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A data-driven framework for the deployment of urban air mobility

Faheem Ahmed

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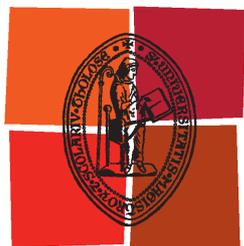
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de Toulouse

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LIST OF ACRONYMS

2D	Two Dimensional
3D	Third Dimensional
ATC	Air Traffic Controller
AI	Artificial Intelligence
ANS	Air Navigation Service
ATM	Air Traffic Management
CAGR	Compound Annual Growth Rate
eVTOL	Electric Vertical Takeoff and Landing
EASA	The European Aviation Safety Agency
FAA	Federal Aviation Administration
GPS	Global Positioning System
GRU	Gated Recurrent Unit
ITS	Intelligent Transport Systems
IoT	Internet of Things
ICT	Information and Communication Technology
LSTM	Long Short-term Memory
MUM	Multidimensional Urban Mobility
MaaS	Mobility as a Service
MAV	Manned Air Vehicle
MAE	Mean absolute error
MSE	Mean square error
NASA	National Aeronautics and Space Administration
ODM	On-demand Mobility

OEMs	Original Equipment Manufacturers
PT	Public Transport
RMSE	Root Mean Square Error
ROI	Return on Investment
STOL	Short Take-Off Landing
TLOF	Touch-down and Lift-Off
UAM	Urban Air Mobility
UAV	Unmanned Air Vehicle
UN	United Nations
UAS	Unmanned Aerial System
UTM	Unmanned Traffic Management
VMT	Vehicle Miles Travelled
VANET	Vehicular Ad Hoc Networks
WoS	Web of Science

GENERAL INTRODUCTION

CONTEXT AND MOTIVATIONS

In recent years, we have witnessed the rapid growth of urbanization, representing a significant challenge to the world. An alarming increase in population growth and environmental problems are becoming more acute across the globe in "Mega Cities" (UN, 2020). The Industry has long been welcomed to these cities because they knew they would retain their existing workforce while providing a safe and healthy environment for employees and businesses to conduct their operations, gradually increasing the attractiveness of urban areas. As a result, growing human demands for food, health, housing, education, security, and urban mobility have emerged. The economic attractiveness of cities has thus generated, through the ages, a rapid increase in the urban population, leading policy-makers to rethink mobility to cope with the density of traffic, infrastructure renewal, safety of the passengers, and sustainable development.

Consequently, public authorities must tackle different kinds of pressure timely concerning the needs of the end-users and providers of urban mobility. End-users want to move for many purposes, e.g., school, work, leisure, etc., and require fast, safe, on-demand, and personalized commuting services. In contrast, service providers, who invested in implementing mobility infrastructures and services, expect a return on their investments (ROI). The regular commute of increasing people will then become more complex, as urbanization increases demand and traffic volume. In this context, convergence tends to shift towards digital platforms offering various on-demand services, more adapted to users' immediate needs. Through intelligent mobility, the renewal of urban mobility has indeed brought out alternatives to usual travel, giving way to soft mobility, the reasoned use of personal vehicles, multi-modality, and international mobility. In addition to digital convergence, tariff convergence also appears to be a critical factor in a successful implementation (Jittrapirom et al., 2017).

However, expanding terrestrial networks to comply with the new needs and constraints is beginning to show its limits. It suggests the conquest of the air to

diversify the mobility offer, as is already done in some large cities that have introduced an air transport mode (helicopters, small carriers, and drones) to transport both humans and goods. Urban mobility stakeholders are adopting a new paradigm by introducing a third-dimension urban mobility mode that will complement or integrate the existing two-dimensional one to address the abovementioned concerns.

RESEARCH OBJECTIVE

In this context, this research work's main objective is to develop a Data-Driven Framework to support Public Authorities and Service Providers in Urban Air Mobility (UAM) deployment, taking into consideration the following constraints:

- Combine the existing land solutions (Maas transportation) with UAM features,
- Mitigate the urban concerns mentioned earlier and facilitate investment in mobility infrastructure and services.

HYPOTHESES OF THE PROPOSED SOLUTION

We conducted the research work under the following hypotheses:

- UAM will complement and integrate, but not replace the existing land mobility,
- UAM is efficient to reduce traffic congestion,
- UAM can provide new business opportunities.

RESEARCH QUESTIONS

The following research challenges were specifically studied and answered:

RQ 1. When it comes to implementing urban air mobility, what are the most significant obstacles and valuable insights to keep in mind, order words, how to integrate air and land modes of transportation; are the current infrastructures ready to accommodate the air mode, etc.?

RQ 2. Can the market viability sustain the required investments for the deployment?

RQ 3. What are the critical components of the resulting mobility system of systems?

RQ 4. Which kind of interoperability concerns should be solved to facilitate communication between the components of the existing mobility frameworks (which are primarily user-centric) and those designed specifically for UAM operation?

POSITIONING AND CONTRIBUTIONS

We adopted a specific approach and methodology to answer these research questions. The corresponding main achievements are summarized in Table 0.1.

Table 0.1 Positioning and main contribution to the research questions studied

	Methodological principles and tools	Main contributions
RQ1	Systematic survey / Bibliometric Analysis	Identification of obstacles and meaningful insights to UAM development
RQ2	Demand prediction / Deep learning	Analysis of the investment viability (go/no go)
RQ3	Complex system design / System Engineering	Proposal of a data-driven framework for UAM deployment and management
RQ4	Integration of UAM with the existing land solutions / Interoperability	Define principles allowing communication between different users (stakeholders)

THESIS OUTLINE

The rest of the manuscript is organized as follows:

- In Chapter 1, a broad state of the art on urban mobility highlights the demography issues and related mobility concerns. For that purpose, we developed a systematic survey to carry out a feasible and effective solution to these concerns.
- In Chapter 2, a specific focus on Urban Air Mobility, considered as a solution to urban mobility concerns, is proposed. The main related concepts and use cases are described, while the systematic survey on UAM we conducted has allowed identifying the main research tendencies and missing links. This provided us with insightful guidance to efficiently deploy a UAM solution.
- In Chapter 3, a major step of such guidance is defined and addressed in a demand prediction issue. To that end, the related scientific challenges are identified and studied, using a methodology based on developing and implementing a deep learning model for temporal data forecasting.
- In Chapter 4, the main principles and the operation of a data-driven framework for multidimensional mobility (including land and air modes) are proposed. The related scientific challenges regarding interoperability issues are specifically addressed, allowing to combine user-centric features with decision-making ones efficiently.
- Finally, the conclusion to this research work is presented in the last chapter, which summarizes our main achievements and findings, describes their limitations, and suggests a direction to solve them and improve the results obtained.

The logic of the manuscript, showing the interrelationship between the different research tasks carried out, is illustrated in figure 0.1.

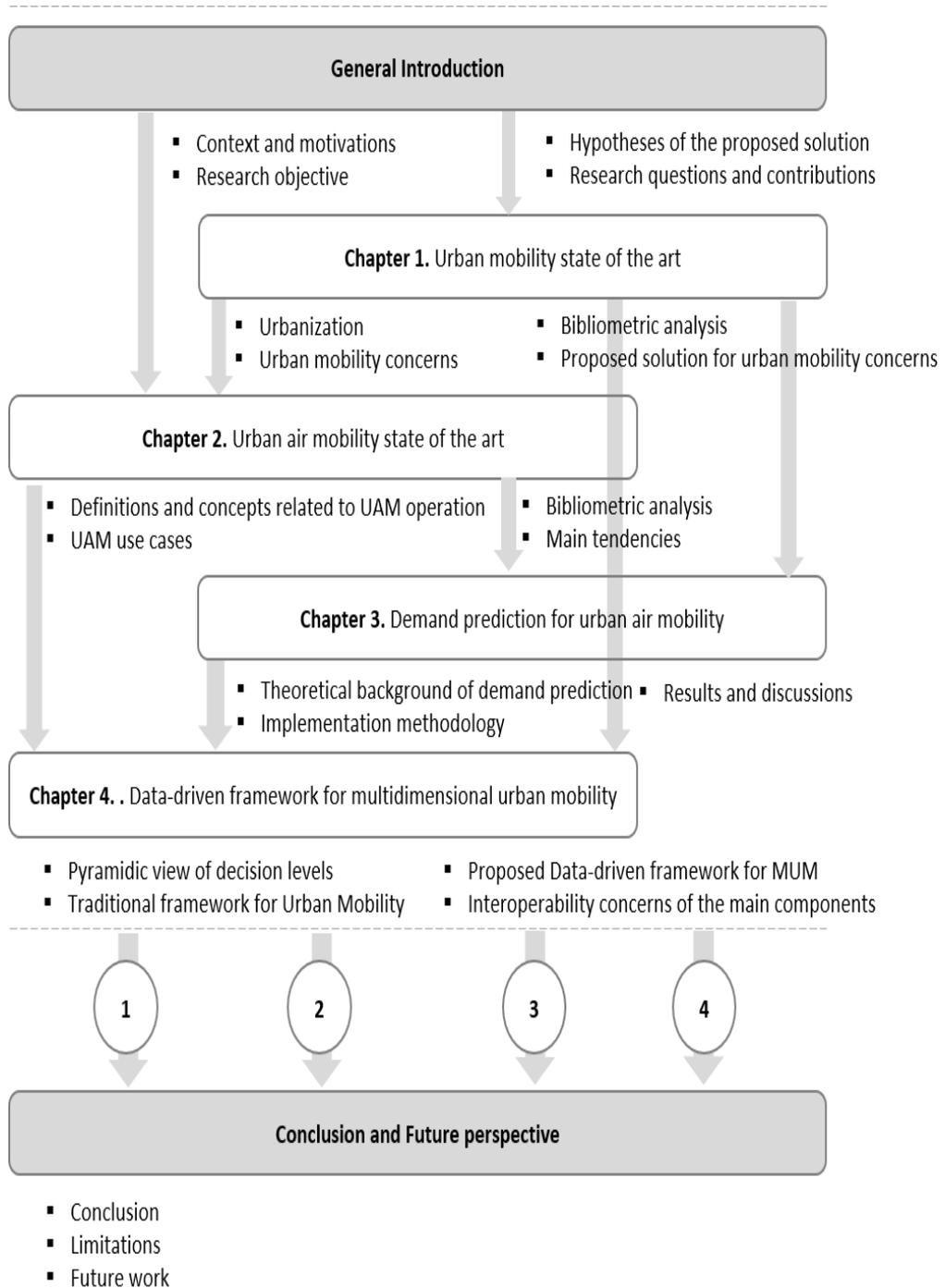


Figure 0.1 Thesis outline

1.
URBAN MOBILITY STATE OF THE
ART

INTRODUCTION

In the introductory chapter, we defined the main objective of this thesis. For a thorough understanding of the related scientific challenges addressed during the research, this chapter gives an overview of the historical studies undertaken within the general frame of urban mobility to solve urbanization concerns. It is organized as follows: Section 1.1 provides a comprehensive literature review and discusses fundamental and essential drivers of urban evaluation. Section 1.2 highlights major urban mobility concerns, among which those related to transportation in the context of demography growth. A systematic review has then been performed using bibliometric analysis to deepen the literature exploration; the corresponding outcomes are presented in Section 1.3, which identifies significant research areas and associated scientific challenges related to urban mobility. Section 1.4 describes a principle of transportation paradigm to mitigate these urban mobility issues within a city. Finally, a summary of the analyses carried out will conclude the chapter.

