DISSERTATION APPROVAL SHEET

Title of Dissertation: ENHANCING DEMAND MODELING FOR ADVANCED AIR MOBILITY USING DATA-DRIVEN LEARNING AND NEUROSYMBOLIC AI

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- Reinforcement Learning
- Advanced Air Mobility
- Trip Demand Modeling
- AI Safety

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- Self-motivated, goal-oriented researcher with 3+ years of experience in data driven computational intelligence/decision models and 8+ years of experience in educational field.
- Strong leadership and communication skills acquired through leadership, research presentations and publications with proven ability to conduct projects both independently and in collaboration.
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Graduate Research Assistant — **Aug 2023 - Present**

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Currently working on the NASA project, a part of University Leadership Initiative (ULI) program "Mobility-Energy-Coordinated Platform for Infrastructure Planning to Support AAM Aircraft Operations". Main contribution involves:

- Develop a rolling horizon algorithm to generate trip requests
- Use data driven and Neurosymbolic approach to project AAM flight demand considering trip requests over time using various features

Research Assistant — **Aug 2022 - Aug 2023**

Embry-Riddle Aeronautical University (FL, USA)

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- Data Pre-processing and Visualization: Perform data gathering, data cleansing, data integration and data visualization.
- Data-driven Modeling for Air Mobility Prediction: Build deep learning models for the prediction of both micro-level and macro-level air mobility.
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- Engaged students in research works/projects of professional competence
- Prepared detailed course plan for the assigned subjects before beginning of each semester
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Dissertation Title: Enhancing Demand Modeling for Advanced Air Mobility Using Data-Driven Learning and Neurosymbolic AI

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Soft Skills

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Publications

Journal

Demand Modeling for Advanced Air Mobility: Challenges, Opportunities, and Future Directions 2026
IEEE Transactions on Intelligent Transportation Systems
Under Review

Demand Forecast and Energy-Aware Portal Siting for Regional Air Mobility 2026
Journal of Air Transport Management
Under Review

A Comprehensive Review of Neuro-symbolic AI for Robustness, Uncertainty Quantification, and Intervenability 2025
Arabian Journal for Science and Engineering
Invited Paper

Quantum AI-Enhanced IoT-Fog Communication: A Survey from Cybersecurity and Data Privacy Perspective 2025
IEEE Communications Surveys & Tutorials

A Survey on Symbolic Knowledge Distillation of Large Language Models 2024
IEEE Transactions on Artificial Intelligence

Neurosymbolic Reinforcement Learning and Planning: A Survey 2023
IEEE Transactions on Artificial Intelligence
Selected for the IEEE CIS Publication Spotlight, Nov. 2024.

Long Short-Term Memory Neural Network assisted Peak to Average Power Ratio Reduction for Underwater Acoustic Orthogonal Frequency Division Multiplexing Communication. 2022
KSII Transaction on Internet and Information Systems

Book Chapter

AI for Android Malware Detection and Classification 2026
AI for Cybersecurity: Research and Practice, IEEE, 2026, pp.419-450.

Conference Proceedings

Urban Air Mobility Flight Demand Modeling for Airports in New York City 2026
AIAA SciTech Forum and Exposition 2026

Integrating Neurosymbolic AI in Advanced Air Mobility: A Comprehensive Survey 2025
34th International Joint Conference on Artificial Intelligence (IJCAI 2025)

Neurosymbolic AI for Travel Demand Prediction: Integrating Decision Tree Rules into Neural Networks 2025
International Wireless Communications & Mobile Computing Conference (IWCMC 2025)

A Data-Driven Approach to Enhancing Gravity Models for Trip Demand Prediction 2025
IEEE Conference on Artificial Intelligence (IEEE CAI)

Regional Air Mobility Flight Demand Modeling in Tennessee State 2025
AIAA SciTech Forum and Exposition 2025

Decoding Android Malware with a Fraction of Features: An Attention-Enhanced MLP-SVM Approach 2024
International Conference on Network and System Security (NSS-SocialSec 2024)

Enhancing Forecasting for Advanced Air Mobility 2024
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Improving Air Mobility for Pre-Disaster Planning with Neural Network Accelerated Genetic Algorithm 2024
IEEE International Conference on Intelligent Transportation Systems (ITSC 2024)

SKGHOI: Spatial-Semantic Knowledge Graph for Human-Object Interaction Detection 2023
International Conference on Data Mining (ICDM) 2023

Guest Lecture

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- IEEE CIS Publication Spotlight Recognition, Issued by IEEE Computational Intelligence Society, Nov 2024

ABSTRACT

Title of dissertation: ENHANCING DEMAND MODELING FOR ADVANCED AIR MOBILITY USING DATA-DRIVEN LEARNING AND NEUROSYMBOLIC AI

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Advanced Air Mobility (AAM), including Urban Air Mobility (UAM) and Regional Air Mobility (RAM), faces fundamental challenges in demand modeling due to the absence of historical operational data, strong spatial and temporal heterogeneity in traveler behavior, and the dominance of black-box machine learning approaches that lack interpretability and behavioral grounding. These limitations restrict the reliability of demand forecasts for policy evaluation, infrastructure planning, and operational design. This dissertation addresses three interconnected challenges in AAM demand modeling: behaviorally grounded adoption modeling, structurally constrained data-driven demand estimation, and interpretable learning under uncertainty.

First Contribution: A Generalized Cost of Trip (GCT) framework is developed to model AAM adoption by integrating monetary cost, travel time valuation,

reliability, and perceived risk. The framework is evaluated across multiple spatial scales, including regional analyses in Tennessee for RAM and a high-resolution taxi-zone based New York City UAM case study. Results show that travel time and cost consistently dominate adoption decisions, while perceived risk plays a secondary role. The analysis reveals pronounced spatial and temporal heterogeneity in urban settings and identifies a consistent adoption threshold, indicating that travelers are significantly more likely to select AAM when air travel constitutes more than approximately 70% of total generalized trip cost.

Second Contribution: To address the limitations of unconstrained data-driven modeling, learning-based methods are integrated with classical optimization and spatial interaction structures. A neural network–accelerated genetic algorithm is introduced to improve computational efficiency in air mobility planning problems involving airport selection and flight allocation. In addition, a machine-learning enhanced gravity model is proposed to capture non-linear spatial, socioeconomic, and transportation relationships that are not represented in traditional formulations, yielding substantial improvements in predictive accuracy and flow representation.

Third Contribution: A Neurosymbolic demand modeling framework is proposed that embeds decision tree–derived symbolic rules within neural network architectures to jointly achieve predictive accuracy and interpretability. By incorporating human-interpretable structure into learning-based models, the framework improves robustness under data sparsity while enabling transparent reasoning about demand drivers.

ENHANCING DEMAND MODELING FOR ADVANCED AIR MOBILITY USING DATA-DRIVEN LEARNING AND NEUROSYMBOLIC AI

by

Kamal Acharya

Dissertation submitted to the Faculty of the Graduate School of the University of Maryland, Baltimore County in partial fulfillment of the requirements for the degree of Doctor of Philosophy
2026

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Dedication

To my beloved parents and my inspiration, Sabita Karki

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I would like to express my sincere gratitude to all those who contributed to the successful completion of this dissertation.

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I would like to sincerely thank my dissertation committee members: Dr. Nirmalya Roy, Dr. Lei Zhang, Dr. Liang Sun, and Dr. Kai Sun for their time, expertise, and constructive feedback. Their diverse perspectives and valuable recommendations greatly enhanced the rigor, clarity, and overall quality of this dissertation.

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Advanced Transportation Mobility (CATM), Grant No. 69A3551747125. These funding sources enabled the successful execution of this research and supported dissemination through leading journals and conferences.

I am thankful to my collaborators, colleagues, and members of the Department of Information Systems at the University of Maryland, Baltimore County (UMBC) for providing a stimulating research environment, computational resources, and continuous academic support. I also appreciate the collaborative research culture at UMBC, which fostered meaningful discussions and intellectual growth.

Finally, I extend my deepest gratitude to Sabita Karki for her unwavering support, patience, and constant encouragement throughout this demanding academic journey. Her understanding, resilience, and belief in me were a continuous source of motivation and strength during challenging times. I also sincerely acknowledge my parents for their support and encouragement, which contributed to the successful completion of this work.

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List of Abbreviations

AAM	Advanced Air Mobility
ADAM	Adaptive Moment Estimation
ADS-B	Automatic Dependent Surveillance-Broadcast
AI	Artificial Intelligence
ALE	Accumulated Local Effects
AMaaS	Air Mobility as a Service
API	Application Programming Interface
ASPM	Aviation System Performance Metrics
ATM	Air Traffic Management
CNS	Communication, Navigation, and Surveillance
CPC	Common Part of Commuters
DBI	Davies-Bouldin Index
DOT	Department Of Transportation
DT	Decision Tree
EASA	European Union Aviation Safety Agency
eSTOL	electric Short Takeoff and Landing
eVTOL	electric Vertical Take-off and Landing
FAA	Federal Aviation Administration
FHWA	Federal Highway Administration
FSM	Four Step Model
FTC	Federal Test Center
GA	Genetic Algorithm
GAV	General Aviation
GBR	Gradient Boosting Regressor
GCT	Generalized Cost of Trip
GDP	Gross Domestic Product
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
GRU	Gated Recurrent Unit
IID	Independent and Identically Distributed
IRS	Internal Revenue Service
LEHD	Longitudinal Employer-Household Dynamics
LODES	LEHD Origin-Destination Employment Statistics
LOTTR	Level of Travel Time Reliability
LSTM	Long Short-Term Memory

MaaS	Mobility as a Service
MAE	Mean Absolute Error
METAR	Meteorological Aerodrome Report
MNL	Multinomial Logit
MSA	Metropolitan Statistical Area
NASA	National Aeronautics and Space Administration
NHTS	National Household Travel Survey
NL	Nested Logit
NN	Neural Network
NSC	National Safety Council
NYC	New York City
OD	Origin-Destination
OMB	Office of Management and Budget
OPSNET	Operations Network
OSRM	Open Source Routing Machine
POI	Point of Interest
PTI	Planning Time Index
R^2	R-Squared
RAM	Regional Air Mobility
ReLU	Rectified Linear Unit
R& D	Research and Development
SHAP	SHapley Additive exPlanations
STOL	Short Takeoff and Landing
SVO	Single Vehicle Operation
TFMSC	Traffic Flow Management System Count
TLC	Taxi and Limousine Commission
TORA	Take-Off Run Available
TRLs	Technology Readiness Levels
UAM	Urban Air Mobility
UAV	Unmanned Aerial Vehicles
VOR	Value of Reliability
VOT	Value of Time
VSL	Value of Statistical Life
VTOL	Vertical Takeoff and Landing

WTP	Willingness to Pay
XAI	Explainable Artificial Intelligence
XGB	Extreme Gradient Boosting

Chapter 1

Introduction

1.1 Motivation

Advanced Air Mobility (AAM) represents a transformative evolution in the aviation and transportation industries [1]. Encompassing concepts like Urban Air Mobility (UAM) [2] and expanding beyond metropolitan areas as Regional Air Mobility (RAM) [3], AAM envisions a future where air transportation is seamlessly integrated into daily life, offering efficient, safe, and sustainable movement of people and goods. This vision is driven by technological advancements in electric propulsion, automation, and materials science, leading to the development of innovative aircraft such as electric vertical take-off and landing (eVTOL) vehicles [4]. The evolution from traditional aviation to AAM is marked by several key developments. Historically, air transportation has been limited to commercial airlines operating between established airports. However, increasing urbanization and congestion have spurred the need for alternative transportation solutions. AAM aims to address these challenges by utilizing low-altitude airspace for short to medium-distance travel, thereby reducing ground traffic and enhancing connectivity [5]. The integration of autonomous systems and advanced air traffic management (ATM) further distinguishes AAM from conventional aviation, promising increased efficiency and accessibility.

Demand modeling plays a critical role in the successful implementation and scalability of AAM systems. Accurate demand forecasts are essential for planning infrastructure investments, designing operational strategies, and formulating regulatory policies. In the context of AAM, demand modeling helps stakeholders understand potential market sizes, user adoption rates, and revenue projections, which are crucial for attracting investment and ensuring economic viability [6]. The unique characteristics of AAM, such as new vehicle types, untested routes, and emerging market segments, present challenges that traditional demand modeling approaches may not adequately address. Factors like public acceptance, regulatory hurdles, technological maturity, and competition with existing transportation modes add layers of complexity to demand forecasting [7]. Specialized demand models are essential for AAM to support informed decision-making in several key areas. For infrastructure development, these models help determine optimal locations and capacities for vertiports and maintenance facilities, ensuring that resources align with demand patterns [8]. In regulatory frameworks, they guide policies on airspace management, safety standards, and certification processes critical for safe AAM integration [9]. These models assist in evaluating the financial feasibility and potential return on investment, providing insights that shape investment decisions in AAM projects. By providing insights into these areas, demand modeling directly influences the strategic direction and operational effectiveness of AAM initiatives.

1.2 The Specific Gap Addressed

While existing studies have explored AAM demand using surveys, discrete choice models, gravity-based formulations, simulation, and machine learning, important limitations remain. Many economic and choice-based models rely on strong assumptions and simplified utility formulations that do not adequately capture non-linear interactions among cost, time, risk, and spatial factors. Conversely, black-box machine learning models can achieve high predictive accuracy but provide limited transparency, making it difficult to explain demand drivers or justify decisions to regulators and stakeholders.

Moreover, most existing approaches focus on a single modeling paradigm or a single spatial scale, limiting their ability to generalize across urban and regional contexts. Few studies systematically integrate economic theory, data-driven learning, and interpretable reasoning within a unified demand modeling framework.

This dissertation specifically addresses the problem of how to model AAM demand in a way that simultaneously balances predictive accuracy, behavioral realism, and interpretability, while remaining applicable across multiple spatial resolutions, including metropolitan regions, census tracts, and high-resolution urban taxi-zone networks.

1.3 Overview and Core Contributions

The research strategy, illustrated in Figure 1.1, is divided into three phases to systematically explore and refine the demand modeling of AAM. Starting from fundamental cost, time, risk and reliability considerations to advanced data-driven methods, and finally integrating Neurosymbolic approaches for enhanced interpretability and predictive power.

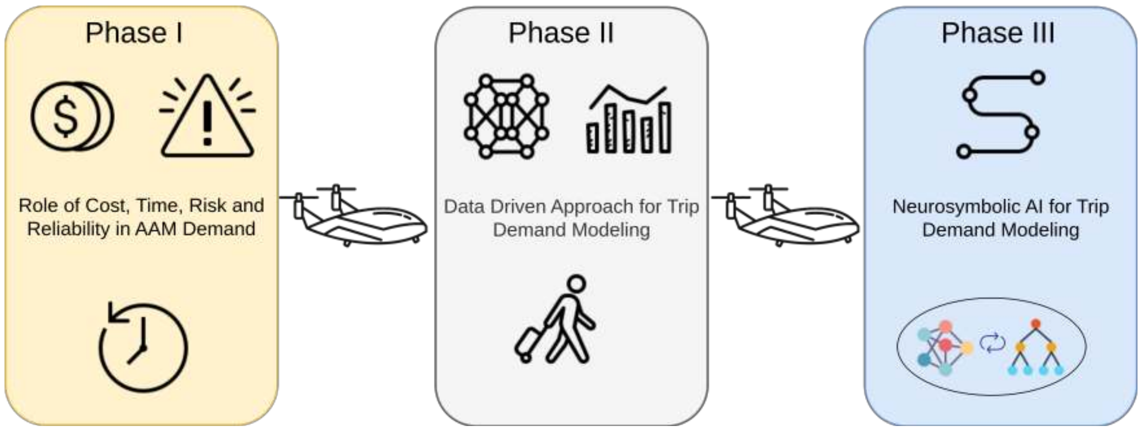


Figure 1.1: Research Approach

1.3.1 Phase I: Role of Cost, Time, Risk, and Reliability Parameters in AAM Demand

In the first phase, a Generalized Travel Cost (GCT) model was developed to encapsulate direct travel costs, the monetary equivalent of travel time, risk involved, and reliability factors. Individual sub-models for cost, time, risk, and reliability were initially constructed, then combined into a comprehensive GCT framework. The resulting GCT values were deployed in a logistic regression setup to examine the probability of choosing between conventional ground transportation and AAM services. Two geographic scales were considered for the experiments: Metropolitan Statistical Areas (MSA) and census tracts in Tennessee, providing a multilevel perspective on AAM acceptance. Findings highlighted cost and time as the most influential parameters, while also revealing a greater preference for AAM when more than 70% of a trip's GCT was associated with air travel. In the New York City case study, the model further reveals strong spatial and temporal variation in switching behavior, with travelers from high-demand taxi zones and longer ground travel times exhibiting a substantially higher probability of shifting to AAM, particularly during peak congestion periods. These observations underscore the interplay between price sensitivity, time efficiency, and perceived safety in shaping early adoption patterns for AAM.

1.3.2 Phase II: Data-Driven Trip Demand Modeling

Building upon the insights from Phase I, the second phase adopted data-driven approaches to further refine AAM demand models. Here, Neural Networks (NN) were integrated with Genetic Algorithms (GA) to expedite convergence in complex optimization tasks. By initializing the GA population with NN-derived solutions, the approach significantly reduced the number of generations needed for the GA to find near-optimal configurations, covering decisions such as flight frequencies and airport selection. Remarkably, even a lightly trained NN meaningfully hastened GA's convergence while preserving solution quality. The second step in this phase involves developing a data-driven enhancement of the traditional gravity model by incorporating machine learning to capture non-linear relationships between spatial, socioeconomic, and transportation features that are not represented in conventional formulations. Extensive empirical evaluation demonstrates significant performance gains in explained variance (R^2), Mean Absolute Error (MAE), and Common Part of Commuters (CPC) metric, confirming the effectiveness of combining data-driven learning with established transportation demand modeling paradigms.

1.3.3 Phase III: Neurosymbolic Approaches to Modeling Trip Demand

The final phase shifts focus to Neurosymbolic Artificial Intelligence (AI), combining the interpretability of symbolic methods with the powerful pattern-recognition capabilities of neural networks. Specifically, Decision Tree (DT) models were merged with NNs to form a hybrid framework for travel demand prediction. In this setup, DTs provide transparent, rule-based boundaries that capture granular traveler behaviors, while NNs handle complex, non-linear relationships in the underlying data. Experimental results demonstrated robust performance gains across metrics such as MAE, R^2, and CPC, particularly when DTs used finely tuned variance thresholds. In addition to delivering higher predictive accuracy, the integrated model offers enhanced explainability, essential for stakeholder trust and policy development.

1.4 Relation to and Advancement Beyond Prior Work

This dissertation advances the state of the art in AAM demand modeling in several key ways. Unlike prior studies that rely solely on economic models or black-box machine learning, this work explicitly integrates economic theory, learning-based methods, and symbolic reasoning within a unified framework. The proposed

GCT formulation extends traditional cost-based analyses by incorporating risk and behavioral thresholds across multiple spatial scales.

Compared to existing machine learning approaches, the learning-augmented gravity models and Neurosymbolic architectures provide both improved predictive accuracy and enhanced interpretability, addressing a major limitation in current data-driven transportation research. Furthermore, the empirical validation across diverse geographic contexts, from statewide regional networks to high-resolution urban taxi zones, demonstrates the robustness and generalizability of the proposed methods.

By positioning interpretability and behavioral realism as core design objectives rather than secondary considerations, this dissertation contributes not only new methodologies but also a principled modeling philosophy for emerging transportation systems.

1.5 Organization of the Dissertation

The remainder of this dissertation is organized as follows:

- Chapter 2 presents the background and preliminaries related to AAM, transportation demand modeling, and Neurosymbolic AI.
- Chapter 3 reviews the related literature on trip generation, distribution, mode choice, and assignment in the context of AAM.
- Chapter 4 examines the role of cost, time, and risk in AAM demand modeling through the proposed GCT framework.

- Chapter 5 develops data-driven approaches for trip demand modeling, including learning-enhanced gravity models and optimization-based methods.

- Chapter 6 introduces Neurosymbolic approaches for interpretable travel demand prediction and discusses their empirical evaluation.

- Chapter 7 concludes the dissertation by summarizing the key findings, discussing limitations, and outlining directions for future research.

Chapter 2

Background and Preliminaries

The goal of AAM is to provide aviation services to underutilized airspace, in both urban and rural areas. While the concept of AAM is not new, recent advancements in aircraft technology have unlocked the feasibility of AAM. Furthermore, the introduction of this technology into the global transportation system establishes a significant market potential, a reduction of emissions in the aviation sector, and possible traffic mitigation strategies. Many studies investigate the financial, environmental, and social aspects of AAM; however, an important component to a majority of these studies includes the quantification of AAM demand. This chapter aims to provide a background of AAM, defining the key components and motivation for this technology, as well as a background in demand modeling and its applications to the transportation industry and AAM.

2.1 Advanced Air Mobility

AAM represents a rapidly evolving domain in aviation technology aimed at revolutionizing air transportation by integrating new air vehicles and operational systems for short and medium-range journeys. It leverages innovative technologies such as eVTOL aircraft, unmanned aerial vehicles (UAVs), and autonomous systems to create efficient, eco-friendly, and accessible modes of transport in urban, suburban, and rural environments [10]. AAM involves the development of aircraft capable of operating in complex, highly automated environments. The primary aim is to address the demand for fast and flexible travel solutions that bypass traditional ground transportation. AAM is expected to transform passenger transport, goods delivery, emergency response, and surveillance, offering significant time savings, reduced traffic congestion, and the potential for sustainable, emission-free travel [11].

Two subsets of AAM include UAM and RAM. UAM is defined as transportation within metropolitan areas, covering flights up to approximately 50 miles. Conversely, RAM provides trips ranging from 50 to 500 miles [3]. It is important to note that these factors further differentiate AAM from conventional commercial trips, as most commercial flights consist of trips above 500 miles [12]. While UAM and RAM both use novel air vehicle designs and advanced ATM technology, the vehicles and supporting infrastructure for each AAM sub-component differ significantly. Due to the limited available space in urban areas, VTOL and eVTOL aircraft are primarily employed for UAM services, which do not require extensive ground infrastructure. Therefore, existing ground infrastructure, such as elevated parking garages or large commercial buildings, may be used as vertiports.

RAM primarily incorporates electric short takeoff and landing (eSTOL) aircraft to cover larger trip distances, connecting areas together within a region. RAM vehicles will require larger take-off run available (TORA) compared to UAM. Differences in TORA lead to larger ground infrastructure requirements, which resemble ground infrastructure requirements for commercial aviation. Many studies have proposed the establishment of RAM portals at underutilized airports across the county [3, 13, 14], which allow for significant savings on infrastructure and overall costs. Vehicle design and infrastructure variations between UAM and RAM technology result in dissimilar social and environmental factors of each AAM subset. For example, public acceptance of eSTOL aircraft could potentially be larger than public acceptance of eVTOL aircraft due to an increased preference towards a larger cabin size. These social and environmental factor dissimilarities between UAM and RAM must be extensively examined when modeling true AAM demand. Comparison between UAM and RAM are summarized in Table 2.1.

AAM encompasses several interrelated concepts, each targeting specific transportation needs and environments. UAM focused on addressing the transportation challenges within densely populated urban areas, UAM aims to provide rapid, on-demand aerial mobility solutions. This includes air taxi services, short-range passenger transport, and intra-city logistics. UAM leverages eVTOL aircraft to navigate congested airspace efficiently, reducing ground traffic and travel times [15]. RAM extends the principles of AAM beyond urban centers, facilitating medium-range travel between cities and regions. It aims to enhance connectivity in areas where traditional ground transport may be time-consuming or less efficient. RAM can support commuter services, regional business travel, and intercity logistics, contributing to economic growth and regional development [3].

Table 2.1: Comparison of Urban Air Mobility and Regional Air Mobility

	Urban Air Mobility	**Regional Air Mobility**
Primary Objective	Mitigate surface congestion and provide rapid intra-city mobility in dense metropolitan areas	Enhance intercity and regional connectivity, particularly in areas underserved by conventional air transport
Representative Aircraft	eVTOL vehicles	eSTOL or regional hybrid-electric aircraft
Propulsion Systems	Predominantly battery-electric; hybrid-electric and hydrogen propulsion under development	Hybrid-electric and hydrogen emphasized; full battery-electric feasible for shorter ranges
Typical Trip Range	$<$ 50 miles (intra-urban)	50-500 miles (short-haul regional)
Infrastructure Requirement	Vertiports or rooftop pads integrated into urban fabric	Conventional runways (short or regional airports), with potential adaptation for eSTOL operations

2.1.1 Use Cases of AAM

AAM represents a paradigm shift in transportation, promising to revolutionize the movement of people and goods, particularly in urban and regional environments. This transformative vision encompasses a diverse array of applications, extending beyond the initial concept of air taxis to include UAM, cargo delivery, emergency medical services, and various other aerial missions [16]. Possible use cases of the AAM are depicted in Figure 2.1.

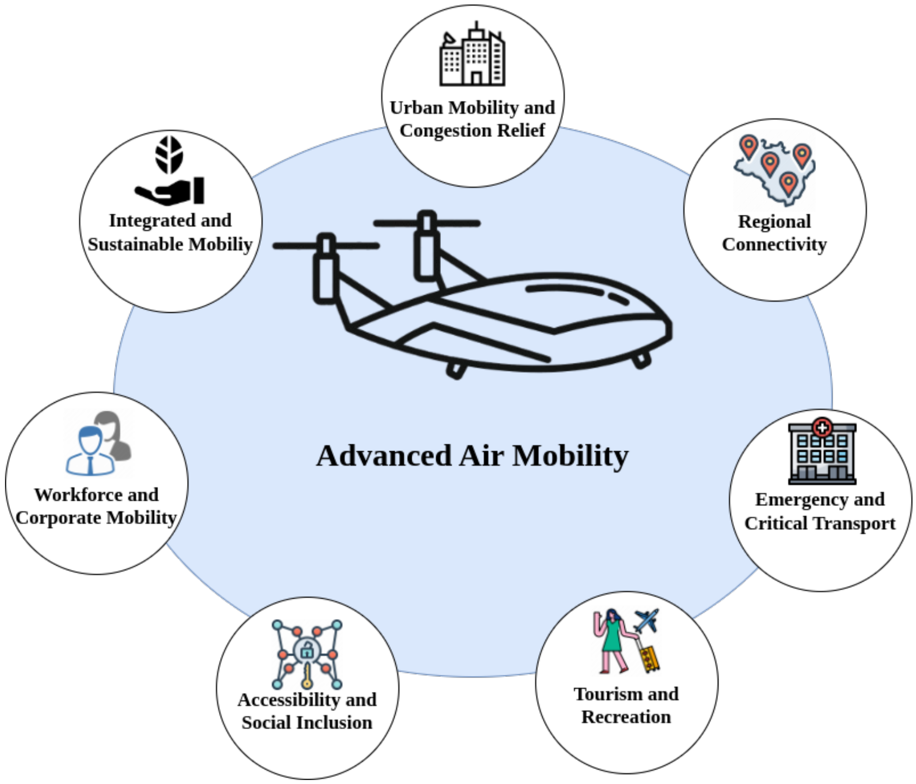


Figure 2.1: Use cases of AAM

Urban Mobility and Congestion Relief

AAM presents a viable solution to urban congestion by introducing an aerial transport alternative to alleviate ground traffic [17]. Short-range eVTOL flights enable efficient point-to-point travel within cities and adjacent suburbs, circumventing terrestrial bottlenecks. By reallocating time-sensitive passenger trips from congested roads, AAM enhances surface transport efficiency and preserves capacity for critical ground-based operations [18]. A strategically planned network of vertiports, synchronized with existing public transit, can optimize system throughput and reduce private vehicle reliance [19].

Regional Connectivity

In regions with limited rail and bus infrastructure, AAM can enhance connectivity by linking smaller cities and rural areas to major economic centers. Utilizing STOL or VTOL aircraft, regional AAM initiatives can reduce travel times while bypassing the high costs of high-speed rail development [20]. By leveraging underutilized regional airports, AAM can maximize existing aviation infrastructure, reducing the need for extensive new investments [3]. Beyond improving accessibility, these services can stimulate local economies by boosting tourism, facilitating inter-city commerce, and expediting logistics. As eVTOL technology advances, increasing reliability and cost-efficiency, AAM has the potential to democratize air travel across diverse geographic regions [21].

Emergency and Critical Transport

AAM can significantly enhance Air Ambulance Service [16] [22], time-critical cargo transport, such as organ delivery [23] and many missions for public good like disaster response, fire-fighting, search and rescue [24]. By utilizing eVTOL aircraft capable of operating in confined or infrastructure-limited areas, AAM can drastically reduce response times in critical situations. Lightweight electric or hybrid aircraft can mitigate noise pollution and emissions, making them well-suited for deployment in sensitive environments. Integrated with real-time dispatch systems and low-altitude ATM, AAM enables rapid deployment to crisis zones, where immediate intervention can be life-saving. As regulatory frameworks advance, the speed and versatility of AAM have the potential to transform emergency response and humanitarian operations.

Tourism and Recreation

The integration of AAM into tourism presents a novel opportunity to enhance traveler experiences through airborne sightseeing and expedited access to remote landmarks [25]. eVTOL flights can offer aerial tours of cityscapes, nature reserves, and coastal regions without requiring extensive ground infrastructure. This exclusivity and time efficiency could drive growth in premium tourism markets while attracting investment in supporting infrastructure, such as vertiports with visitor amenities. With quieter and more environmentally sustainable operations than conventional helicopters, AAM aligns with the rising demand for eco-conscious travel, offering a unique and innovative tourism experience [26].

Accessibility and Social Inclusion

AAM can enhance social equity by bridging accessibility gaps between underserved communities and major commercial or healthcare centers by utilizing the underutilized federal, state, and local investment in nation's local airports [3]. By reducing travel time for residents in remote or economically disadvantaged areas, subsidized or shared aerial ride services could provide a cost-effective alternative to lengthy and expensive commutes. Additionally, eVTOL aircraft can be designed with enhanced accessibility features, such as optimized cabin layouts and improved boarding processes for individuals with reduced mobility. When integrated into multimodal transportation networks, AAM has the potential to expand access to essential services, employment opportunities, and education, serving as a critical equalizer for populations traditionally constrained by inadequate public transit [24].

Workforce and Corporate Mobility

AAM has emerged as a transformative solution for corporate and workforce mobility by significantly reducing travel time and enhancing accessibility for business professionals. On-demand eVTOL flights bypass road congestion and limited regional flight schedules, optimizing workforce efficiency, particularly in industries requiring rapid prototyping or multi-site collaboration. Study [27] highlight that AAM has contributed to workforce and corporate mobility, as seen in Joby Aviation's expansion, which strategically positioned manufacturing employees near Research and Development (R&D) facilities to facilitate efficient business operations and talent retention. Another study [28] indicate that AAM enhances intermodal connectivity, reducing reliance on long-distance ground transportation for business professionals and executives, thereby fostering flexible work arrangements and corporate expansion. Urban planning frameworks also acknowledge AAM's potential in integrating business travel into regional transportation strategies, improving accessibility to business hubs and strengthening economic development [29].

Integrated and Sustainable Mobility

AAM aligns with the global transition toward sustainable transportation by complementing electrification efforts in automobiles, trains, and buses. Leveraging renewable energy for eVTOL battery charging and integrating with regional transit networks, AAM can provide an eco-friendly first-and-last-mile solution [30]. Collaboration between AAM operators and urban planners is essential for optimizing routes, reducing noise pollution, and ensuring vertiport infrastructure seamlessly integrates with multimodal transport hubs. As a key component of future smart cities, AAM encourages policymakers and industry leaders to adopt forward-thinking energy and sustainable mobility practices [31].

