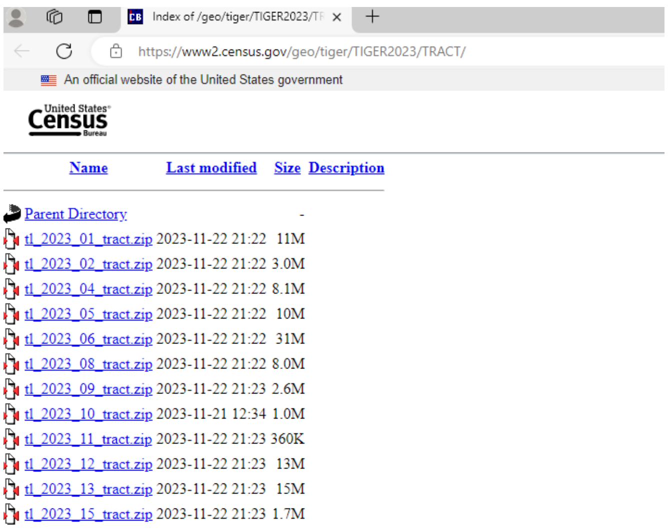
Census Tract update in Connecticut (CT_tractcrosswalk_2022.xlsx)

- **tract_fips_2020 (string):** The census tract FIPS in 2020.
- **Tract_fips_2022 (string):** The census tract FIPS in 2022.

APPENDIX F: DATASET DOWNLOAD AND PROCESS

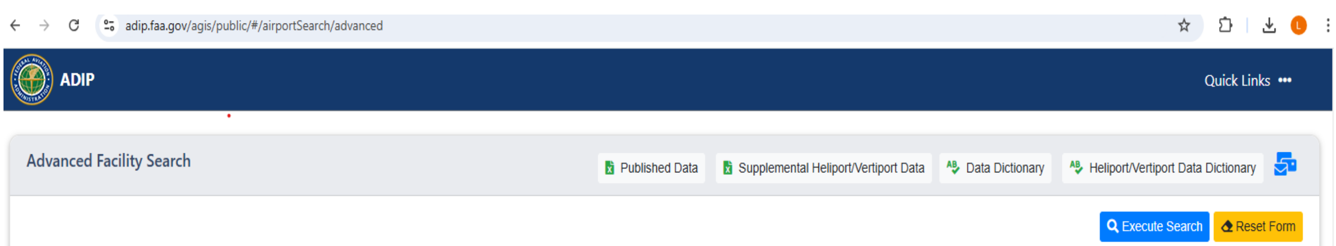
Location of Census Tract:

We downloaded the datasets from the FTP of the Census website: https://www2.census.gov/geo/tiger/TIGER2023/TRACT/, which provides the census tract geographic information for each county. These files were then imported into ArcGIS Pro (version 3.1.0) to merge all census tracts into a single shapefile layer. Subsequently, ArcGIS Pro was used to determine the centroid location of each census tract, and the dataset of census tract centroid longitudes and latitudes in the CSA was exported.



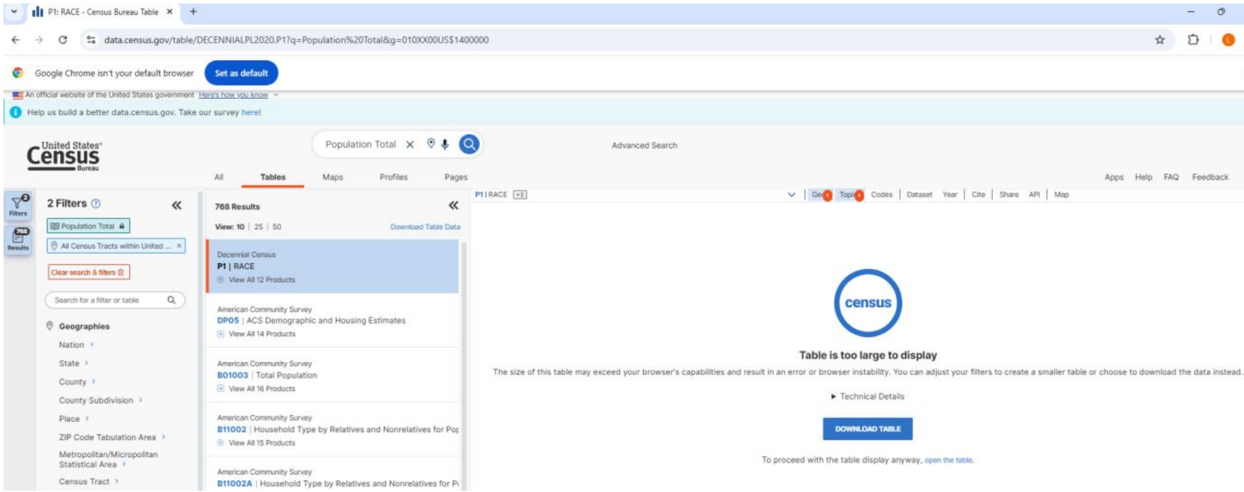
Location of airports in CSA:

We downloaded the airport location data from the FAA website: https://adip.faa.gov/agis/public/#/airportSearch/advanced, which provides the locations of all airports in the United States. This file was then imported into ArcGIS Pro (version 3.1.0) to determine whether each airport location falls within the CSA boundaries. Subsequently, the dataset of airport and CSA cross-tables for all airports was exported. The Python script **Airport.py** is used to filter the list of airports based on the sponsor's request, specifically selecting airports with itinerant Air Carrier numbers equal to or greater than 10 per year. This process generates the target list of airports within the CSA.



Census Tract Population:

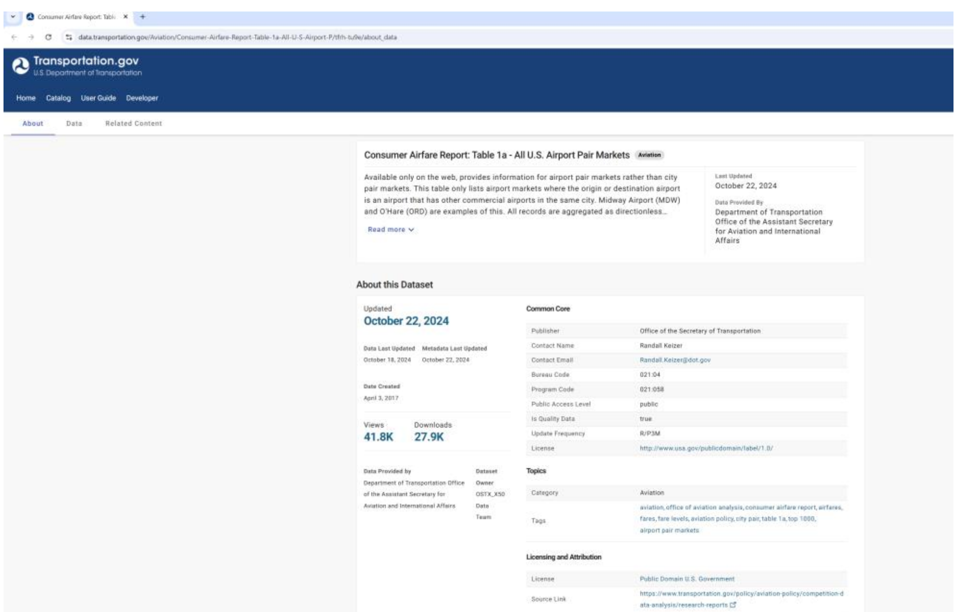
We downloaded the census tract-level population data from the Census website: https://data.census.gov/table/DECENNIALPL2020.P1?q=Population%20Total&g=010XX00US$1400000, and the webpage is shown below.



The downloaded files include numerous columns, and we selected the first three: "GEO_ID," "NAME," and "P1_001N," to create a new Excel file containing the census tract ID, census tract name, and total population for each census tract.

Airfare:

We downloaded the airport-paired airfare data from the U.S. Department of Transportation, available at https://data.transportation.gov/Aviation/Consumer-Airfare-Report-Table-1a-All-U-S-Airport-P/tfrh-tu9e/about_data.