1.1. URBANIZATION

As urbanization has accelerated in recent decades, it has posed a massive challenge to the world's infrastructure, which must now deal with the consequences. As a result of globalization, an alarming increase in population, transportation, economic, social, and environmental issues are becoming more severe in "Mega Cities" all over the globe, particularly in developing countries (UN, 2020). A report regarding urbanization has shown that a growing percentage of the population is concentrated in urban settlements. Cities have been foreseen to expand their share of the world population from 52 percent in 2010 to 66 percent by 2050 (D.Little, 2018) (See figure 1.1). Figure 1.1 shows a CAGR(Compound annual growth rate) that will be increased from -0.1 to +1.5 percent p.a (per annum) to m people (million people).

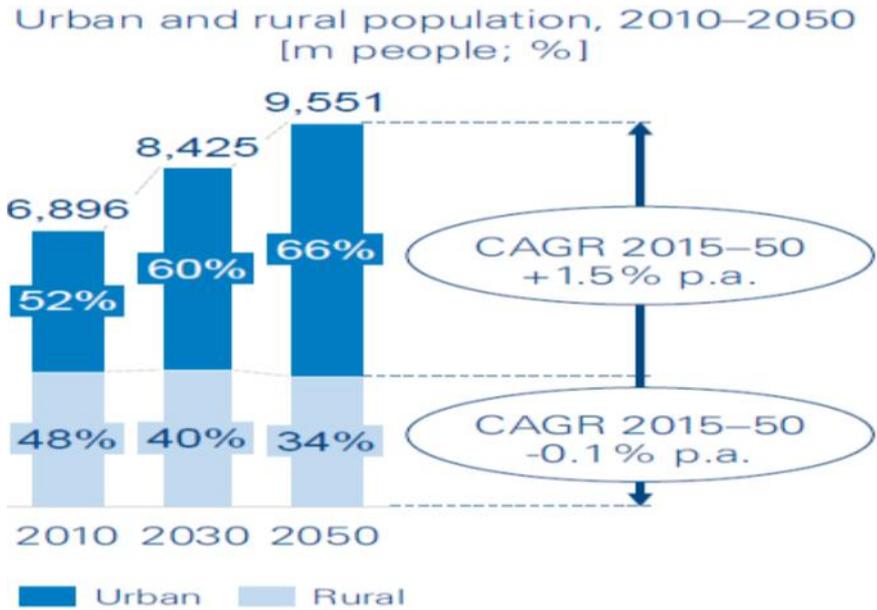


Figure 1.1 Global demography growth

In addition, a United Nations (UN) report presented that megacities were a solution to the ever-growing needs of the population developed, with hopes of economies of scale, both for the governments and the businesses in various

domains such as construction, manufacturing, and supply chain (UN-Habitat, 2020).

- **Key drivers of urban evaluation**

Industries were welcomed to these cities since they knew they could hold their workforce and provide a flourishing environment for the workers and the enterprises. Then, with these advancements came their increasing human demands, i.e., food, health, housing, education, security, climate change, and urban mobility. Some arrived sooner than expected, and some were not expected and were only discovered after such Mega Cities came into being. Despite their massive size and often enough accommodation for its residents, the flux of population from different parts of these cities to others has become a significant challenge over time. While considering different economic classes, which are equally important in maintaining the equilibrium of these cities, the various resources and challenges of commuters need to be better understood before planning or upgrading such cities (See figure 1.2).

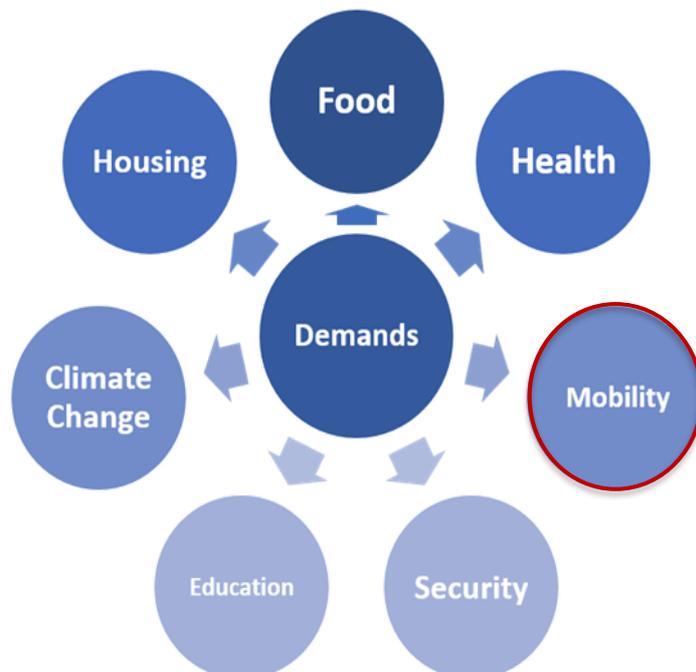


Figure 1.2 Key drivers of urban evaluation

The regular commute of increasing people will become more complex as urbanization increases demand and traffic volume. As a result, the distance travelled in cities is projected to triple. People need urban mobility services to promote work, trade, and innovation effectively. Cities, on the other hand, have a certain quantity of space. Urban transportation networks are already failing to keep up with ever-increasing traffic loads and are in danger of collapsing. Every year, millions of hours are wasted on the roads in certain cities; in Los Angeles, for example, each person wastes an average of 102 hours delayed in traffic. Congested traffic impacts communities' better lifestyle and the illness and disability due to emissions, noise, air pollution, and injuries. These issues must be addressed by emerging and rapidly developing cities. For example, air pollution in the Indian city of Pune (India) grew by 35% in 2010, with vehicles as the primary source of emissions (Becker et al., 2018). Thus, with above mentioned key drivers of urban evaluation, we will discuss the demand evaluation of urban mobility in the next section in detail.

- **The demand evaluation of urban mobility**

Studies on urban mobility predict a growing demand, especially in terms of passengers and goods in the future: according to (D. Little, 2018), in the year 2010, a trillion passenger-km per annum mobility demand is 25.8 % that, will be 48.4 % in the year 2050, almost double in the percentage of current demand, and urban goods mobility demand per annum is 9.5% in the year 2010 and will be 28.5% in the year 2050, it is almost triple in the percentage of current demand (See figure 1.3).

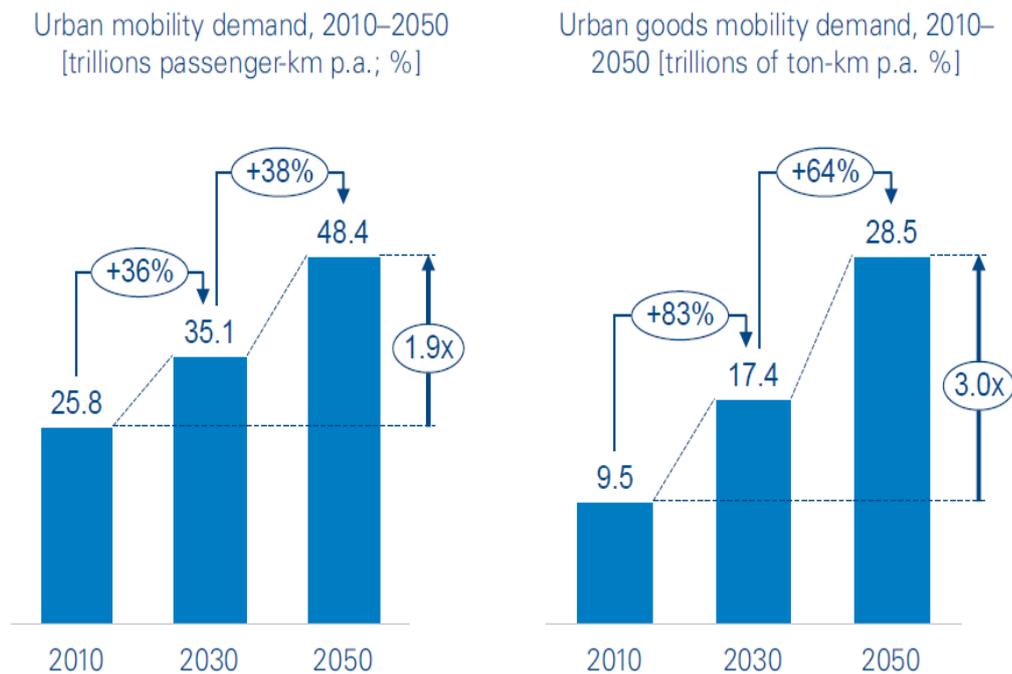


Figure 1.3 The demand evaluation of urban mobility

The rapid growth of urban mobility demand introduces a range of urban mobility concerns, such as traffic congestion, infrastructure, passenger safety, environmental pollution. As detailed in the next section, these concerns must be addressed swiftly.

1.2. URBAN MOBILITY CONCERNS

In the literature, several mobility concerns are discussed but mainly discussed above-stated problems, i.e., traffic congestion, infrastructure, the safety of the passengers, and environmental pollution (See figure 1.4).



Figure 1.4 Urban mobility concerns

1.2.1. Traffic congestion

Urbanization creates many traffic-related problems, and congestion has proved to be a significant concern. A recent study on road traffic congestion measures towards a sustainable and robust transportation system and results showed that traffic congestion costs the United States about 2.9 billion gallons of fuel and more than 121 billion dollars each year (Qiao, 2021). There is a constant increase in the number of vehicles while the road system and parking areas remain the same, commute will become problematic. However, the problem of congestion cannot be eradicated by merely initiating infrastructure projects, such as bridges, roads, railway networks. Increases in population and auto ownership and increased vehicle miles traveled (VMT) due to urban sprawl have hampered traditional road size expansion. Current efforts have emphasized using new technologies and principles to reduce traffic congestion by utilizing existing transport infrastructure. Technology has evolved as a tool to solve human problems and make lives more accessible, and it is greatly helpful in reducing congestion. Connected and

autonomous vehicles, for example, are likely to enhance traffic flow, minimize car servicing wait times, and increase the flexibility of today's roadway system. It is essential to note other factors responsible for traffic jams like accidents, maintenance work, and futile transportation systems, which need to be tackled as well, both individually and as a part of the overall solution.

1.2.2. Infrastructures

A report on fundamental challenges in transportation indicated that infrastructure is one of the main concerns in the urban mobility sector. Most other issues depend on fixing this critical issue (Samuels, 2018). A chain of railway networks, roads, footpaths, airports, and other infrastructure projects facilitates transportation. These need to be planned according to the projected needs of each community and in places where new projects are not possible. Rejuvenation or, at the very least, maintenance projects can be implemented to make sure that the systems work as expected, helping prepare for increased or decreased flow accordingly.

1.2.3. Environmental pollution

Energy consumption has colossally enhanced due to urban transportation. Consequently, pollution has increased. When combined with annoying noise, it has made the lives of urban residents miserable, as it is highly harmful to their physical and mental health (Ortego et al., 2017). For example, pollution kills 600,000 people in Europe. Every year, the government spends more than \$1600 billion (Mingrone et al., 2015), while negative impacts on the environment such as emission of CO₂ and pollutants and noise nuisance are caused by urban mobility.