2.2 Demand Modeling

Demand modeling is a critical component of transportation planning, enabling stakeholders to forecast usage patterns, allocate resources efficiently, and make informed decisions about infrastructure investments. As an evolving mode of transportation, various studies have been conducted to identify the factors influencing demand. Among these, trust and safety emerge as key determinants, as highlighted by the study [32]. Figure 2.2 shows the myriad elements that influence AAM demand, ranging from technological advancements and economic considerations to social perceptions and environmental impacts.

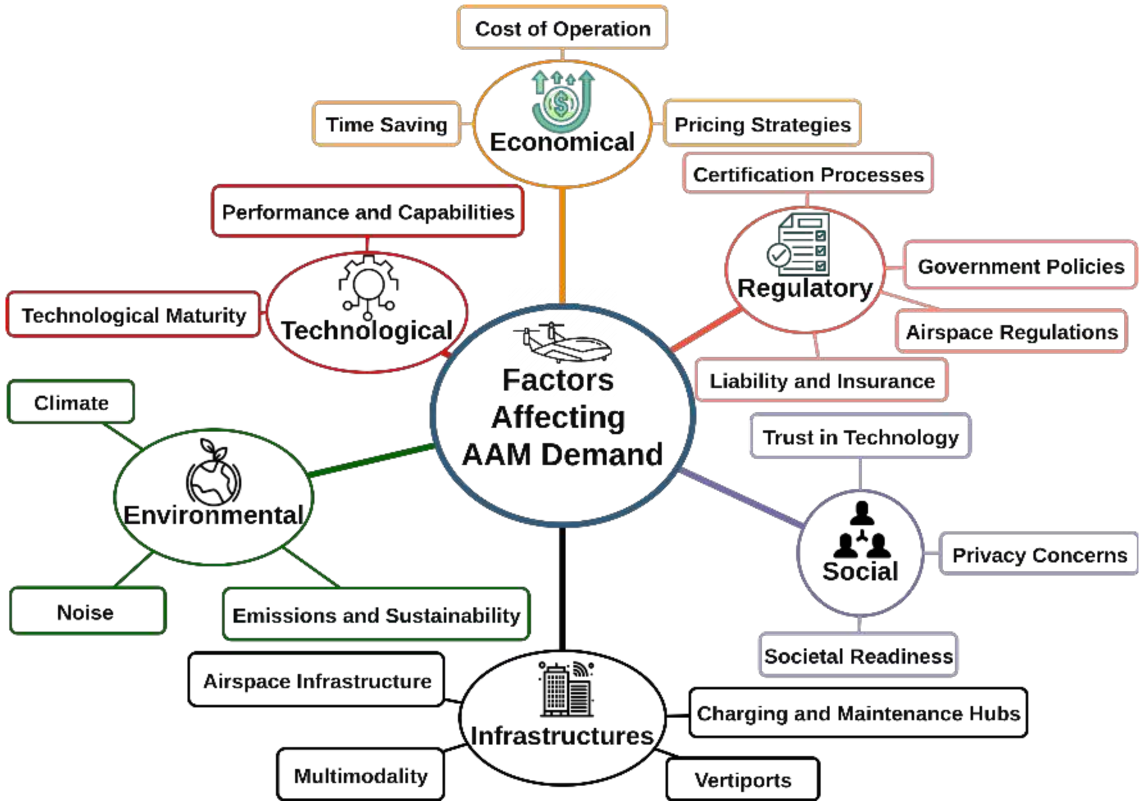


Figure 2.2: Factors Affecting AAM Demand

2.2.1 Technological Factors

Performance and Capabilities

Key performance attributes, like range, speed, payload, and autonomy, determine AAM's applicability across urban and regional contexts. Higher ranges and speeds enable broader market reach beyond dense city cores, while increased payloads facilitate cost-effective, multi-passenger or cargo transport [33]. Autonomous operation reduces labor costs and mitigates pilot shortages, though it raises new challenges in safety assurance and system reliability [34].

Technological Maturity

The maturity of AAM technologies is quantified through Technology Readiness Levels (TRLs) [35] which is a key determinant of investor trust and regulatory progress. Systems with higher TRLs are more likely to gain financial backing, expedite certification and public acceptance. Interoperability with existing air traffic control and multimodal systems reduces systemic friction, enhances coordination, and supports sustained growth in mixed-use airspace environments [36]. Breakthroughs in electric propulsion, lightweight composites, and avionics directly enhance vehicle performance and reduce costs, broadening market accessibility [6]. More importantly, the sector's ability to rapidly adopt emerging technologies like high-density batteries, AI-based navigation, and resilient communication systems ensures long-term relevance and adaptability to regulatory, operational, and societal shifts [37].

2.2.2 Economic Factors

Pricing Strategies

Affordability is pivotal for AAM adoption. Research shows that aligning fares with current premium ground transport and short haul flights is essential to attract a broader user base and promote frequent usage [33]. Dynamic pricing, adjusting fares in real time based on demand, has been demonstrated to improve profitability and operational efficiency in analogous on-demand mobility services [38]. However, studies caution that excessive price volatility can erode user trust and satisfaction [39]. Households with higher income levels show significantly greater openness to premium transport modes, positioning AAM as a viable option in affluent markets [40]. AAM can reduce travel times by over 50%, delivering substantial opportunity cost savings for business users [41]. Economic growth further strengthens AAM adoption by enabling infrastructure investment and increasing consumer purchasing power, thereby expanding market potential [42].

Cost of Operation

The economic viability of AAM depends heavily on minimizing operational expenditures, including energy consumption, maintenance, crew, and infrastructure costs. Electric propulsion systems offer substantial reductions in direct operating costs compared to conventional aircraft, particularly in maintenance and energy requirements [43]. Cost-efficiency improves further as operations scale: high-frequency services and fleet expansion enable economies of scale, lowering the cost per passenger-kilometer [44]. Studies emphasize that optimal fleet configuration, route design, and turnaround efficiency are crucial for controlling unit costs and maximizing resource utilization [45]. Fleet sizing and scheduling models demonstrate that strategic deployment can significantly impact per-flight operational expenses [39].

Time Saving

A primary economic advantage of AAM is substantial time savings, especially in congested urban environments. [46] found that for many trips under 50 km, eVTOLs cut travel time by 3% to 13% compared to car or public transport, making the service competitive for medium-range routes. Similarly, [41] documented time savings of 22–23 minutes on typical 50 km routes in Paris, which justify higher fares and appeal especially to time sensitive travelers. These reductions lower opportunity costs, offering professionals and high-value users more productive time, stimulating demand where time efficiency is paramount.

2.2.3 Regulatory Factors

Airspace Regulations

Low-altitude airspace regulations critically shape AAM operations. [47] emphasized the need for well-defined UAM corridors and structured traffic rules to ensure safe integration with conventional aircraft. Research [48] highlights the importance of multi-domain traffic management systems for coordinating autonomous vehicles in low-altitude Class G airspace. Empirical work on low-altitude airspace design frameworks, including concepts for strategic deconfliction and dynamic path planning, underscores the necessity of route capacity management, no-fly zones, and altitude curfews [49, 50]. Additionally, city-scale studies propose advanced surveillance infrastructure to monitor and manage AAM traffic, mitigating risks around sensitive zones [51].

Certification Processes

Rigorous airworthiness and safety standards are vital, but significantly extend development timelines and inflate costs, delaying market entry [52]. The incorporation of novel systems such as distributed electric propulsion, AI enabled automation, and software-led flight controls, poses certification challenges under existing frameworks, necessitating updated methods for evaluating airborne software and autonomy [34]. Human pilot licensing requirements contribute to operational costs and limit scalability. Standard commercial pilot training is extensive and expensive. Leveraging simulators and adaptive training could reduce this burden [53]. Regulatory allowances for autonomous operations could lower staffing costs and expand service reach, provided robust safety validation methods are accepted.

Government Policies

Government subsidies and incentives are pivotal in shaping AAM adoption. Study [54] shows that R&D subsidies and purchase incentives significantly reduce manufacturing costs and drive technological innovation. In the AAM context, such financial mechanisms like tax credits for electric aircraft, infrastructure grants, or subsidies for vertiport deployment can lower provider entry costs, stimulate investment, and encourage early uptake [55]. Tax reliefs for green aviation components can offset higher upfront costs and promote sustainable practices within the industry [55].

Liability and Insurance

As autonomous systems increasingly replace human pilots, liability attribution shifts toward manufacturers, operators, and software developers, amplifying legal exposure and complicating risk allocation [56]. High initial insurance premiums are expected due to sparse historical data and uncertainty in risk assessment, which may constrain market entry and scalability [57]. However, integrating secure, event-based logging systems such as blockchain can enable transparent post-incident analysis and reduce premium volatility over time [58]. As operational datasets mature, insurers can refine underwriting models, improving affordability and fostering investor confidence.

2.2.4 Social Factors

Trust in Technology

Users are significantly less willing to use remotely piloted or highly autonomous AAM vehicles compared to those with onboard pilots, largely due to diminished trust in automation and remote-control systems [59]. Trust varies across viability, independence, self-governance, with higher risk scenarios often resulting in lower user confidence [60]. Moreover, comprehensive reviews of human autonomy teaming in AAM stress that measurable trust outcomes depend on transparent communication, visible system safeguards, and gradual exposure through simulations and real-world trials [61].

Privacy Concerns

Privacy issues surrounding real-time tracking and data use pose significant barriers to AAM adoption. Precise location data such as that used for navigation and operational monitoring can reveal sensitive personal information, causing users to hesitate [62]. AAM providers may collect continuous flight-path and geo-temporal data connected to user trips, raising concerns about surveillance and misuse. Innovative privacy preserving mechanisms like anonymized air-credit systems for trajectory allocation demonstrate technical paths to mitigate this risk, enabling secure, consent based data sharing without exposing personal values [63].

Societal Readiness

Societies with higher acceptance of innovation and lower uncertainty avoidance as per Hofstede cultural model, exhibit stronger openness toward autonomous air services, while risk-averse cultures demonstrate slower uptake [64]. A meta-analysis on shared mobility found that trust and perceived risk, both culturally mediated, affect willingness to use new transport modes [65]. Media representation further shapes public sentiment, balanced coverage can boost acceptance, whereas sensational reporting on malfunctions can amplify fear and resistance [66]. Tailored communication and inclusive design are necessary to overcome initial disinterest and skepticism in underserved communities [67]. Research [68] indicates that integrating shared autonomous modes into public transit systems can close transit access gaps, especially in suburban or underserved urban areas.

2.2.5 Infrastructures

Vertiports

Optimal vertiport placement near high-demand zones is essential to maximizing coverage and convenience for users [69]. Clustering vertiports in urban centers reduces access times and supports higher-frequency, flexible routing, directly influencing user adoption [70]. Moreover, integrating vertiports into urban planning such as embedding intermodal hubs along highways or transit corridors enhances interconnectivity, minimizes transfer friction, and elevates operational throughput [71].

Charging and Maintenance Hubs

Efficient charging and maintenance infrastructure is foundational to eVTOL deployment and network scalability. Research [72] underscores that charging demand at vertiports is driven by flight frequency and scheduling, directly affecting turnaround times and service availability. Grid capacity must be expanded to support high-tempo operations, with onsite energy storage and smart power management essential to maintain reliability [73]. Moreover, network-level simulations using tools like VertiSim reveal that balancing fleet size with charging and maintenance capacity is key to optimizing passenger delays, energy use, and operational costs [74].

Multimodality

Combining eVTOL segments with ground transport in urban settings demonstrated, integrating highway-access vertiports and ride share services can measurably reduce total door-to-door journey time and enhance ridership [75]. Embedding AAM within Mobility-as-a-Service (MaaS) frameworks as air mobility as a Service (AMaaS) yields improvements in user accessibility through consolidated booking and fare systems, and contributes to enhanced operational robustness across the transportation ecosystem [76].

Airspace Infrastructure

High-precision positioning and situational awareness systems enhanced by multisensor fusion are necessary for urban environments where Global navigation satellite system (GNSS) signals are degraded, ensuring accuracy, continuity, and reliability [77]. German Aerospace Center studies emphasize the importance of unified traffic coordination supporting high-density operations without disrupting traditional air traffic [78]. Furthermore, emerging Communication, Navigation, and Surveillance (CNS) architectures, including integrated 5G based systems, promise robust low-altitude connectivity and airspace awareness that align with future ATM vision [79].

2.2.6 Environmental Factors

Emissions and Sustainability

Urban eVTOLs often emit more CO_2 per passenger-kilometer than battery electric cars due to energy-intensive hover segments, but they outperform traditional helicopters by nearly 50% [41]. Electric propulsion in AAM vehicles promises substantial emission reductions compared to conventional aircraft, but actual benefits depend heavily on the energy source mix and lifecycle emissions [80]. Lightweight eVTOL vehicles, operating at optimal speeds, with high seat occupancy, minimal hover time, and powered by a clean energy grid, can offer environmental advantages over traditional fossil-fueled ground transportation [81].

Noise

Noise emissions from eVTOLs and other AAM vehicles are a major obstacle to community acceptance, especially in dense urban environments. National Aeronautics and Space Administration (NASA)'s UAM Noise Working Group highlights substantial gaps in current noise assessment models and recommends dedicated optimization of vehicle design, flight operations, and certification procedures to mitigate acoustic impact before widespread deployment [82]. Noise aware air traffic management systems, which optimize altitude and route planning, offer promising reductions in community exposure through multi-objective optimization balancing noise, safety, and demand [83].

Climate

Adverse and unpredictable weather driven by climate change directly threatens AAM service reliability and safety. Wind turbulence, gusts in urban wind tunnel zones can degrade vertiport throughput by over 50% during seasonal peaks, compromising scheduling and network resilience [84]. Large scale Meteorological Aerodrome Report (METAR) analysis reveals that cloud cover, wind, precipitation, and low temperatures can halve flyable hours between different U.S. regions annually, significantly impacting service viability and geographic deployment strategies [85]. To mitigate these risks, simulation optimization models incorporating wind variability suggest adaptive fleet sizing, buffer schedules, and dynamic charging policies to maintain operational continuity [86].

2.3 Milestones in Air Transportation and Demand Modeling

Fully understanding the motivation behind AAM and the necessity of demand modeling requires a brief knowledge of aviation history and demand modeling approaches. The goal of this section is to equip the reader with a knowledge of key air transportation milestones throughout history, while highlighting the culminating factors requiring a push for novel air technology. Furthermore, the evolution of demand modeling techniques is also explored.

2.3.1 Evolution of Advanced Air Mobility

Aviation has existed for the previous 120 years, with the first engine-powered, sustained flight occurring in the early 1900's and the first scheduled commercial flight in 1914 [87]. One of the advancements that transformed the commercialization of civil aviation was the introduction of the jet engine in the early 1950's, with the development of the de Havilland Comet aircraft [88]. The introduction of the jet engine brought forth the "jet age" of aviation. The jet engine revolutionized longer and faster flights, and made commercial aviation more affordable. Following this breakthrough, the development of airports and airlines boomed in the 1960's. In the United States, early airlines adopted a point-to-point routing model, which established nonstop flights between cities [89]. Following the Airline Deregulation Act in 1978, many airlines adopted the hub and spoke model, using regional airlines to connect smaller airports to large network hubs [90]. While this model offered many benefits over the point-to-point model, short-haul trips often became infeasible due to high trip costs and longer trip times by requiring connections between hubs. Ultimately, the use of small regional aircraft to provide point-to-point transportation was drastically reduced. Recent advancements in eSTOL technology have motivated the use of smaller aircraft to provide regional transport services at lower operating costs [3], offering a strong alternative to ground transportation for trips between 50 and 500 miles.

Other efforts to provide short distance flights included the use of helicopters within metropolitan areas [45]. While early flights from the 1940's to 1980's faced numerous safety concerns and incidents, significant improvements in vehicle safety have allowed for modern, on-demand helicopter services to re-emerge in certain areas. Currently, high operating costs of these services significantly limit the number of consumers who are able to use the service and further limits accessibility. However, the use of eVTOL aircraft is expected to significantly reduce the prices of these trips, with estimated trip prices ranging from \$0.23 to \$7.73 per passenger-km in the long-term [91].

Overall, concerns of ATM strategies, airport capacity issues, and aviation-generated pollution have grown throughout recent years [92]. Furthermore, high operating costs of conventional aircraft severely limit short-distance mobility within the air transportation system. These factors have contributed to the need for AAM, which experienced an exponential growth in interest since the late 2010's [93]. The integration of AAM with the modern air transportation system is expected to significantly reduce these concerns, while unlocking affordable and accessible air transportation for shorter trips. Significant strides are being made to upgrade and create sustainable infrastructure and continue the development and certification of advanced air vehicles. Many agencies such as the Federal Aviation Administration (FAA), European Union Aviation Safety Agency (EASA), and other regulatory agencies around the globe have created frameworks for airspace integration and infrastructure design [29, 94]. In 2025, aviation authorities from the United States, Australia, Canada, New Zealand, and the United Kingdom developed a road map for AAM aircraft type certification to align airworthiness and certification standards [95]. The streamlining of AAM aircraft certification among these countries ensure a widely accepted certification process that prioritizes aircraft safety and reliability. These efforts aim to continually improve advanced air vehicle development, operations planning, and airspace integration.

The FAA aims to integrate operations into existing locations within the next five years. However, companies like Joby Aviation are in the late stages of aircraft certification and expect to begin operations in 2026. Further airspace integration efforts, infrastructure development, operations planning, and aircraft certification are some of the next steps in aiding AAM to reach technological maturity within the next 20 to 30 years.

2.3.2 Evolution of Demand Modeling Approaches

Fundamental transportation modeling has existed since the early 1950s [96], with an economic-specific focus on the demand growth of the automotive industry. At the same time, direct demand forecasting models were employed to project the demand for air transportation, but struggled with accuracy issues [97]. Statistical models grew popular in the 1970's, and the emergence of discrete choice models contributed to the improvements of mode choice modeling methodologies. These models were eventually used to improve the Four-Step Travel Demand Model (FSM) framework, which was later modified and improved to capture aspects of the evolving demand of air transport services beginning in the early 2000's [98].

The increase in computational resources and widespread data has motivated the use of simulation-based models within the last 20 years. Agent-based models have gained significant popularity in recent years due to their ability to capture complex modeling scenarios while considering individual users, or agents. These models are scalable to complex environments, and may be used to inform researchers of user preferences in stochastic transport systems [99]. Furthermore, these models may be adapted to various demand quantification scales. Similarly to simulation-based models, machine learning has been motivated by advances in compute power and data availability. Machine learning models offer potential for regression and classification-based tasks, including time-series demand forecasting, trip-pricing prediction, and other tasks that are complimentary to air transport demand forecasting [100]. While discrete choice, simulation-based, and machine learning models all contain advantages and disadvantages in modeling the air transport industry, the hybridization of models has proven to be effective and may minimize disadvantages of each approach in certain cases [101].

Surveys [102], mode choice models [90], simulation models [103], and machine learning models [104] are among the techniques that have been used to forecast AAM demand. These models have been applied to various scenarios, ranging from the macro scale to highly granular spatial resolutions. It is important to note that no singular demand model encompasses all types and scales of demand. Therefore, extensive analyses of all demand modeling methodologies must be explored to capture the variability of AAM demand as technology continually progresses.

A timeline summarizing key events in the push for AAM services and the emergence of demand modeling techniques is shown in Figure 2.3.

2.4 Neurosymbolic AI

Neurosymbolic AI represents a convergence of two historically distinct paradigms in AI: the data-driven, inductive learning methods by neural networks and the rule-based, deductive reasoning structures central to symbolic AI. Figure 2.4 shows the overview of the interaction of two AI methods to give Neurosymbolic approach. Neural network models leverage large scale data to learn distributed representations like feature vectors through backpropagation, achieving remarkable performance in

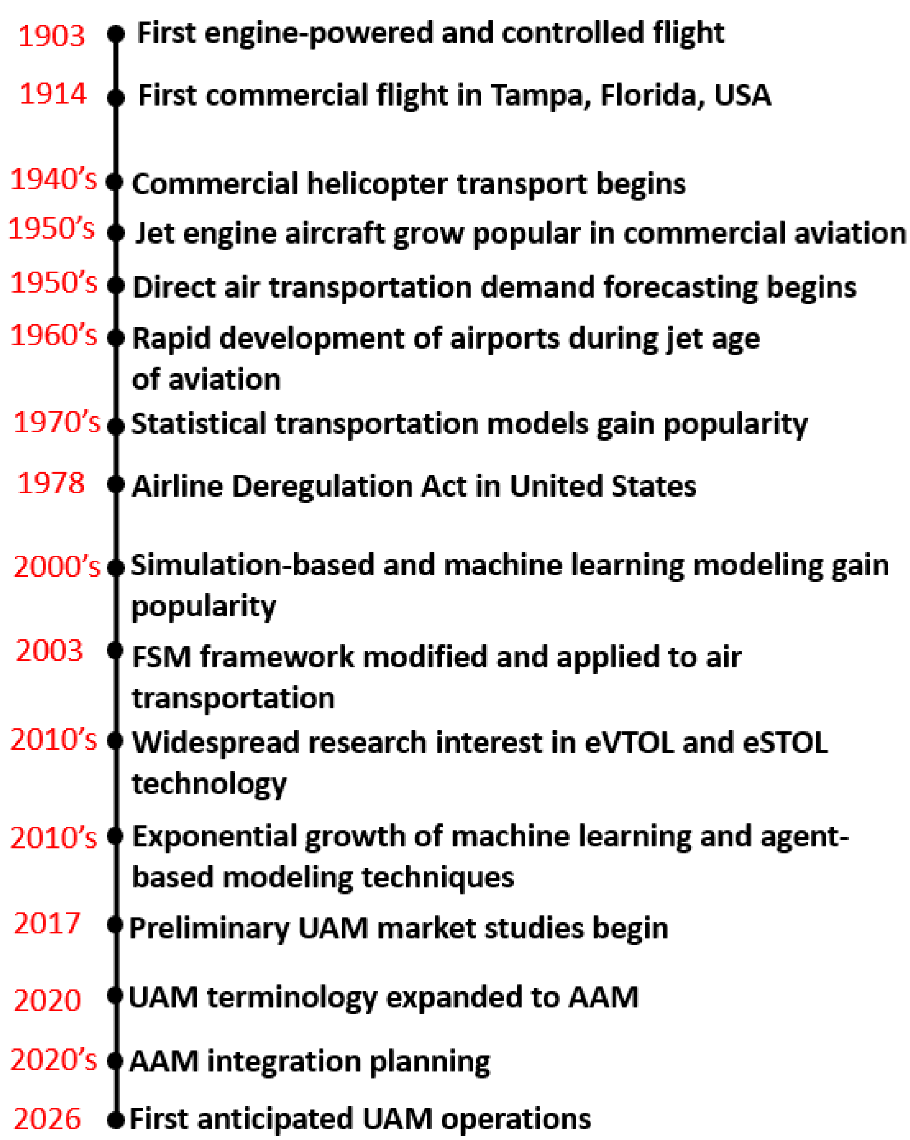


Figure 2.3: Timeline of Air Transportation and Demand Modeling Approaches

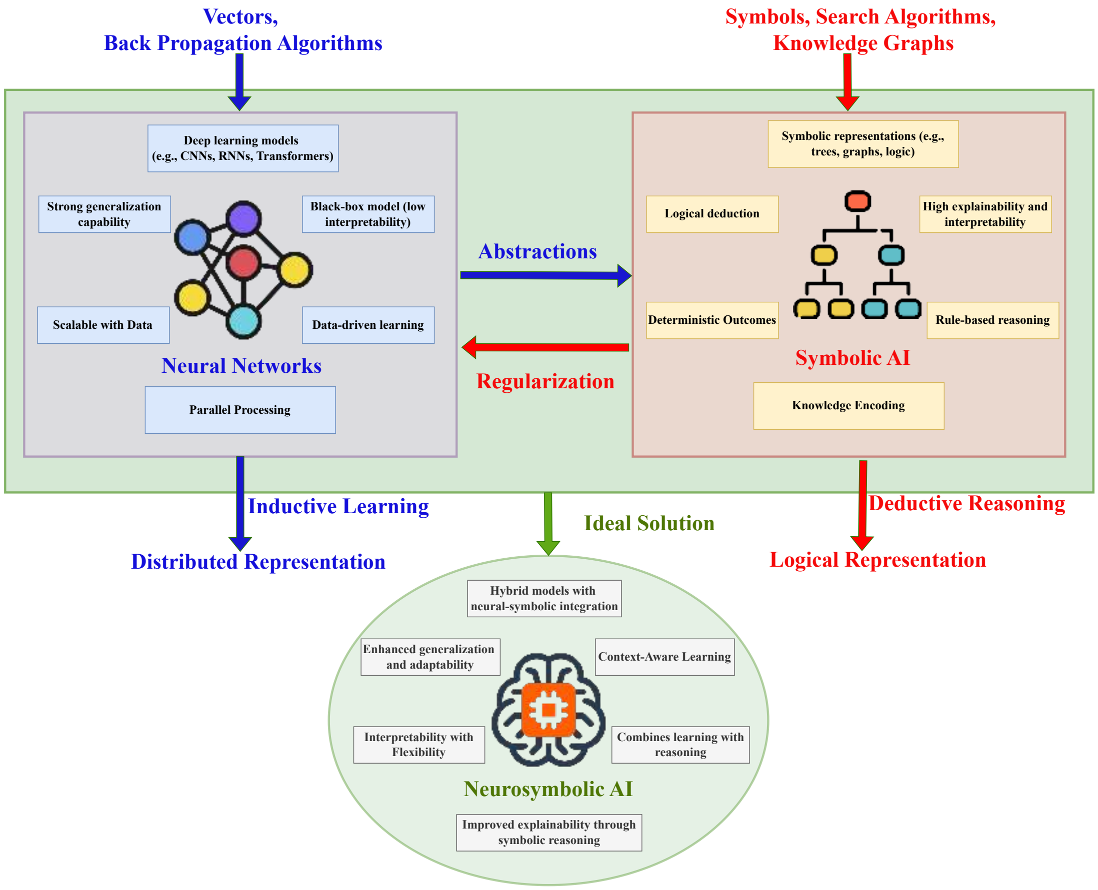


Figure 2.4: Overview of Neuro-symbolic AI

perception tasks such as image recognition, natural language understanding, and speech processing [105]. Meanwhile, symbolic AI focuses on manipulating symbols, building knowledge graphs, and applying logical inference rules to derive consistent and explainable outcomes [106]. While each approach holds distinct advantages, neither alone entirely satisfies the broader vision of human like intelligence, which demands both robust pattern recognition and high-level reasoning.

In Neurosymbolic AI, the goal is to unify these paradigms, thereby capitalizing on their complementary strengths. The “inductive learning” capacity of neural networks excels at discovering latent patterns from unstructured or noisy data and generalizing to new instances. Symbolic AI, on the other hand, operates with explicit knowledge representations, enabling interpretability, rule based reasoning, and systematic extension to new tasks via logical inference. By integrating both, a Neurosymbolic system aspires to harness the efficiency and scalability of neural networks while preserving the transparency and verifiability inherent in symbolic reasoning [107]. A key driver behind this integration is the quest for explainability. Neural networks, despite their impressive predictive power, are often criticized as "black boxes" because their internal decision processes are challenging to interpret and debug. Symbolic representations, however, allow for explicit explanations and traceable decision paths. In combination, Neurosymbolic AI methods aim to provide human-interpretable logic behind predictions [107]. For instance, in a hybrid architecture, the neural component can process raw data, transform it into a symbolic representation, and then employ a symbolic inference engine to arrive at a logically consistent conclusion. Another advantage of Neurosymbolic approaches lies in lifelong learning and knowledge transfer. Symbolic AI systems excel at retaining structured knowledge, once a rule or fact is learned, it can be utilized and updated without having to retrain the entire system. Neural models, on the other hand, often need retraining or fine-tuning to adapt to new tasks or domains. When combined, the system can incrementally incorporate new symbols, facts, or inference rules while leveraging the feature extraction prowess of the learned neural components.

Building on the developments in Inductive Learning and Deductive Reasoning, Neurosymbolic AI emerges as an "ideal solution" that seeks to combine data-driven generalization with robust logical formalism. This synergy enables novel capabilities, such as (i) extracting structured knowledge from raw data, (ii) dynamically generating new symbolic representations for novel concepts learned by the neural network, and (iii) using knowledge-based reasoning to refine and guide neural inference. Taken together, these advancements pave the way for AI systems that can reason, learn, and explain, moving us closer to the original vision of AI as a field that aspires to replicate the richness and versatility of human intelligence.

2.4.1 Classification of Neurosymbolic AI

Numerous researchers have contributed frameworks for understanding how neural and symbolic paradigms can be effectively combined to form Neurosymbolic systems. This section synthesizes three foundational perspectives that provide taxonomies for classifying and analyzing Neurosymbolic AI architectures. Figure 2.5 provides a simplified visualization of the eight dimensions along with their axes.

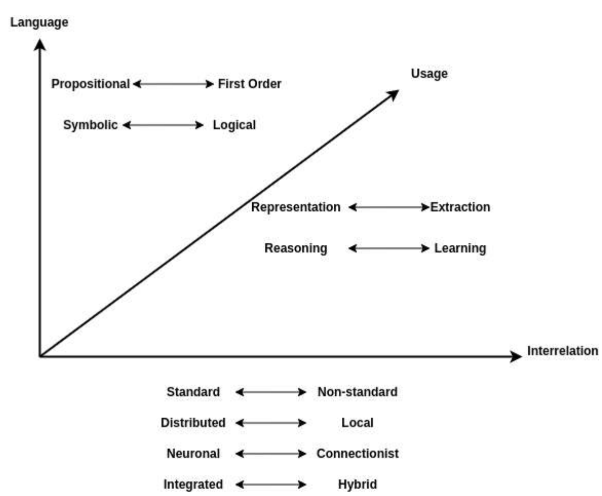


Figure 2.5: Classification by Sebastian and Pascal

2.4.1.1 Sebastian and Pascal's Classification

To systematize the diverse landscape of Neurosymbolic AI, Sebastian and Pascal [108] propose a multidimensional classification framework that organizes existing approaches along three principal axes: Interrelation, Language, and Usage. Each axis is subdivided into several independent dimensions, allowing for granular differentiation between systems.

2.4.1.2 Henry Kautz's Classification

Henry Kautz identified six distinct types of Neurosymbolic architectures, each defined by how neural and symbolic modules interact [109]. These types reflect increasing degrees of architectural coupling and cognitive inspiration. Table 2.2 provides the summary of the classification of Neurosymbolic as purposed by Henry Kautz.

2.4.1.3 Yu's Classification

The primary methodology for categorizing Neurosymbolic AI is based on the mode of integration between symbolic and neural components. This results in three core architectures: learning for reasoning, reasoning for learning, and learning–reasoning [110]. Table 2.3 shows various approaches used by Yu to classify the Neurosymbolic AI.

Table 2.2: Classification by Henry Kautz

Classification	Characteristic Features
Symbolic Neuro symbolic	Symbolic input is converted to feature vectors for the neural networks which give final results in the symbolic form
Symbolic[Neuro]	Neural pattern recognition subroutine within a symbolic problem solver
Neuro | Symbolic	A cascade from neural network into symbolic reasoner
Neuro: Symbolic $\rightarrow$ Neuro	Symbolic rules are input which are compiled so that their knowledge end up in the neural network
Neuro_{Symbolic}	Uses direct encodings of logical statements into neural structures
Neuro[Symbolic]	Embed symbolic reasoning inside neural engine to enable both superhuman and super combinatorial reasoning

Table 2.3: Classification by D. Yu and et al.