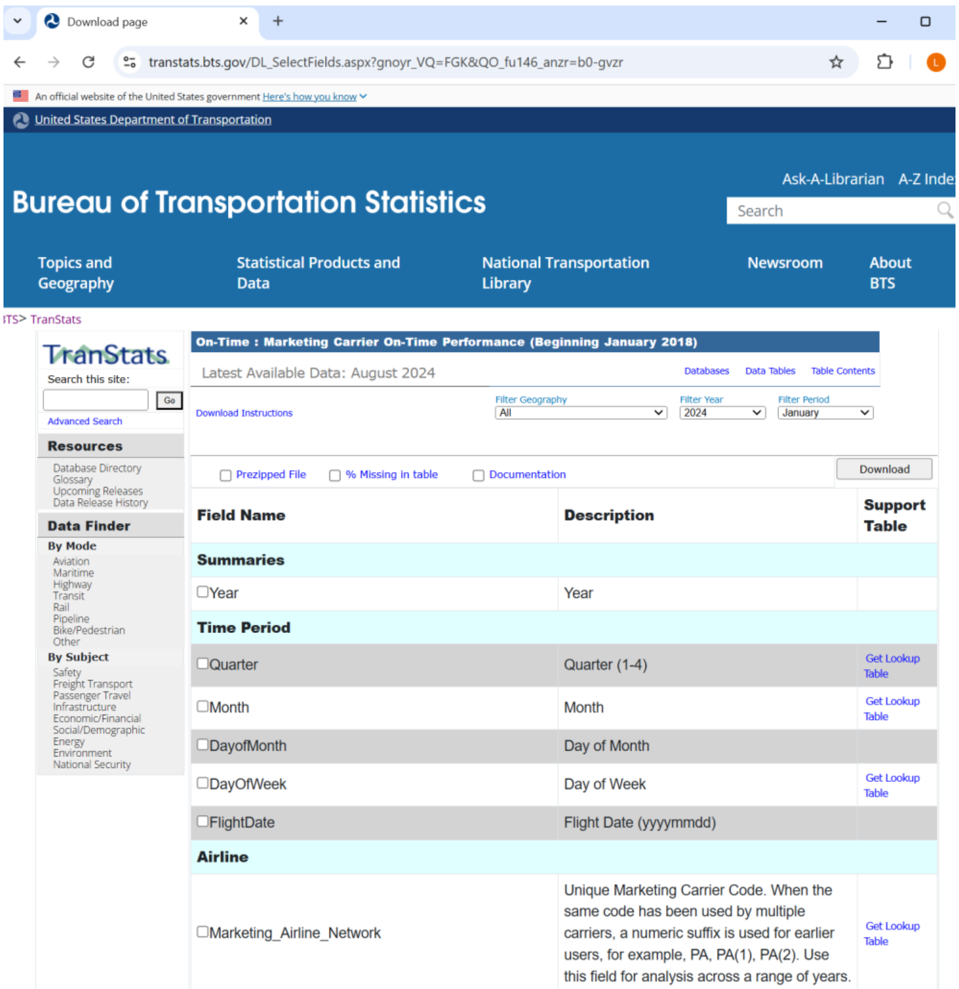


Then, we used the Python script **Airfare.py** to process the downloaded CSV file. We focused on airfare data from 2023 and selected SFO as the destination airport, as it is the most popular route in CSA. The average airfare was calculated across all four quarters of 2023 for each airport. The output is the average airfare for each airport in CSA.

On Time Performance:

We downloaded the on-time performance data for each airport from the BTS website at the following link:

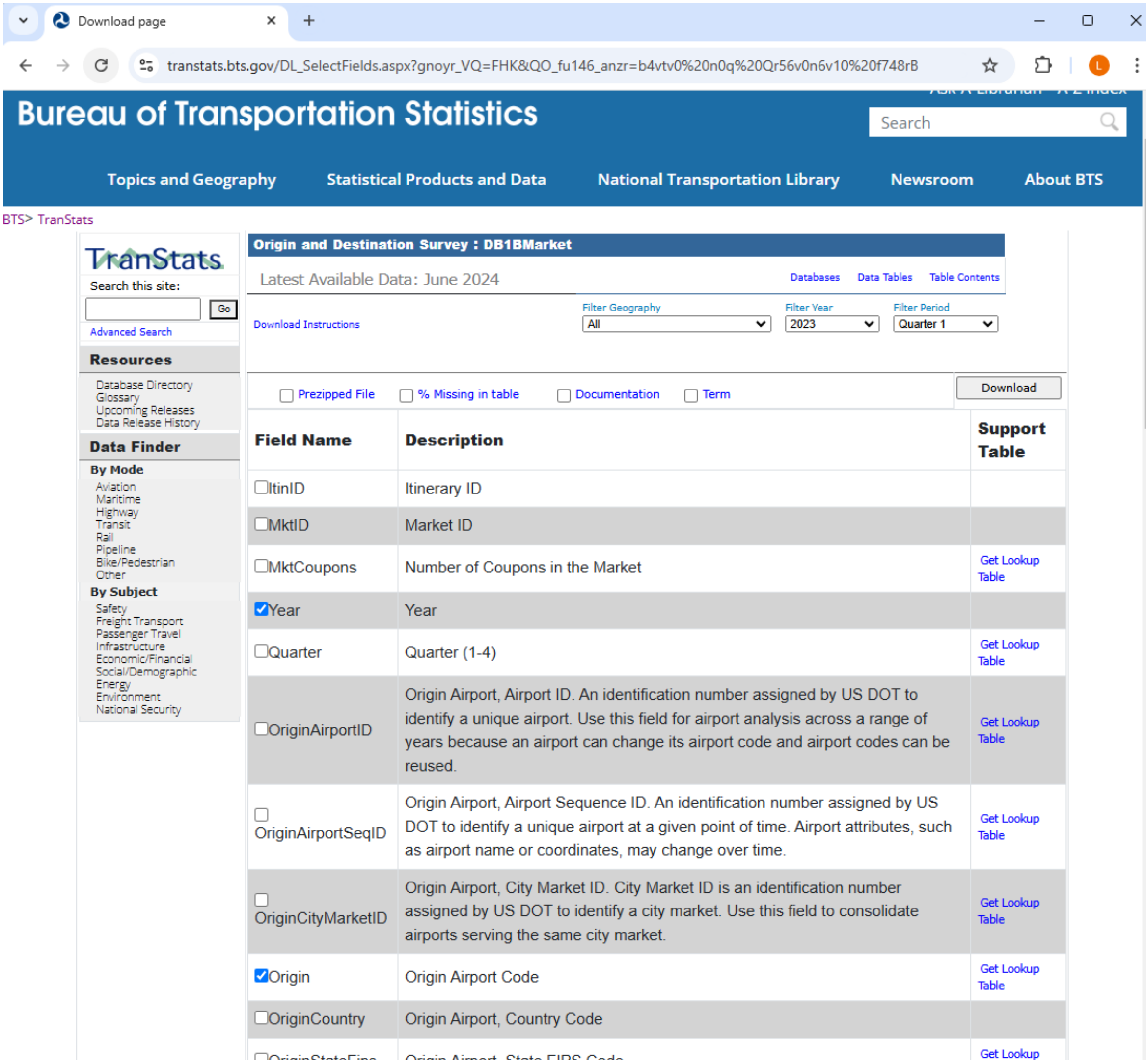
https://www.transtats.bts.gov/DL_SelectFields.aspx?gnoyr_VQ=FGK&QO_fu146_anzr=b0-gvzr.



We selected only the year, origin airport, departure delay indicator (DepDel15), and canceled flight indicator for the year 2023 across all months. After downloading the 12 months of datasets, the Python script **ontime.py** was used to process the data and generate the on-time performance for each airport.

Transfer in Airport:

We downloaded the route information from DB1B market of BTS website at the following link: https://www.transtats.bts.gov/DL_SelectFields.aspx?gnoyr_VQ=FHK&QO_fu146_anzr=b4vtv0%20n0q%20Qr56v0n6v10%20f748rB.