1.2.4. Safety of the passengers

The more congested the traffic in urban areas is, the more accidents, injuries, and deaths are probable. According to Kiba-Janiak and Witkowski, many accidents occur due to increased traffic (Kiba-Janiak & Witkowski, 2019). Some countries have experimented with rules like allowing only a specific segment of cars (e.g., cars with odd or even registration numbers) on roads on certain days. Nevertheless, there is also a decreased sense of safety among the commuters to follow these rules.

In the next section, we will focus on a bibliometric analysis of scientific research to see the current research trends, associated challenges, and solutions presented in the literature in the context of urban mobility.

1.3. URBAN MOBILITY RESEARCH AREAS

(Tomaszewska & Florea, 2018), using the VOSviewer analytic tool, write a bibliometric study of the scientific literature on urban mobility within the context of smart city and intelligent transport systems (ITS). The analysis included the research area, publications, citations, and the most frequently used keywords. Developed a theoretical framework for research trends based on a scientific literature survey and generated a map depicting the relationships between the investigated keywords (See figure 1.5).

The methodology involved the following four stages:

1. Selection of the research criteria:

- Scientific articles listed in the Web of Science database referring to "urban smart mobility" or "urban intelligent transport system" in their topic;
- Scientific articles in the Scopus database refer to "urban smart mobility" or "urban intelligent transport system" in titles, keywords, or abstracts.

2. Selection of a period and type of documents:

The central portion of the map displays the most often occurring keywords. Some trends may be seen in the data (the size of the point and typeface used to symbolize each keyword indicate how frequently it appears). First, the resulting network has many connections and seems quite dense. Authors were able to see how frequently each item appeared in the network and how often the pieces were cited together. It was also easier to group the data under investigation into clusters colored on the map.

The first cluster, named "Computer simulation of urban traffic," encompasses a wide range of computer science subjects, such as Vehicular Ad Hoc Networks (VANET), Simulation, Data Collection, and Computer Vision, as well as their transportation, traffic control, and surveillance applications. One of the most essential (and fast-developing) advancements in Computer Vision is machine learning techniques, notably artificial neural networks, for resolving some of the most challenging challenges in urban transportation. Traffic accidents are expected to be reduced if embedded technologies based on computer vision. Computer vision and video analysis for traffic assessment in intelligent transportation systems are becoming more common. Cluster 1's next research focus is on Vehicular Ad Hoc Networks (VANETs), which include security characteristics, difficulties, and threats, as well as routing obstacles. Two future research directions in computer simulation of urban traffic that have been identified in the literature are the creation of efficient algorithms for controlling urban traffic and simulating traffic networks.

The second cluster, "Urban Public Transportation," integrates Computer Science concepts with those unique to public transportation in cities. Through the use of the Gamification concept and ubiquitous smart devices. Crowdsourcing and crowd-sharing data establish the foundations for the considerable data size to boost the efficiency of public transit services. Machine learning may help install smart parking systems, traffic signal controllers, and other applications and improve mobility. Among the most significant recent research trends in urban public transportation that have been identified in the literature are those that

emphasize the possibility of prioritizing public transport while also minimizing journey time.

The third cluster, "Urban smart transport planning," is in the middle of the map and addresses the general concept of a smart city. As previously said, smart mobility is only one aspect of the smart city concept, but it is an important one that is linked to other concepts like smart environment. The primary responsibility of government agencies is to plan, regulate, and implement innovative solutions that improve public transit accessibility and reliability. Urban smart transportation planning is a broad field of research that looks into issues that affect other clusters. The establishment of specialized lanes for public transit and the allocation of incentives for electric mobility are among the planning projects, all of which aim to improve and extend the current urban infrastructure. Many practical actions in this area come by sharing good practices among cities that have applied smart city qualities rather than research. Researchers provide qualitative and quantitative ways for evaluating the quality of planning solutions, such as travel time, emission estimates, and clients served within a specific time limit. Many academics have recognized the importance of sustainable mobility, urban planning, transportation planning, and transportation engineering in various fields. As the problem of urban congestion intensifies, researchers' interest in planning and building urban transportation systems is expected to grow soon.

The fourth cluster, "Urban Transportation Innovations," has been extensively researched over the previous decade and fundamentally reflects a new mobility issue: bringing creative ideas to urban transportation while maintaining the sustainability goal. EU places a strong focus on technological novelty and intelligent (green) solutions for urban transportation networks, allocating significant money to research in this area. The purpose of these projects is to integrate high-quality, more accessible services into the urban transportation network, and passengers will benefit from better comfort and real-time multimodal information. Future research will concentrate on autonomous vehicles, the

integration of innovative shared mobility services with conventional public transportation, and the emissions reductions issues caused by traffic congestion.

The fifth cluster, "Data Fusion in ITS," focuses on data extraction and utilization related to building smart applications to reduce air pollution, auto traffic, and congestion. As well as highlighting the Mobility as a Service (MaaS) concept, which provides exact, actual, customizable mobility information services for travel planning, online booking, payment and journey time. For ITS systems, the Global Positioning System (GPS) has grown in popularity in recent years, and it is now a common technology for supplying location data. Analytical tools will leverage data from connected automobiles to predict vehicle breakdowns and assist users in quickly diagnosing vehicle issues, detecting the reason, and guiding them to the closest location of the ride service. MaaS (Mobility as a Services) is a new study concept and creative transportation idea that can transform current transportation services into innovative services. MaaS is becoming more powerful as a result of advancements and exploration in wireless communication information services such as 4G and 5G networks, which are becoming more prevalent.

Because it contained one of the less frequently recurring phrases, the sixth cluster, "Intelligent solutions in urban traffic," was placed on the map's borders. Smart traffic lights, intelligent, autonomous cars, and traffic control should focus on future intelligent solutions research. ITS potential benefits, such as real-time traffic management and providing users with reliable and up-to-date information (including unforeseen road occurrences), have been extensively investigated and documented.

Only three components make up the final and smallest cluster 7, "security and safety of urban computing," which is crucial ("safety" into "smart mobility" within and outside the city). Proposed a cloud computing platform for Intelligent Transportation Systems called "ITS-Cloud," which would improve road safety, transportation efficiency, informed travel choices, travel reliability, traffic resilience, and environmental protection. Recent research in urban computing

security has primarily focused on increasing data reporting systems supervised using accurate data made public.

These evaluations lead to the following findings from a scientific standpoint:

- Between 2000 and 2017, academics' interest in the studied topic of research increased methodically;
- The findings allow researchers in the fields of computer science and transportation to recognize intelligent transportation systems and smart urban mobility as rapidly evolving research characterized by significant concerns for future cities, with researchers in these fields contributing the majority of the field's contributions;
- In the last five years, there has been a significant increase in the number of research publications on urban mobility;
- Government organizations, corporations, and researchers can use the results of this research to identify trends in the urban mobility business and make appropriate decisions to improve people's quality of life;
- Smart cities, intelligent transportation systems, sustainability, public transit analytics, and big data were among the study's central themes;
- Infrastructure, urban planning, and transportation systems are not being developed with industrial developments and population forecasts in future cities in mind "as much as they should.";
- Although traffic congestion has an immediate impact on the environment, air quality, the economy, and ultimately human health are only given modest consideration;
- In the future, machine learning will be used in a broad range of smart devices and applications, not just mobility and transportation systems;

- Based on keyword co-occurrence in publications related to intelligent transportation systems or smart urban mobility, they propose seven clusters;

After assessing this bibliometric study and searching for potential research gaps in the examined context, infrastructure, climate change, noise, air pollution, and city congestion were common issues in the scientific literature that are still unresolved completely.

As a result, we presented air mobility as a complementary solution in the following section to address these issues.

1.4. AIR MOBILITY INVESTIGATIONS

- **Mobility redefined by the industry4.0**

According to (D.Little, 2018), big data, artificial intelligence (AI), the internet of things (IoT), and the introduction of new energy sources are among the major technological breakthroughs of industry 4.0 (See figure 1.6).

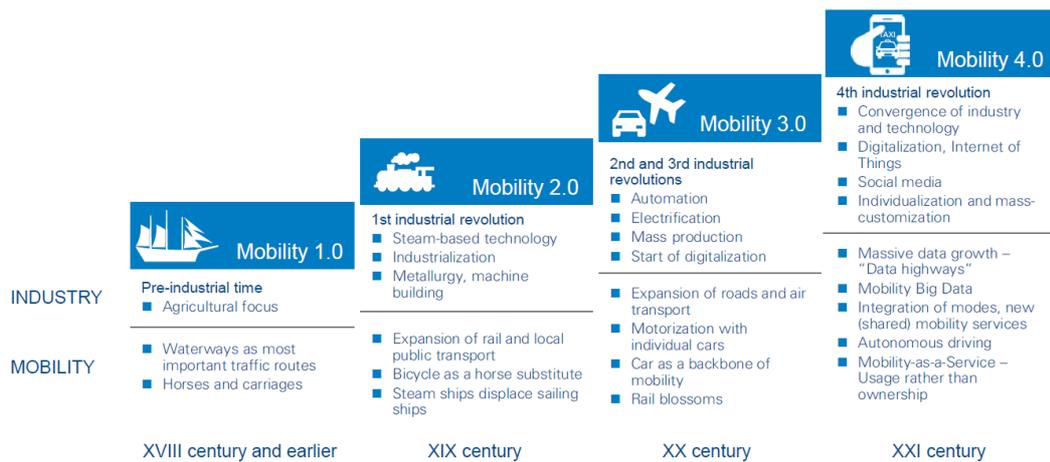


Figure 1.6 Mobility redefined by the industry4.0

The increased efficiency of algorithmic data processing, aided by artificial intelligence, enables new mobility services, such as real-time journey optimization that make greater use of existing mobility assets.

Artificial intelligence's recent breakthroughs are development in and of themselves, as they have paved the way for self-driving cars. IoT advancements are also having a significant impact on the future of mobility since they create a modern, ongoing communication channel amongst mobility stakeholders, allowing for more data collection and sharing. According to several recent evaluations, the Intelligent Transportation Systems (ITS) business will grow by double digits every year across all market areas. Smart traffic control, passenger information systems, and parking management systems are just a few examples of these ITS. Finally, mass production of modern, lightweight energy sources, such as lithium-ion batteries, would enable economies of gauge and increased journey choices, accelerating the acceptance of electric mobility solutions.

In the era of Mobility 4.0, parts of a cyber-physical system, like artificial intelligence, big data, and the internet of things are expected to be used more and more in urban mobility systems. Even though urban mobility services are critical components of the smart city, digitalization is expected to solve some major issues such as traffic congestion, a lack of public transportation capacity, a lack of infrastructure, and emissions, which would be mitigated through digital services. Indeed, urban mobility stakeholders are looking for better solutions such as sharing services (car sharing, bike sharing, etc.), smart parking lots (Resident Parking Zones (RPZ), On-Street Parking Permits Charge, etc.), vehicle technology (Driverless Cars, Autonomous Cars, Car Charging Stations, etc.), zone management (Pedestrian Accessible Zone, Ultra Low & Low Emission Zone, Congestion Charge Zone, Sharing Traffic Data), transportation solutions (Integrated Ticket Pricing, Free of Charge Multi Mod Using, Smart Free Journey Assistance, Incentives; Non busy time scheduling deduction, Mobility Increasing Support Payment) are capable of dealing with the complex problems caused by urban mobility (Inac & Oztemel, 2022).