Classification	Characteristic Features
Learning for reasoning	Neural network play the role of the helper, it extracts the important symbols and information so that the search space of the symbolic system narrowed down
Reasoning for learning	Symbolic system act as a helper, it provides symbolic knowledge to the neural network from where the final decision is made
Learning-reasoning	Uses symbolic and neural systems as an alternate process. They both complement each other to give the final results

Chapter 3

Related Works

A key challenge in AAM demand modeling is that the mode is not yet in common use, so traditional travel data must be extrapolated or augmented to predict how many travelers would opt for air taxis or shuttles. The FSM [111] is a well established framework in transportation planning that decomposes travel behavior into four sequential stages: trip generation, trip distribution, mode choice, and route assignment. Its structured nature provides a clear and logical progression for modeling individual and aggregate travel decisions, making it an ideal baseline framework for understanding and forecasting mobility patterns. While FSM has limitations in capturing temporal dynamics and behavioral realism, its long-standing use in urban and regional transportation studies provides a comparative benchmark against which modern, data-driven approaches can be evaluated. Figure 3.1 presents the FSM–AAM demand modeling framework, highlighting the four-step process of trip generation, distribution, mode choice, and route assignment, together with the supporting methodologies specifically adapted for AAM demand forecasting.

3.1 Trip Generation: Identifying Potential AAM Trips

Trip generation for AAM usually starts with existing trip patterns and then narrows down the subset that AAM could plausibly serve based on distance, time,

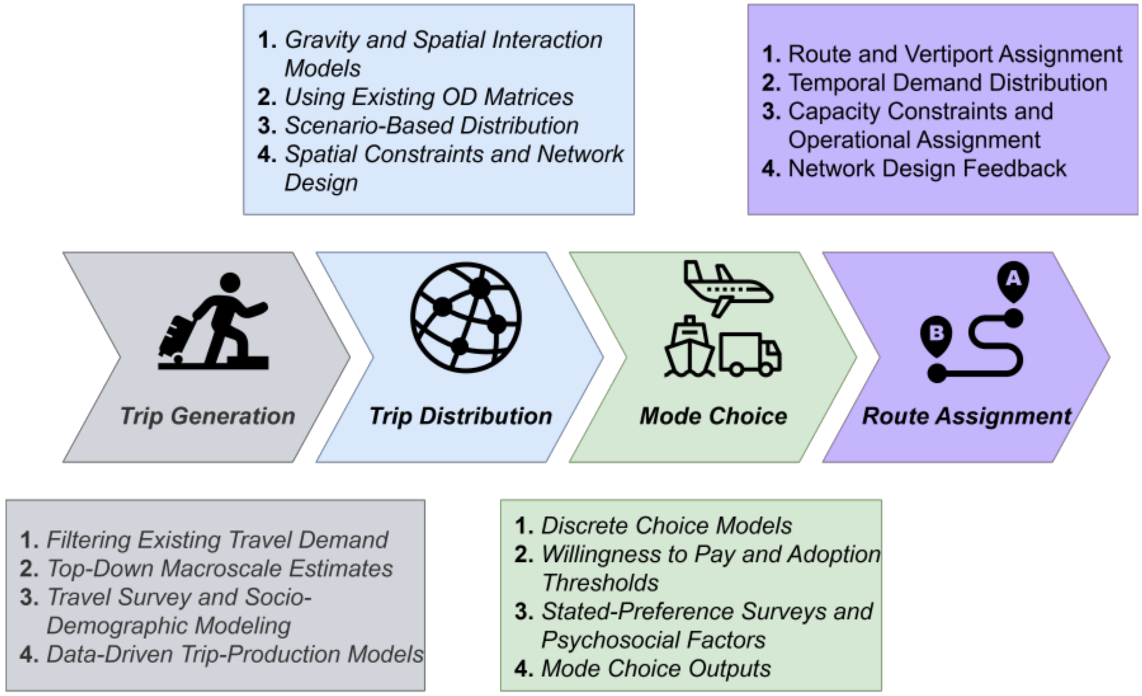


Figure 3.1: FSM–AAM Demand Modeling Framework: Four-Step Process with Supporting Methodologies

or trip type. Macroeconomic methods have been used for high-level estimates [112], while regional studies use travel survey data or commuting flows [113]. This stage sets the upper bound of potential AAM trips before considering competition with other modes.

3.1.1 Filtering Existing Travel Demand

A common method is to start from existing travel surveys or trip tables and filter those trips that meet criteria for AAM. The study [114] used the U.S. Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES) commuting dataset at the census-tract level and then filtered out the trips that satisfy the AAM requirement by distance, defining UAM eligible trips as <150 km and RAM trips as 150–800 km. This yields a set of candidate trips that AAM could serve, based on trip length. Similarly, a study [115] identified urban trips over 45 minutes by car as the pool of potential air taxi trips. This approach assumes AAM will draw from existing travel demand rather than create entirely new trips.

3.1.2 Top-Down Macroscale Estimates

Other researchers estimate trip generation at a city or regional level using aggregate socio-economic factors. [116] developed a top-down methodology to estimate the UAM demand of individual cities, globally based on city population and Gross Domestic Product (GDP) per capita. They first predict total passenger-kilometers traveled in a city and then disaggregate that total into trip segments by distance, purpose, and income level. This provides an estimate of how many passenger trips fall into distance ranges suitable for UAM. Such macro-scale models essentially generate trips by linking economic activity to travel demand at a high level, a technique useful for forecasting in cities lacking detailed travel surveys.

3.1.3 Travel Survey and Socio-Demographic Modeling

Some studies leverage traditional travel demand generation models, which relate trip production to demographics. In the study [115], the authors identified potential AAM markets by analyzing 486 urbanized areas using demographic and congestion-related metrics. Urban regions were filtered based on population size and density to focus on areas most suitable for AAM deployment. These filtered regions were further indexed using travel time, commute stress, and annual congestion costs, ensuring that the selected metropolitan areas reflected realistic baseline mobility needs before estimating demand for VTOL and eVTOL services. Another regional study [117], estimated commuter trips in Northern California by focusing on home-work travel in census data, then identified how many of those commuters could feasibly switch to UAM given available vertiport locations.

3.1.4 Data-Driven Trip-Production Models

Recent AAM research now supplements conventional socio-demographic trip counts with high-resolution built environment variables and uses non-linear machine-learning regressors to learn trip-generation rules directly from data. The study [118] develops a machine learning enhanced gravity model for Tennessee and New York by integrating 27 geographic and economic features into a gradient boosting framework, yielding substantial improvements over the traditional model. SHapley Additive exPlanations (SHAP) analysis reveals that travel time, distance, and income at both origin and destination are the most influential factors, with non-linear thresholds such as a sharp rise in demand once inter-county travel time exceeds about 70 minutes.

3.2 Trip Distribution: Spatial Flow of AAM Trips

Trip distribution for AAM either adapts classical models for origin-destination (OD) estimation or uses scenario assumptions for how trips spread in space. Key factors include travel time advantage and infrastructure connectivity. The outcome of this stage is typically a set of candidate OD pairs with potential AAM demand, which then feeds into mode choice analysis.

3.2.1 Gravity and Spatial Interaction Models

Several studies distribute trips using gravity models analogous to those in surface transportation. [115] applied a simplified gravity model to distribute trips between census tracts, by assuming equal likelihood of individual trip interchanges between tracts after controlling for distance or travel time. In their model, any OD pair where AAM travel time would not be faster than driving was dropped, effectively limiting distributed trips to those OD pairs that favor air travel time-wise. [119] constructed a global gravity model for air passenger demand between city pairs. Their model forecasts intercity travel demand and then identifies which city pairs might support AAM routes by 2042. While gravity remains the work-horse for OD forecasting, several studies show that intervening-opportunity and radiation formulations capture the long tail of OD flows better in monocentric settings. The research by Chen et al. [120] developed a novel ensemble model with conditional intervening-opportunity to improve ride-hailing travel mobility estimation. This model, tested on more than 25 million ride-hailing trips from Hangzhou and Ningbo, China, significantly outperformed baseline models.

3.2.2 Using Existing OD Matrices

In city-specific studies, researchers often leverage observed OD matrices from travel surveys or transportation models. Study [121] focussed Milan used the metropolitan travel demand model to obtain baseline OD flows for different trip purposes and then tested scenarios of adding vertiport locations. By starting with an existing OD matrix, they ensure that the spatial distribution of trips is realistic. Similarly study [122] used New York City (NYC) taxi trip data to find clusters of trip endpoints. This effectively captures a distribution of where trips concentrate, guiding placement of vertiports in high-demand corridors.

3.2.3 Scenario-Based Distribution

Some global studies bypass detailed distribution modeling by assuming representative patterns or scenarios. Researchers [123] divided cities into clusters and assumed each city in a cluster shares a similar trip distance distribution and UAM adoption rate. They did not explicitly compute OD flows for each city, but rather estimated total UAM passenger-kilometers per city and assumed a typical distribution of those trips.The study [124] similarly provided low/high demand scenarios for global UAM by 2035–2050, applying a uniform set of OD distribution assumptions for all viable cities in terms of population and GDP. These scenario-driven methods implicitly handle distribution by broad assumptions, they focus on total demand rather than detailed flows, but still consider factors like average trip lengths and city layout in an approximate way.

3.2.4 Spatial Constraints and Network Design

Distribution in AAM is also influenced by where infrastructure is or will be located. Some studies incorporate this by limiting OD pairs to those connected by available vertiports or airports. In the Tennessee AAM study, every trip is assumed to travel via one of 70 existing airports and each census tract's trips are assigned to its nearest airport for the air-leg [114]. This effectively distributes trips not freely between any two points, but only along specific hub-to-hub routes. Likewise, in an airport shuttle context, trips are explicitly distributed between city zones and the airports by allocating airport passenger ground trips to different city districts based on their population share [115]. These approaches recognize that initial AAM networks will be vertiport based, so demand distribution must be linked to those nodes.

3.3 Mode Choice Modeling: Modal Split for AAM

The mode choice step is critical, as it predicts what share of trips will actually choose AAM over other modes. Because AAM is a new mode with no historical ridership, researchers have used a variety of techniques to model mode choice.

3.3.1 Discrete Choice Models

The most prevalent approach is to extend logit models to include AAM as a mode. Qu et al. [125] explicitly focus on developing a nested logit model for Chengdu that nests AAM with similar modes. They calibrated the model on existing modes and then introduced UAM with utility parameters derived from stated preference data or assumed values. Most other studies likewise use multinomial logit models to estimate mode split. [115] constructed a utility function with key attributes and calibrated its coefficients using survey data, then applied an multinomial logit model to compute probabilities for choosing AAM vs car, taxi, transit, etc. By fitting the model to known mode shares in the status quo, they ensured reasonable sensitivity. Their model predicted essentially zero AAM uptake for short or expensive trips, but non-trivial shares for trips where AAM offered time savings at an acceptable cost. Coppola et al. [121] in Milan also used random utility models and included perceptual factors in the utility to capture public acceptance effects. Their mode choice model showed airport shuttle use of UAM could reach 2–5% of airport trips, whereas intra-city air taxi trips might capture only 1–3% of local trips, partially due to competition from efficient ground modes in that city.

3.3.2 Willingness to Pay and Adoption Thresholds

Some studies simplify mode choice by using willingness-to-pay (WTP) thresholds or value-of-time comparisons. Instead of a full logit curve, they assume travelers will choose AAM if certain conditions are met. A study [115] noted that trips longer than 30 minutes by car are the most likely to shift to AAM, since shorter trips do not save enough time to justify the high cost. Another study found surface transport is only competitive with AAM for trips under 10 km [103]. These insights often come from comparing door-to-door travel times. [126] showed that in South Florida, only trips >45 min by car would see a net time benefit from AAM once one accounts for getting to and from vertiports. Rather than computing a precise probability, such threshold-based approaches classify which trips would definitely choose AAM if available. [116] and [124] incorporated a WTP-based mode split. They correlated mode choice directly with income and essentially allocated a fixed proportion of eligible trips to UAM based on a price sensitivity analysis. [116] reported that at low fares of $0.30 per passenger-km, UAM mode share could reach 3.2–8.5%, but if fares rose to $0.90/km, mode share would drop to around 0.5–1.3%.

3.3.3 Stated-Preference Surveys and Psychosocial Factors

A few works have used survey data to enhance mode choice models. [127] conducted a stated-preference survey in Munich, presenting respondents with hypothetical trip options including UAM, to explore preferences for transportation modes in a UAM environment. They found factors like safety, privacy, and noise could also influence choice, beyond just time and cost. Such survey-informed models can introduce mode specific penalties in the utility. Coppola et al.'s inclusion of a vertical flight discomfort factor is one example, which reduced UAM's utility for some travelers despite time savings [121]. Even if AAM is technically faster, some portion of travelers might not choose it due to fear of new technology or aversion to flying over urban areas [121]. Incorporating these factors refines the modal split predictions. The Milan study [121] found the probability of choosing UAM drops sharply if vertiport access time is high or if ample rail alternatives exist, reflecting real-world behavior that convenience and familiarity of existing modes can outweigh a new mode's raw speed.

3.3.4 Mode Choice Outputs

The end result of mode choice modeling in these studies is typically an estimated AAM mode share for the given scenario. [115] projected about 0.5% of total trips in a city could be captured by early AAM services under conservative assumptions. [121] found a few percent of specific market segments might go to UAM. [116] performs sensitivity analyses at this stage by varying AAM price, vehicle speed, vertiport density, or congestion levels to see how mode share changes. A consistent finding is that AAM demand is very sensitive to price and service level. There are breakpoint fare levels beyond which demand collapses, and improvements like higher aircraft speed or more vertiports substantially raise mode share in simulations.

3.4 Assignment and Network/Temporal Allocation

The final stage, assignment, deals with how AAM trips are routed through the network and in time. In AAM demand studies, this stage has been less emphasized, but a few important considerations and approaches emerge:

3.4.1 Route and Vertiport Assignment

When a study identifies OD pairs for AAM, the next step is to determine the flight routes or network usage. [125] took the OD matrix from their modal split and examined the spatial distribution of UAM trips in Chengdu, proposing specific routes to prioritize for initial operations. By simulating which OD pairs had the highest UAM flow, they identified corridors where establishing routes would be most beneficial. In regional models like the Tennessee study, assignment is inherent in the methodology, each trip was assigned to a route that goes from origin tract to the nearest local airport, flies to a destination airport, then goes to the destination tract [113]. Likewise, airport shuttle scenarios naturally assign trips to the route between city and airport. [128] studied a business shuttle air taxi service in which they estimated the user base for a dedicated route, they find eVTOL aircraft significantly increases the expected user base compared to helicopters for same mission.

3.4.2 Temporal Demand Distribution

Some research has considered when AAM trips would occur and how to allocate them in time. [115] included a constraint for time-of-day and weather in their demand model. They assumed operations might be limited to daylight and good weather, which effectively caps the number of flights that can be assigned to each hour of the day. In their Monte Carlo simulations, they also varied demand across an average day rather than assuming uniform demand. While not a detailed scheduling, this recognized that AAM demand will likely be higher during peak commuting hours or event surges. They assume an average day OD matrix and do not fully model dynamic assignment, but they note that peak congestion and peak travel demand could constrain AAM operations.

3.4.3 Capacity Constraints and Operational Assignment

A crucial aspect related to assignment is accounting for limited infrastructure or vehicle availability. Instead of a flow assignment equilibrium, the AAM analog is checking that the predicted trips can be served by a finite fleet and vertiport capacity. The study [115] introduced constraints after mode choice for an assignment feasibility check. They applied capacity limits and pruned trips that could not be served within those constraints. This led to their estimate that only 0.5% of total trips could be served after accounting for infrastructure limits, even though unconstrained demand would have been higher. While most high-level demand studies don't do a full operations simulation, a few have optimization or simulation components. Rothfeld et al. [103] performed an agent-based simulation of UAM operations in Munich to see how vehicles could serve trips across an urban area, explicitly routing each aircraft and observing where delays might occur. Such simulations assign individual trip agents to vertiport links and can reveal queuing or airspace conflicts if demand is high.

3.4.4 Network Design Feedback

Some studies integrate assignment considerations back into earlier stages. For instance, Rajendran & Zack [122] and Yedavalli & Cohen [129] approached vertiport network design by considering demand hotspots and trying to place infrastructure optimally. By iteratively assigning tentative trips to provisional networks, they refined where vertiports should go to best capture demand. The study [122] used a clustering algorithm to assign high-demand trip clusters to potential vertiport locations, effectively doing a coarse assignment of trips to closest station and evaluating metrics like average trip distance to a station.

Chapter 4

Role of Cost, Time, Risk, and Reliability Parameters in AAM Demand

4.1 Demand Modeling of Advanced Air Mobility at Metropolitan Statistical Areas and Census Tract Level for Tennessee State

4.1.1 Introduction

The exponential growth of urban populations and the geographic dispersal of employment hubs have escalated demand for efficient transportation solutions, impacting both workforce mobility and economic productivity. Traditional ground-based transit systems, despite their established infrastructure, struggle to meet the increasing demand, leading to extended travel times, higher fuel consumption, and substantial economic losses from congestion. According to the 2023 Urban Mobility Report by the Texas A&M Transportation Institute[1],"The total travel delay increased from 4.5 billion hours in 2020 to 8.5 billion hours in 2022. Similarly, wasted fuel increased from 1.9 billion gallons to 3.3 billion gallons. The congestion costs increased significantly, from \$113 billion in 2020 to \$224 billion in 2022 and the travel volume increased from 1.38 trillion miles traveled in 2020 to 1.515 trillion

[1] 2023 URBAN MOBILITY REPORT: https://static.tti.tamu.edu/tti.tamu.edu/documents/mobility-report-2023.pdf. Last accessed on [May 9th 2024]

miles in 2022." The solution to all the problems is AAM, which is an emerging form of aviation that includes electric, autonomous aircraft for transportation.

AAM being advanced form of aviation is used for transportation in several ranges and on the basis of which it is divided into two different categories, UAM and RAM. At their foundation, UAM and RAM share numerous similarities, such as the recognition of the benefits of advanced electrified propulsion architectures, increased utilization, and Single Vehicle Operation (SVO)/autonomy in drastically reducing operational costs. However, UAM and RAM diverge significantly in the markets they serve and their infrastructural needs. UAM primarily uses eVTOL aircraft to access urban cores through newly developed vertiports, whereas RAM utilizes the extensive network of underutilized existing airports across the United States, eliminating the necessity for vertical takeoff and landing capabilities [3]. Operation range of UAM is less than 150 km whereas for RAM this range is 150-800km [130]. With rapid advancements in electric propulsion and autonomous systems, the AAM market emphasizes sustainability and efficiency to address urban congestion and environmental issues. Implementing AAM services presents several challenges and interdisciplinary constraints that companies must address, including decisions regarding the placement of air taxi stations, effective routing and coordination of thousands of air taxis across the network, and advanced data analytics to forecast demand in real-time. Companies must work to minimize passenger commute time and costs while maximizing the efficiency of on-demand ride-sharing. Operational issues such as developing pricing strategies, evaluating first and last-mile delivery options, and monitoring critical metrics like air taxi battery status and maintenance needs also need to be addressed.

This study specifically focuses on modeling the demand for AAM as a passenger transportation mode. To achieve this, the initial step involves assessing the demand for AAM services by analyzing existing trip demand data and identifying trips that qualify for AAM. The trip demand is examined at the MSAs level and census tracts level within Tennessee. We have considered all the 70 airports in the Tennessee as hubs for AAM operations in case of census tracts and 12 airports in case of MSAs which are nearest to the population centroid of the corresponding MSAs.

This study contributes to the growing body of research on AAM by addressing several key challenges unique to this sector.

- First, it highlights the specific demand dynamics that differentiate AAM from both traditional aviation and public transportation, filling a gap in the literature that has often focused on UAM within singular city contexts.

- Second, by introducing a novel cost, time and risk modeling framework that factors in both regional and urban contexts, this study demonstrates how AAM can serve as a complementary transportation mode, optimized for varying trip distances and user needs.

- Finally, we present a probabilistic demand model that incorporates uncertainties in traveler preferences, offering insights into how AAM might adapt to both routine and fluctuating demand patterns.

4.1.2 Related Work

The study by Rajendran [122] introduces a two-phase clustering methodology for optimizing air taxi station placements in urban settings. The first phase, termed "warm start," innovatively generates initial clustering seeds by integrating multi-modal transportation data, focusing on existing transportation hubs and patterns to predict potential high-demand areas for air taxis. The second phase involves an iterative clustering process that refines these initial placements by incorporating practical constraints such as estimated demand and operational feasibility. Potential passengers for air taxi services were identified using assumptions proposed in the Uber white paper [131] and additional assumptions by the researcher. The Davies-Bouldin Index (DBI) [132] was employed as the validity metric for the clustering algorithm. The dataset used consists of 300 million records of yellow and green taxi trips spanning from January 2014 to December 2015.

In a subsequent study by Rajendran [104], the dataset from the 2019 study [122] was enhanced with environment-related features like temperature and wind speed. This study employs a data-driven approach to forecast the spatiotemporal demand for air taxi services in NYC using logistic regression, artificial neural networks, random forests, and gradient boosting. The methodology hinges on the aggregation and clustering of geographic and temporal data to refine the prediction model's accuracy, leveraging k-means clustering to segment the city into distinct areas for detailed demand analysis. This spatial segmentation facilitates the exploration of demand patterns across different city regions, enhancing the strategic allocation of air taxi resources. By categorizing demand into three levels: low, moderate, and high, the study aids in operational planning and resource distribution, thereby optimizing air taxi services to meet varying urban mobility needs effectively.

Ahmed [133] explores the potential for implementing UAM by forecasting market demand through deep learning methodologies. Utilizing a dataset of 150,000 ground taxi service records from the NYC Taxi and Limousine Commission from 2012 to 2020, the study employs deep learning models such as Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Transformer to predict UAM demand. They introduced a parameter called the demand ratio, which is the product of passenger numbers and the distance, where a high ratio indicates high demand and vice versa. After calculating the demand ratio, various machine learning models were applied to predict it. A study in Chengdu, China [125] presents a demand forecasting model for UAM with other urban transportation modes using a nested logit (NL) and multinomial logit (MNL) model. Results show that UAM is more competitive for trips over 15 km, with a share rate increasing by 0.73% per additional kilometer.

This paper [117] investigates the feasibility of UAM landing sites and develops a fare model analysis for the Greater Northern California region, focusing on commuting passengers traveling to work from home and back. The study uses an all-electric, autonomous, multi-rotor aircraft with VTOL capabilities. The researchers aim to optimize landing site locations using census tracts, estimate demand potential, and evaluate life-cycle costs. They analyze three scenarios with 200, 300, and 400 landing sites, concluding that 300 sites offer a practical balance between demand capture and economic viability. The study includes a fare model, proposing a base fare of $20 for 20 miles plus $1 per additional mile, targeting a competitive fare structure of $1 to $1.25 per passenger-mile. The analysis employs datasets like the National Household Travel Survey, American Community Survey, and Zillow data to refine site selection and cost estimates. Results suggest that UAM can significantly reduce travel time and congestion, but further research is needed to address public acceptance, reliability, and infrastructure development.

4.1.3 Methodology

Flight demand forecasting of AAM is an complicated approach to handle as it is affected by the number of different factors. Being new and flourishing technology, it is very complicated to analyse how many of the total trip request generated can be converted into the AAM demand. The whole process can be visualized through the FSM [111] approach as shown in Figure 4.1. The FSM in transportation planning encompasses four interconnected stages to predict traffic flows and travel demands. Trip generation estimates the number of trips originating and ending in different zones based on socio-economic and demographic factors, producing a count of trip productions and attractions. Trip distribution then allocates these trips between zones, using models like the gravity model to account for the influence of travel cost and distance, resulting in origin-destination matrices. Mode choice analyzes these matrices to determine the mode of transportation (car, bus, airlines etc.) travelers use, influenced by factors such as cost, time, and convenience. Final step, route choice assigns the trips to specific routes in the transportation network, optimizing for factors like travel time and congestion, particularly during different times of the day, to simulate actual traffic flow patterns.

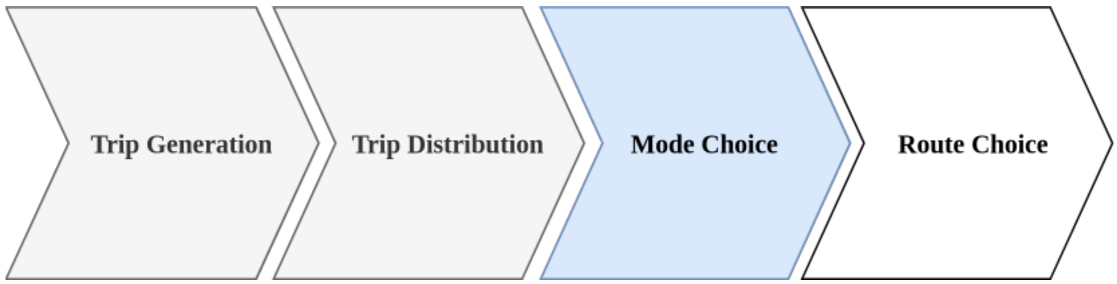


Figure 4.1: Four Step Model for travel demand modeling

Our focus is on the mode choice i.e. third step of FSM shown by light blue color in the Figure 4.1. First two steps, trip generation and distribution are used as the supplements to help for the choosing the means of transportation. The last step of route choice represented by the white shade is out of the scope of this work as we focus only on the assignment of the generated trips to the mode of transportation.

Our approach for AAM demand modeling is shown in the Figure 6.2. It consists of several components for trip demand generation, risk modeling, cost modeling time modeling, GCT calculation and finally predicting the AAM demand. Details about these are provided in the upcoming sections. Various datasets that have been used in the research are mentioned in the Table 4.1.

The distances whenever used with the ground transportation are the driv-

[2] Gazetteer Files: https://www.census.gov/geographies/reference-files/2019/geo/gazetter-file.html. Accessed on [May 9$^{\text{th}}$ 2024]

[3] Distance Matrix API: https://developers.google.com/maps/documentation/distance-matrix. Accessed on [May 9$^{\text{th}}$ 2024]

Table 4.1: Datasets Used in the Research

Name	**Details**
NSC Injury Facts [134]	Number of fatalities during Transportation
USDOT VSL Dataset [135]	Monetary equivalent of reducing one death in population
LODES Dataset [136]	OD pairs in census tract level
NHTS Dataset [137]	Trip Demand in MSA level
Gazetteer Files [2]	Centroid of population of MSA
Bureau of Transportation Statistics DB1BMarket Dataset [138]	Ticket Price for the airlines
IRS Standard Mileage Dataset [139]	Standard Mileage Rates(cents/miles)
FAA Airport Dataset [140]	Block time of the flights
Bureau of Transportation Statistics Dataset [141]	Distance between the airports
Google Map API[3] or Open Source Routing Machine (OSRM) [142]	Distance and Time of Ground transportation
US Bureau of Labor Statistics [143]	Median hourly wages

ing distance we obtain from the Open Source Routing Machine (OSRM) [142] or Google Map Application Programming Interface (API), which calculates the distance based on the actual road path, including turns and other deviations from a straight line. On the other hand, distance used with the airlines is orthodromic or spherical distance which is the great circle distance between airports. To calculate the orthodromic or spherical distance between two points on the Earth's surface, we use the Haversine formula [144] given below:

$$d = 2r \cdot \arcsin\left(\sqrt{\sin^2\left(\frac{\Delta\varphi}{2}\right) + \cos(\varphi_1)\cdot\cos(\varphi_2)\cdot\sin^2\left(\frac{\Delta\lambda}{2}\right)}\right) \tag{4.1}$$

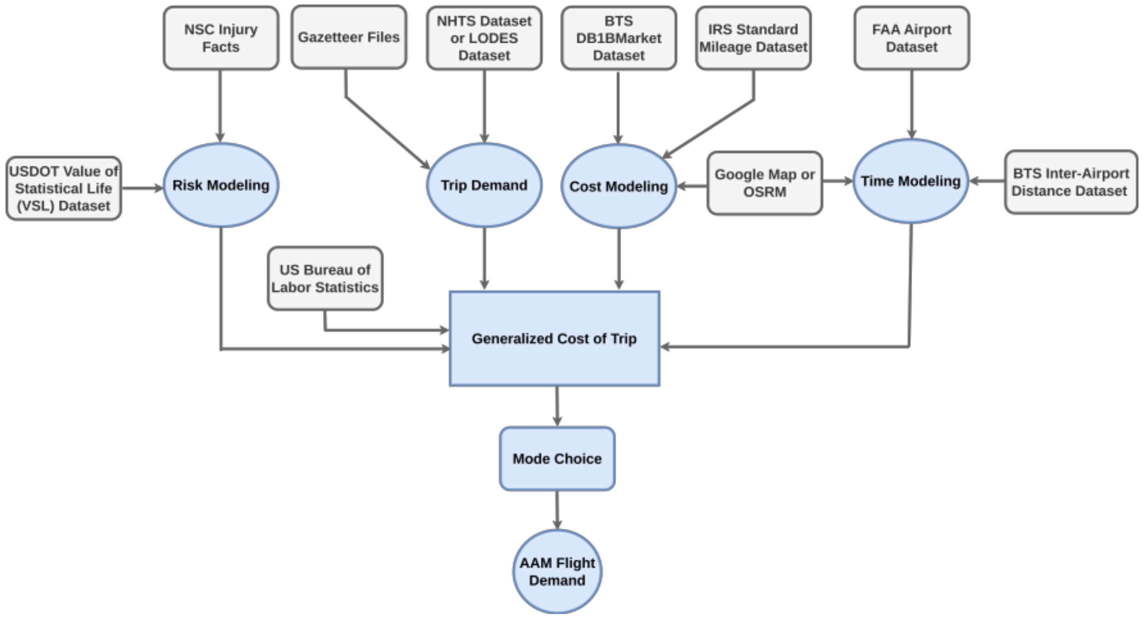


Figure 4.2: Approach for AAM demand modeling

where:

- d: Great-circle distance between the two points.
- r: Radius of the Earth, r is approximately 6371 km (kilometers) or 3958.8 miles.
- φ_1 and φ_2: Latitudes of the two points in radians.
- $\Delta\varphi = \varphi_2 - \varphi_1$: Difference in latitude between the two points.
- $\Delta\lambda = \lambda_2 - \lambda_1$: Difference in longitude between the two points, where λ_1 and λ_2 are the longitudes of the points in radians.

Region Selection

Tennessee has been chosen as the focal point of our research due to its strategic position in advancing AAM initiatives. The state's innovation ecosystem is anchored by notable institutions like Whisper Aero and the University of Tennessee, which contribute significantly to research and technology development in advanced air mobility. On the geographical level we focussed on the trip demand on census tract level and MSA level.

Census tracts are relatively permanent statistical subdivisions, ensuring consistency in data collection over time. However, adjustments are made to adapt to population shifts: tracts exceeding 8,000 inhabitants are split into smaller units with extended numeric codes, while those falling below 1,200 are merged with neighboring tracts and assigned new codes. Minor boundary corrections are permitted to reflect changes in local geography. These modifications are meticulously documented, allowing for accurate demographic and economic comparisons from decade to decade[4]. We mapped the 1701 census tracts into one of the 70 airports to develop them as the hub for the AAM for the trip demand generated from each of these locations.