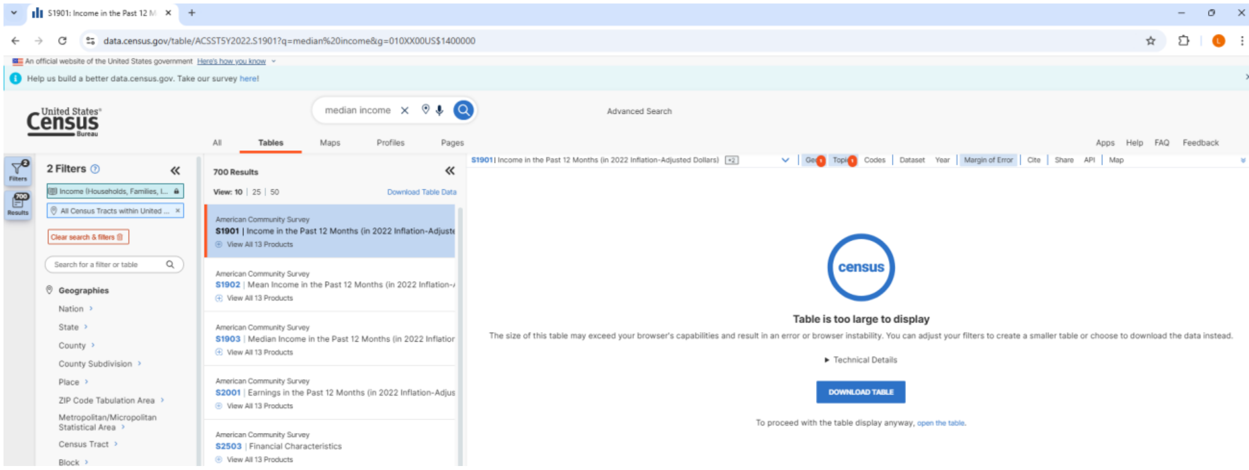
We selected the fields “Year,” “Origin,” “Dest,” “AirportGroup,” and “Passengers” and set the filter year to 2023 with the filter period as Quarter 1 for downloading. After downloading the dataset, we used the Python script **Connect.py** to process the data and generate the connecting rate for each airport.

Median Household Income:

We downloaded median household income data at the CSA and census tract levels from the U.S. Census. The data can be accessed at the following link:

https://data.census.gov/table/ACSST5Y2022.S1901?q=median%20income&g=010XX00US$3300000 (CSA)

and
https://data.census.gov/table/ACSST5Y2022.S1901?q=median%20income&g=010XX00US$1400000 (Census Tract).



From the downloaded dataset, we selected three columns: “GEO_ID,” “NAME,” and “S1901_C01_012E” (estimated median household income) to create a new Excel file for further processing.

APPENDIX G: METHODOLOGY REFINEMENT WITH GROUND TRUTH DATA

Once actual data becomes available, the initial model will be evaluated by comparing its predictions with the actual system outputs. The error will be measured as the difference between the model's predictions and the observed values. This error can be quantified using metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), or Root Mean Squared Error (RMSE). The RMSE equation is listed below:

$$E_i = 1/n \sum_{i=0}^{n} (P_{count} - P_{count}(\beta, \mu_n))^2 \tag{1}$$

Where: E_i is the initial error reported, P_{Count} is the actual airport passenger, $P_{Count}(\beta, \mu_n)$ is the proposed model predicted and n is the total number of observations from the *i*th airport. We assume that model refinement will be specific to each airport, given that the utility function varies from one airport to another. While the initial model will be broadly applicable to all airports, subsequent refinements will be tailored to the specific characteristics of each airport.

To reduce the error, the model parameters will be fine-tuned to better fit the data. This process involves adjusting the coefficients or other parameters within the model. Once the model is improved, the error will be recalculated to evaluate the performance of the revised model:

$$E_u = 1/n \sum_{i=0}^{n} (P_{count} - P_{count}(\beta, \mu_n))^2 \tag{2}$$

Here, E_u is the error from the revised model. To determine the model improvement, the difference in the error can be observed as follows:

$$\Delta E = E_i - E_u \tag{3}$$

If $\Delta E > 0$, means the error is reduced. The acceptability of the error is often judged by whether the error reduction reaches a plateau or becomes negligible (ϵ), indicating that further refinements are unlikely to produce significant improvements.

$$\frac{\Delta E}{E_i} < \epsilon \tag{4}$$

Where ϵ is a small threshold value that represents the tolerance for error reduction. If this condition is met, it suggests that the model's performance is near its optimal level, and the error is within an acceptable range. Conversely, if the reduction in error is small or negligible over successive iterations, this might suggest that the model has reached its best possible performance, and further tuning may not be necessary.