Regulation is a key driver of advancement since it aims to build more environmentally friendly transportation options. In recent months, numerous cities and nations have approved rules prohibiting the sale of cars with gasoline and diesel combustion engines in the long run, with alternative engines (electrical, hydrogen) gradually replacing them: the Netherlands by 2030, Norway by 2035, and France and the United Kingdom by 2040. China has announced that gasoline and diesel automobile production will be phased out in the coming years. Original Equipment Manufacturers (OEMs) in China would be compelled to sell at least 8% of new electric or plug-in hybrid vehicles. From 2020 onwards, the percentage will be at least 12 percent.

The rapid growth of electric vehicle demand is a clear sign of this trend. Over 1.2 million electric vehicles were sold worldwide in 2015. By 2025, the population is predicted to reach 26.2 million. Similarly, most developed-world cities and countries have enacted laws to integrate newer forms of mobility (such as electric bikes and car-sharing) into urban centers and manage parking space and usage.

- **Pressures on public authorities**

There is a different kind of pressure that public authorities must tackle timely concerning the needs of the end-users and providers (See figure 1.7).

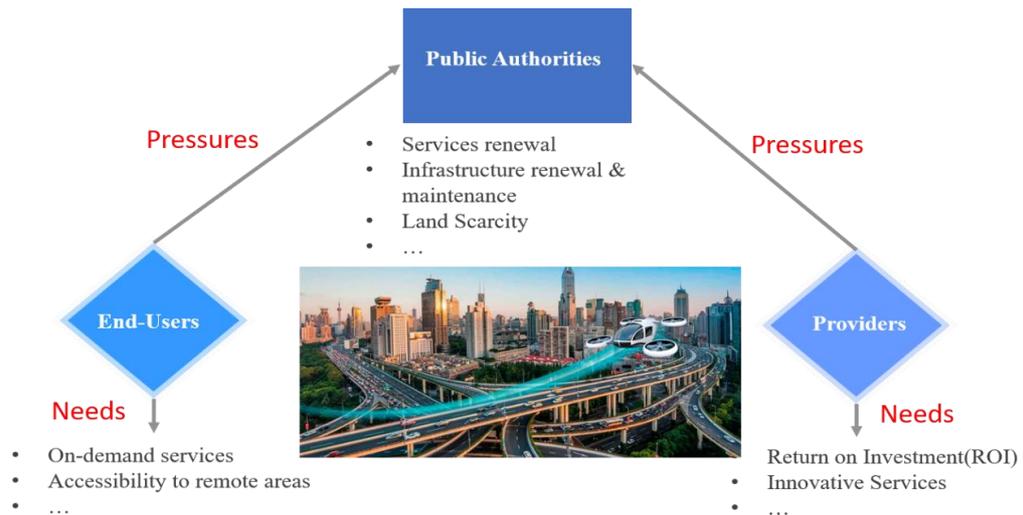


Figure 1.7 Pressures on public authorities

- *End-users.* End-users want to move from location A to B, e.g., schools, work, and leisure. So, he required mobility-on-demand, fast and innovative services to commute and personalized services.
- *Providers.* Providers are referred to as mobility operators (Public and Private) and solution providers (Technology Companies). Who invested their money and expecting (ROI) return on investment.
- *Public Authorities.* In their capacity as a supervisory and regulatory body, the public authorities must determine which partnerships and regulations to implement, as well as which services to provide, and in what manner. Public Authorities are regulators regulating different rules and procedures to deliver sustainable urban mobility to end-users and financial benefit to service providers. Considering other pressures such as Land utilization (Scarcity), Infrastructure renewal and maintenance, i.e., roads, bridges, railway stations, and airports. Including all these pressures, public authorities are more concerned with providing all the above needs sustainably since urban mobility causes negative impacts on the environment such as emission of CO₂ and pollutants and noise nuisance. Therefore, while making policies to handle the pressures above, public

authorities should consider these pressures in sustainable development.

Urban mobility stakeholders are now adopting a new paradigm of urban air mobility (UAM) to lessen these pressures. This third-dimensional urban mobility mode will complement or integrate two-dimensional urban mobility modes.

- **Multi-dimensional urban mobility**

Currently, the concept evolved as a multi-dimensional urban mobility delivery model. A user’s primary mobility needs are met through different modes of urban mobility offered by a service provider and anticipated as a viable solution for sustainable urban mobility (See figure 1.8).

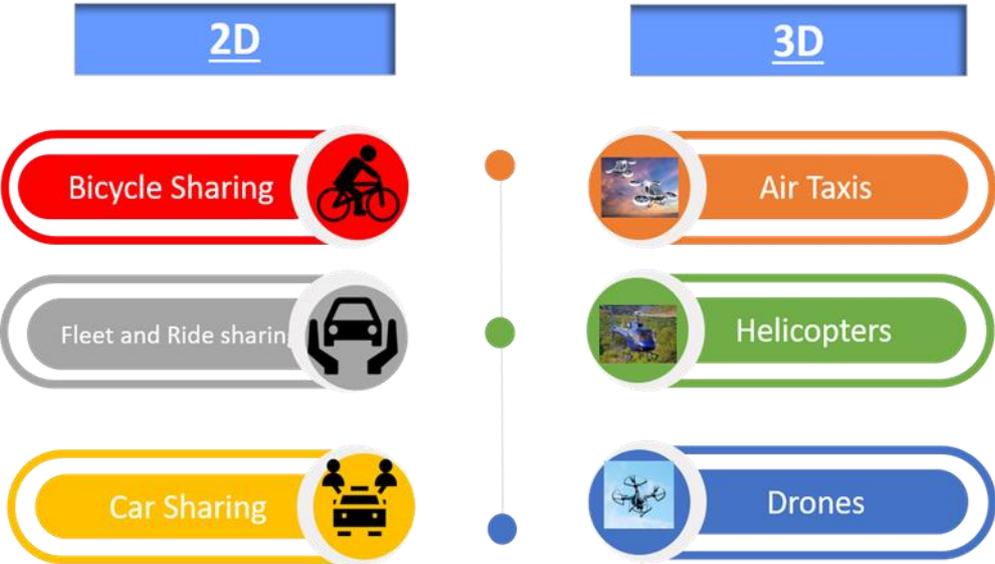


Figure 1.8 Multi-dimensional urban mobility

The expansion of terrestrial networks to comply with the new needs and concerns discussed prior are beginning to show its limits and suggest the conquest of the air to diversify mobility. Urban mobility systems are taking on a new dimension to alleviate the burden on ground-based transportation networks. It is already being done in some large cities that have implemented an air transportation mode UAM (helicopters, air taxis, drones, and other similar vehicles) to transport people and goods. Multi-modal shared mobility systems provide customers with

more accessible transport options, as demonstrated by decreased demand for parking spaces, the abandonment of car ownership, and reduced environmental impacts resulting from lower emissions.

CONCLUSION

As we have demonstrated, demographic growth has given rise to several urban concerns, among which transport issues which are critical. Furthermore, the system that characterizes urban mobility is complex and includes different aspects to be considered: the infrastructures (mobility, telecommunications), the modes of transport and their corresponding offers, the different services (mobility, telecommunications), which require to take into consideration the needs of the all the urban mobility stakeholders (end-users, service providers, public authorities). The literature review carried out has also shown that many studies undertaken, especially in the frame of the smart city research area, have provided valuable solutions to mobility issues. Intelligent transport has indeed enabled decision-makers to address urban concerns, i.e., traffic congestion, environmental pollution, safety, infrastructures, etc. However, these solutions are insufficient to cover emerging new needs in megacities, especially for on-demand services. This is why we have argued that a paradigm change from 2D to 3D mobility is necessary to study the expansion of land modes with air means of transportation.

2.
**URBAN AIR MOBILITY STATE OF
THE ART**

INTRODUCTION

Chapter 1 exhibited that several relevant research studies have been conducted to address urban concerns, including mobility issues. But the growing need for on-demand services, decreased demand for parking spaces, substantial car ownership, lesser environmental impacts, land utilization (scarcity), emergency services, reducing the cost of infrastructure renewal and maintenance, i.e., roads, bridges, railway stations, airports. Including all of these requirements, urban mobility stakeholders require a viable solution for sustainable urban mobility. This has led us to suggest that air transport mode should be evaluated to complement the existing land modes has led us to suggest that air transport should be explored to complement the existing land modes. The resulting system of systems, combining these two types of urban travel, is therefore complex, while its deployment requires the consideration of several constraints and uncertainties. This chapter aims to investigate the use cases and research work in the field of air mobility to provide reliable guidance to decision-makers and ensure a successful implementation. For that purpose, section 2.1 presents the main concepts related to the urban air mobility paradigm, while section 2.2 gives an overview of the most representative use cases. To deepen the investigation of the literature on this hot topic, we decided to perform a systematic review, which is briefly explained and justified in section 2.3, followed in section 2.4 by the presentation of the corresponding methodology and the main key findings of this survey described in section 2.5. Finally, a summary of the analyses carried out concludes the chapter.

2.1. DEFINITIONS AND CONCEPTS RELATED TO UAM OPERATION

This section will first identify and highlight the most often used definitions of UAM available in the literature, then describe the main concepts behind a UAM operation.

According to Thipphavong and co-authors, “*Urban Air Mobility (UAM) is an emerging concept of air transportation using quiet and efficient manned and unmanned vehicles to conduct on-demand, scheduled operations, e.g., emergency medical evacuations, rescue operations, humanitarian missions, newsgathering, ground traffic flow assessment, weather monitoring, package delivery, and passenger transport*” (Thipphavong et al., 2018). In contrast, Airbus goes beyond the conceptual view and precise that UAM a kind of vehicle: “*an aerial vehicle concept for passenger transportation offer a more reliable and more environmentally desirable alternative to reduce congestion on transport networks*” Airbus (2017). As an outcome of these definitions, focusing on the previously presented urban mobility, UAM is the third dimension of mobility. It is a highly efficient solution for the traffic issues of cities in which two-dimensional capacity cannot cope with the exponentially increasing number of vehicles and subsequent accident frequency and pollution therein.

Traditional UAM operation is depicted in Figure 2.1, which can characterize the process of a multimodal UAM service. The associated platform enables on-road auto rides for the first phase of the journey, namely, drive from the pickup site to a vertiport/vertistop (the field intended for the take-off of helicopters and short take-off planes). Passengers will then switch from/to ground transportation at each vertiport's access and egress sites. Each vertiport has a boarding, disembarking, and TLOF (Touch-down and Lift-Off) area. As part of the multimodal service operation, passengers will first travel by ground transportation to their designated vertiport. They will be sent to waiting rooms after arriving at a vertiport, where they can wait for a short period before boarding via corresponding

gates. After reaching a certain height, the aircraft will take off from a vertipad and cruise to another vertiport. Passengers must then go through a similar transfer procedure when the plane lands at the destination vertiport's vertipad before boarding ground transit to their destinations (drop-off) (Wu & Zhang, 2021).