MSAs are defined by the Office of Management and Budget (OMB) and are used by federal statistical agencies for collecting, analyzing, and publishing statistical data about specific geographic regions. An MSA is essentially a region that consists of one or more counties that contain an urbanized area of 50,000 or more inhabitants. Prior to December 2003, Tennessee had seven MSAs. Under the new

[4] Census Tracts: https://www2.census.gov/geo/pdfs/education/CensusTracts.pdf.Last accessed on [July 29$^{\text{th}}$ 2024]

Table 4.2: Metropolitan Statistical Areas in Tennessee State

Metropolitan Statistical Areas	**CBSA code**	**Counties Included**
Chattanooga, TN-GA	16860	Hamilton, Marion, Sequatchie, Catoosa (GA), Dade (GA), Walker (GA)
Clarksville, TN-KY	17300	Montgomery, Christian (KY), Trigg (KY)
Cleveland, TN	17420	Bradley, Polk
Jackson, TN	27180	Chester, Madison, Crockett
Johnson City, TN	27740	Carter, Unicoi, Washington
Kingsport-Bristol-Bristol, TN-VA	28700	Hawkins, Sullivan, Scott (VA), Washington (VA), Bristol (VA)
Knoxville, TN	28940	Anderson, Blount, Campbell, Grainger, Knox, Loudon, Morgan, Roane, Union
Memphis, TN-MS-AR	32820	Fayette, Shelby, Tipton, DeSoto (MS), Tate (MS), Marshall (MS), Tunica (MS), Benton (MS), Crittenden (AR)
Morristown, TN	34100	Hamblen, Jefferson
Nashville-Davidson-Murfreesboro-Franklin, TN	34980	Cannon, Maury, Cheatham, Davidson, Dickson, Hickman, Macon, Robertson, Rutherford, Smith, Sumner, Trousdale, Williamson, Wilson

Table 4.3: Nearest Airports from MSA

Airports	**IATA Code**	**MSA (City)**
Nashville International Airport	BNA	34980 (Nashville)
Memphis International Airport	MEM	32820 (Memphis)
McGhee Tyson Airport	TYS	28940 (Alcoa)
Lovell Field Airport	CHA	16860 (Chattanooga
Tri-Cities Airport	TRI	28700 (Blountville)
Elizabethton Municipal	0A9	27740 (Elizabethton)
Scott	0M1	RTN3 (Parsons)
Outlaw	CKV	17300 (Clarksville)
Crossville Memorial	CSV	RTN1 (Crossville)
Hardwick	HDI	17420 (Cleveland)
Humboldt Municipal	M53	27180 (Humboldt)
Moore-Murrell	MOR	34100 (Morristown)

guidelines in December, three more were added, bringing the total to 10 MSAs [145]. Detail about these MSAs are presented in the Table 4.2. Counties in the east which don't fall under MSAs are grouped as TN-NonMSA areas(E) and similarly for the west are grouped as TN-NonMSA areas(W) with CBSA code as RTN1 and RTN3 respectively[5]. We collected the monthly passenger OD data for two year 2021 and 2022. We mapped the 10 MSAs and two TN-NonMSA into one of the 70 airports to develop them as the hub for the AAM for the trip demand generated from each of these locations. The details are provided in Table 4.3 and visualized in Figure 4.3.

[5] Federal Highway Administration: https://www.fhwa.dot.gov/policyinformation/analysisframework/04.cfm.Last accessed on [May 9th 2024]

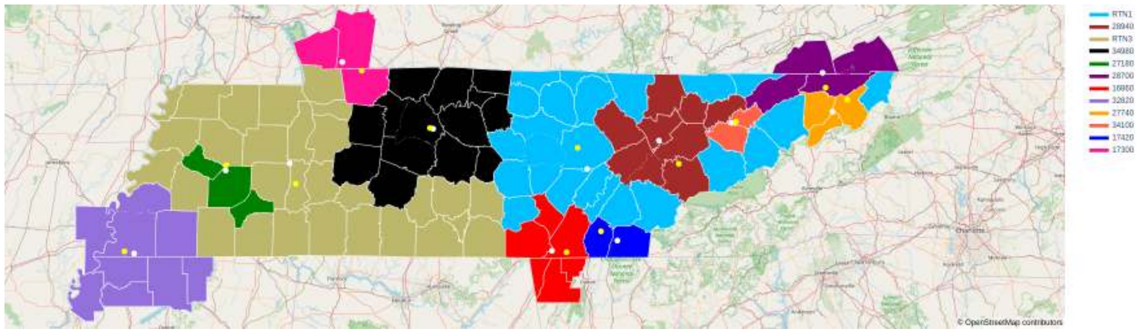


Figure 4.3: MSAs with corresponding nearest airports in Tennessee State Region

Trip Demand

The first two steps of the FSM model are trip generation and trip distribution, which serves as the supplements to our work for choosing the means of transportation. The trip demand data from the LODES dataset is specified at the census tract level, and trip demand data from the Next-Generation National Household Travel Survey (NHTS) is specified at the MSA level. It is presumed that travel originates from the population centroid of the origin and ends at that of the destination. We collect the OD data for the year 2020. First we analyze all the trips data, and later we filtered out the trip that satisfy the AAM requirement which is range of the distance should be from 150 to 800 KM for RAM and less than 150 KM for UAM.

We have the following assumptions for the trips:

1. All trips are generated from the centroid of population of origin.

2. Ground transportation trip consists of distance travel from centroid of origin to centroid of destination.

3. AAM trip consists of ground transportation from centroid of origin to the

nearest hub airport and then AAM flight to destination airports and finally ground transportation from destination airports to the centroid of destination.

Cost Modeling

One critical factor is the cost estimation associated with each trip demand for each mode of transportation. Given that the trip demand data from the LODES dataset is specified at the census tract level and NHTS at the MSA level, it is presumed that travel originates from the population centroid of the origin and ends at that of the destination. These driving cost calculations contribute to evaluating the total expenses related to complete door-to-door driving trips and the driving segments of journeys that include multiple modes, such as trips to and from airports.

Ground Transportation

The standard mileage rate is a set amount per mile that taxpayers in the United States can use to calculate vehicle expenses for business, charitable, medical, or moving purposes instead of tracking actual costs like fuel, maintenance, and repairs. This rate simplifies record-keeping and expense reporting for individuals using their vehicles for these purposes. The costs of driving are calculated using the standard mileage rates provided by the United States Internal Revenue Services (IRS), coupled with driving distance estimates derived from the OSRM or Google Map API.

$$C_G = d * \beta \tag{4.2}$$

where

- C_G is cost of trip per mile per passenger for ground transportation
- d is driving distance derived from the Google Map Distance Matrix API Service or OSRM
- β is standard mileage rates provided by the United States Internal Revenue Services

Air Transportation

The cost of the ground transportation portion of the trip can be calculated from the above mentioned steps. But the costs tied to air travel hinge on various factors including distance, service class, booking lead time, time of day, day of the week, competitive presence, and airline concentration at the point of origin or destination. This study does not delve into modeling airfares across multiple explanatory variables, but instead adopts a straightforward model that correlates passenger cost with distance. Data for this model is sourced from the DB1B database maintained by the Department Of Transportation (DOT), which contains a 10% sample of all tickets sold in the United States for the years 2021 and 2022. This database comprises three components: the ticket, market, and coupon databases. For this analysis, the market database is employed to extract airfare data by filtering the flights based on their destination or arrival in the Tennessee state.

Time Modeling

Another crucial element in the decision-making process of travelers is the evaluation of the travel time linked with each mode of transportation. Accurately assessing the time savings in travel is essential to highlight the appeal of air transportation compared to ground-based options.

Ground Transportation

Driving times are calculated using the OSRM or Google Map API. For door-to-door journeys via automobile, the starting point and endpoint are assumed to be the population centroid of the origin and the destination, respectively.

Air Transportation

The total travel time comprises several components: the drive from the origin to the departure airport, the duration spent at the departure airport, the flight time between the departure and destination airports (which may include layovers), the time spent at the destination airport, and finally, the drive to the final destination. The time for the first and last part of the trip which are ground transportation can be obtained from the above-mentioned methods using the OSRM or Google Map API. For the aviation time, we perform the block time calculation for its modeling.

The block times are the periods from when the aircraft's brakes are released at departure to when they are set upon arrival, are regressed from the two years 2021 and 2022 from Aviation System Performance Metrics (ASPM) dataset. The ASPM dataset is accessible through an online access system provided by the FAA and delivers comprehensive data regarding flights to and from the ASPM airports, as well as all flights operated by ASPM carriers. We used its data for city pair analysis, determining block time duration.

Risk Modeling

Risk modeling plays a crucial role in assessing and incorporating the various risks associated with different modes of transportation. The aim is to quantify the risk factors and include them in the overall cost calculation, thereby providing a more comprehensive estimate of the true cost of a trip. In our case, we calculate the number of fatalities for each mode of transportation. The Value of Statistical Life (VSL) is an economic measure used to quantify the benefit of reducing the risk of death. It represents the monetary value society is willing to pay to save a life [146]. With the help of those two we can find the monetary equivalent of the risk involved during each mode of transportation calculated as:

$$R_m = VSL * \Lambda_m \tag{4.3}$$

where

- m is mode of transportation, either ground or AAM
- R is the risk of trip
- VSL is the amount society is willing to pay to save a life
- Λ is a number of fatalities per mile

Given that the dataset spans the years 2021-2022, the dataset for the VSL from those two years is obtained and averaged to determine the required VSL for this study from the US DOT [135].

Ground Transportation

When analyzing motor-vehicle fatality trends across states, various fatality rate estimates can be employed to evaluate relative risk. Like calculating the total number of motor-vehicle deaths among state residents per 100,000 population, calculating the number of traffic deaths occurring in a state per 100 million vehicle miles traveled or calculating the number of traffic deaths per 10,000 registered vehicles. These three rate calculations offer distinct perspectives on fatality risk among states. In our study we used the second one which is based on the fatalities per 100 million vehicle miles travel. For the ground transportation parameter Λ_G is obtained from the dataset provided by National Safety Council (NSC).

Air Transportation

For the ground transportation section of the trip, above-mentioned methods can be deployed for the risk calculation. For commercial scheduled air travel, which is among the safest modes of transportation, the lifetime odds of a fatality for an aircraft passenger in the United States are negligible. For our study to calculate the number of fatalities for air transportation per million miles from the airplane crashes dataset provided by NSC.

Generalized Cost Modeling

To model the mode choice of travelers, researchers often begin with disaggregate models that estimate the utility of each transportation mode, factoring in attributes of both the travelers and the transportation modes. However, calibrating utility functions with numerous attributes can be complex and often requires extensive surveys. To simplify this, the study [128] proposed using the concept of GCT, which considers two main components: the monetary cost (C_m) of the trip and the opportunity cost, calculated as the traveler's value of time (W) multiplied by the door-to-door journey time (T_m). The monetary cost includes direct expenditures such as fuel or ticket prices, while the opportunity cost reflects the economic value of time spent traveling, calculated by averaging the median hourly wages in origin and destination. The negative sign preceding the individual terms in the equation (3), corresponds to the disutility associated with the increase in trip cost, trip time and risk involved during the trip.

$$\begin{aligned} GCT_G &= -C_G - W * T_G - R_G \\ GCT_A &= -C_A - W * T_A - R_A \end{aligned} \tag{4.4}$$

where

- A is air transportation mode
- G is ground transportation mode
- GCT is generalized cost of trip
- C is cost of trip per mile per passenger

- W is average median hourly wage of origin and destination

- T is time duration of trip

- R is monetary equivalent of risk of trip

The GCT for AAM trip is determined by summing the GCT of the corresponding ground and air transportation segments.

$$GCT_{AAM} = GCT_G + GCT_A \tag{4.5}$$

Mode Choice

The GCT metric is suitable for a deterministic choice model, which assumes that individuals are perfectly rational in their decision-making process. However, this approach may overlook other aspects of individual decision-making that analysts do not fully understand. To account for these uncertainties, a probabilistic-based choice model is more desirable, where the probability of choosing a transportation mode is considered instead of a deterministic choice. This probabilistic model represents the true utility as the sum of the systematic component of the utility and a random error term.

$$\begin{aligned} U_{\mathrm{G}} &= GCT_{\mathrm{G}} + \epsilon; \\ U_{\mathrm{AAM}} &= GCT_{\mathrm{AAM}} + \epsilon \end{aligned} \tag{4.6}$$

where

- U is utility for trip

- GCT is generalized cost of trip

- ϵ is the error associated

The behavior of travelers when faced with transportation mode options is simulated using discrete choice models, which estimate the probability of selecting a specific mode. These models, such as the logit and conditional logit models, vary based on assumptions about the distribution of the error component (ϵ) of the utility model. A common assumption is that the error term follows an independent and identically distributed (IID) Gumbel distribution, resulting in the multinomial logit model [147]. This model provides a closed-form expression for the choice probability as a function of the differences between the utilities of the transportation modes. By incorporating the variability in individual preferences through the error term, discrete choice models offer a probabilistic framework that more accurately reflects real-world decision-making. The probability of choosing the transportation mode (air or ground) can be expressed as:

$$\begin{aligned} P_{\text{AAM}} &= \frac{1}{1 + e^{(U_{\text{G}} - U_{\text{AAM}})}} \\ P_{\text{AAM}} &= \frac{1}{1 + e^{(GCT_{\text{G}} - GCT_{\text{AAM}})}} \end{aligned} \tag{4.7}$$

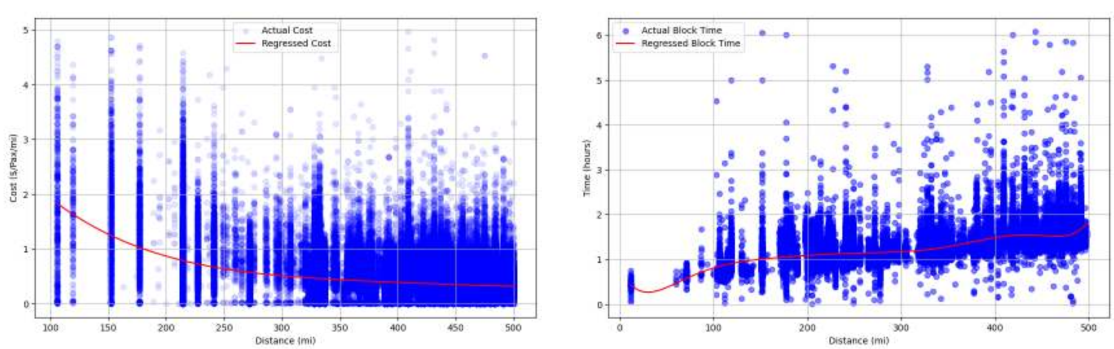
where

- P_{AAM} is Probability of selecting AAM
- U is utility for trip
- GCT is generalized cost of trip

4.1.4 Evaluation and Discussion

Cost Modeling

The regression analysis depicted in Figure 4.4a illustrates the relationship between passenger cost per mile and travel distance for air travel within Tennessee. The analysis reveals a clear inverse relationship between cost per mile and travel distance, indicating that shorter flights tend to have a higher cost per mile compared to longer flights. This trend aligns with the economies of scale in air travel, where fixed costs are distributed over a greater number of miles in longer flights, thereby reducing the cost per mile. Also, the variability in costs is more pronounced for shorter distances, likely due to factors such as demand fluctuations, service class variations, and competition.



(a) Cost Regression Analysis For Airlines (b) Block Time Regression Analysis For Airlines

Figure 4.4: Regression Analysis

Time Modeling

Research on block time in various industries has shown that it tends to increase with distance, but not exponentially [148]. In the airline industry, scheduled block times have been found to grow more linearly or with some polynomial relationship, influenced by factors such as air traffic growth, airport congestion, flight delays, takeoff, landing, and cruising times. Keeping this context under consideration, we employ polynomial fit for the time modeling.

The regression analysis illustrated in the Figure 4.4b examines the relationship between block time (in hours) and travel distance (in miles) for air travel. The scatter plot, showing actual block times (blue dots) and the regressed block time (red line), reveals a positive correlation between block time and distance, indicating that longer flights generally require more time. However, there is a significant variability in block times, especially for shorter distances, likely due to factors such as airport congestion, layovers, and flight scheduling irregularities. The regression line shows that block time increases with distance but not linearly, reflecting efficiency gains on longer flights. Notably, around distances of 480 miles, block time increases more rapidly, possibly due to the inclusion of more itineraries with layovers, adding extra time at transit airports. While block time generally rises with travel distance, operational factors contribute to considerable variability.

Risk Modeling

The analysis shown in Figure 4.5 indicates that ground transportation presents a significantly higher fatality risk compared to air travel over distances up to 500 miles, with risks increasing more sharply for ground travel. The logarithmic scale of the graph illustrates that ground travel risk starts around 10^{-5} and approaches 10^{-4}, while air travel risk remains substantially lower, starting around 10^{-7} and barely exceeding 10^{-6}. This considerable disparity underscores the relative safety of air travel, even though both modes show increasing risks with distance. However, the monetary values of the risk associated with both transportation modes are negligible compared to other costs incurred, such as time and actual expenses.

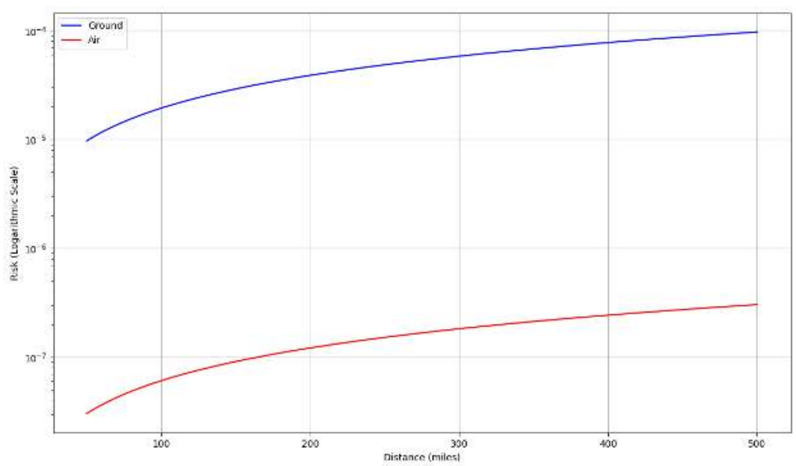


Figure 4.5: Risk modeling for different modes of Transportation

Generalized Cost Modeling

The regression analysis depicted in Figure 4.6 examines the relationship between the GCT in dollars and travel distance in miles for two transportation modes:

AAM and ground transportation. The analysis shows that the GCT for ground transportation increases linearly with distance, indicating a consistent rise in costs as travel distance extends. In contrast, the GCT for AAM exhibits a non-linear pattern, initially increasing, then slightly decreasing, and finally stabilizing, suggesting that AAM travel may become more cost-efficient over certain distances. This pattern likely reflects the fixed costs and economies of scale associated with AAM travel, which become more pronounced over longer distances. For longer distances, the GCT for AAM stabilizes around 200.

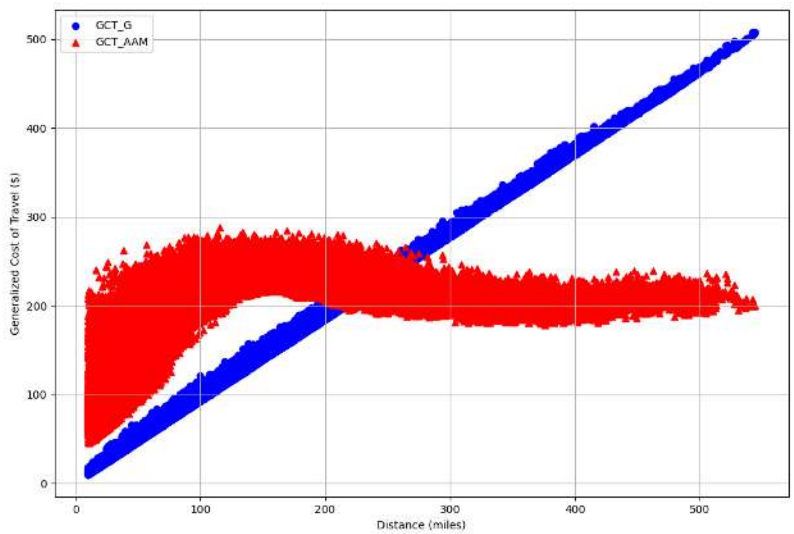


Figure 4.6: Regression Analysis For Generalized Cost of Trip

Mode Choice

We performed the calculation for finding the probability of choosing the mode of transportation between AAM and ground transportation using equation (5). The Figure 4.7 depicts the likelihood of selecting various transportation modes relative to distance. Initially, as distance increases, the probability of opting for ground transportation remains higher but then progressively declines, indicating a preference for AAM over longer distances. For distances up to approximately 200 miles, ground transportation is more frequently chosen. However, beyond around 250 miles, AAM becomes the favored mode. This pattern reveals a critical distance threshold where the likelihood of choosing AAM exceeds that of ground transportation, emphasizing its increasing appeal for extended trips. The Figure 4.8 shows that apart from the threshold distance, the demand for AAM is also higher in trips where the percentage of GCT of air transportation exceeds 70% of the total GCT for AAM.

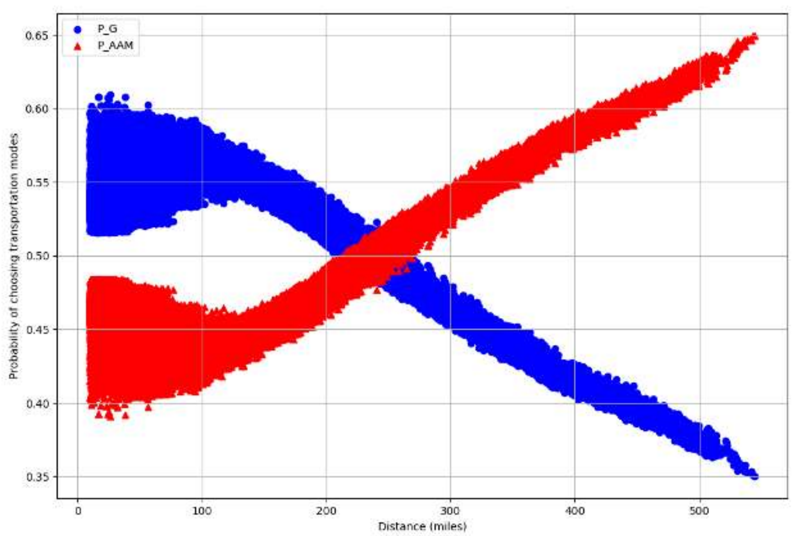


Figure 4.7: Probability of choosing transportation mode

The Table 4.4 presents comparative data on the average characteristics of trips involving AAM and non-AAM modes of transportation. It is evident that AAM trips, on average, exhibit larger GCT in air transportation (\$182.16) less in GCT by ground transportation (\$24.96) compared to non-AAM trips which is \$151.07 and \$27.30 in air and ground transportation respectively, highlighting the extended air

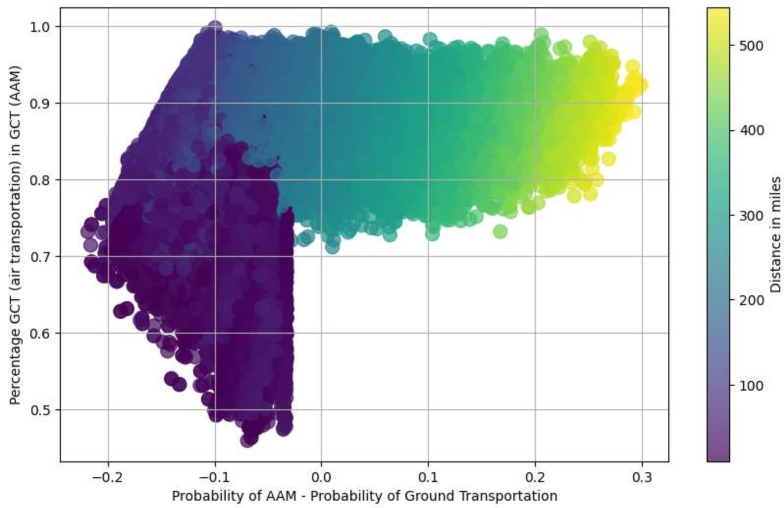


Figure 4.8: Percentage of GCT_A in GCT_{AAM} vs difference of P_G and P_{AAM}

Table 4.4: Mean Values for AAM and Non-AAM Trips at census tract level

Variable	**Non-AAM**	**AAM**
GCT by Air Transportation ($)	151.07	182.16
GCT by Ground Transportation ($)	27.30	24.96
Time in Ground Transportation (hours)	0.73	0.67
Distance by Ground Transportation (miles)	23.39	21.40
Distance by Air Transportation (miles)	72.98	273.19
Time in Air Transportation (hours)	0.58	1.18
Distance between OD (miles)	87.88	318.53
Ground Transportation time between OD (hours)	1.86	6.06

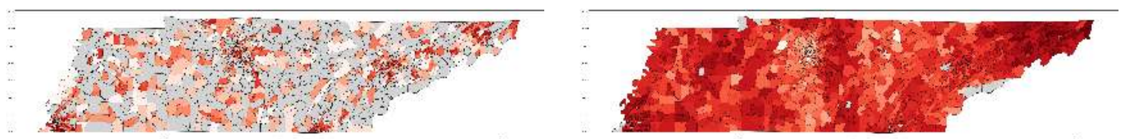
travel associated with AAM. Ground transportation distances and time durations are reduced in AAM trips (21.40 miles and 0.67 hours) compared to Non-AAM trips (0.73 hours and 23.39 miles), suggesting less ground segment connectivity in AAM networks. However, AAM trips demonstrate significantly longer distances and time duration by air (273.19 miles and 1.18 hours) than Non-AAM trips (72.98 miles and 0.58 hours), indicating that AAM is potentially more suited for longer-distance travel where traditional ground travel is deemed inefficient. Furthermore, average distance between origins and destinations is 318.53 miles in comparison to 87.88 miles for non-AAM trips.

Table 4.5 presents a comparison of trip demand features between all trips and those attributed to AAM. The data is broken down by age, earnings, and industry sectors. For age, individuals aged 30-54 make up the largest percentage of both, indicating a dominant demographic in travel demand. In terms of earnings, those making over $3333/month represent the largest share for both trip categories, suggesting higher-income individuals are frequent travelers. Industry-wise, the 'Other Services industry' holds the highest percentage for both trip types.

Table 4.5: Comparison of Trip Demand Features

Features	**Sub-categories**	**All (%)**	**AAM (%)**
Age	29 or younger	23.47	22.88
	30 - 54	53.28	53.34
	55 or Older	23.25	23.78
Earning	$1250/month or less	23.51	26.59
	$1251/month to $3333/month	32.06	29.49
	Greater than $3333/month	44.43	43.92
Industry	Goods Producing	16.91	10.89
	Trade, Transportation, and Utilities	21.61	33.75
	Other Services industry	61.48	55.36

The Figure 4.9 illustrate distinct distributions for job and home locations within the Tennessee state's census tracts. Jobs are densely concentrated in central Tennessee, particularly around Nashville, as well as in the eastern region near Knoxville, and in the southwestern area near Memphis, indicating major urban centers with high employment opportunities. In contrast, residential areas, while also concentrated around these cities, display a broader spread across the region, suggesting a more dispersed living pattern typical of suburban and extended urban areas. This distribution pattern highlights the centralization of employment in urban hubs and the wider spread of residences, which likely influences commuting flows in Tennessee.



(a) Spatial Distribution of Jobs

(b) Spatial Distribution of Residential Areas

Figure 4.9: Census Tracts for AAM OD pairs in Tennessee

The Figure 4.10 highlights that more densely populated MSAs exhibit higher RAM trip demand, as seen at origin points like 27740, 32820, and 34980. These high-demand MSAs consistently show elevated trip counts, particularly during peak months. The demand pattern also varies seasonally, with months later in the year (darker bars representing October, November, and December) typically reflecting increased demand compared to earlier months. This seasonal rise may be attributed to factors such as holiday travel, tourism, and seasonal events.

4.1.5 Conclusion

In this research paper, the cost, time, and risk models were developed for AAM and ground transportation. These models were subsequently utilized to create the GCT model to predict the likelihood of AAM being chosen as the preferred

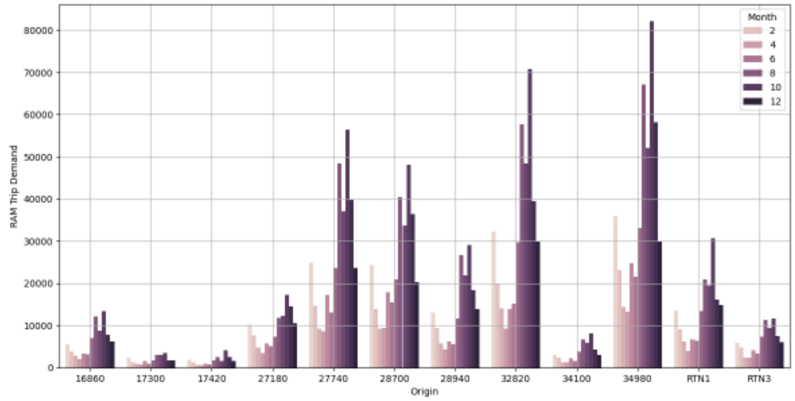


Figure 4.10: Monthly RAM Trip Demand for Each Origin at MSA level

mode of transportation. The proposed model indicated that, for Tennessee, trip demand generated is more likely to constitute AAM trip demand if air transportation contributes more than 70% to the GCT and if the trip distance exceeds 250 miles.

4.2 Urban Air Mobility Flight Demand Modeling for Airports in New York City

4.2.1 Introduction

Rapid urbanization in recent decades has posed significant global challenges, particularly in the domains of mobility, environmental sustainability, and quality of urban life. Metropolitan regions such as NYC exemplify these pressures, where growing population density has led to substantial traffic congestion, resulting in commuters losing an average of 150 hours each year in traffic delays [149]. The consequences of such congestion extend beyond temporal inefficiencies, contributing to reduced economic productivity, increased air pollution, elevated vehicle operating costs, higher accident rates, and a general decline in commuter well-being. In response, many urban dwellers have adopted alternative travel strategies, such as using mass transit systems or modifying commute schedules to avoid peak traffic. However, these alternatives often involve trade-offs in terms of convenience, flexibility, and comfort.

Against this backdrop, AAM has emerged as a promising paradigm aimed at alleviating urban mobility constraints. AAM encompasses a new class of aviation operations that leverage autonomous eVTOL aircraft to transport people and goods in a safe, efficient, cost-effective, and environmentally sustainable manner. The framework of AAM is broadly categorized into UAM and RAM, with the former focused on short-distance intra-city routes and the latter on medium-range intercity transport [3].

This study concentrates on the deployment potential of UAM within NYC, particularly with respect to trips connecting the city's three major airports: John F. Kennedy International (JFK), LaGuardia (LGA), and Newark Liberty International (EWR). By leveraging recent advancements in electric propulsion and autonomous flight systems, UAM aims to offer flexible, on-demand, and sustainable air transportation that can effectively mitigate surface congestion and complement existing urban transport networks.

The successful integration of UAM into urban ecosystems, however, hinges on addressing a complex set of interdisciplinary challenges, including infrastructure development, regulatory frameworks, airspace integration, pricing models, and accurate demand forecasting. The core objective of this research is to assess the feasibility and demand potential of UAM services for NYC airport trips by analyzing travel behavior using ground-based trip data. We utilize detailed trip records from the NYC Taxi and Limousine Commission (TLC)[6], aggregated at the taxi zone level, to identify critical origin-destination patterns and infer demand trends.