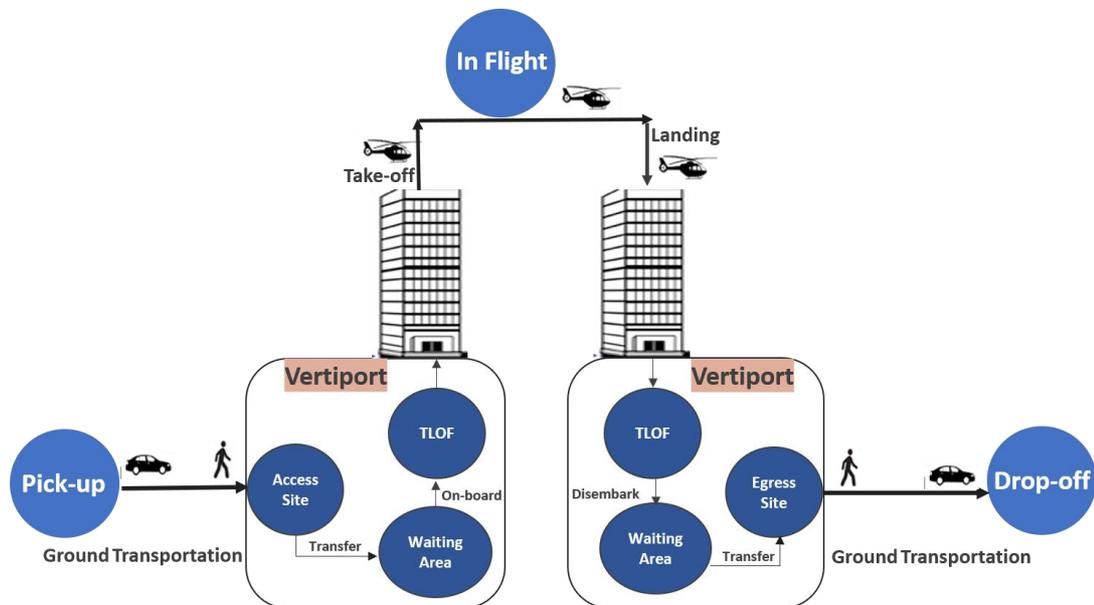


Figure 2.1 Concept of UAM operations

The following section presents an overview of some historical and recent UAM use cases based on the definitions and concepts presented in this section.

2.2. UAM USE CASES

This section explores some previous and recent examples of UAM services. Let us mention that UAM is not a new notion. The novelty of the paradigm is to bring it in the field of mass transportation, which induces many technological, social, economic, and environmental challenges that the present research work tries to structure in a meaningful and straightforward manner.

Indeed, UAM services utilizing helicopters can be traced back to the 1940s. Helicopters were used by Los Angeles Airways to move people and mail around the city of Los Angeles from 1947 to 1971. They took people and mail from

Disneyland to the airport (LAX). In 1968, Los Angeles Airways had two incidents due to mechanical failure, and the company was forced to shut down (Harrison, 2017, as referenced in Thippavong et al., 2018). New York Airways used helicopters to transport passengers between Manhattan locations and New York City's three major airports from 1953 to 1979. This service, too, was terminated due to a series of mishaps caused by mechanical failure (Thippavong et al., 2018). These early UAM operations were active for over two decades before being shut down due to safety concerns; this explains why we have highlighted urban mobility concerns in our definition of UAM. Besides, these historical examples demonstrate the potential importance of similar (although safer) UAM services to customers today. More importantly, however, essential rescue services can benefit from flood, fire, and medical emergencies.

Many authors acknowledged that UAM could safely and efficiently integrate with current urban mobility services. Several recent examples are available. For instance, Airbus revealed “EMS Airbus” for emergency medical services. The “EU-Funded AiRMOUR” project lays the path for manned and unmanned emergency medical services to fly in the air (Airbus, 2017). In turn, “Air Insight Group Services” used drones for delivery and “Uber Copter” to provide flights from Lower Manhattan to JFK. The typical cost of an 8-minute one-way flight is between \$200 and \$225 per person, including private ground transportation on both ends of the journey (*Uber Copter to Offer Flights From Lower Manhattan to J.F.K. - The New York Times*, 2019)(See figure 2.2).



EMS Airbus
<https://www.airbus.com/helicopters/civil-missions/ems.html>



EU-Funded AiRMOUR
<https://www.unmannedairspace.info/latest-news-and-information/eu-funded-airmour-project-paves-way-for-flying-manned-and-unmanned-emergency-medical-vehicles/>



AirInsight Group Services
<https://airinsight.com/uam-insight-3-october-2019-ups-drone-delivery-now-an-airline/>



Uber Copter to Offer Flights From Lower Manhattan to J.F.K.
<https://www.nytimes.com/2019/06/05/travel/uber-helicopter-nyc-jfk.html>

Figure 2.2 Examples of UAM services

In Europe, the UAM initiative is being supported by the Commission (2018) as part of the European Innovation Partnership in Smart Cities and Communities (EIP-SCC). Simultaneously, the US National Aeronautics and Space Administration (NASA) is developing a framework to integrate UAM airspace studies in the USA to encourage other partners and stakeholders to collaborate on their investigations to increase understanding and knowledge base of the research findings (Thippavong et al., 2018).

A review of the industry revealed some current and potential players in the UAM landscape. Participants include established aerospace companies such as Bell Helicopters, Boeing, and Airbus and well-capitalized companies not traditionally in the aviation business, such as Uber and Larry Page's 3 KittyHawk, and startups such as Joby and Terrafugia. Many people point to the success of the Airbus subsidiary Voom, which operates an app-based on-demand helicopter service in So Paulo, Brazil. "The world's first truly on-demand helicopter booking platform," they claim. With Voom, you can book a helicopter ride for up to 80% less than

traditional helicopter services. Uber has taken some practical steps toward enabling UAM operations in the first place. The company has formed partnerships with various stakeholders, including aircraft and battery manufacturers, real estate companies, cities, and charging station manufacturers, to create a network that allows future customers to access urban air transportation easily. By 2023, they hope to be running full-scale operations. Soon, the Emirate of Dubai intends to launch an air taxi service. Dubai's Road and Transit Authority (RTA) recently flew the Volocopter 2X without passengers to demonstrate how it works. The New Zealand government has partnered with Zephyr Airworks to create a path to certification for Kitty Hawk's Cora aircraft. Kitty Hawk chose New Zealand's Civil Aviation Authority as a launchpad because the country has a dynamic economy and "the respect of the global regulatory community." This collaborative effort hopes to be operational within three years. The White House report that launched the UAS Integration Pilot Program includes policy language to encourage the safe development of a UAS application involving human transportation. The UAS IPP can be used for a variety of purposes. Some may propose an urban air taxi application that aligns with UAM's vision (Lascara et al., 2018).

The following section emphasizes the systematic review's need and importance briefly.

2.3. WHY THE SYSTEMATIC STATE OF THE ART?

As UAM is a new study area with much potential for expansion, it is critical to assess existing scientific research contributions in the literature to develop an efficient business model. Therefore, we conduct a bibliometric analysis, a popular and thorough methodology for studying and analyzing significant amounts of scientific data. It makes it possible for us to dissect the evolutionary subtleties of a particular field while also providing insights into the recent developments. Bibliometric analysis can assist researchers in getting over their apprehensions about dealing with large amounts of bibliometric data and advancing aggressive

retrospectives of their respective research fields. Bibliometric analysis can be classified into science mapping and performance analysis. Performance analysis considers the contributions of research components, i.e. (authors, institutes, countries, citations, etc.), while science mapping considers their relationships, e (keyword co-occurrence, co-author co-occurrence, etc.).

Researchers use bibliometric analysis for several purposes, including identifying the latest advancements in articles and journals, collaboration trends, and examining the philosophical underpinnings of a specific domain in the existing literature (Verma & Gustafsson, 2020).

Moreover, the introduction of scientific databases, i.e., Scopus and the Web of Science, has acquired extensive bibliometric data. The development of bibliometric analysis tools such as Gephi, Leximancer, and VOSviewer has effectively analyzed such data, resulting in a recent upsurge in scholarly interest in bibliometric analysis (Donthu et al., 2021).

The adopted methodology, a systematic state of the art, will be framed in the following section. The resulting analyses provide stakeholders with meaningful insights to assess UAM demand based on current research trends and associated barriers and challenges.

In the next section, we will use the VOSviewer software and the WoS analytic feature to do a systemic state-of-the-art (bibliometric analysis) to find and analyze current research areas and their barriers and challenges.

2.4. METHODOLOGY OF SYSTEMIC STATE OF THE ART

In this section, a 4-steps methodology is adopted for an assessment of UAM current research trends, based on searching the most frequently used keywords, as suggested in (Tomaszewska & Florea, 2018): (i) selection of the research areas, (ii) definition of the search period and the type of document, (iii) bibliometric analysis, and (iv) analysis of co-occurrence.

1. *Selection of the research criteria.* At this step, we search for scientific articles recorded in the Web of Science database (WoS). We are combining the most relevant keywords related to the topic, i.e., urban air mobility, air taxi, air ambulance, emergency evacuation air service, medical emergency air service, eVTOL (electric Vertical Takeoff and Landing), on-demand urban air mobility, manned air vehicle (MAV), unmanned air vehicle (UAV). These keywords were combined using the logical operator OR, double quotes, and * asterisk operator to get more accurate required results.
2. *Definition of the search period and the type of the document.* At this stage, we have chosen the range from 1975 to 2021. We found 1,012 documents in the WoS core collection database. The resulting search showed that the first article was published in 1979, titled “HELICOPTER AIR AMBULANCE IN A RURAL-COMMUNITY” in an “EMERGENCY MEDICAL SERVICES” Journal, written by Hill, Martin P. Then, we exported these complete records and cited references into CSV file format.
3. *Bibliometric analysis.* At this step, using the file obtained previously as input, we used both WoS and VOSviewer analytical tools. For a further comprehensive analysis, i.e., count of publication year-wise, a sum of citations year-wise, the most popular subjects in articles, countries, and organizations are more active in this research area and current research areas associated with UAM.
4. *Analysis of co-occurrence.* At this step, using the same input file, we used the VOSviewer software. A network visualization and exploration software tool allows users to construct maps based on network data. Indeed, the software assists in creating and visualizing a map of keywords and the links between them, taken from the volume of scientific publications in the input file (extracted from the WoS database). Networks of scientific publications, journals, researchers, affiliations, countries, keywords, and concepts are all examples of constructed maps. Co-authorship, co-occurrence, citations

(including co-citations), and bibliographic connections can all be used to connect items.

After applying this methodology, we obtained several meaningful and interesting insights discussed and analyzed in detail in the following section.

2.5. KEY FINDINGS OF SYSTEMATIC STATE OF THE ART

This section presents the study's key results and a detailed analysis of several UAM research areas, the associated barriers, and challenges for UAM implementation. We will first start with the main tendencies presented in the following sub-section.

2.5.1. Main tendencies of the UAM research activities

It is worth mentioning that most authors consider UAM as a new and untested concept. Figure 2.3 clearly shows that the trends of scientific publication are increased exponentially in recent years. When the number of papers published in each successive year is analyzed, a modest rise in interest can be seen after 2001 and a substantial increase after 2015. Since 2015, the number of articles in the WoS database on the studied topic has surpassed 50 practically every year and has exceeded 100 in the last three years. It is noteworthy to note that in the first five months of 2021, there have already been over 50 publications.

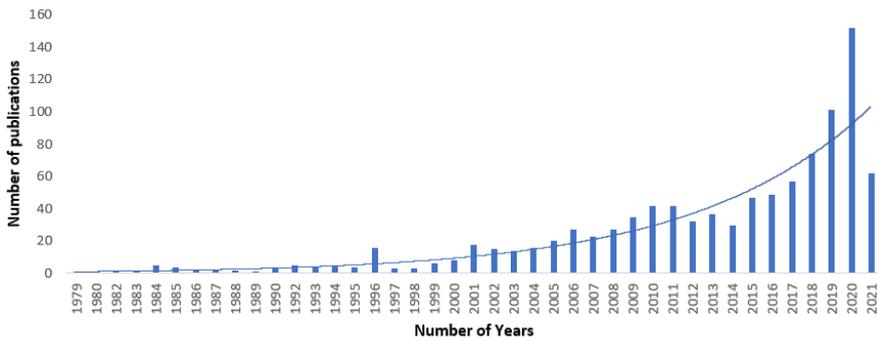


Figure 2.3 Publications year wise

As a result, Figure 2.4 illustrates that the sum of citations also increased as the number of publications increased over time. Only in 2020 will it have about 1200 citation indexes, indicating a solid research collaborative culture in this field. It is interesting to note that there have already been over 400 citations in the first five months of 2021. Although the total number of publications in the studied topic is relatively small compared to other research areas, it is clear from the above trends that the subject is gaining importance, offering real opportunities to leverage investment potential.

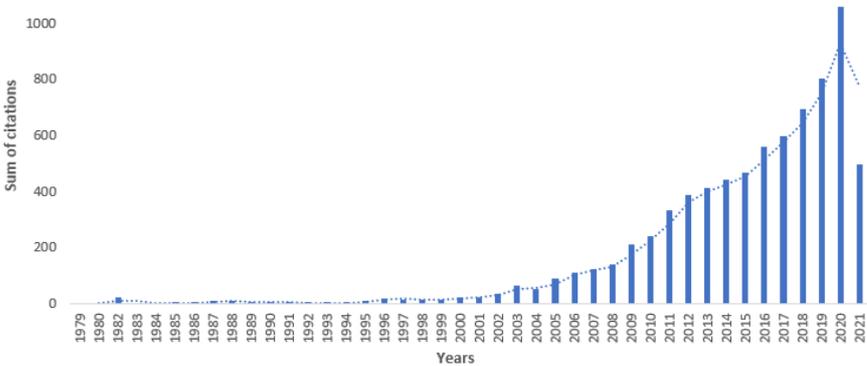


Figure 2.4 Sum of times cited by year

Figure 2.5 shows the five most common study fields of publications, which is an interdisciplinary research topic. “Engineering” is the most predominant field, with more than 200 articles, followed by “Computer Science” and “Automation control systems” (over 50). Surprisingly, “Transportation” is not the predominant field of research; this shows that UAM development is not just a matter of mobility offers

or services and requires addressing multidisciplinary challenges and barriers (as stated above).

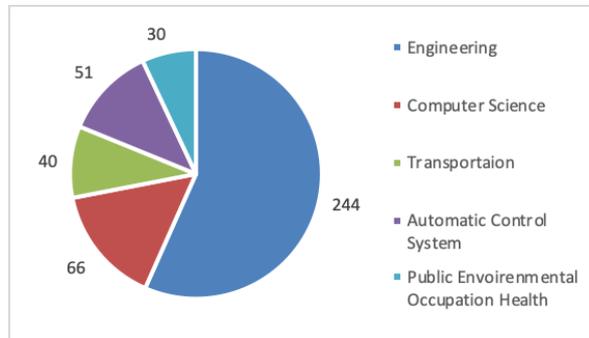


Figure 2.5 The top 5 fields of research

Figure 2.6 illustrates the top 15 countries and organizations that are actively engaged in research activities in the field of UAM. The graph shows that the USA is currently ahead of the rest of the world. However, China, the United Kingdom, Turkey, Germany, and other European and Asian countries, are aware of the relevance and importance of this research subject and are following the lead of the United States.

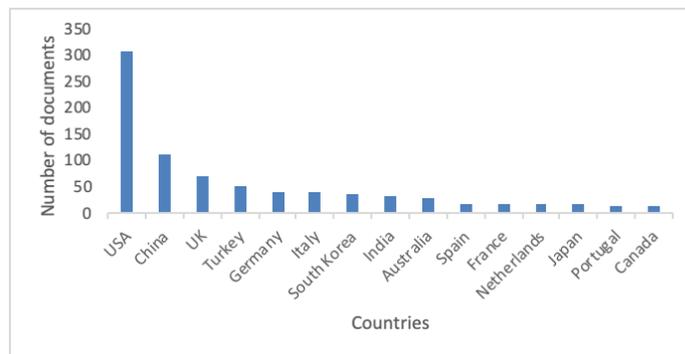


Figure 2.6 Top 15 Countries and regions

Figure 2.7 shows the list of the top 10 institutions enthusiastically participating and investing funding to promote scientific research in UAM: most organizations actively involved in this field are in the USA (e.g., NASA and Johns Hopkins University).

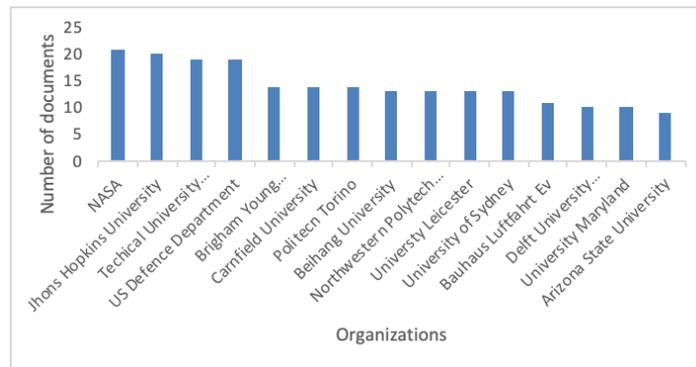


Figure 2.7 Top 10 organizations

Table 2 presents the top 5 cited papers about their respective domains and highlights the main issue addressed.

Table 2.1 The top 5 cited publications

Reference	Domain/Issue	Times Cited
Nigam N, Bieniawski S, Kroo I, Vian J. (2012) https://doi.org/10.1109/TCST.2011.2167331	Surveillance/ Control of Multiple UAV's	212
Maguire BJ, Hunting KL, Smith GS, Levick NR (2002) https://doi.org/10.1067/mem.2002.128681	Emergency Medical service/ estimate the occupational fatality rate	192
De Marqui Junior, C., Erturk, A., & Inman, D. J. (2009) https://doi.org/10.1016/j.jsv.2009.05.015	Energy harvesting/ converting ambient vibration energy to usable electrical energy	182
Han, Z., Swindlehurst, A. L., & Liu, K. J. R. (2009) https://doi.org/10.1109/TVT.2009.2015953	Wireless ad hoc networks/ Optimization location and movement of UAV's	161
Bledsoe, B. E., Wesley, A. K., Eckstein, M., Dunn, T. M., & O'Keefe, M. F. (2006). https://doi.org/10.1097/01.ta.0000196489.19928.c0	Health/ Transport trauma patients	104

Once again, transportation issues are not among the topics addressed in the most cited articles. Instead, specific domains such as unmanned air vehicles, emergency, energy conversion, UAV location optimization, and health are more addressed. It further demonstrates UAM development's multidisciplinary complexity, requiring appropriate guidance to achieve successful implementation, as envisioned in this study.

surveillance, emissions, numerical simulation, real-time systems, mission planning, and intelligent sensors were studied. From 2015 to the present, this network map highlights current research areas in yellow, which includes, i.e., vehicle design and manufacture, regulations, infrastructure, operations, integration with other transportation modes, public acceptance, simulation and modelling, demand estimation, and prediction.

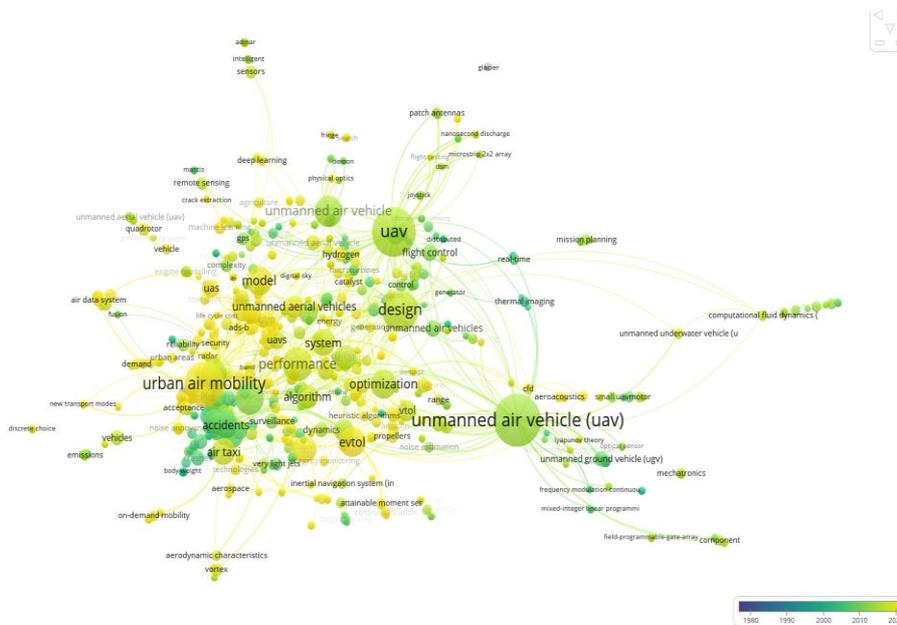


Figure 2.9 Highlighted UAM research trends over time

We identified various active research areas through these results, which are discussed in depth in the following. Indeed, while analyzing the relationships between keywords, we identified a few significant research areas for successful UAM implementation. Vehicle design and manufacturing, Regulations, Infrastructures, Operations, Integration with other transport modes, Public acceptance, Simulation and modelling, and demand prediction (See figure 2.10).

Vehicle design	<ul style="list-style-type: none"> • <i>Technological requirements</i> • <i>Classification</i>
Regulatory aspects	<ul style="list-style-type: none"> • <i>Certifications</i> • <i>Policies</i>
Infrastructure requirements	<ul style="list-style-type: none"> • <i>Ground infrastructure</i> • <i>UAM traffic management</i>
Operations	<ul style="list-style-type: none"> • <i>Inter or Intra-city</i> • <i>Market actors</i>
Potential users and public acceptance	<ul style="list-style-type: none"> • <i>Choice factors for UAM</i> • <i>Socio-demographic factors</i>
UAM simulation and modeling	<ul style="list-style-type: none"> • <i>Infrastructure requirements or operational constraints(e.g. identifying suitable locations for UAM stations etc.)</i> • <i>Integration of UAM within existing public transport</i>
Demand	<ul style="list-style-type: none"> • <i>Viability</i> • <i>Demand-supply ratio</i>

Figure 2.10 UAM current research areas

Vehicle design and manufacturing. A vital component of a successful UAM transport system implementation appears to be designing and constructing suitable VTOL aircraft. Simultaneously, prospective suppliers and the aviation industry continue to see it as a viable and profitable option. Performance benchmarks were used for electrical power transmission, distributed propulsion, and systems battery storage. (Shamiyeh et al., 2018). Two fundamentally distinct eVTOL configurations were examined for their features and work performance. NASA commissioned a market report to predict that air taxis and airport shuttles will be in high demand in the United States in the immediate future, with 55,000 regular trips operated by 4100 aircraft. New aircraft must be created to meet improved performance, service, and production demands to serve this market. The specifications and boundary limits for UAM aircraft design are many and, in some situations, new as compared to conventional aircraft design. UBER's Elevate whitepaper is the most wide-ranging collection of uniform standard requirements for air taxis currently available (Holden & Goel, 2016).