While prior studies have explored UAM demand in NYC using taxi datasets for purposes such as identifying optimal vertiport locations [122], classifying trip intensity levels [104], and estimating demand shares [133], these efforts have largely neglected the influence of travel time reliability on commuter preferences. Similarly, international studies such as those conducted in Jakarta, Indonesia [150], and Chengdu, China [125], have applied data-driven and simulation-based approaches to evaluate demand under varying operational and demographic scenarios, yet have failed to incorporate temporal uncertainty as a critical factor.

To bridge this gap, our study introduces the Value of Reliability (VOR) as a key determinant in travel mode selection. We quantify how variations in travel time and distance contribute to travelers' likelihood of switching from conventional ground-based options to UAM. By embedding VOR within the GCT framework, this research offers a more realistic and behaviorally grounded assessment of UAM demand potential in NYC, with broader implications for multimodal urban transport planning and policy.

[6]TLC: `https://www.nyc.gov/site/tlc/about/tlc-trip-record-data.page`. Last accessed on [May 18$^{\text{th}}$, 2025]

4.2.2 Related Work

UAM has been studied extensively as a potential solution for airport access challenges in metropolitan regions. The literature converges around three major themes: (i) demand modeling and behavioral adoption, (ii) cost and time competitiveness, and (iii) infrastructure optimization. While these works provide strong foundations, most fail to explicitly account for *travel time reliability*, which is a critical determinant of user adoption. This study addresses that gap by embedding VOR into the GCT framework for NYC airport access.

Discrete choice methods dominate the UAM adoption literature. Coppola et al. [121] demonstrated through a stated-preference (SP) survey that willingness-to-pay is significantly higher for airport shuttle services compared to intra-city UAM, particularly among business travelers. Building on this, Coppola and colleagues later developed a random-utility model for [151], integrating perceptions of safety and low-altitude flight into the mode-choice framework.

At the international level, Jakarta [150] and Chengdu [125] have served as testbeds for embedding UAM into the four-step travel demand model. These studies often relying on multinomial or nested logit structures to forecast adoption despite the absence of an existing user base. Such studies illustrate the transferability of behavioral models across diverse contexts. At the national scale, Kotwicz Herniczek et al. [152] integrated Census employment flows, travel times, and mode choice into a reproducible UAM demand model, offering a reference framework for regional-to-national scaling. Machine learning has recently gained traction in this domain.

Ahmed et al. [133] compared deep learning approaches (LSTM, GRU, Transformer) against econometric baselines, showing strong forecasting accuracy for short-horizon predictions, which can complement discrete choice models.

The Uber Elevate White Paper [131] remains the cornerstone for eVTOL operating cost assumptions, outlining phased declines driven by scale economies, battery improvements, and regulatory maturation. Many UAM studies have used these estimates for early, scale-up, and mature scenarios. For travel time, mean savings have been the central focus. However, agencies such as Federal Highway Administration (FHWA) emphasize that reliability, quantified through indices such as the Planning Time Index (PTI) and Level of Travel Time Reliability (LOTTR), carries an independent and often substantial value to users [153, 154]. Building on this, our study integrates VOR within the GCT, directly quantifying the influence of variability on airport access adoption.

Infrastructure placement has also been a critical research focus. Jin et al. [8] introduced robust optimization models for vertiport siting that account for demand uncertainty. Recent industry commitments underscore the timeliness of these analyses. Archer Aviation and United Airlines' 2025 announcement of an NYC airport UAM network demonstrates the market focus on short, high-value airport access trips and validates academic emphasis on this use case.

Despite these advances, most demand studies emphasize average travel time and cost while overlooking reliability. This omission reduces behavioral realism, particularly in congested cities like NYC, where day-to-day travel variability is high. By embedding VOR into the GCT and applying it to high-resolution NYC TLC data, this study provides a more comprehensive and policy-relevant framework for forecasting UAM demand.

4.2.3 Methodology

Our methodological framework for modeling UAM demand is illustrated in Figure 4.11. The approach comprises of several key components, beginning with the acquisition and preprocessing of trip demand data. This is followed by the development of cost, time, distance, and speed models, which are integral to the computation of the GCT. The final stage involves demand prediction for UAM services based on the derived GCT metrics. Each of these components is elaborated in detail in the subsequent sections.

In this study, we distinguish between two types of distance metrics based on the transportation mode. For ground transportation, we use driving distance as reported in the TLC dataset, which accounts for actual road networks, including detours, turns, and route irregularities. Conversely, for UAM services, we use orthodromic distance, also known as great-circle or spherical distance which represents the shortest path between two geographic coordinates, typically calculated between airports and taxi zones.

Region Selection

For this study, we select NYC as the focal region to evaluate the potential demand for UAM services. NYC offers a unique and compelling environment for such

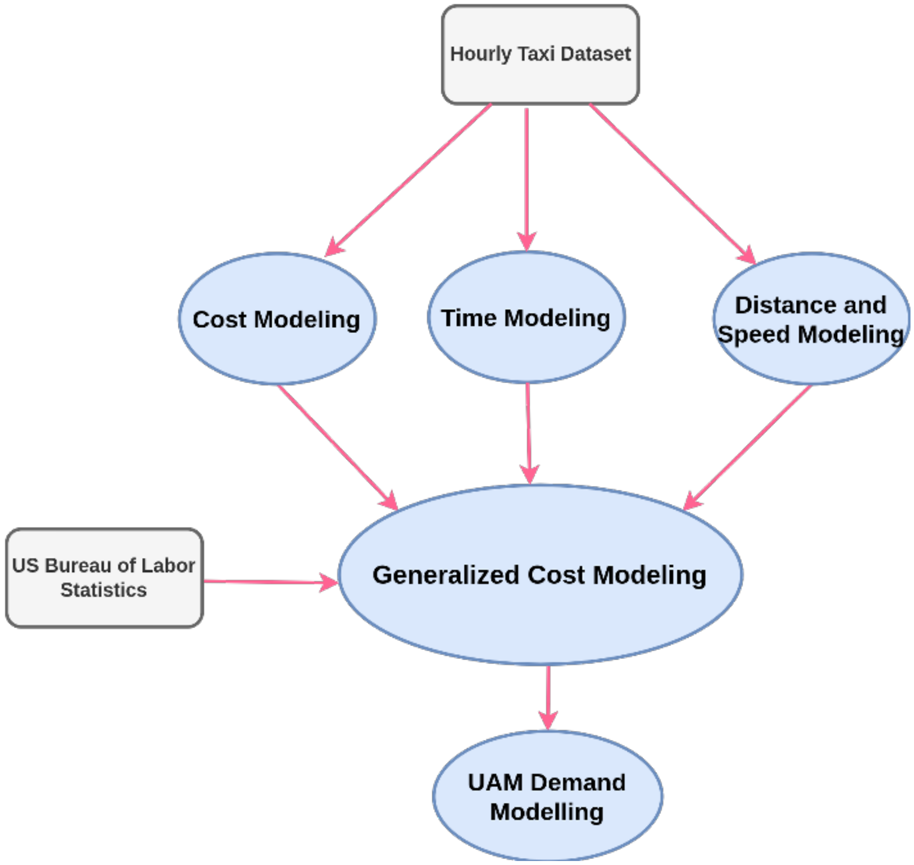


Figure 4.11: Approach for UAM demand modeling

research due to its high population density, significant traffic congestion, extensive use of for-hire vehicles, and the presence of multiple major airports in proximity to the urban core. The city's rich, high-resolution transportation datasets publicly available through the NYC TLC, further support robust empirical analysis. Moreover, NYC has been at the forefront of transportation innovation and serves as a representative model for dense, multimodal urban ecosystems globally, making it an ideal candidate for UAM feasibility assessment and demand forecasting.

At the geographical level, our analysis is conducted using taxi zones, which serve as the spatial resolution for modeling origin-destination (OD) travel demand.

Taxi zones are standardized spatial units defined by the NYC Taxi and Limousine Commission, and are central to the collection and publication of trip-level mobility data, including pickup and dropoff locations encoded through unique Taxi Zone IDs.

In the context of urban mobility research, taxi zones offer a practical compromise between spatial granularity and user anonymity. The city is divided into 263 taxi zones, each representing a geographically bounded area and assigned a unique identifier. These zones replace precise GPS coordinates with interpretable spatial categories, thereby facilitating scalable analysis of large mobility datasets. Taxi zones are essential for conducting OD-based analyses, travel demand modeling, accessibility assessment, and policy simulations. They also enable systematic examination of movement patterns across NYC's five boroughs and key intermodal nodes, such as its three primary airports.

The three major airports in NYC: JFK, EWR, and LGA are represented in the TLC dataset by taxi zones 132, 1, and 138, respectively. These zones serve as critical nodes in our analysis of airport-bound trip demand and are key targets for assessing the potential role of UAM in alleviating airport access congestion. Additional details on the taxi zones are given in Figure 4.12.

Dataset Collection and Pre-processing

The data processing pipeline for this study begins with the acquisition of trip-level records from the NYC TLC. We collect comprehensive datasets for the entire year of 2023, encompassing Yellow Taxi, Green Taxi and High-Volume For-

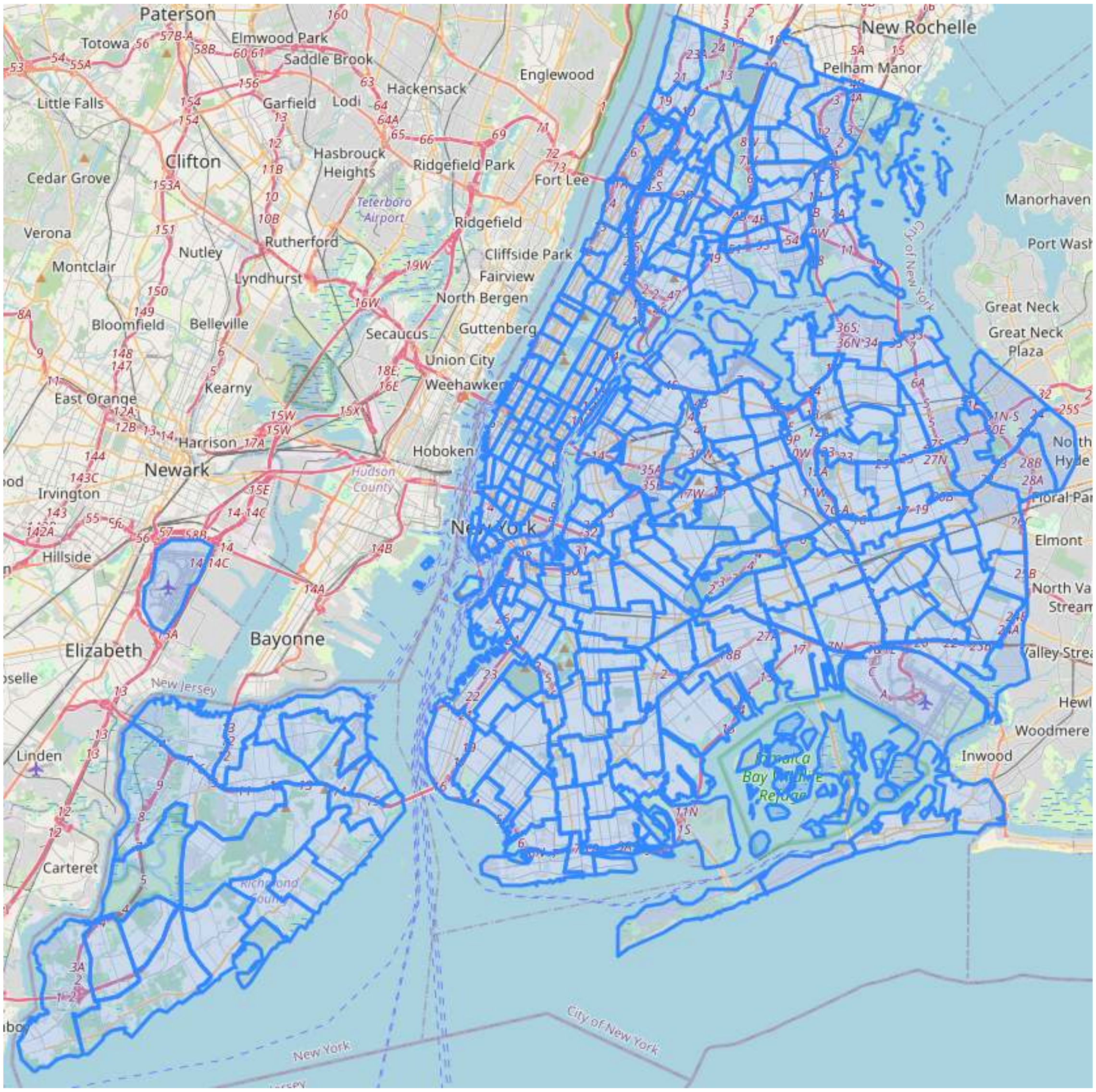


Figure 4.12: Taxi Zones in New York City

Hire Vehicles (HV-FHV) records. The subsequent pre-processing steps, illustrated in Figure 4.13, are carried out to ensure the integrity, consistency, and analytical relevance of the dataset for UAM demand modeling.

Our overall process starts with the data collection from TLC Trip Data. We collect the data for Yellow Taxi, Green Taxi and FHV and HV-FHV for the entire year of 2023. Then we pre-procesee data as shown in the Figure 4.13. It consists of following steps:

- **Data Collection:** Trip data from all three vehicle categories (Yellow, Green and HV-FHV) is retrieved for the period January–December 2023.

- **Handling Missing Values:** Records with missing or null entries in critical fields such as pickup or drop-off location IDs, timestamps, trip distance, and fare amount is excluded from the dataset.

- **Handling Outliers:** We filter out anomalous records exhibiting implausible values, such as excessively high fares, unrealistically short trip durations, or zero distances, to mitigate the influence of outliers on downstream analysis.

- **Removing unwanted taxi zones:** The TLC defines a total of 265 taxi zones, among which Zone 264 and Zone 265 are designated as "Unknown Pickup" and "Unknown Dropoff" respectively. Trips involving these zones are excluded to ensure spatial accuracy and reliability.

- **Filtering Airport Trips:** For this study, we retain only the trips that either originate from or terminate at the three major NYC airports: JFK (Zone 132), EWR (Zone 1), and LGA (Zone 138), removing all unrelated trips.

- **Converting to Hourly data:** The clean dataset is then aggregated into an hourly Origin-Destination (OD) format, capturing the frequency of trips between each relevant taxi zone and the selected airports, thereby facilitating temporal demand analysis.

Figure 4.13: Data Processing Pipeline

Cost Modeling

The cost modeling component of this study distinguishes between two transportation modes: traditional ground-based services (Yellow Taxis, Green Taxis and HV-FHV) and emerging UAM services.

For ground transportation, the trip-level fare data provided in the TLC dataset is directly utilized, which is provided as the base fare. In contrast, the cost estimation for UAM services is derived from projections outlined in the Uber Elevate White Paper, which provides cost benchmarks for UAM operations based on the maturity of eVTOL technologies and expected operational efficiencies. According to the report, the cost of UAM trips is expected to follow a declining trend across different developmental phases: the early market entry phase, scale-up phase, and long-term maturity phase. These projected costs factor in aircraft production costs, battery technology improvements, regulatory progress, infrastructure development, and fleet utilization rates.For this study, we adopt phase-based cost assumptions from Uber's estimates to model realistic fare scenarios for UAM trips.

Table 4.6: Airports in NYC under consideration for UAM Demand

Airports	**IATA Code**	**Taxi Zone ID**
John F. Kennedy International Airport	JFK	132
LaGuardia Airport	LGA	138
Newark Liberty International Airport	EWR	1

Time Modeling

The time component in our modeling framework is treated separately for traditional ground transportation and UAM services, reflecting the operational characteristics of each mode.

For ground-based transportation (Yellow Taxis, Green Taxis and HV-FHV), trip duration is directly obtained from the TLC trip records, which provide actual travel times from pickup to drop-off. These trip times inherently capture real-world traffic conditions, including congestion, signal delays, and route variability, making them a reliable basis for estimating ground travel duration between taxi zones and airports. In contrast, UAM travel time is estimated using specifications outlined in the Uber Elevate White Paper, which provides a breakdown of total flight duration into its key components: takeoff, cruising, and landing. This composite model enables time estimation based on the orthodromic distance between origin and destination points. The total flight time is calculated using assumed average cruising speeds of eVTOL aircraft along with fixed durations for ascent and descent phases.

Generalized Cost Modeling

The GCT framework integrates multiple dimensions of traveler burden into a unified cost metric. It reflects not only the direct monetary expenditure associated with a trip but, also the opportunity cost of time and the cost associated with reliability. This comprehensive approach enables a more behaviorally grounded comparison between conventional ground-based transport and emerging UAM services.

The GCT is composed of three primary components:

- Monetary Cost (μ_c): This is the actual base fare paid for a trip.
- Opportunity Cost of Time ($VOT \times \mu_T$): VOT represents the economic worth of time spent traveling, calculated using the average hourly wage across the NYC[7]. The average travel time μ_T is multiplied by VOT to estimate the opportunity cost.
- Reliability Cost (VOR): To account for variability in travel conditions, we incorporate the VOR [153], the monetary equivalent of additional uncertainty faced by travelers. This includes time variability (σ_T) and distance variability (σ_D), which may arise from traffic congestion, weather disruptions, or road detours. The variability in distance is converted into time units by dividing by the average speed (μ_v) to maintain dimensional consistency.

The GCT for ground transportation is therefore defined as:

$$GCT_{Taxi} = \mu_c + VOT * \mu_T + VOR * \sigma_T + VOR * (\sigma_D/\mu_v) \tag{4.8}$$

[7]FRED: https://fred.stlouisfed.org/series/SMU36935610500000003. Last accessed on [September 30$^{\text{th}}$, 2025]

For UAM services, the cost structure is simpler, given the standardized and predictable nature of air travel operations. The GCT for UAM is defined as:

$$GCT_{UAM} = C_m * D + VOT * (D/S) \tag{4.9}$$

where:

C_m = cost per mile for UAM (estimated using Uber Elevate white paper projections),

D = orthodromic (great-circle) distance between origin and destination,

S = average cruising speed of eVTOL aircraft,

VOT = value of time for the traveler.

This dual-mode GCT formulation allows us to compare taxi and UAM options for the same origin-destination pairs, facilitating the prediction of potential mode-switching behavior under varying cost, time, and reliability scenarios.

In this study, we adopt a cruise speed range of 125-175 mph and a cost-per-passenger-mile range of USD \$5-\$15 because these values represent the most evidence-grounded estimates for near-term airport shuttle AAM operations. Multiple authoritative analyses, including NASA's Urban Air Mobility Market Study [155], Hader's 2024 unit–economics model [156], and the Steer AAM ridership and cost forecast [157], converge on this cost band when realistic assumptions are made regarding pilot operations, battery depreciation, landing fees, and load factors. Likewise, published performance projections for airport-shuttle class eVTOL aircraft consistently place cruise speeds in the 125–175 mph range. The NASA UAM Market

Study, which used the Uber Elevate reference design as its baseline vehicle, assumes a nominal cruise speed in the range of 125-175 mph for short-haul airport access missions [158]. Furthermore, industry-reviewed performance assessments confirm that next-generation ducted-fan aircraft such as the Lilium Jet target maximum cruise speeds of 155 mph [159]. We divide the UAM development into three phases based on the following assumptions of cost and cruising speed.

- Early Phase: Cost is assumed to be $15/mile and speed to be 125 mph
- Mid Phase: Cost is assumed to be $10/mile and speed to be 150 mph
- Mature Phase: Cost is assumed to be $5/mile and speed to be 175 mph

Mode of Choice

While the GCT metric is well-suited for deterministic decision frameworks where travelers are assumed to choose the mode consistently with the lowest perceived cost, it falls short in capturing the inherent variability and uncertainty present in real-world decision-making processes. Deterministic models assume perfect rationality, uniform preferences, and complete information, which may oversimplify the behavioral complexities of travel choices.

To address these limitations, we adopt a probabilistic choice modeling approach that accounts for unobserved heterogeneity in individual preferences, perception errors, and contextual influences that are not captured by measurable cost components alone. In this framework, the utility of each transportation alternative is modeled as the sum of a systematic component, represented by GCT, and a random error term that captures unobserved factors:

$$U_{\text{Taxi}} = GCT_{\text{Taxi}} + \epsilon;$$
$$U_{\text{UAM}} = GCT_{\text{UAM}} + \epsilon \tag{4.10}$$

Here, ϵ denotes the random error component, assumed to be IID across alternatives. A common and analytically convenient assumption is that ϵ follows a Gumbel distribution, which leads to the formulation of the Multinomial Logit (MNL) model [147].

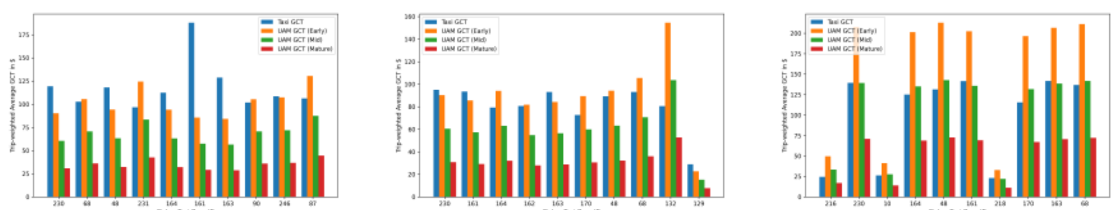
Under this assumption, the probability of selecting UAM over traditional ground transportation is given by:

$$P_{\text{UAM}} = \frac{1}{1 + e^{(U_{\text{Taxi}} - U_{\text{UAM}})}} = \frac{1}{1 + e^{(GCT_{\text{Taxi}} - GCT_{\text{UAM}})}} \tag{4.11}$$

This formulation allows us to probabilistically model traveler behavior by incorporating the influence of observed trip costs and unobserved factors that may affect mode choice. By doing so, discrete choice models provide a more behaviorally realistic framework for forecasting mode-switching behavior, especially in the context of emerging technologies like UAM, where uncertainty and user perception play a critical role.

4.2.4 Results

Figure Figure 4.14 reports the trip-weighted average GCT for the top ten pickup taxi zones serving all three major NYC airports. The corresponding breakdown for EWR is shown in Figure 4.14a, where all top-ten contributing zones originate from Manhattan. Several centrally located zones, specifically 161, 163, 164, 230, and 48 experience severe congestion, resulting in UAM achieving a lower GCT than taxis even during its early operational phase. For LGA, illustrated in Figure 4.14b, eight of the top ten zones are located in Manhattan, while zones 132 and 129 fall within Queens. Central Manhattan zones again exhibit lower UAM GCT beginning in the early phase. Among the two Queens zones, 132 (JFK Airport) only demonstrates a lower UAM GCT once the system reaches its mature phase, whereas zone 129 shows UAM benefits starting as early as the initial phase. Figure 4.14c presents the detailed results for JFK Airport, where three of the contributing zones lie in Queens and the remainder in Manhattan. Here, the dominant pattern indicates that UAM's GCT becomes consistently lower than that of taxis primarily in the mature phase.



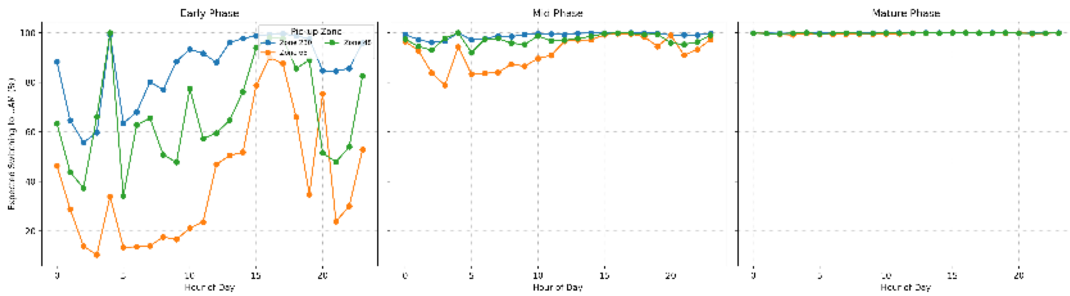
(a) EWR (b) LGA (c) JFK

Figure 4.14: GCT of Top Ten Pick Up Taxi Zones by Trip Volume for Airports

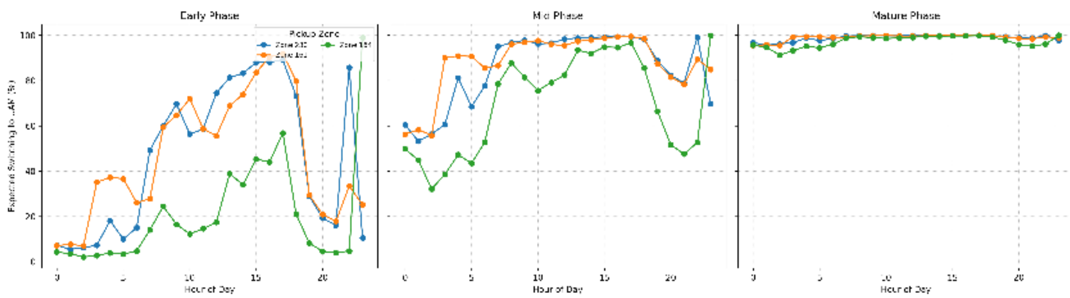
Figure 4.15 presents the hourly switching rates across different UAM development phases for the top three pickup taxi zones serving NYC's three major airports. The corresponding results for EWR are shown in Figure 4.15a, where all three zones originate from Manhattan. In the early phase, only trips occurring during peak hours exhibit notable switching behavior; however, as UAM transitions into more advanced phases, the proportion of trips shifting to UAM increases substantially, approaching nearly 100% in the mature phase. Figure 4.15b reports the patterns for LGA Airport. Similar to EWR, the top three contributing zones are located in Manhattan, and the temporal switching trends mirror those observed earlier: elevated switching during busy hours in the early phase, followed by progressively higher adoption rates as UAM technology matures. For JFK Airport, depicted in Figure 4.15c, switching probabilities remain below 20% for most hours of the day during the early phase. Nonetheless, these values rise sharply with each successive phase, illustrating rapid improvements in UAM competitiveness over time.

Figure 4.16 presents the trip-weighted average GCT across NYC boroughs. The borough-level breakdown for EWR is shown in Figure 4.16a. Except for Staten Island and Brooklyn, all boroughs exhibit lower UAM GCT beginning in the early phase. For these two boroughs, the UAM GCT progressively declines as the technology matures. For LGA (Figure 4.16b) and JFK (Figure 4.16c), the patterns are similar: UAM initially shows higher GCT during the early phase but demonstrates a steady reduction with each subsequent phase. As maturity increases, UAM ultimately achieves lower GCT values than taxis, highlighting its growing competitiveness.

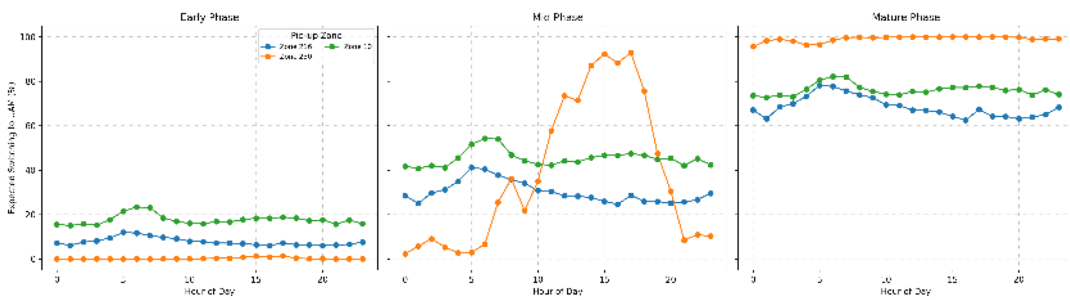
Figure 4.17 illustrates the hourly switching rates across UAM development phases for the three major NYC boroughs. The corresponding analysis for EWR is presented in Figure 4.17a. For Manhattan and Brooklyn, switching rates increase steadily with UAM maturity, and even in the early phase, peak-hour trips exhibit



(a) Newark Liberty International Airport



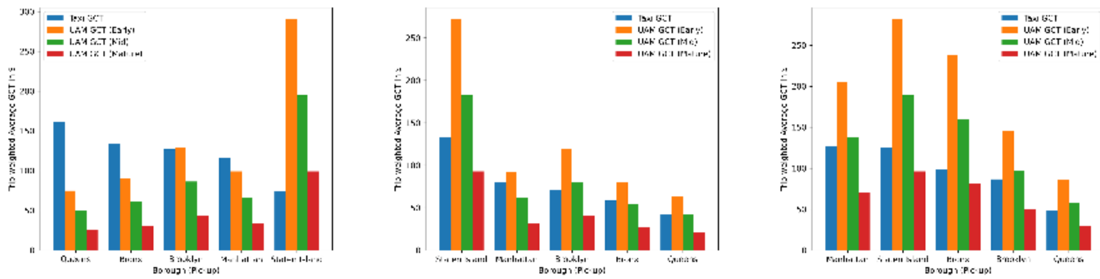
(b) LaGuardia Airport



(c) John F. Kennedy International Airport

Figure 4.15: Hourly Switching Probability of Trips From Top Three Pick Up Taxi Zones

noticeably higher switching probabilities. In Queens, elevated switching is already evident during the early phase. Figure 4.17b provides the results for LGA Airport, showing consistent patterns across all three boroughs: switching intensifies with each phase and approaches nearly 100% during the mature stage, with busy-hour



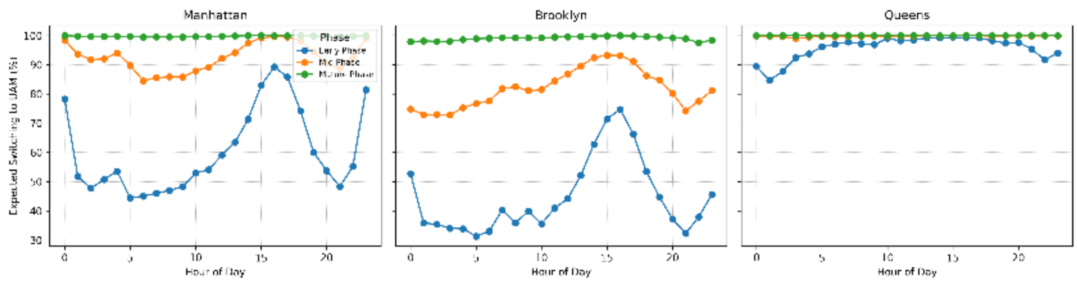
(a) EWR (b) LGA (c) JFK

Figure 4.16: Average GCT of Trips from Borough to each airport

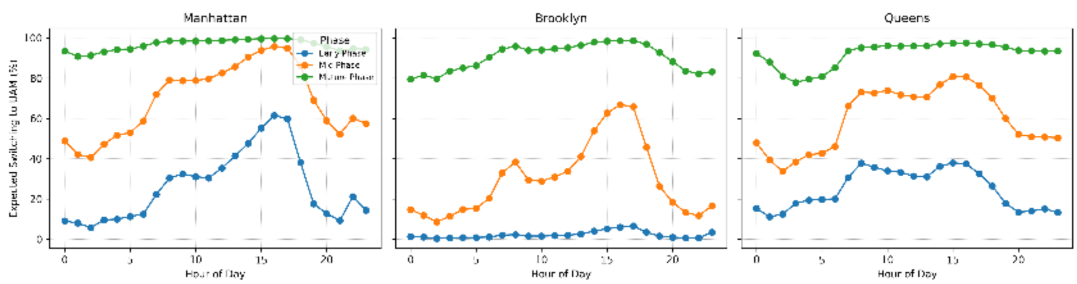
trips displaying the highest early-phase adoption. A similar trend is observed for JFK Airport in Figure 4.17c, where all three boroughs follow the same progression seen in the LGA results: modest switching in the early phase, pronounced increases in the mid phase, and near-complete switching by the mature phase.