Furthermore, because public acceptance is strongly dependent on low noise emissions, their demand would directly impact a UAM vehicle's success or failure. UAM noise characteristics should blend in as feasible with the current urban

background soundscape to guarantee public acceptance. It corresponds to a decibel level that is 15 decibels lower than that of a typical light helicopter (Uber, 2018).

Regulations. Proper regulations, which comprise well-defined certification criteria and laws controlling the UAM market itself, are critical research areas for a successful UAM launch. Safety and certification criteria would obstruct commercial aviation operations in urban areas. The European Aviation Safety Agency (EASA) and the Federal Aviation Administration (FAA) in the United States are currently debating certification regulations. EASA is also working on airspace rules, with the first draft of a structure released in mid-2020. The proposed UAVs (drones) laws should establish the types and modalities of airspace, while the U-Space definition should determine airspace access (SESAR Joint Undertaking, 2017). U-space serves as a backbone for ordinary unmanned aerial system (UAS) and UAM operations along with connecting manned aviation, air navigation service (ANS) authorities, air traffic management (ATM), and providers. On the other hand, predicting regulatory reactions to introducing a new mode of transportation is complicated.

Infrastructure. Ground infrastructure, ATMs, and sufficient communication infrastructure are required for UAM (Straubinger & Rothfeld, 2018). Most UAM vehicles now under development, according to the ground infrastructure layouts and designs and effective UAM operations, will need specialized UAM infrastructure. To determine the highest chance of public acceptance depends on the best use of available land to build suitable sites for UAM (Cohen, 1996). Specific regulations on how air traffic control would manage those sites, the consequent impact on the vicinity, and how the local recipient community will view this, whether the infrastructure can handle it or not (Vascik & Hansman, 2017).

Regarding land use, (Rothfeld et al., 2020) conducted evaluation studies of how local people would be affected by the services and what impact the city would potentially have on the city itself. The necessary ground infrastructure location selection is represented in (Fadhil, 2018) to discover the ideal sites for UAM

stations, combine demand and supply-side criteria. There are several aspects to examine further, including work density, median income, current noise, population density, and ground-based transportation connectivity. According to Fadhil's respondents, the most significant aspect is the proximity to large transportation hubs, i.e., airports or major train stations. UAM ground infrastructure can be installed on barges over water, roofs, on top of existing ground transportation infrastructure, and within highway intersections. Various vertiport topologies are presented, such as pier topologies, linear and satellite utilizing current heliports as a study platform (Vascik & Hansman, 2019). Nonetheless, the amount of space required for UAM infrastructure could be a major bottleneck for vehicle throughput. An evaluation process is proposed in (Mueller et al., 2017) that includes an evolutionary discussion of potential starting points for on-demand mobility, as well as the following airspace integration principles:

- It does not necessitate the installation of extra air traffic controller (ATC) infrastructure,
- ATC is not burdened with additional tasks,
- Traditional airspace users are not hampered in their activities,
- Will fulfill all applicable safety standards and levels,
- Operational scalability will be prioritized,
- Wherever possible, flexibility will be allowed, although structure will be required.

Operations. UAM supports both intra-city and inter-city flying operations. For instance, short take-off and landing (STOL) services are adequate for intra-city applications. In contrast, electrical vertical take-off and landing (eVTOL) capabilities are required for inter-city services (Rothfeld et al., 2020). Aside from that, in an intra-city environment, the necessity for low-noise propulsion and autonomy is greater. Whether carried out in private or public transport, on-demand or scheduled activities distinguish the various operational principles (Nneji et al., 2017). The UAM industry is made up of several sub-markets and market

participants. Two of the many potential actors to consider are the service providers and the vehicle owners.

Integration with other transportation modes. UAM is not supposed to be a public transportation system. As a result, seamless integration with current forms of mobility, particularly public transportation (PT), is essential. However, since UAM is expected to consume significantly more energy than ground transportation (Patrick M. Condon, 2009), the capacity limiting factor is predicted to be vertiports (Ploetner et al., 2020). When it comes to the funding structure of most transportation options, policymakers should strive for UAM structures that complement rather than compete with PT. The elimination of good public transportation networks is likely to diminish city transportation efficiency and is incompatible with long-term sustainability goals. A similar debate is happening in the field of self-driving cars, which is likely to have substantial ramifications for other modes of transportation, particularly public transportation (M Kamargianni & Matyas, 2017). Transfer people from rural areas to the city's public transportation service area, may be a viable choice for effective integration. This could be particularly useful in geographically separated places with little ground connectivity, i.e. islands, mountains, and areas separated by lakes and rivers. Another option is to give service when public transit is unavailable or inconvenient. From fully integrated ticketing to merely permitting physical transfers across modes, the degree of integration might vary.

Public acceptance. One of the essential considerations in debates about UAM implementation is public acceptance. The vehicles' type and amount of noise and the time of day and height at which they fly are essential considerations for public acceptance (Yedavalli & Mooberry, 2019). Mode preference competition with private cars, public transit, and self-driving taxis in the context of UAM service is presented by (Fu et al., 2019) and used multinomial logit models to show that safety, trip duration, and cost of travel were some of the most important factors influencing the public's decisions. Age, salary, household composition, and gender are among socio-demographic factors influencing mode choice. UAM is expected

to drastically reduce travel time, especially on lengthy routes where defined time demands for boarding and deboarding are no longer important. The probit model was utilized by (Eker et al., 2020) to analyze how demographic factors and prior travel habits could affect public views of the UAM's aids and downsides. Many other variables, such as gender, age, income level, educational history, and regular driving patterns, were considered statistically significant. A case study of Upper Bavaria in Germany (Al Haddad et al., 2020) provided a framework for selecting predictors for a multi-criteria analysis of UAM evaluation. The most critical factor impacting acceptability was security, followed by cost, duration, and service qualities. In addition, consumer and public acceptance are contingent on providing a transparent service and technology and educating individuals on how to assure data privacy and safety and protection for both system non-users and users.

Simulation and modelling. Simulation and modeling research is still in its early phases. Research is underway on infrastructure specifications and organizational constraints (Rothfeld et al., 2019). UAM mode will be introduced to be integrated into transportation simulation systems, specifically MATSim (Horni et al., 2016), “an open-source simulation software for building large-scale agent-based transport simulations.” It is also interesting to see a first analysis of how the systems performed in an agent-based simulation. MATSim's features are easily expandable, agent-based, ideal for individualistic transportation options, and particularly essential elements that encourage the use of UAM transportation models and support user-specific outcome assessments (Balac et al., 2018). An overview of these areas has been provided in (Rothfeld et al., 2020), focusing on the principal acceptance criteria, specific modeling approaches, perception of the potential passengers' worth of time, and possible effects of welfare and UAM implementation those using the systems. On-demand UAM is a new means of transportation, and it can be integrated into traditional transportation simulation systems (Balac et al., 2019) to extend these modelling capabilities by permitting the design of UAM stations and flight networks. However, for eVTOL operations, UAM stations in transport simulation currently require pre-defined locations. A methodology is proposed in

(Vascik & Hansman, 2017) and (Fadhil, 2018) to identify the best locations for vertiports or vertistops. These studies use present helicopter pads, limited fly regions, and population density in the case of Los Angeles/California.

Demand estimation and prediction. A qualitative approach to demand estimation is necessary for the scenario of new or future on-demand services like UAM. However, UAM services are equipped with sensors and enabled with IoT; they provide a vast amount of data, i.e., journey, GPS traces, location, weather conditions, time of pickup/drop-off, number of passengers traveled, and battery efficiency (Rajendran & Shulman, 2020). Processing and then analyzing these data may allow extracting insightful information for decision-makers.

Our analysis of these current research areas identified significant barriers and key scientific challenges that must be resolved to deploy UAM, as detailed in the following sub-section successfully.

2.5.3. Barriers and scientific challenges for UAM implementation

This section examines the potential barriers and associated challenges for UAM adoption. According to a NASA report, these barriers are mostly related to economics, safety and security, demand, and public acceptance (NASA, 2018). Detect-and-avoid capabilities, Unmanned Traffic Management (UTM), emergency procedures, data security, operator certification, flight over people, regulatory restrictions, weather mitigation are examples of safety and security barriers. Economic barriers include yearly reductions in trip costs, initial infrastructure expenditures, and annual infrastructure expansion. Proven safety records, pilot training, and noise and visual interruption are all examples of public acceptability barriers. Demand-related barriers include competing modes (train, bus, bike, ride-sharing), an annual increase in urban passenger trips, or air market share as a percentage of total urban passenger travels. These barriers are linked with market viability and important events or tipping moments that indicate viability (Mayakonda et al., 2020). Several stakeholders are tasked with removing these

barriers, including government planning agencies, regulators, and manufacturers. Such stakeholders must know forecasted demand for UAM to plan for and progress toward UAM profitability properly. Strong demand for UAM is projected, as indicated by the significant amount invested in developing vehicle technology.

Along with these barriers, there are several key scientific challenges to solve to adopt UAM successfully, i.e., Ride-matching, optimizing fleet procurement and pricing strategy for on-demand mobility, Infrastructures, Dynamic routing and integration of ground and UAM transportation scheduling, Pilot and pilotless training, and scheduling, Leveraging a MaaS (Mobility as a Service) and Demand prediction.

Ride-matching. Refers to a procedure of assigning one of the vehicles to passengers on their availability. For any ride-hailing on-demand service, efficiently matching passenger demand with the availability of the vehicle is a big challenge, and it is also essential to reduce client wait time and empty journeys on the road or in an air taxi (Rajendran & Shulman, 2020). The type of ride-hailing request determines another challenge of ride-matching. For example, the vehicle carries a single client from one location to another on the same journey. Several specific client requests co-occur with close to origin and destination locations.

Optimizing fleet procurement and pricing strategy for on-demand mobility. The pricing strategy for an on-demand service is a critical issue since it directly affects income and balance of the supply and demand (Saharan et al., 2020). The cost-cutting problem of getting the optimal fleet of vehicles for each configuration is also linked to the UAM domain. Since UAM vehicles take a long time to manufacture, forecasting demand before launching service is critical, unlike regular on-road ODM services. The second challenge is offering fare to the traveler as pricing, e.g., the base charge, duration, distance, booking, promotions, and ridesharing discounts, all of which influence the trip cost.

Infrastructure. It includes charging, maintenance, and multiple takeoff and landing capabilities. It is a huge challenge to identify the best location and assess the size of these amenities, particularly vertiports (Rajendran & Zack, 2019). Thus,

before choosing a suitable location, it is essential to figure out how many sub-stations are necessary for each of these types and the arrangement of these services. However, there are various conflicting elements to consider from customer demand while choosing a facility for effective network operations. For example, the operational cost, public access, demographic coverage, and construction feasibility are just a few of the critical criteria related to UAM infrastructures (Farahani et al., 2010).

Dynamic routing and integration of ground and UAM transportation scheduling. Developing an effective dynamic routing algorithm that bridges the gap between trip cost, client waiting time, and vehicle idle time is an enormous challenge. Although, many dynamic routing algorithms have been created in recent years to detect the location with the help of the GPS (Global Positioning System) (Wang et al., 2020). Another challenge is to provide cost-effective network operations; a combined scheduling approach must be used to integrate both modes of transportation.