4.2.5 Conclusion

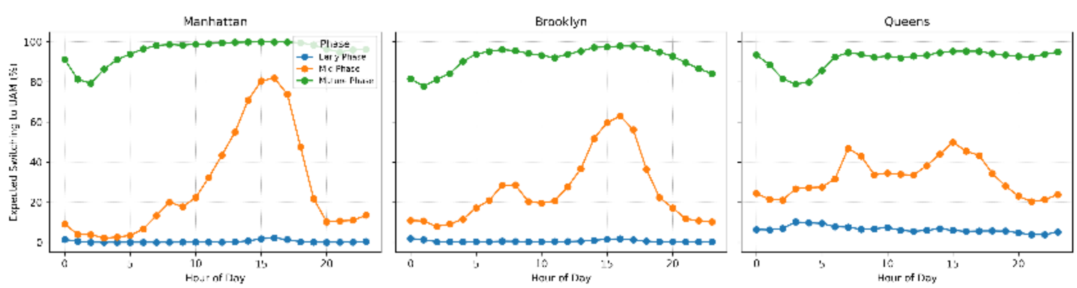
This work presents a data-driven framework to estimate UAM demand for airport access in New York City using 2023 TLC trip records, socio-economic indicators, and geospatial taxi-zone features. By incorporating monetary cost, value of time, and value of reliability into the GCT, the model provides a realistic comparison between taxi and UAM services across early, mid, and mature operational phases. Results show strong spatial and temporal differentiation: central Manhattan exhibits UAM competitiveness even in early phases, while Queens and Brooklyn reach favorable GCT thresholds as technology matures. Hourly switching analyses further reveal that reliability-sensitive peak periods drive the highest adoption rates. These



(a) Newark Liberty International Airport



(b) LaGuardia Airport



(c) John F. Kennedy International Airport

Figure 4.17: Hourly Switching Probability of Trips from Borough to Airports

findings demonstrate that UAM becomes increasingly advantageous under both congestion and technological advancement. The proposed framework offers a scalable foundation for future work in vertiport siting, pricing strategies, and multimodal integration to support UAM deployment in major metropolitan regions.

4.3 Phase I Contributions, Significance, and Impact

Phase I converts the AAM feasibility into testable, numerically grounded adoption conditions using a GCT perspective that is consistent across a regional (Tennessee) and a dense urban (NYC airport-access) regime. The key technical output is not another descriptive demand map; it is an empirically supported statement of when AAM becomes behaviorally competitive. In Tennessee, the analysis identifies two sharp conditions associated with mode switching: (i) AAM is favored primarily beyond an intercity distance threshold of approximately 250 miles, and (ii) adoption is concentrated in trips where the air segment dominates the door-to-door burden, empirically observed when the air-transport component exceeds roughly 70% of total GCT. In NYC, the framework exposes equally consequential heterogeneity: central Manhattan airport corridors exhibit UAM competitiveness earlier than outer-borough corridors, and hourly switching concentrates during peak, reliability-stressed periods, with switching rates rising toward near-complete adoption in mature-phase assumptions. These quantitative thresholds and phase-wise adoption patterns are the core scientific deliverables of Phase I because they translate technology and network assumptions into falsifiable behavioral predictions.

Equally important, Phase I is intentionally critical about what does not drive adoption. Although the fatality-rate disparity between ground and air travel is orders of magnitude, the monetized risk term is shown to be negligible relative to time and fare components in the GCT budget. It implies that early AAM markets will not be unlocked by marginal improvements in safety messaging alone; they will be unlocked by time savings under congestion and, in urban settings, by reliability advantages that reduce variability penalties. The practical impact is therefore direct and restrictive: Phase I supports deployment decisions that prioritize (i) longer-distance regional ODs where ground travel is structurally inefficient, and (ii) congested, high-variability urban airport-access corridors where reliability-sensitive travelers face the greatest generalized-cost burden.

Chapter 5

Data-Driven Trip Demand Modeling

5.1 Improving Air Mobility for Pre-Disaster Planning with Neural Network Accelerated Genetic Algorithm

5.1.1 Introduction

Emergency situations are an unavoidable phenomenon and their impact on the aviation cannot be neglected. Yearly, many people move from one place to another due to the impact of fatal emergency caused by natural disasters such as hurricanes [160, 161]. Typically, in anticipation of a natural disaster, there is a significant surge in population movement towards safer areas. This leads to a marked increase in traffic across all modes of transportation, including airways, commencing approximately one week prior to the projected date of the disaster's impact. As the demand for air travel and daily commuting intensifies, the availability of aircraft becomes increasingly limited. This situation arises due to the heightened need for transportation resources during these critical times. There is an essential requirement for integrating a meticulously calibrated and validated traffic incident response module into the process of modeling and simulating evacuation scenarios [162], focusing on maintaining the normal operation routine of the evacuation airport and airspace while still increasing the outgoing capability for passengers.

An effective air mobility evacuation plan is distinguished by its capacity to not only maintain the regular flow of air traffic, but also smoothly handle the increased demand for outbound flights [163]. Nevertheless, previous research that has devised evacuation plans frequently relies on utilizing the full capacity of an airport, sometimes leading to disruptions in the ongoing air mobility operations and causing panic among the people. In many instances, there is an advance anticipation of emergency situations, providing a substantial window of opportunity to develop thorough evacuation strategies prior to the occurrence of the actual emergency, which has not been utilized in the previous works.

This study focuses on the efficient evacuation without disrupting the regular airport schedule. To achieve this, we make use of the non-critical capacities of the chosen airport, which are typically allocated for military and General Aviation (GAV) operations. Through a temporary reallocation of management resources from these less critical functions, we facilitate the coexistence of evacuation flights alongside standard air traffic. The primary contributions of this study encompass:

- We propose a novel pre-disaster scheduling framework that optimize the outbound capacity of an airport affected by the ongoing emergency situation, while ensuring normal airspace operations.
- We explore the possibility of integrating the GA with NN to reduce the required number of iterations and size of population pool towards optimal solution.
- We investigate the generalization ability of the NN to airports on which it was

not originally trained for aiding the GA.

- We evaluate our solution extensive with real flight operation data.

5.1.2 Related Work

Machine learning algorithms, such as deep learning and reinforcement learning, are being increasingly explored and applied in the context of air mobility for emergency evacuation situations. These advanced computational techniques offer the potential to optimize and enhance the efficiency of air transportation during critical evacuation scenarios.

In [164], a method to predict the time mean speed of freeways during hurricane evacuation using LSTM is presented. In [165] a reinforcement learning based approach is proposed for emergency resource allocation in the air transportation system, specifically for hurricane evacuation. They formulated the flight dispatch as an online maximum weight matching problem, aiming to add more flights for evacuation while minimizing airspace complexity and air traffic controller workload.

A machine learning enabled Adaptive Air Traffic Recommendation System for Disaster Evacuation is proposed in [166], which aims to optimize the use of available resources to transport people from evacuated areas to safe places during extreme weather conditions. The system was composed of an offline learning component and an online planning component, and balances the trade-off between airspace complexity and evacuation efficiency. To tackle the uncertainty in the air route network, a machine learning model was developed to predict the delay situation using real-time airport and weather information.

Another research work in [167] utilized a spatial-temporal graph data mining approach for predicting air mobility. The proposed approach formulates the air transportation network as a graph structure and constructed a graph data set from airline on-time performance data. Spatial-temporal graph NNs were then applied to predict three measurements related to air mobility: number, average delay, and average taxiing time of departure and arrival flights at various airports in the United States.Several other works have delved into the utilization of machine learning models regarding historical flight data, automatic-dependent surveillance-broadcast (ADS-B) data, and meteorological data. These endeavors aimed to forecast micro-level phenomena, like flight punctuality [168–170], and macro-level dynamics encompassing regional airspace and airport aspects, such as flight delays and traffic flow [171–173].

GA has been used in few of the researches focused on the aviation scheduling. In [174], GA was used in flight scheduling in the simulation environment, focusing on optimizing flight timings, gate assignments, and crew schedules to enhance operational efficiency and reduce costs. Another study [175] used the GA to optimize the routing of cargo flights, taking into account factors such as fuel consumption, flight times, and cargo capacity.

The existing research focuses on harnessing machine learning algorithms to enhance evacuation plans and resource allocation during emergencies. Our research more specifically exploits the characteristics of approaching natural disaster scenarios, such as hurricanes, in which provide a valuable evacuation and planning window exists before the impact. During this lead-up period, we proactively optimize air traffic by scheduling additional evacuation flights in advance. This scheduling is facilitated by tapping into the non-critical aviation capabilities of airports, ensuring that a predetermined number of flights are scheduled without disrupting regular air traffic. Consequently, when the actual emergency occurs, there is no rush for the remaining evacuations. Our innovative approach not only maximizes the outbound capacity of affected airports but also places strong emphasis on safeguarding uninterrupted airspace operations.

5.1.3 Methodology

Problem Formulation

We performed a comprehensive analysis of aircraft capabilities at nine major airports in Florida. This analysis encompassed an examination of the operational records of various aircraft categories, including air carrier, air taxi, GAV, and military aircraft. In this context, an air carrier refers to an aircraft with a seating capacity exceeding 60 seats, while an air taxi aircraft can accommodate a maximum of 60 seats. GAV covers all civilian aircraft movements involving takeoffs and landings, excluding those categorized as air carrier or air taxi. Military aircraft activities, encompasses military takeoffs and landings as provided by FAA and the Federal Test Center (FTC).[1].

[1]FAA Operations Network (OPSNET): https://aspm.faa.gov/aspmhelp/index/OPSNET_Reports__Definitions_of_Variables.html. Last accessed on [July 29$^{\text{th}}$ 2024]

For increasing airport capability before the day-of-impact, we employ the capabilities of General Aviation and Military Operations to minimize the impact on regular Air Carrier and Air Taxi traffic. We want to minimize the potential delay of these newly added flight while keep them favorable to passengers. To achieve this objective, we introduced two metrics: the mean of combined non-commercial capability denoted as c and its standard deviation represented by s. c signifies the average value of the number of operations (landing and takeoff) of GAV and military aircraft at the airports, calculated from historical data. This metric serves as a reference for evaluating the effectiveness of airport capabilities during emergency scenarios. For each destination airport, the two metrics at the time-of-arrival gauge its potential capability to accept incoming flights.

Mathematically, our objective is to devise an hourly evacuation flight schedule that maximizes Σc and simultaneously minimizes Σs across all added flights. And thus optimizing the use of GAV and military aircraft capabilities while ensuring efficient and reliable evacuation procedures.

The complete research framework of our project is presented in Figure 5.1, where our primary focus was the utilization of GA to formulate an evacuation plan. We endeavored to enhance the efficiency of this process through the incorporation of NN.

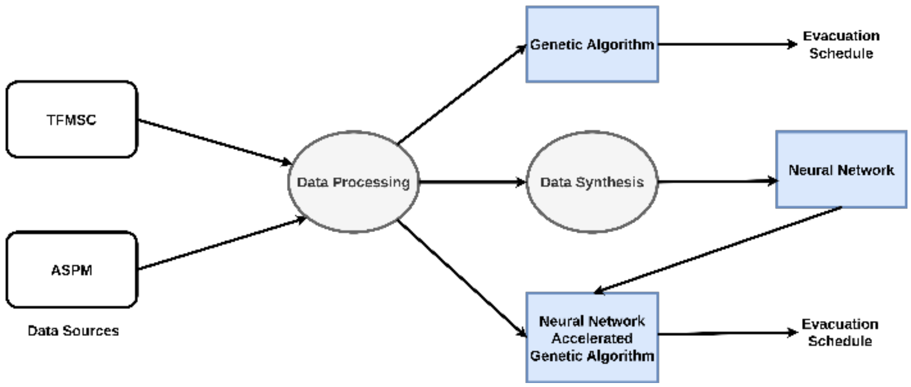


Figure 5.1: Research Process

Data Processing

Our dataset is gathered from the FAA data repository for the initial two months of 2023. The data was sourced from multiple datasets to comprehensively address our research objectives, which encompass the following:

- Traffic Flow Management System Counts (TFMSC) [176]: This dataset aids in assessing the combined capabilities of the airports which are essential for gauging the potential of GAV and military operations during evacuation scenarios.

- Aviation System Performance Metrics (ASPM) [140]: The ASPM dataset is accessible through an online access system provided by the FAA and delivers comprehensive data regarding flights to and from the ASPM airports, as well as all flights operated by ASPM carriers. We can use its data for city pair analysis, determining flight duration and retrieving the top ten destinations airports.

We structured the TFMSC dataset on an hourly basis, and for each hourly time slot, we calculated two significant statistical metrics: the mean of combined capability c and its corresponding standard deviation s. We combined data from 9 major Florida airports and their corresponding top ten destination outside Florida as in Figure 5.2.

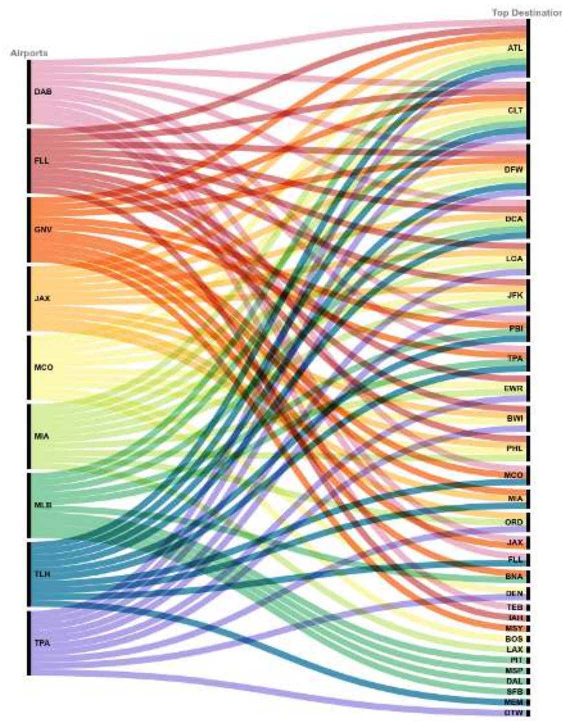


Figure 5.2: Top ten destination airports from the nine major airports in Florida

Genetic Algorithm

The GA operates by identifying optimal chromosomes from a population pool, employing the principles of crossover and mutation over multiple generations. In the context of our specific problem, a chromosome is symbolized as a list containing 10 elements, with each element assigned a value of either 1 or 0. These 10 elements correspond to the decision of whether to select or reject flights to the top ten destination airports from the evacuating airport. The effectiveness of a chromosome is evaluated through a fitness function. This fitness function is formulated using the equation specified below:

$$FitnessScore = 0.5 * p + 0.2 * c - 0.3 * s - penalty \tag{5.1}$$

where

- p is the popularity value of the destination airport based on the number of flights from evacuating airport
- c is the mean of the combined capability
- s is the standard deviation of the combined capability
- *penalty* equals to 1 when choosing more number of flights in destination airports beyond the capability of evacuating airport

To enhance the effectiveness of our GA, several strategies were incorporated to optimize the evacuation strategy selection process. These strategies were fine-tuned to prioritize certain factors and balance trade-offs during decision-making.

- *Positive Influence of Popularity and Capability*: In the pursuit of creating more effective evacuation strategies, the algorithm was configured to place a positive emphasis on p and c. These incentives the algorithm to prioritize airports with higher popularity and greater capabilities in order to maximize the utilization of well-equipped and frequently used airports.

- *Minimization of Delay Expectations*: To mitigate potential delays arising from disparities in the c across different hours of the day, s was introduced with a negative weight which prompts the algorithm to favor airports with lower standard deviation values, thus reducing the variability in evacuation efficiency.

- *Penalties for Over-complicated Planning*: In order to avoid an unrealistic scenario where the algorithm selects too many airports, a penalty mechanism was introduced which comes into play when the selection of airports surpasses the combined capability of the evacuating airport. By penalizing such instances, the algorithm is encouraged to strike a balance between maximizing the fitness score and adhering to practical constraints.

Data Synthesis

For the purpose of training NN, an extra step involving data synthesis was introduced. In this process, the airport for which the evacuation strategy was under development was deliberately omitted from the dataset. This was done to ensure that the model did not have access to the testing data while being trained. In our case, we removed data of DAB airport to synthesize the training data for NN. Data from all other eight airports was amalgamated, encompassing attributes such as the mean combined capability (c), and the standard deviation (s) of c along with the popularity (p) of the top ten destination airport and their corresponding c and s. From these attributes, the best possible combination of the destination airports were determined and added to complete the dataset.

Neural Network Predictor for Optimal Solution

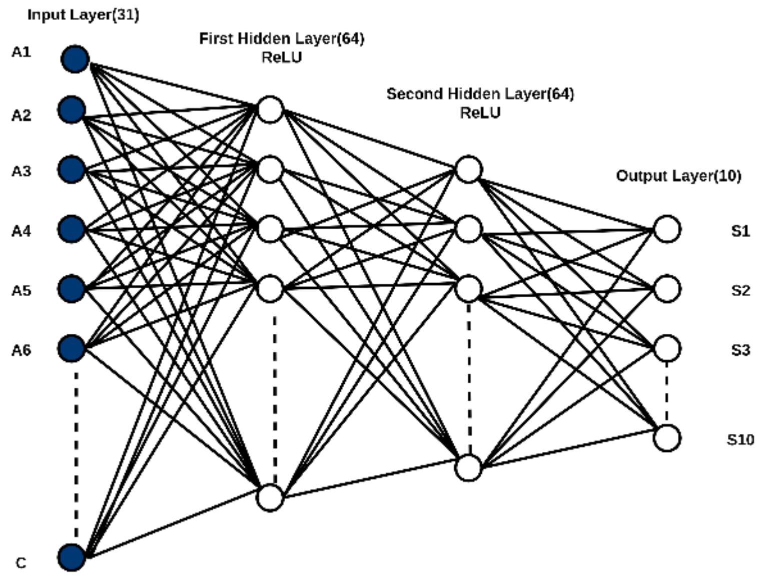


Figure 5.3: Neural Network Architecture

A simple NN model consisting of two hidden layers, as depicted in Figure 5.3, was deployed to enhance the efficiency of GA. This model underwent training using a synthetic dataset generated by Algorithm 2. The NN model takes in 31 input variables, marked A1 to A30, that capture the popularity, mean capability, and the standard deviation in mean capability of the top ten destination airports for evacuation. In addition to these, there is an additional input, designated as C, which specifies the mean capability of the evacuating airport. The model's output is a 10-bit representation identifying the chosen destination airports for evacuation. Through training with the synthetic dataset, the model was able to learn patterns and connections among various attributes, thereby gaining the ability to accurately predict which destination airports should be selected for evacuation at any given hour of the day.

Integration of Neural Network to Genetic Algorithm

In this phase, we integrated the GA given in Algorithm 2 with the trained NN model to facilitate a quicker convergence of the algorithm. We aim to harness the predictive power of the NN to initialize the population for the GA. In line 12 of Algorithm 2 instead of replacing the entire old population with the new population obtained by GA, we introduced NN for also contributing to the population pool. This process of generating the population by NN and adding to the population tool involved two approaches:

Approach 1: Population generated by the NN are directly added to the pool by replacing the random population generated by the GA.

Approach 2: In this approach, before inserting the population generated by NN, the population is sorted in descending order on the basis of fitness score. The lower order of population are replaced by the population generated by NN.

5.1.4 Evaluation and Discussion

This section focuses in evaluating the performance, accuracy, and efficiency of the developed methodologies.

Genetic Algorithm

We used only GA to find the optimal evacuation flight schedules originating from DAB airport. The algorithm was initiated with a population size of 15 and executed for 5 generations. The population size and number of generations were systematically increased by factors of two and five to explore their impact on the algorithm's performance. During this iterative process, it was observed that the algorithm exhibited a substantial convergence trend when the population size was set to 75 and the number of generations was increased to 25, as in Figure 5.4. The observed convergence trend suggests that a population size of 75 with 25 generations struck a balance between exploration and exploitation, leading to optimal results in terms of identifying the most effective evacuation flight schedules from the selected airport.

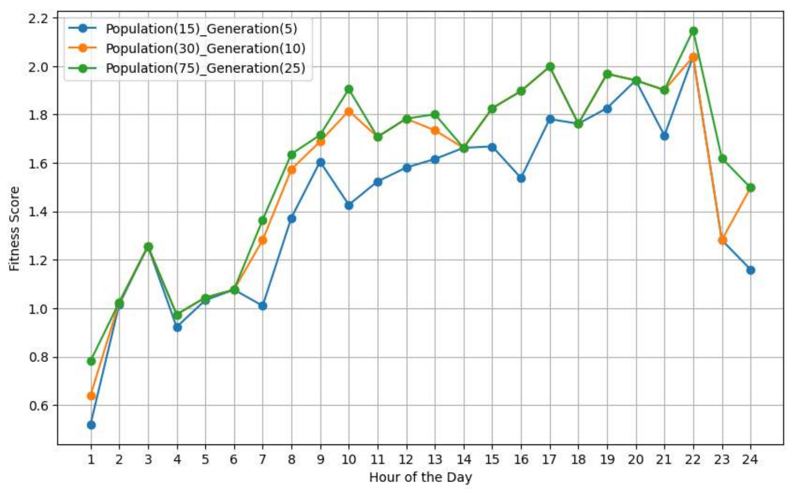


Figure 5.4: Fitness Score for various combination of population size and number of generation for Genetic Algorithm during different hour of the day.

Neural Network

The NN was trained using the synthesized dataset outlined in Algorithm 2. During training, the NN was exposed to varying numbers of epochs, namely, 5, 15, and 25. And it was observed that convergence commenced at approximately

25 epochs. Prior to convergence, there was a notable performance fluctuation, as depicted in Figure 5.5.

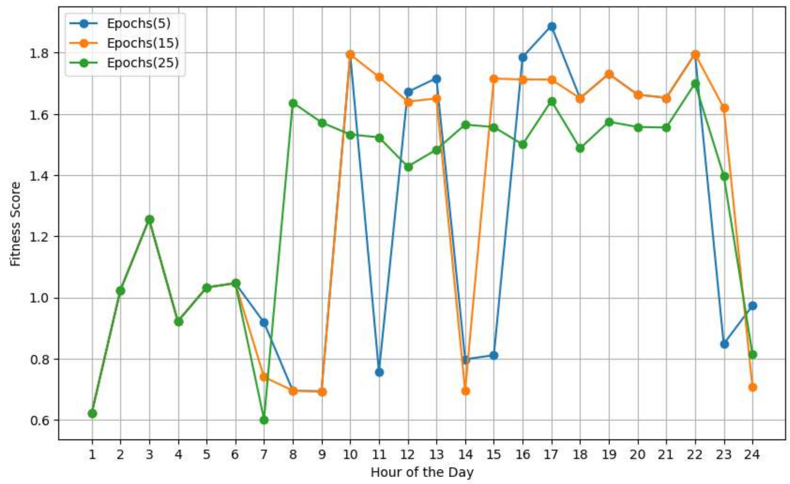


Figure 5.5: Fitness Score for various neural networks trained under different number of epochs

Combination of Genetic Algorithm and Neural Network

To demonstrate the effectiveness of the Neural Network-accelerated Genetic algorithm. We select sub-optimal scenarios for each method individually and merge them to find an optimal scenario. Specifically, the GA with a population size of 15 and 5 generations and the NN trained for only 5 epochs respectively. The combined approach, referred to as the "NN-accelerated GA," leveraged the predictive capabilities of the NN to enhance the parent population generation for the GA. The strategy entailed using the NN to produce parent candidates, which were then integrated into the parent pool. The GA was then employed to refine the parent pool further. Parents were added based on the fitness score, considering the NN-generated parents alongside those generated by the GA itself.

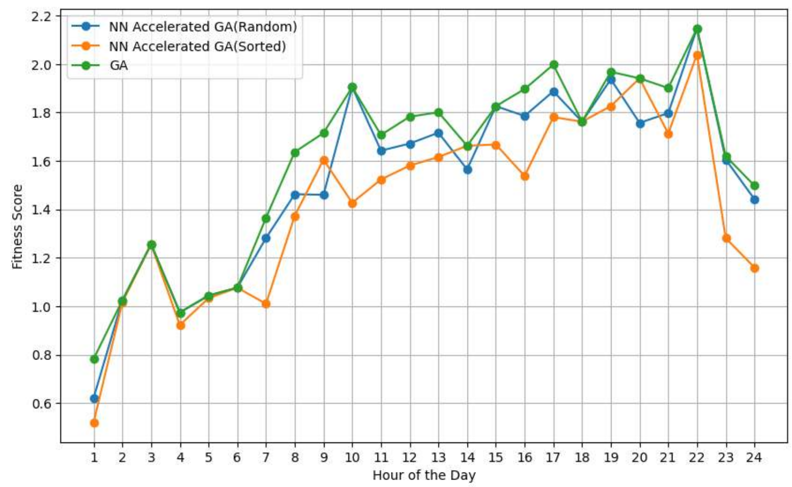


Figure 5.6: Fitness Score of GA and two different NN accelerated GA

We compared two methods: random addition of NN-generated parents and the selective removal of the least-fit population. In the latter approach, we ranked the entire population pool in descending order based on their fitness scores. The least-fit populations were then replaced by the parents generated by the NN. The results from this experiment, as depicted in Figure 5.6, revealed that the strategy of random addition of parents from the NN yields better outcomes than the approach of selectively removing the least-fit populations.

As depicted by Figure 5.7, we found that the prediction of the number of flights by GA iterated for 25 generations with population size of 75 and NN accelerated GA with the strategy of random removal , is almost identical except in the midnight scenario. The reason might be due to the fact the number of flights in the DAB airport in that time duration is very random, sometimes they have few flights but most of the time number of flights during those time is almost none. Another

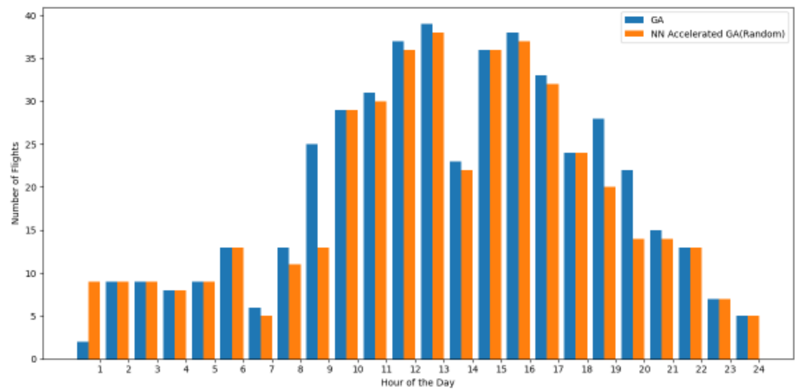


Figure 5.7: Number of evacuation flights scheduled by the GA (having population size of 75, iterated for 25 generations) and NN accelerated GA (NN trained for 5 epochs and randomly replacing the population in population pool of GA having population size of 15 and iterated for 5 generations).

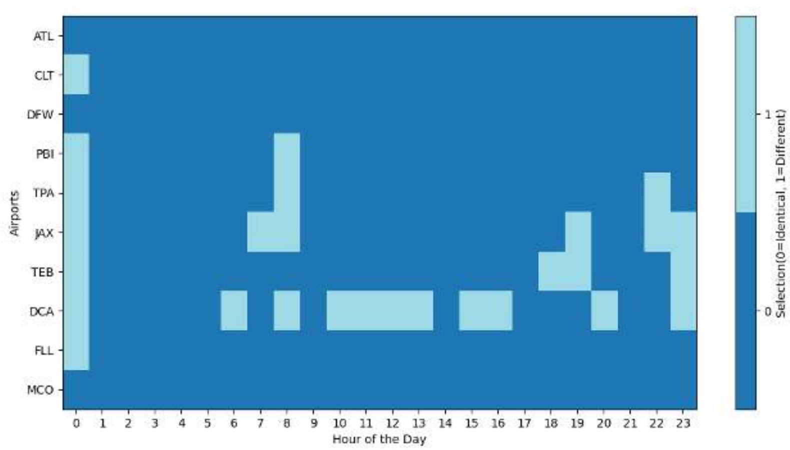


Figure 5.8: Comparison of selection of the airports for evacuation by GA (having population size of 75 and iterated for 25 generations) and NN accelerated GA (NN trained for 5 epochs and randomly replacing the population in population pool of the GA having population size of 15 and iterated for 5 generations)

Figure 5.8 provided detail about the selection of top ten destination airports by same two models. As shown in the figure, we found that most of the time airport selection by both of them are identical.

5.1.5 Conclusion

In this research, we delved into the utilization of GA to develop a novel pre-disaster evacuation planning framework for advanced air mobility. We leverage the non-commercial flight capability of impacted airports to ensure that evacuation plans minimally affected routine airspace operation. We proposed a neural network accelerated genetic algorithm to derive our solution with smaller computational overhead. We found that GA exhibited slower convergence when operated independently with higher population pool and generations, its performance significantly improved when assisted with a NN model trained for a mere 5 epochs. This integration yielded comparable results in terms of fitness function, flight numbers, and airport selection. This intriguing finding underscores the NN's ability to expedite GA's convergence, even when trained on data from different airports, showcasing its generalization capabilities.

5.2 A Data-Driven Approach to Enhancing Gravity Models for Trip Demand Prediction

5.2.1 Introduction

Transportation planning plays a crucial role in ensuring efficient movement of people and goods across various modes of transport. Accurate predictions of trips between geographic zones are foundational to this process, supporting decisions related to infrastructure development, public transit scheduling, and urban growth management [177]. One of the most widely used models for predicting trip distributions is the gravity model, which, despite its simplicity, has been applied across different domains for several decades [178]. With the increasing complexity of trip patterns and the availability of detailed datasets, the need for sophisticated prediction models has become critical [179].

While the gravity model [180] is valuable for its ease of use and interpretability, it has notable limitations, particularly in its ability to account for non-linear relationships and the influence of various socio-economic factors. With the rise of data-driven approaches, machine learning has emerged as a powerful tool to enhance the predictive capabilities of traditional models. Recent advances in data availability, including high-resolution geographic, economic, and travel behavior datasets, offer new opportunities to refine these models and improve their performance.

This study addresses the critical need to enhance trip prediction models by proposing a data-driven extension to the traditional gravity model. We incorporate multiple datasets spanning geographical, economic, social, and travel patterns from counties in two states, Tennessee (TN) and New York (NY) into a machine learning enhanced framework. By doing so, we aim to improve the accuracy and flexibility of trip predictions, offering a more robust tool for transportation planners.

The key contributions of this paper are:

- First, we integrate a diverse array of datasets to enhance the traditional gravity model's ability to capture complex, non-linear relationships between variables.
- Second, we apply machine learning techniques to improve the accuracy and scalability of trip demand predictions.
- Third, we validate the enhanced model with real-world data from counties in TN and NY, achieving up to 50% improvement in predictive accuracy over traditional methods.

5.2.2 Related Work

Transportation planning has long relied on predictive models to forecast trip distributions between geographic zones, with the gravity model being one of the most widely used approaches. The gravity model, first adapted from Newton's law of gravitation, estimates the flow of trips between two locations based on their population sizes and the distance between them [181]. The traditional gravity model is expressed as:

$$T_{ij} = \frac{P_i \cdot P_j}{d_{ij}^{\beta}} \tag{5.2}$$

where T_{ij} is the interaction between the locations i and j, P_i and P_j represent the "masses" of the two locations, d_{ij} is the distance between them, and β is the distance decay parameter, which reflects how interaction decreases with increasing distance.

Despite its widespread application in urban planning, public transit allocation, and infrastructure development, the gravity model has inherent limitations, particularly when dealing with the complexities of modern transportation systems [182]. These limitations stem primarily from its inability to capture non-linear relationships and account for various socio-economic factors that influence travel behavior.

Over time, the gravity model has been enhanced with modifications to better reflect real-world complexities. These include adjustments for population and distance effects. For instance, the inclusion of exponents on the population terms $(P_i^\lambda, P_j^\alpha)$ allows for modifications based on factors such as income or infrastructure that influence interaction beyond population size. Similarly, the distance term (d_{ij}^β) can be tailored to reflect varying distance decay effects, such as travel [183]. The generalized modified equation is as follows:

$$T_{ij} = k\frac{P_i^\lambda \cdot P_j^\alpha}{d_{ij}^\beta} \tag{5.3}$$

where k is a scaling constant that adjusts the model for different magnitudes of flow, such as daily or monthly movements.

Another significant expansion to the gravity model involves considering the spatial pattern of origins and destinations, commonly referred to as the spatial structure [184]. Spatial structure encapsulates the arrangement and distribution of locations in space and their influence on interaction patterns. In the expanded model, spatial interaction (T_{ij}) is formulated as a function of three distinct vectors:

$$T_{ij} = f(O_i, D_j, S_{ij}) \tag{5.4}$$

where:

- O_i: A vector of origin attributes, representing the characteristics of the originating location (e.g., population, economic output, or accessibility);
- D_j: A vector of destination attributes, representing the characteristics of the destination location (e.g., attractiveness, size, or infrastructure);
- S_{ij}: A vector of separation attributes, capturing the effects of spatial separation, such as distance, travel costs, and intervening opportunities.

Researchers have attempted to improve the accuracy of the gravity model by incorporating additional variables, such as travel cost, income disparities, and land-use characteristics [185]. Although these modifications improve the model's performance in certain contexts, they often fail to address its rigidity when applied to heterogeneous datasets or complex travel patterns. As transportation systems grow more data-rich, the need for more sophisticated, adaptable models has become evident.

Recent advancements in data availability and machine learning offer new opportunities to overcome the gravity model's limitations. Machine learning techniques, such as random forests, neural networks (NNs), and support vector machines, are particularly suited to handling non-linear relationships and high-dimensional interactions between variables [186]. These methods have demonstrated success in various transportation contexts, improving the predictive accuracy of trip demand models. For instance, Ref. [187] applied machine learning to bus passenger demand forecasting, significantly improving model performance over traditional methods. Similarly, AI-based models have shown promise in predicting ride-hailing demand and traffic congestion [188] [189].

However, while machine learning has been applied to enhance predictive models in transportation, few studies have specifically focused on integrating these techniques with the gravity model. Ref. [190] made strides in this direction by introducing a deep gravity model for mobility flow generation based on geographic data, but comprehensive studies that incorporate diverse, multi-dimensional datasets into gravity models remain limited. Refs. [191] and [192] demonstrated the potential of combining machine learning with detailed geographical and socio-economic data for trip destination prediction. Nonetheless, there remains a need for further exploration of how machine learning can specifically address the traditional gravity model's predictive limitations.

This study contributes to the literature by proposing a machine-learning-enhanced gravity model that integrates a wide range of geographical, economic, social, and travel pattern data. By doing so, it aims to improve the predictive accuracy of trip distributions, providing a more robust tool for transportation planners.

5.2.3 Methodology

The methodology consists of two phases: first, the implementation of the traditional gravity model as a baseline, and second, the development of a machine-learning-enhanced gravity model that accounts for non-linear relationships between variables as depicted in Figure 5.9.

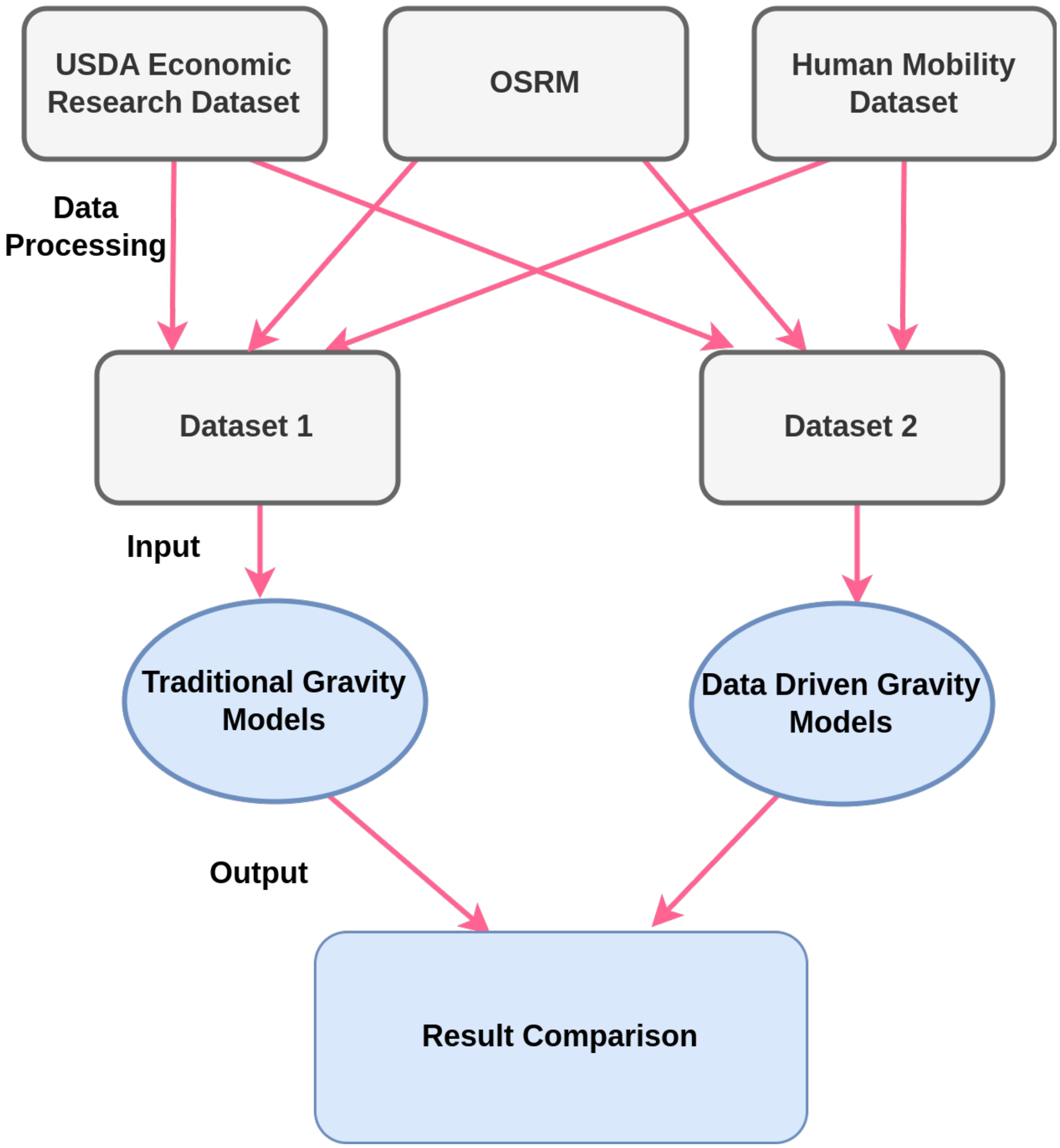


Figure 5.9: Research Process

Table 5.1: Description of Feature Categories

Category (Numbers)	Description
Land Use Counts (7)	F1: Natural, F2: Agricultural, F3: Residential, F4: Commercial, F5: Public, F6: Industrial, and F7: Military purposes.
Points of Interest (8)	F8: Education, F9: Commerce, F10: Public Services, F11: Healthcare, F12: Recreation, F13: Heritage, F14:Transport, and F15: Miscellaneous.
Roads (3)	F16: Highways, F17: Roadways, and F18: Streets.
Terminals (1)	F19: Includes the total count of airports, railway stations, bus stations, etc.
Structures (1)	F20: Total building count within each county.
Economic Features (5)	F21: Unemployment percentage rate, F22: Median Household Income, F23: % of State Median Household Income, F24: Percentage of people in poverty, and F25: Percentage of children (0-17) in poverty.
Education (1)	F26: Includes percentage of population completing college.
Population (1)	F27: Provides population count for each county.

Study Area

We selected two states, TN and NY, as the study area. TN has been chosen due to its diverse geographic and demographic composition, making it an ideal region for studying and modeling trip demand patterns. Similarly, NY has been selected as a complementary area of focus due to its high-density urban environments and extensive transportation networks. Together, TN and NY offer distinct yet complementary perspectives—one rooted in regional and rural contexts and the other in densely populated metropolitan areas—enabling a more comprehensive analysis of trip demand across varying geographical and demographic settings.

At the geographical level, our research focuses on modeling trip demand across counties, which serve as stable administrative subdivisions. Counties provide a consistent framework for data collection and analysis. Although their boundaries generally remain fixed, rare administrative adjustments or annexations can cause changes. However, such adjustments are infrequent, and counties typically retain their boundaries despite population changes, ensuring the continuity of demographic and economic analysis across different time periods. This dual focus on TN and NY allows us to explore mobility solutions in both regional and urban contexts, enriching the scope and applicability of our findings.

Data Collection

The data for this study was collected from various sources to ensure the inclusion of key factors influencing trip distribution.

The multiscale dynamic human mobility flow dataset [193] provides extensive spatiotemporal data on U.S. population movements since January 1, 2019. Compiled from anonymized mobile phone location data sourced by SafeGraph[2], this dataset documents origin-to-destination population flows at the census tract level on daily bases. Its detailed granularity and temporal coverage make it a valuable resource for applications in transportation planning. For this study, the daily dataset from March 15, 2021, to April 15, 2021, was extracted. OSRM [194] was utilized to obtain geographical features for counties and also to find the distance and time of

[2]SafeGraph: https://www.safegraph.com/

trip between those counties. The data related to economy, population and education were sourced from the USDA Economic Research Service[3]. All datasets underwent cleaning, standardization, and were merged using county-level identifiers. Missing values were imputed using median substitution, and numerical variables were scaled to facilitate comparability across features. Ultimately, 27 features were prepared for each county, under eight different categories, as shown in Table 5.1.

We compile the two sets of datasets by merging the mobility dataset with the others.

- Dataset 1 is based on the original gravity model input, which only considers the population and distance of origin and destination counties as the input, along with the time of travel between the two counties.

- Dataset 2 contains the other geographical, economic and social features along with the previous features.

Table 5.2: Comparison of Gravity Models for TN and NY

Model	Metric	TN			NY		
		Traditional	Data-Driven	% Improvement	Traditional	Data-Driven	% Improvement
Neural Networks	MAE	0.1026	0.0622	39.38%	0.0879	0.0320	63.59%
	R^2	0.8274	0.9406	13.68%	0.6444	0.9762	51.48%
	CPC	0.7206	0.8412	16.73%	0.6295	0.9085	44.32%
Random Forest	MAE	0.0420	0.0402	4.29%	0.0255	0.0208	18.43%
	R^2	0.9746	0.9781	0.36%	0.9755	0.9874	1.22%
	CPC	0.9121	0.9169	0.53%	0.9291	0.9456	1.78%
Gradient Boosting	MAE	0.1070	0.0957	10.56%	0.0620	0.0527	15%
	R^2	0.8814	0.9180	4.15%	0.9395	0.9654	2.75%
	CPC	0.7554	0.7894	4.50%	0.8231	0.8631	4.86%

[3]USDA: https://www.ers.usda.gov/data-products/county-level-data-sets

Models Implemented

We have implemented various machine learning model

Random Forest: We implemented a Random Forest model to leverage its capability of handling high-dimensional data and capturing non-linear relationships through ensemble learning. A randomized search cross-validation was employed to tune hyperparameters, optimizing the model's performance. The hyperparameter space included the number of trees, maximum tree depth, minimum samples required to split a node, minimum samples required for a leaf node, and the number of features considered for splitting. The randomized search, performed over 20 iterations with five-fold cross-validation, selected the optimal combination of hyperparameters based on minimizing MAE.

Deep Neural Network: We implemented a deep neural network model for predicting population flow and optimized its performance using Optuna. The model architecture featured five fully connected layers with ReLU activation functions, conditional batch normalization, and dropout regularization for preventing overfitting. To fine-tune the model, Optuna was used to optimize key hyperparameters, including the learning rate, dropout rate, and batch size. The search space explored learning rates between 1e-5 and 1e-3, dropout rates from 0.1 to 0.5, and batch sizes of 16, 32, and 64. The objective was to minimize the validation MAE. The Adaptive Moment Estimation (ADAM) optimizer, with a final tuned learning rate of 0.00097, was paired with L1 loss to handle the regression task. The optimal hyperparameters were a learning rate of 0.00097, a dropout rate of 0.111, and a batch size of 64.

Gradient Boosting: We utilized a Gradient Boosting Regressor (GBR) to model the data, optimizing its performance through randomized hyperparameter tuning. The hyperparameters tuned included the number of estimators (n_estimators), learning rate, maximum tree depth (max_depth), minimum samples required to split a node (min_samples_split), minimum samples per leaf (min_samples_leaf), and subsampling rate (subsample). A randomized search cross-validation (RandomizedSearchCV) was conducted across 10 parameter combinations with two-fold cross-validation to minimize computation time. The best model configuration identified a subsample of 0.9, 500 estimators, a learning rate of 0.05, a maximum depth of 5, with a minimum of 2 samples for splitting and 2 samples per leaf. The optimized model was then trained on the full training dataset, and its performance was evaluated on the test set.

Table 5.3: Top 10 Features for Models in TN and NY

State	**Model**	**Ranked Features (1–5)**	**Ranked Features (6–10)**
TN	Neural Networks	Distance, Time, F27-D, F27-O, F26-D	F4-O, F4-D, F25-O, F17-D, F20-D
	Random Forest	Time, F11-D, F14-O, F26-D, F27-D	F16-D, Distance, F18-O, F5-O, F8-O
	Gradient Boosting	Time, F26-D, F16-D, F27-D, F14-O	F11-D, F17-D, Distance, F8-O, F18-O
NY	Neural Networks	Time, Distance, F12-D, F5-D, F20-O	F5-O, F10-O, F8-D, F10-D, F14-D
	Random Forest	Time, Distance, F22-D, F8-D, F21-D	F26-D, F13-D, F23-D, F8-O, F19-D
	Gradient Boosting	Time, Distance, F26-D, F8-D, F21-D	F20-O, F23-D, F16-O, F16-D, F4-D

5.2.4 Evaluation and Discussion

In this study, we utilized three evaluation metrics to assess the performance of our model: R^2, MAE, and CPC. The mathematical background for each of these metrics is as follows.

R-squared (R^2)

R^2 also known as the coefficient of determination, measures the proportion of variance in the dependent variable that is explained by the independent variables in the model. A R^2 value closer to 1 indicates that the model explains a higher proportion of the variance, implying better fit. Mathematically, it is expressed as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{5.5}$$

where:

- y_i is the actual value,
- $\hat{y}_i$ is the predicted value,
- $\bar{y}$ is the mean of the actual values, and
- n is the number of data points.

Mean Absolute Error (MAE)

MAE is a metric that measures the average magnitude of errors in the model's predictions, without considering their direction. It is given by the formula:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{5.6}$$

where:

- y_i is the actual value,
- $\hat{y}_i$ is the predicted value, and
- n is the number of data points.

Common Part of Commuters (CPC)

CPC, also known as the Sørensen-Dice index, is a metric used to measure the similarity between the generated flows (y_g) and real flows (y_r) in flow generation models. CPC ranges from 0 to 1, where 1 indicates a perfect match between the generated and real flows, and 0 signifies no overlap between them. When the total generated outflow equals the real total outflow, the CPC metric becomes equivalent to the accuracy of the model, measuring the fraction of trips assigned to the correct destination. CPC is computed as:

$$CPC = \frac{2\sum_{i,j}\min(y_g(l_i, l_j), y_r(l_i, l_j))}{\sum_{i,j} y_g(l_i, l_j) + \sum_{i,j} y_r(l_i, l_j)} \tag{5.7}$$

where:

- $y_g(l_i, l_j)$ represents the generated flow from location l_i to location l_j,
- $y_r(l_i, l_j)$ represents the real flow from location l_i to location l_j, and
- The summations are over all possible origin-destination pairs (i, j).

Table 5.2 shows a comparison of gravity models for trip demand prediction across TN and NY, highlighting the significant advantages of data-driven approaches.

NNs demonstrate the most notable improvement, with the data-driven model reducing the MAE by more than half and substantially increasing R^2, showcasing the effectiveness of non-linear models when incorporating more complex, data-driven features. Random Forest exhibits robust performance in both traditional and data-driven approaches, with the data-driven model slightly improving MAE and R^2, emphasizing the consistency of ensemble methods in capturing complex relationships. Gradient Boosting also achieves notable enhancements, with reductions in MAE and increases in R^2, particularly in the data-driven model, suggesting its suitability for predicting trip demand across varying contexts. Overall, the data-driven models consistently outperform traditional methods, with NNs leading the improvements, especially in high-density urban areas like NY.

Table 5.3 presents the top 10 ranked features for the data-driven models in TN and NY for trip demand prediction. SHAP [195], a method to interpret machine learning models by quantifying the contribution of each feature, is used to identify the top 10 impactful features for Neural Network outputs while feature importance analysis is used for Random Forest and Gradient Boosting. In TN, for NNs, Random Forest, and Gradient Boosting, key features include distance, time, population count (F27-O), and education (F26-D). These highlight the importance of geographical and educational indicators in regional contexts. For NY, similar features such as distance, time, and population count remain critical across all models, but additional features like public services (F10-D), transportation facilities (F19-D), and commerce-related factors (F9-D) gain prominence, reflecting the urban environment's complexity.

We then performed trip segmentation analysis by categorizing trips into Short (up to 61.78 miles), Medium (61.79 to 171.44 miles), and Long (above 171.44 miles) based on distance thresholds derived from the dataset's 33rd and 66th percentiles, ensuring balanced trip distribution. The result of the analysis is shown in Figure 5.10. NNs excel in dense urban settings like NY, particularly for Short and Medium Trips, due to their ability to capture non-linear patterns. However, they struggle with Long Trips in TN, where data sparsity poses challenges. Random Forest demonstrates consistent performance across all trip segments and geographies, showcasing its adaptability to diverse data distributions. Gradient Boosting performs well in NY for Medium and Long Trips but falters in TN, reflecting the need for model optimization in regional contexts.

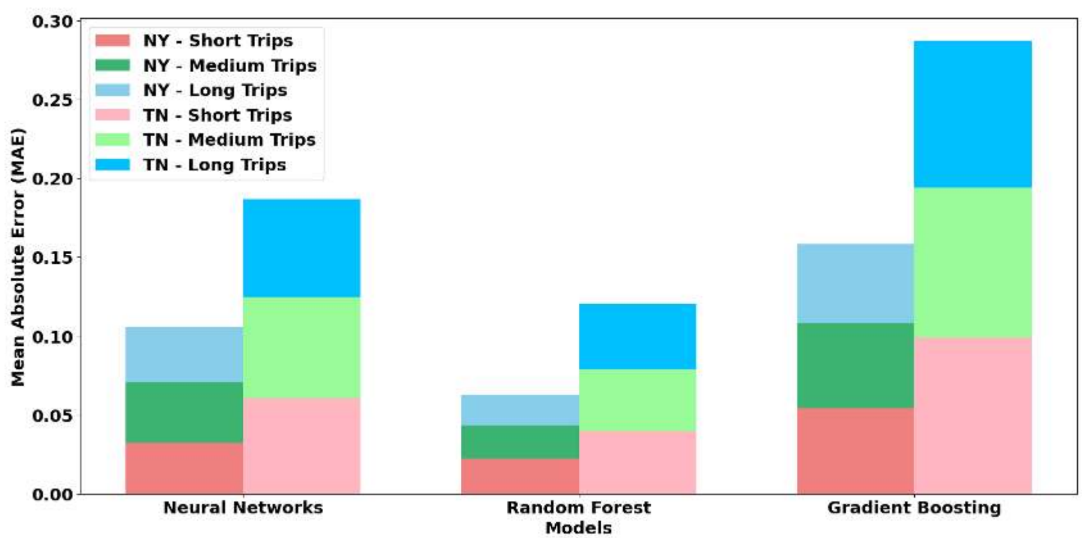


Figure 5.10: MAE Comparison of Models for NY and TN by Trip Distance

Figure 5.11 compares MAE of NNs, Random Forest, and Gradient Boosting models across NY and TN, with distinctions between weekday and weekend travel patterns. NNs show relatively balanced performance between weekday and weekend predictions in both NY and TN, though the errors are noticeably higher in TN for both scenarios, suggesting their limitations in handling sparsity and variability in data from a less dense region. Random Forest consistently demonstrates the lowest MAE among all models, both in NY and TN, across weekdays and weekends. This reflects its robustness in adapting to varying data characteristics, including urban (NY) and rural (TN) environments. However, a slight increase in MAE for TN compared to NY indicates that even Random Forest is not immune to the challenges posed by sparse and heterogeneous datasets. Gradient Boosting, on the other hand, exhibits the highest MAE across all settings for TN, particularly on weekdays, where the error is significantly larger than on weekends. This suggests that the model's sensitivity to sparse and less structured data is amplified during periods of higher variability, such as weekday travel. In contrast, its performance in NY is more competitive, with lower errors across both weekdays and weekends, showcasing its strength in environments with richer and more predictable data patterns.

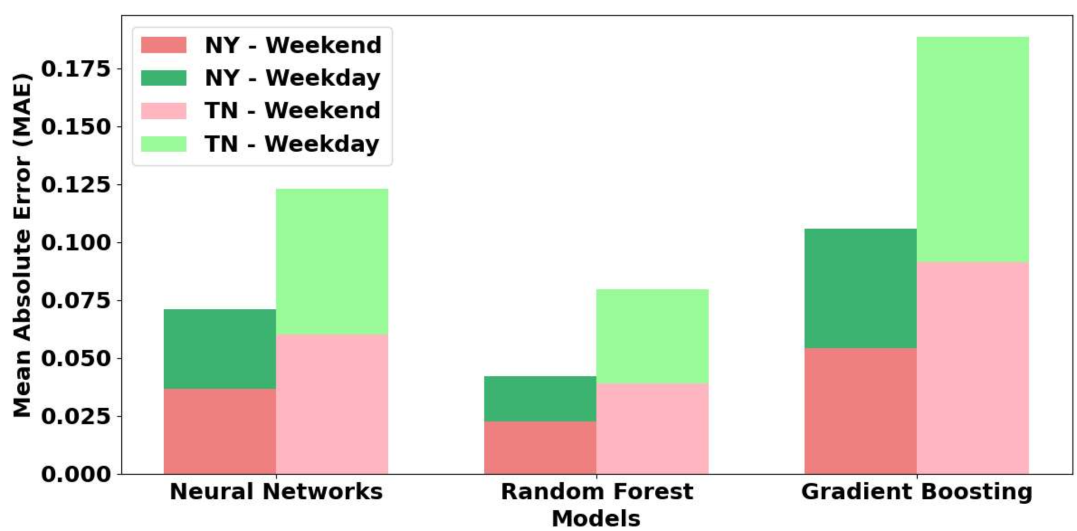


Figure 5.11: MAE Comparison of Models for NY and TN by Days

5.2.5 Conclusion

This study highlights the substantial benefits of integrating machine learning techniques, such as NNs, Random Forests, and Gradient Boosting, into traditional gravity models for trip demand prediction. By leveraging a diverse set of geographical, economic, social, and travel-related features, the data-driven models consistently outperformed traditional approaches, with reductions in MAE ranging from 10% to over 60%, and significant improvements in R^2 and CPC, showcasing enhanced predictive accuracy and reliability. NNs demonstrated the most notable improvements, particularly in high-density urban environments like New York, achieving an R^2 of 0.976 and a CPC increase of over 44%. The analysis of top-ranked features, including distance, time, population, and economic factors, further underscores the adaptability of machine learning models to varying regional and urban contexts. Future work could explore the incorporating real-time data, such as GPS and social media activity, to enhance dynamic predictions. Additionally, integrating environmental factors, such as weather and air quality, could provide a more comprehensive understanding of their impact on trip demand patterns.

5.3 Phase II Contributions, Significance, and Impact

Phase II makes a decisive methodological contribution by demonstrating that data-driven mobility modeling is only meaningful when it simultaneously satisfies operational feasibility and statistical fidelity. Rather than treating evacuation scheduling, trip-demand prediction, and gravity-model enhancement as independent exercises, this phase exposes their shared limitation: classical formulations fail precisely when systems are stressed during emergencies, under congestion, or across heterogeneous regional–urban regimes. Phase II responds by coupling learning-based inference with optimization-aware structure, showing that demand estimation and planning must be co-designed. The contribution is therefore not incremental accuracy improvement but a reframing of how mobility models should be evaluated: success is defined by whether a model can (i) respect real operational constraints and (ii) generalize across spatial and temporal heterogeneity without collapsing under sparsity or non-linearity.

Critically, Phase II substantiates this reframing with quantitative evidence that reveals both strengths and boundaries. The enhanced gravity formulation delivers substantial gains over the traditional model only when rich geographic and socio-economic structure is admitted: neural networks reduce MAE by 39.38% in Tennessee and 63.59% in New York, with corresponding increases in R^2 to 0.9406 and 0.9762, and CPC exceeding 0.90 in dense urban settings. These gains are not uniform; ensemble models exhibit robustness across regimes but plateau in improvement, while neural models excel in dense, data-rich contexts and degrade under sparsity, exposing a fundamental trade-off between expressiveness and stability. In parallel, the NN-accelerated evolutionary scheduler shows that near-equivalent evacuation plans can be achieved with an order-of-magnitude reduction in genetic search effort, yet deviations during low-activity (midnight) periods highlight that learning cannot compensate for inherently stochastic operational regimes. This critical insight elevates Phase II beyond performance reporting: it delineates where data-driven methods are reliable, where they are fragile, and why subsequent modeling phases must incorporate stronger structure and reasoning.

Chapter 6

Neurosymbolic Approaches to Modeling Trip Demand

6.1 Neurosymbolic AI for Travel Demand Prediction: Integrating Decision Tree Rules into Neural Networks

6.1.1 Introduction

Travel demand prediction plays a critical role in transportation planning, infrastructure development, and resource allocation [196]. Accurate forecasting of travel demand between regions, such as counties, enables stakeholders to optimize transportation networks, reduce congestion, and make informed decisions regarding public infrastructure investments. As urbanization accelerates and mobility patterns become increasingly complex, robust and reliable methods for demand prediction are essential for meeting the dynamic needs of commuters while improving the efficiency of transportation systems.

Predicting travel demand between counties presents a significant challenge, as it requires modeling complex relationships between spatial, economic, and mobility factors. Traditional methods, such as statistical and time-series models [197], often struggle to capture the nonlinear and multidimensional interactions inherent in real-world travel data [198]. While these approaches provide simplicity and interpretability, they fail to address the intricate dependencies that drive travel demand.

NNs on the other hand, excel at learning these complex patterns due to their advanced capabilities. However, their "black-box" nature limits interpretability, which is critical in transportation applications where transparency and accountability are essential. With the increasing availability of high-resolution mobility and economic datasets [199, 200], there is a growing demand for advanced methodologies that can effectively uncover and model these hidden patterns while maintaining a balance between accuracy and interpretability.

In this paper, we propose a novel Neurosymbolic approach as shown in the Figure 6.1 that integrates DT rules with NNs to enhance both the interpretability and predictive power of travel demand prediction models. DTs are used to extract interpretable if-then rules that capture key travel patterns and relationships between features, while NNs are employed to model nonlinear interactions and improve accuracy. By encoding DT rules as additional input features for the NN, we bridge the gap between symbolic and neural learning paradigms. Extensive experiments demonstrate that our approach significantly improves predictive performance, as measured by metrics such as MAE, R^2, and CPC, especially when using rules selected with fine variance thresholds.

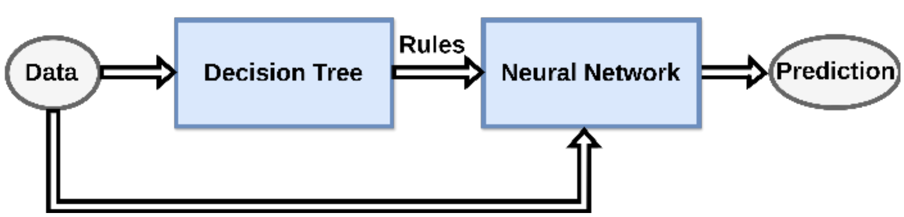


Figure 6.1: Neurosymbolic Approach Used in the Research

Our work represents a significant advancement in demand modeling by integrating the interpretability of DTs with the predictive accuracy of NNs within a unified framework. While previous research has largely focused on neural approaches or, in some cases, independently explored symbolic methods, limited attention has been given to explainable artificial intelligence (XAI) [201] in this context. Crucially, no prior studies have investigated the application of Neurosymbolic Artificial Intelligence (Neurosymbolic AI) [202] in the domain of travel demand modeling. This study is the first to explore the synergy between NNs and symbolic models for predicting travel demand. Further, our methodology incorporates variance-based rule selection, providing a novel mechanism to effectively balance model complexity with interpretability, setting it apart from existing hybrid approaches.

6.1.2 Related Work

Traditional methods for predicting travel demand have relied heavily on statistical models, such as gravity models [183] and logistic regression techniques [203]. Regression analysis has also been utilized to predict the demand for RAM [204] and AAM [114]. These models often assume linear relationships and may not effectively capture the complex, nonlinear interactions present in transportation systems.

With the advent of machine learning, more sophisticated models have been employed to improve prediction accuracy. NNs have been widely used due to their ability to model nonlinear relationships and learn from large datasets [205]. In the context of travel demand prediction, NNs have demonstrated superior performance over traditional statistical methods by capturing intricate patterns in mobility data [104]. They have also been employed as a supportive tool to enhance genetic algorithms, leading to improved outcomes [206]. However, a significant limitation of NNs is their lack of interpretability. The "black-box" nature of these models makes it challenging for practitioners to understand the underlying decision-making processes, which is crucial in transportation planning where transparency and explainability are essential [207]. To address this black-box puzzle, two distinct branches of AI come into play: XAI [201] and Neurosymbolic AI [202]. XAI focuses on providing explanations for AI models, typically after the training process. In contrast, Neurosymbolic AI integrates neural learning with symbolic reasoning directly within the model's architecture, creating a more inherently interpretable framework.

Various recent research has explored the application of XAI in various aspects of trip demand prediction, from forecasting overall travel demand to understanding individual mode choices. Hu et al. [208] tackled the challenge of predicting population inflow using mobile device location data, comparing various tree-based models and interpretation techniques. Their study revealed that boosting trees outperformed other models and that while feature importance rankings were consistent across models, the choice of importance measures and hyperparameter settings did influence the results. Moving from a nationwide perspective to a city-wide focus, Kim et al. [209] investigated the dynamic relationship between taxi and ride-hailing services in New York City. Their two-stage modeling approach combined linear regression with a long short-term memory network to predict taxi demand, effectively capturing the influence of ride-hailing services, day of the week, weather conditions, and holidays. This study demonstrated the potential of interpretable deep learning models for developing active demand management strategies, such as quota control systems, to balance demand between different modes and mitigate congestion. Kim [210] examined travel mode choice in Seoul, employing extreme gradient boosting (XGB) [211] and interpretation techniques like variable importance, interaction analysis, and accumulated local effects (ALE) [212] plots. The study not only demonstrated the accuracy of XGB but also revealed the importance of trip- and tour-related variables, age, and number of trips on tour in influencing mode choice decisions. Another study [213], achieves explainable or interpretable AI by employing two key techniques: variable importance analysis and SHAP [195] analysis. Variable importance analysis identifies the input variables, such as trip distance, traveler's age, and weather conditions, that have the most significant influence on the model's predictions, revealing the strongest predictors of travel mode choice. SHAP analysis then quantifies the impact of each feature, like annual income and car/bicycle ownership, on the prediction for individual instances, providing a deeper understanding of how these factors work together to shape travel mode decisions.

In the transportation domain, no studies have been found that focused on Neurosymbolic approaches for travel demand prediction. Despite the potential advantages, there is a gap in the literature regarding the application of Neurosymbolic AI to travel demand prediction. Existing studies have only investigated post training accuracy and interpretability of demand prediction models. Our work addresses this gap by proposing a Neurosymbolic framework that leverages DT-extracted rules alongside NNs to predict travel demand between counties.

Table 6.1: Summary of Related Works

Method(s)	**Limitations**
Gravity model [183]	Limited in capturing complex, nonlinear interactions Sensitive to parameter calibration
Regression Approaches [203] [113] [214]	Overlook higher-order interactions among variables Tends to underperform with large high-dimensional data
Neural Networks [205] [104] [209]	Black-box nature hinders interpretability High computational cost for large-scale problems
Hybrid: Genetic algorithm + NN [206]	Limited transparency in how NN and GA interact Potentially high training complexity
XAI approaches [213]	Focuses on general frameworks rather than domain-specific solutions Post-hoc explanations are provided
Boosting trees [208] [210]	Feature importance sensitive to hyperparameter changes Potential biases if location data is not representative

6.1.3 Methodology

The Figure 6.2 illustrates the methodological workflow for predicting travel demand using DT and NN. It begins with data integration from diverse sources, including geospatial, economic, and mobility datasets, to form the Initial Dataset. This dataset is processed and refined into the Final Dataset, ensuring feature relevance and quality. Rules are extracted using DTs with varying depths, resulting in a Dataset of the Rules, which is further refined based on variance thresholds to produce the Dataset of the Selected Rules.

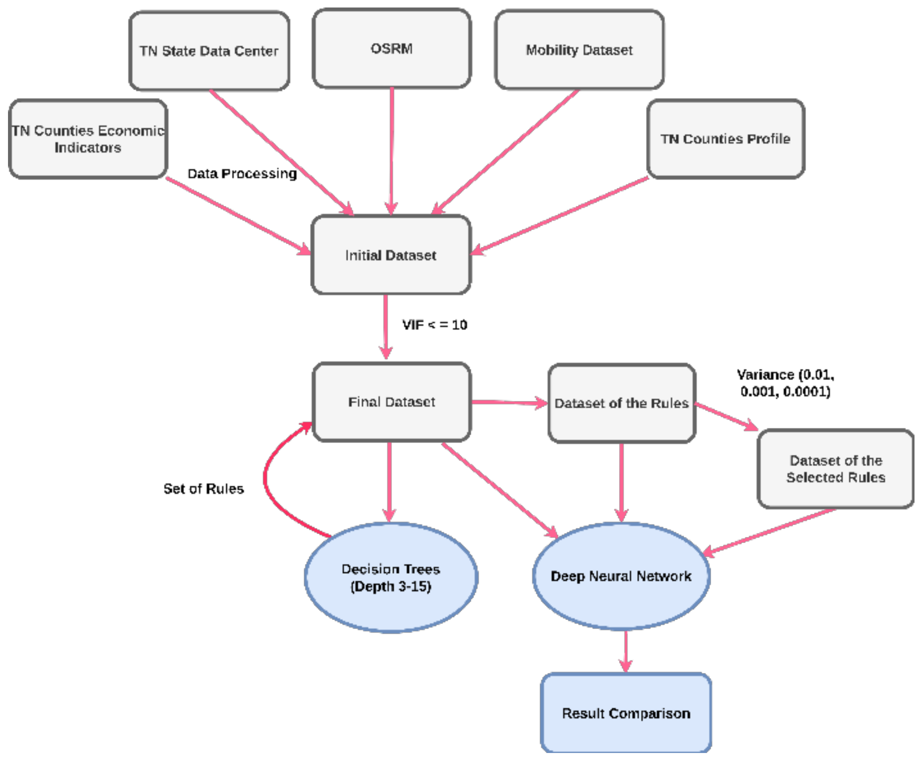


Figure 6.2: Methodology of the Research

Data Collection and Preprocessing

The data for this study was collected from various sources to ensure the inclusion of key factors influencing trip distribution. Table 6.2 lists the various datasets used in this research.

The multiscale dynamic human mobility flow dataset [193] provides extensive spatiotemporal data on U.S. population movements since January 1, 2019. Compiled from anonymized mobile phone location data sourced by SafeGraph, this dataset documents OD population flows at the census tract level on daily bases. Its detailed granularity and temporal coverage make it a valuable resource for applications in transportation planning. For this study, the daily dataset from March 15, 2021, to April 15, 2021, was extracted. The OSRM was utilized to obtain geographical

Table 6.2: Datasets Used in the Research

Name	**Details**
Mobility Dataset	Multiscale Dynamic Human Mobility Flow Dataset [193]
Population Dataset	Tennessee State Data Center [215].
Distance and Time Between Counties	Open Source Routing Machine (OSRM) [194]
Geographical features	Open Source Routing Machine (OSRM) [194]
Economic features	Tennessee Economic Indicators [216]
Tennessee County Profiles	Tennessee Commission on Children and Youth [217]

features for counties within Tennessee, while economic data was sourced from the Boyd Center for Business and Economic Research. County profiles and rankings were obtained from datasets provided by the Tennessee Commission on Children and Youth. All datasets underwent cleaning, standardization, and were merged using county-level identifiers. Missing values were imputed using median substitution, and numerical variables were scaled to facilitate comparability across features. Ultimately, 11 features were prepared for each county.

- **Land Use Counts:** Consists of two features: NaturalAreaCounts and PublicAreaCounts representing natural area counts like forest, agricultural etc. and public area counts which includes places like residential, commercial, industrial etc. respectively.

- **Points of Interest (POI):** Counts of POIs like educational places, commercial, healthcare, entertainment etc. within the counties.

- **Roads:** Classified into two categories: MajorRoads and OtherRoads.

- **Transportation:** Includes the total count of airports, railway stations, bus stations, etc.

- **Economic Features:** Consists of three features: Unemployment Rate, Employed Population, and Sales Tax Revenue.

- **Ranking:** Overall ranking of the counties in TN based on health, economic well-being, education etc.

- **Population:** Provides population count for each county.

Above features of both origin and destination counties were merged with the mobility dataset to obtain the initial dataset which consists of 22 columns for representing the features of origin and destination, 2 columns that provides time and distance required to travel from one county to another, one column that specify the day either weekday or weekend and last column provide the number of flows between the counties.

A multicollinearity check was performed to ensure that all features in the final dataset had a variance inflation factor (VIF) ≤ 10. This step eliminated redundant or highly correlated variables. After doing so we end up with the dataset that contains 10 features along with the population flow column, making it an 11 column dataset.

Decision Tree Rule Extraction

We employed DT as a method to derive interpretable rules that elucidate the relationships between features and target variables. The process of rule extraction and subsequent feature generation involves several stages, as outlined below:

Construction of Decision Trees with Various Depths: DTs of varying depths, ranging from 3 to 15, were constructed to balance the trade-off between model interpretability and predictive accuracy. Shallow trees emphasize interpretability by isolating the most significant features driving the outcomes, while deeper trees capture complex, nonlinear relationships. This variation enabled a comparative evaluation of model complexity versus performance, ensuring the retention of valuable information from both simple and complex feature interactions.

Extraction of Rules from Decision Trees: After training the DTs, the paths from root nodes to leaf nodes were traversed to extract if-then rules. Each path represents a rule delineating a subset of the data based on conditions imposed on input features. These rules encapsulate the underlying patterns and thresholds, enabling a clear understanding of the decision-making process for specific predictions. Table 6.3 shows the rules that were extracted from the DT of depth 3.

Generating Dataset of the Rules

The extracted rules from the DT were then applied to the final dataset to generate a new set of features. These features were encoded as binary indicators, where each feature corresponds to a rule: a value of 1 indicates that the rule's

Table 6.3: 8 Rules Extracted from Decision Tree of Depth 3

Conditions	**Mean Value**
distance_miles $\leq$ 46.08 AND POIs_Destination $>$ 323.0 AND POIs_Origin $>$ 307.0	31,867.81
distance_miles $\leq$ 46.08 AND POIs_Destination $>$ 323.0 AND POIs_Origin $\leq$ 307.0	9,709.81
distance_miles $\leq$ 46.08 AND 323.0 $\geq$ POIs_Destination $>$ 243.0	6,492.03
46.08 $<$ distance_miles $\leq$ 58.77 AND NaturalAreaCounts_Destination $>$ 935.5	2,728.70
distance_miles $\leq$ 46.08 AND POIs_Destination $\leq$ 243.0	1,648.22
distance_miles $>$ 58.77 AND POIs_Destination $>$ 773.5	544.09
46.08 $<$ distance_miles $\leq$ 58.77 AND NaturalAreaCounts_Destination $\leq$ 935.5	515.81
distance_miles $>$ 58.77 AND POIs_Destination $\leq$ 773.5	106.32

conditions are met, and a value of 0 indicates otherwise. We generated various datasets corresponding to the various depths and different number of rules from it.

Table 6.4: Rules and Variance-Based Rules at Different Tree Depths

Depth	**All Rules**	**Rules Selected by Variance**		
		0.01	**0.001**	**0.0001**
3	8	6	8	8
4	16	7	14	16
5	32	11	24	32
6	64	15	32	58
7	116	18	46	101
8	202	20	60	163
9	324	20	83	251
10	505	23	103	374
11	753	20	128	531
12	1069	18	157	735
13	1485	14	164	992
14	2006	8	174	1278
15	2628	5	171	1595

To ensure the relevance and practicality of the newly generated rule-based features, a systematic filtering process was implemented. Rules with minimal variance, specifically those falling below thresholds of 0.01, 0.001, and 0.0001, were excluded. As a result, we have four different datasets for rules: one that has all rules and three others with the rules having variances of 0.01, 0.001 and 0.0001 respectively for different depths of DTs. Table 6.4 provides an overview of the total rules generated, and the rules selected based on variance thresholds at various tree depths. As the tree depth increases, the total number of rules (‘All Rules‘) grows exponentially, reflecting the increasing complexity of the DT model. The rules selected by variance thresholds decrease with higher granularity. For example, at a depth of 15, while 2628 rules are generated, only 5 rules are selected at the 0.01 variance threshold, 171 at 0.001, and 1595 at 0.0001. This trend underscores the importance of variance-based rule selection in simplifying the model while retaining the most relevant and impactful rules.

Neural Network Implementation

To integrate the rules into the NN, we generated 60 distinct datasets derived from the rules extracted from DTs. These datasets were used to train the NN, alongside the final dataset, to assess how different combinations of rules and tree depths influence the NN's performance. Table 6.5 provides the details about the dataset used in the training process.

6.1.4 Experiments and Results

In this study, we utilized three evaluation metrics to assess the performance of our model:R^2, MAE, and CPC.

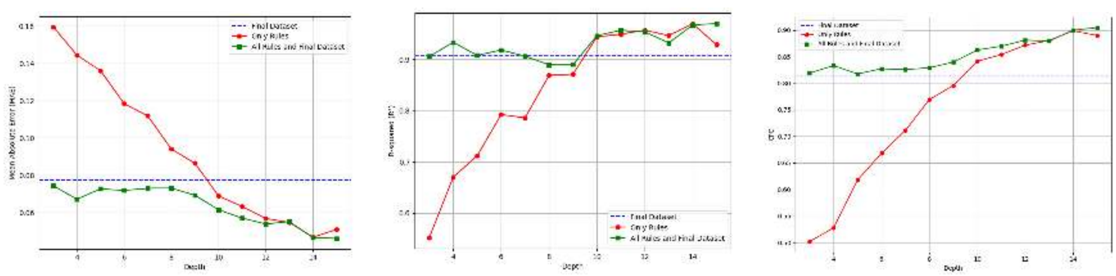
Results

Figure 6.3 highlight a notable performance gap between the NN model trained on the Rules Dataset and the NN model trained on the Combined Dataset. The NN model trained on the Combined Dataset consistently achieves lower MAE and higher R^2 and CPC across all depths of the decision tree used for rule extraction.

Table 6.5: Summary of Generated Dataset Configurations

Dataset Type	**Description**	**Count**	**DT Depths**
Final Dataset	Baseline dataset used for evaluation	1	-
Rule-Only Datasets	Extracted rules only	12	3–15
Rules + Final Dataset	Rules and baseline dataset	12	3–15
Rules (Variance 0.01) + Final	Rules filtered (variance $\leq$ 0.01) and combined with baseline	12	3–15
Rules (Variance 0.001) + Final	Rules filtered (variance $\leq$ 0.001) and combined with baseline	12	3–15
Rules (Variance 0.0001) + Final	Rules filtered (variance $\leq$ 0.0001) and combined with baseline	12	3–15

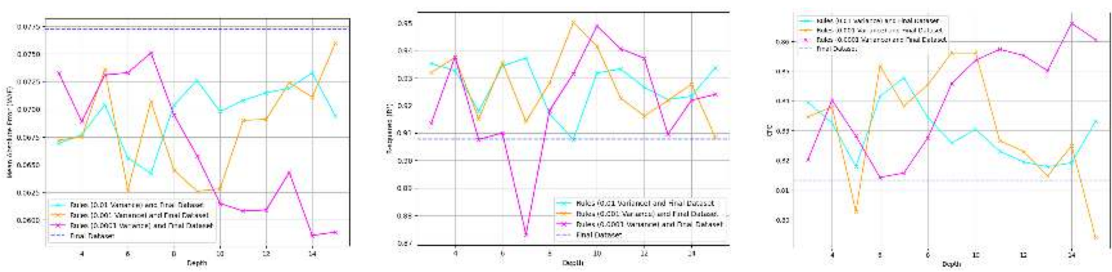
In contrast, the NN model trained on the Rules Dataset exhibits a limited ability to capture complex non-linear relationships, even as the tree depth increases. However, this performance gap narrows progressively, and the NN model trained on the Rules Dataset surpasses the baseline model, which is trained on the Final Dataset, at approximately depth 10.



(a) Mean Absolute Error (b) R^2 (c) Common Part of Commuters

Figure 6.3: NN performance on Final, Rules and Combined dataset

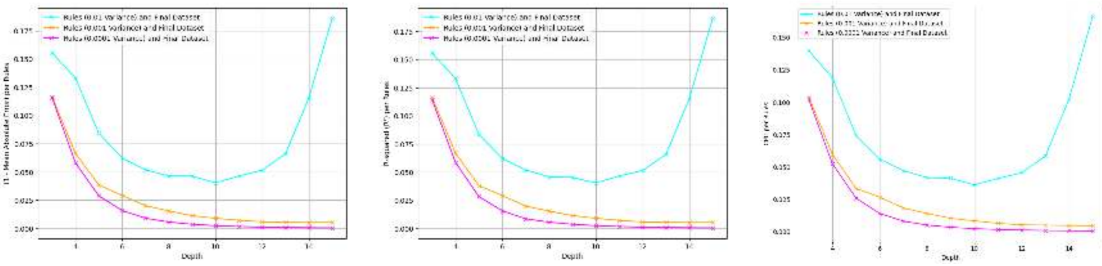
The MAE in Figure 6.4a shows variability across different variance thresholds and depths. The rules selected with a variance threshold of 0.0001 consistently result in lower MAE values, indicating better predictive performance, particularly at greater depths. Conversely, rules selected with higher variance thresholds (0.01 and 0.001) exhibit higher MAE, especially at shallow depths. All the dataset are better than the baseline one. The R^2 metric in Figure 6.4b highlights the fluctuation in model performance based on different variance thresholds. The rules with a variance threshold of 0.0001 achieve the highest R^2 values at most depths, indicating superior model fit. Rules with thresholds of 0.01 and 0.001 show fluctuating R^2, reflecting inconsistencies in capturing relationships as depth increases. Similar pattern are seen in the Figure 6.4c that evaluates the alignment of predicted and observed commuter patterns. Rules with a variance threshold of 0.0001 exhibit consistently higher CPC values, particularly at greater depths, demonstrating their effectiveness in capturing commuter overlaps. Rules with thresholds of 0.01 and 0.001 show lower and more fluctuating CPC values, indicating reduced alignment.



(a) Mean Absolute Error (b) R^2 (c) Common Part of Commuters

Figure 6.4: NN performance on various sets of rules selected based on variances

Figure 6.5 reveals critical inefficiencies in the NN model trained on various combinations of rules as tree depth increases. At shallow depths, the performance per rule is high due to a smaller, more impactful rule set. However, as depth increases, the proliferation of rules leads to diminishing contributions per rule, particularly for variance thresholds of 0.0001 and 0.001, which select many redundant or less impactful rules. In contrast, for a threshold of 0.01, fewer but more selective rules result in improved performance per rule at greater depths, particularly beyond depth 10. This selective behavior highlights the limitations of static rule selection, as R^2 and CPC per rule also exhibits similar trends. While thresholds of 0.0001 and 0.001 perform well at lower depths, their performance diminishes with increasing depth.



(a) Mean Absolute Error (b) R^2 (c) Common Part of Commuters

Figure 6.5: NN performance per rules on different datasets

6.1.5 Conclusion

This study proposed and evaluated a hybrid framework that integrates DT-based symbolic rules with NNs for travel demand prediction. The key findings demonstrate that incorporating DT rules significantly enhances model performance across multiple metrics, achieving up to 24.19% reduction in MAE, 1.79% improvement in R^2, and 6.49% in CPC. Rules selected at finer variance thresholds were particularly effective in capturing nuanced relationships, leading to improved predictive accuracy and alignment with observed commuter patterns. Future research will aim to overcome the limitations of this study by exploring dynamic rule selection methods, adaptive variance thresholds, and more efficient mechanisms for integrating symbolic rules into NN architectures. Expanding the dataset to incorporate diverse, real-time data sources will enhance the framework's applicability across various scenarios.

6.2 Phase III Contributions, Significance, and Impact

Phase III contributes by demonstrating that predictive accuracy alone is an insufficient criterion for trustworthy mobility modeling, and that explicit symbolic structure is required to stabilize learning under feature proliferation, non-linearity, and spatial heterogeneity. By extracting decision rules from DTs of increasing depth and embedding them as structured inputs to NNs, this phase establishes a principled mechanism for injecting human-interpretable constraints into otherwise opaque learning pipelines. The contribution is not the existence of rules per se, but the empirical demonstration that how rules are selected and integrated determines whether interpretability enhances or degrades performance. Quantitatively, Phase III shows that while raw rule sets grow exponentially with depth, only a small subset of rules carries meaningful signal; variance-based filtering exposes this sharply, with as few as 5 rules at a variance threshold of 0.01 retaining explanatory power at high depth. This directly challenges the common assumption that richer symbolic representations monotonically improve learning, and reframes rule extraction as a problem of selective abstraction rather than exhaustive enumeration.

The empirical results further establish that symbolic rules function most effectively as complements, not substitutes, for data-driven representations. NNs trained solely on rule-derived features underperform the baseline at shallow depths and only surpass it near depth 10, whereas models trained on the combined dataset (original features plus selected rules) consistently achieve lower MAE and higher R^2 and CPC across depths. Performance gains are non-trivial but deliberately bounded: incorporating DT rules yields up to a 24.19% reduction in MAE, alongside improvements of 1.79% in R^2 and 6.49% in CPC, with the strongest and most stable gains observed when rules are filtered at the strictest variance threshold (0.0001). Crucially, Phase III exposes a diminishing-returns regime: as depth increases, performance per rule declines sharply due to redundancy, particularly for permissive thresholds that admit hundreds of low-variance rules. This negative result is itself a contribution, as it identifies the structural failure mode of naïve rule injection and motivates the need for adaptive, context-aware symbolic selection.

Chapter 7

Conclusion and Future Research Directions

AAM, encompassing UAM and RAM, represents a transformative shift in the transportation ecosystem by enabling fast, flexible, and potentially sustainable aerial travel for short and medium range trips. Despite rapid advancements in electric propulsion, autonomy, and air traffic management, the widespread deployment of AAM services remains heavily dependent on accurate demand forecasting, public trust, economic feasibility, and regulatory readiness. Traditional transportation demand modeling approaches face notable challenges when applied to AAM due to the absence of historical operational data, evolving user perceptions, and the increasing reliance on black-box machine learning models that lack interpretability.

The primary objective of this dissertation was to enhance demand modeling for AAM by integrating data-driven learning with Neurosymbolic AI. The goal was to improve predictive accuracy while preserving interpretability and transparency, which are critical for stakeholder trust and policy adoption. To achieve this objective, the research was structured into three complementary phases, each addressing a key limitation of existing AAM demand modeling approaches.

7.1 Key Findings

Phase I: Role of Cost, Time, and Risk in AAM Demand

The first phase of this research developed a GCT framework that jointly captures direct monetary cost, value of travel time, and risk-related components. Unlike conventional demand models that emphasize cost or time independently, the proposed GCT formulation provides a holistic representation of traveler decision-making in the context of AAM.

Empirical evaluation conducted at the MSA and census tract levels in Tennessee, as well as at the urban scale using NYC taxi data, yielded several important findings. Cost and time consistently emerged as the most influential determinants of AAM adoption, while perceived risk played a secondary but non-negligible role during early adoption phases. Results further indicated that travelers exhibited a significantly higher probability of selecting AAM when air-based travel accounted for more than 70% of the total generalized trip cost. This highlights the importance of minimizing ground access and egress penalties through strategic vertiport placement and service design.

Additionally, urban-scale analysis revealed pronounced temporal variations in AAM adoption likelihood, underscoring the role of congestion and peak-period dynamics. These findings validate the relevance of generalized cost modeling for AAM and provide quantitative insights to support infrastructure planning, pricing strategies, and operational policy decisions.

Phase II: Data-Driven Trip Demand Modeling

The second phase focused on enhancing classical transportation demand modeling approaches through data-driven methods. Two major contributions were realized in this phase.

First, the integration of NNs with GAs for air mobility and pre-disaster planning demonstrated that even lightly trained neural models can substantially accelerate GA convergence. By initializing GA populations using NN predictions, the hybrid approach achieved comparable optimization outcomes while significantly reducing computational overhead. This contribution is particularly relevant for large-scale, time-sensitive planning problems where computational efficiency is critical.

Second, this dissertation proposed a machine-learning-enhanced gravity model for trip demand prediction. By capturing non-linear relationships among spatial, socio-economic, and transportation-related features, the enhanced model achieved substantial improvements over the traditional gravity model. Empirical results showed more than a 50% increase in R^2, over a 60% reduction in MAE, and notable gains in the CPC metric across both Tennessee and New York study regions. These results demonstrate that classical demand models, when augmented with modern learning techniques, can outperform purely black-box approaches while maintaining interpretability.

Phase III: Neurosymbolic Approaches to Modeling Trip Demand

The third phase introduced a Neurosymbolic demand modeling framework that integrates DT based symbolic rules with NNs. This hybrid architecture was designed to address the interpretability limitations of conventional machine learning models while retaining strong predictive performance.

Experimental results indicated that the Neurosymbolic model consistently improved predictive accuracy relative to standalone neural networks, achieving reductions in MAE and improvements in R^2 and CPC. More importantly, the symbolic rules extracted from decision trees provided transparent, human-interpretable explanations of travel behavior. These explanations enable domain experts and policymakers to validate model outcomes, assess behavioral plausibility, and build trust in data-driven demand forecasts.

The use of variance-based rule selection allowed the model to capture nuanced behavioral patterns, improving alignment with observed commuter flows. Overall, this phase demonstrated that interpretability and accuracy are not mutually exclusive, and that Neurosymbolic AI offers a promising pathway for trustworthy and deployable AAM demand models.

7.2 Scientific and Practical Contributions

This dissertation makes several original contributions to the fields of transportation systems, artificial intelligence, and advanced air mobility.

From a theoretical perspective, the research introduced a unified cost, time and risk framework for AAM demand modeling grounded in generalized travel cost theory. It further extended Neurosymbolic AI concepts to large-scale transportation demand prediction problems.

From a methodological perspective, the dissertation proposed NN-accelerated genetic optimization for air mobility planning, developed a machine-learning-enhanced gravity model that preserves interpretability, and designed a Neurosymbolic hybrid architecture combining symbolic reasoning with neural learning.

From an applied perspective, the proposed methods were validated using real-world datasets from Tennessee and New York City, yielding policy-relevant insights into pricing strategies, infrastructure planning, and adoption thresholds for AAM services.

7.3 Limitations of the Study

Despite its contributions, this research has several limitations. The reliance on proxy mobility datasets and static snapshots limits the ability to fully capture real-time and seasonal dynamics in travel demand. The generalizability of results may vary across regions with different socio-economic characteristics, regulatory environments, and infrastructure availability. Additionally, the use of fixed variance thresholds for symbolic rule extraction introduces rigidity that may not optimally adapt to heterogeneous datasets. Finally, operational constraints such as weather disruptions, airspace capacity limitations, and real-time system failures were not explicitly modeled in this study.

7.4 Future Research Directions

Several promising research directions emerge from this work. Future studies may incorporate real-time and streaming data sources, including weather forecasts, traffic conditions, and event-based signals, to enable adaptive AAM demand prediction. Adaptive Neurosymbolic rule-selection mechanisms that dynamically adjust thresholds based on data distribution and uncertainty represent another important avenue. Further integration of demand models with vertiport location optimization, fleet scheduling, and airspace management frameworks would enhance operational realism. Additionally, embedding uncertainty quantification and probabilistic reasoning within Neurosymbolic systems could improve trustworthiness in safety-critical decision-making. Finally, human-centered and policy-oriented evaluations leveraging interpretable models can support regulatory approval and public acceptance of AAM services.

7.5 Concluding Remarks

This dissertation demonstrates that the future of AAM demand modeling lies at the intersection of data-driven intelligence and symbolic reasoning. By integrating generalized cost theory, machine learning, and Neurosymbolic AI, this research advances both the predictive accuracy and interpretability of AAM demand models. The proposed frameworks provide transparent, scalable, and trustworthy tools to support informed decision-making as AAM transitions from conceptual vision to operational reality. The methodologies developed in this work offer a robust foundation for future research and practical deployment in next-generation air transportation systems.

7.6 Publications

Conference Papers

- **Kamal Acharya**, Katherine Vasiloff, Zhenbo Wang, Houbing Song, Liang Sun, "Urban Air Mobility Flight Demand Modeling for Airports in New York City", AIAA SCITECH 2026 Forum, p. 1475. 2026.

- **Kamal Acharya**, Mehul Lad, Liang Sun, Houbing Song, "Neurosymbolic Approach for Travel Demand Prediction: Integrating Decision Tree Rules into Neural Networks", International Wireless Communications and Mobile Computing (IWCMC), 2025.

- **Kamal Acharya**, Iman Sharifi, Mehul Lad, Liang Sun, Houbing Song, "Integrating Neurosymbolic AI in Advanced Air Mobility: A Comprehensive Survey", Proceedings of the Thirty-Fourth International Joint Conference on Artificial Intelligence (IJCAI-25), Survey Track, 2025.

- **Kamal Acharya**, Mehul Lad, Houbing Song, Liang Sun, "Regional Air Mobility Flight Demand Modeling in Tennessee State", AIAA SCITECH 2025 Forum, AIAA-2783, 2025.

- **Kamal Acharya**, Mehul Lad, Liang Sun, Houbing Song, "Demand Modeling for Advanced Air Mobility", 2024 IEEE International Conference on Big Data, pp. 2855–2863, 2024.

- Mehul Lad, **Kamal Acharya**, Liang Sun, Houbing Song, “Enhancing Forecasting for Advanced Air Mobility”, 2024 IEEE International Conference on Big Data, pp. 2908–2913, 2024.

- **Kamal Acharya**, Alvaro Velasquez, Yongxin Liu, Dahai Liu, Liang Sun, Houbing Song, “Improving Air Mobility for Pre-Disaster Planning with Neural Network Accelerated Genetic Algorithm”, 2024 IEEE International Conference on Intelligent Transportation Systems, 2024.

- Safayat Bin Hakim, Muhammad Adil, **Kamal Acharya**, and Houbing Herbert Song. ”Decoding Android Malware with a Fraction of Features: An Attention-Enhanced MLP-SVM Approach.” In International Conference on Network and System Security, pp. 187-209. Singapore: Springer Nature Singapore, 2024.

- Lijing Zhu, Qizhen Lan, Alvaro Velasquez, Houbing Song, **Kamal Acharya**, Qing Tian, and Shuteng Niu. ”Skghoi: Spatial-semantic knowledge graph for human-object interaction detection.” In 2023 IEEE International Conference on Data Mining Workshops (ICDMW), pp. 1186-1193. IEEE, 2023.

Journal Papers

- **Kamal Acharya**, and Houbing Song. ”A Comprehensive Review of Neurosymbolic AI for Robustness, Uncertainty Quantification, and Intervenability.”

Arabian Journal for Science and Engineering (2025): 1-33 (**Invited Paper**).

- Antônio Roberto L. De Macêdo, Senthil Kumar Jagatheesaperumal, Kelton Augusto Pontara Da Costa, **Kamal Acharya**, Houbing Song, Mohsen Guizani, and Victor Hugo C. De Albuquerque. "Quantum ai-enhanced iot-fog communication: A survey from cybersecurity and data privacy perspective." IEEE Communications Surveys & Tutorials (2025).

- **Kamal Acharya**, Waleed Raza, Carlos Dourado, Alvaro Velasquez, and Houbing Herbert Song. "Neurosymbolic reinforcement learning and planning: A survey." IEEE Transactions on Artificial Intelligence 5, no. 5 (2023): 1939-1953 (**IEEE CIS Publication Spotlight**, Nov. 2024.).

- **Kamal Acharya**, Alvaro Velasquez, and Houbing Herbert Song. "A survey on symbolic knowledge distillation of large language models" IEEE Transactions on Artificial Intelligence (2023)

- Waleed Raza, Xuefei Ma, Houbing Song, Amir Ali, Habib Zubairi, and **Kamal Acharya**. "Long Short-Term Memory Neural Network assisted Peak to Average Power Ratio Reduction for Underwater Acoustic Orthogonal Frequency Division Multiplexing Communication." KSII Transactions on Internet & Information Systems 17, no. 1 (2023).

Book Chapter

- Safayat Bin Hakim, Muhammad Adil, **Kamal Acharya**, Houbing Herbert Song, "AI for Android Malware Detection and Classification," in AI for Cybersecurity: Research and Practice , IEEE, 2026, pp.419-450.

Under Review

- **Kamal Acharya**, Waleed Raza, Katherine Vasiloff, Zhenbo Wang, Liang Sun, Houbing Song, "Demand Modeling for Advanced Air Mobility: Challenges, Opportunities, and Future Directions", IEEE Transactions on Intelligent Transportation Systems.

- Katherine Vasiloff, **Kamal Acharya**, Md Arifin Arif, Zhenbo Wang, Houbing Song, Fengyu Wang, Liang Sun "Demand Forecast and Energy-Aware Portal Siting for Regional Air Mobility", Journal of Air Transport Management.

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