Pilot and pilotless training and schedule. Due to the long training period and high human cost of UAM, determining the ideal number of pilots is difficult. Human resources costs are the aviation industry's second-largest expense. Pilots are assigned based on aircraft maintenance schedules, remaining shift time, and vehicle charge availability. As a result, research into incorporating the prospects mentioned earlier for pilotless VTOL designs is a big challenge. It might be pursued while considering aspects like the willingness of customers to fly in an unmanned aircraft.

Leveraging a MaaS (Mobility as a Service). MaaS is a multimodal transportation service that is integrated, smooth, and supplied through a digital end-user interface in which diverse mobility providers are encouraged to collaborate and interconnect to work as an ecosystem (Maria Kamargianni et al., 2016). Thus, integrating a new mode, such as UAM, into intermodal transportation may become an immense challenge for the future.

Demand Prediction. Several challenges pertain the demand prediction. The first one is that the UAM industry lacks historical data. Therefore, it is difficult to

predict demand analytically. The second is based on capital requirements and operating expenses, which are expected to rise in the near future, putting a strain on the consumer base. The third one is that public perception of UAM is difficult to determine based on factors like safety, boarding, screening, long-distance traveling choice (NASA, 2018). Thus, using traditional public transportation data, such as taxis, buses, and trains, to build more effective artificial intelligence-based demand prediction models is a complex and intriguing future challenge.

CONCLUSION

This chapter discussed the latest research trends in urban air mobility using the Web of Science database that showed exponential growth in scientific contributions, including vehicle design and manufacture, regulations, infrastructure placement, operations, integration with other modes of transportation, public acceptance, simulation, and modelling, demand estimation. According to this literature review, future challenges to be solved include ride-matching, optimizing fleet procurement and pricing strategy for on-demand mobility, infrastructure renewal, dynamic routing and integration of ground and UAM transportation scheduling, pilot and pilotless training and scheduling, leveraging MaaS, and demand prediction. The study also showed that this is a new subject field, and there is still much potential active research required for the successful implantation in megacities around the world. We believe that demand prediction is a critical step towards successful deployment to guide decision-makers. It allows analyzing the market viability and gives insight into service providers who may want to optimize their investments. This related research work will be performed in the next chapter.

3. DEMAND PREDICTION FOR URBAN AIR MOBILITY

INTRODUCTION

In Chapter 2, we reviewed the relevant research work undertaken in the field of UAM and showed that some scientific challenges are yet to be solved, especially to cope with the growing need for on-demand services. In order to provide valuable advice to policymakers (public authorities) and service providers, we have also concluded that the viability of the market needs to be explored. To this end, this chapter investigates demand prediction in the context of UAM. In particular, we consider the hypothesis of taxi-based air mobility, using a benchmark dataset for ground taxis provided in the literature. The idea is to propose a predictive model that will be extended to realistic air transport scenarios, considering the transfer learning approach. This chapter is organized as follows: Section 3.1 discusses the machine learning pipeline concept and theoretical background of the main studies on air taxi demand prediction available in the literature. Section 3.2 presents a description of the dataset used in this study. Section 3.3 gives the detailed analysis of UAM demand prediction using different state-of-the-art Deep Learning (DL) approaches whose respective performances will then be compared. Section 3.4 exposes and discusses the experimental results. Section 3.5 describes the principle of transfer learning to propagate the knowledge obtained from the benchmark dataset to any model trained on the new UAM dataset. Finally, we conclude this chapter with a summary of important insights.

3.1. THEORETICAL BACKGROUND

This section describes the theoretical background of demand prediction. Before reviewing detailed studies on UAM demand prediction, it is important to understand the machine learning pipeline concept, which includes many steps for predicting demand.

3.1.1. Machine Learning Pipeline

A machine learning pipeline is a way for formalizing and organizing the processes required to deploy a machine learning model. Machine learning pipelines are sequential steps that handle everything from data extraction and preprocessing to model training and deployment.

The one presented in this section is concerned with supervised learning, using tabular data, as illustrated in Table 3.1. In this table, X_j ($j=1,2,\dots$) represents a given input feature, y represents the output (the variable to predict), a continuous variable in our case study.

Table 3.1 General structure of tabular data in supervised learning

Samples	X1	X2	...	y
1				
2				
...				

The following steps have to be followed to accomplish a demand prediction task. It starts (as shown in figure 3.1) with step 1, data acquisition that includes data collection from different sources, e.g., sensors, physical measurements, analysis (physical, chemical, etc.). Since urban mobility uses and generates a huge amount of data, we can consider big data, real-time data, and velocity of data as critical aspects while storing this huge data. Then perform some data fusion techniques to build a dataset for the next step, 2, data preprocessing. First, we clean

the data to detect and fix incorrect or missing values in the data pre-processing step. For example, we may discover many data anomalies with zero, negative, or illogical values. We can also do feature engineering in this step which means we can perform some calculations to create a new dataset feature. This step allows putting the data in a format compatible with the machine learning algorithms used in step 3. The third step of the pipeline consists of building or using an appropriate machine learning model, e.g. (SVM, KNN, Random Forest, etc.), which depends on many parameters like type of data (image, text, voice, time-series, etc.) In step 4, these models are trained and tested by setting different tuning hyperparameters to achieve an efficient performance. For example, in this study, we will use the following hyperparameters:

Embedding size: An embedding size is a relatively low-dimensional space into which you can translate high-dimensional vectors. Embeddings make it easier to do machine learning on large inputs like sparse vectors representing words.

Hidden layers: Hidden layers are the layers between the input layer and output layer.

Batch size: Mini batch size is the number of sub samples given to the network after which parameter update happens.

Learning rate: The learning rate defines how quickly a network updates its parameters.

Epochs: The number of epochs is the number of times the whole training data is shown to the network while training.

In step 5, we used different evaluation metrics to evaluate the performance of implemented models. When evaluating machine learning models, choosing the right metric is also critical. It aims to estimate the generalization accuracy of the future (unseen/out-of-sample) data. For example, for the classification problem, we have metrics such as confusion matrix, precision, recall, F1 score, Log loss, and for the regression problem, we have Mean Absolute Error (MAE), Mean Square Error (MSE), and Root Mean Square Error (RMSE). This study uses RMSE as an evaluation metric to evaluate performance.

The RMSE is the most commonly used metric for regression tasks (see equation 3-1). This is calculated by taking the square root of the average squared distance between the actual and predicted scores.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (3 - 1)$$

Here, y^i denotes the true score for the i^{th} data point, and \hat{y}^i denotes the predicted value.

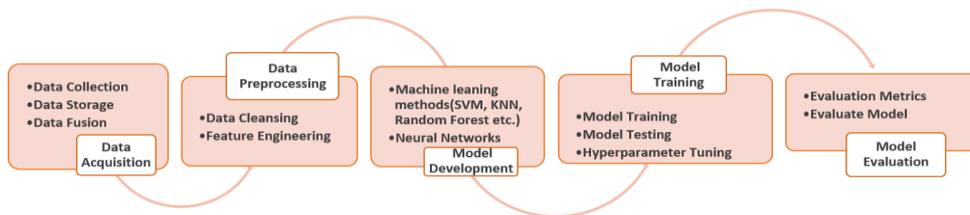


Figure 3.1 Machine learning pipeline

3.1.2. Machine Learning-Based Studies On-Demand Prediction

Predicting demand for UAM has proven difficult because the UAM sector lacks historical data. Besides, the other challenges are capital requirements; in the near-term market. Operating costs are likely to be high, influencing the consumer base. Public perception of air taxis is difficult to determine based on factors, i.e., customer safety, pre-boarding screening, long-distance travel choice, etc. (NASA Mobility UAM Market Study, 2018). Therefore, the objective of this work is to understand the value of demand to the development of UAM and develop a

general model to predict more accurate demand for UAM using available taxi data. The following research question is pursued to achieve these objectives:

How will demand prediction help for UAM business model implementation decision-making for different stakeholders on available taxi data?

To answer this research question, we will first discuss various approaches to solving the aforementioned scientific challenges, described in more detail in the following sub-section.

Several approaches have been proposed to resolve the aforementioned inherent difficulties and predict customer demand for UAM. Two of these approaches have been discussed in the literature (i) using qualitative methods to gain the subjective opinions of potential customers and experts, such as focus groups and scientifically structured surveys (ii) using quantitative methods to use other mobility provider's historical data, i.e., taxi service, ridesharing service, etc.

Since most of these studies in scientific literature used historical data to predict demand for UAM, very little qualitative research is currently available to predict demand for UAM. While discussing the qualitative approach (Garrow et al., 2018) conducted a survey, and their findings show that the rich people will first adopt UAM because they give more value to time over the cost. One more significant result is that the top three business sectors for attracting clients are inter-city transfers, airport transfers, and frequent travellers. Other surveys are also done by (Garrow, Binder et al., 2018) to estimate consumers' willingness to pay for air taxis in densely populated areas of the US. A sampling strategy (Garrow et al., 2019) is used to construct a 100-question survey that considers the impact of several constructs (e.g., lifestyle, personality, perceptual, attitudinal, sociodemographic). These questionnaires are adopted and used a discrete choice model by (Boddupalli, 2019) to collect the opinions of 2,500 passengers from five major cities of the USA and predict their perception regarding UAM. The study's main finding is that air taxi demand is very segmented, and the most influential factors were trip time and cost. At the same time, income had no significant influence on planning. The commuting mode can also indicate reasons that impact

demand for new means of transportation like UAM. In an urban setting, economic considerations like trip fares and individual income are also main indicators of mode preference.

Interestingly, the preferences of higher-income people are mixed, with some preferring private vehicles and some preferring on-demand taxis (Sivasubramaniyam et al., 2020). Some other impacts are listed in the scientific studies, i.e., parking space and crowding (Ye & Titheridge, 2017). In addition to economic factors, age and gender affected transportation modes. According to the study of (Chee & Fernandez, 2013), males use more public transport than females. As an age example, (Tyrinopoulos & Antoniou, 2013) was discovered that commuters aged 35 to 44 had a higher preference for driving their vehicle.

This qualitative research will determine infrastructure requirements, such as the location of these vertiports, the number of vertiports required, pricing strategies for fleet procurement, and the number of air taxis to be procured or manufactured during the UAM implementation process, among other things. The fact that these high-risk actions are expected to have a negative impact on revenue and efficiency means that they will have an impact on UAM service providers' medium to long-term strategies.

Regarding sustainable development goals (SDGs) discussed in the literature, (Mudumba et al., 2021) presented an emissions computation framework for predicting CO₂ emissions for any UAM trip. The framework calculates trip emissions using UAM for part or all of the journey and compares them to trips made by electric cars. The results show that a region's grid emission index significantly impacts how much CO₂ is released into the air when an electric vehicle is used in the Chicago and Dallas metropolitan areas. As of the region's low grid emission index, trips involving electric vehicles such as non-autonomous electric vehicles (BEV) and UAM are more environmentally friendly than gasoline automobiles in the Chicago region. Because of the high grid emission index in the Dallas region, the benefits of using UAM are not as noticeable as the benefits of driving a gasoline automobile in this region.

Since UAM services are in the experimental stage, it may be possible to use analytical methods used to predict demand once these services are operational. Few studies use traditional transportation mode data to predict future demand. The machine learning method is applied to time-series data by (Moreira-Matias et al., 2013) and (Jiang et al., 2019) to predict the count of short-distance passenger requests (5–60 minutes) for online car-hailing services based on the LS-SVM model. However, since they do not use a trend model, it is difficult to improve it further. Two deep learning architectures (Rodrigues et al., 2019) are used to combine text knowledge with time-series data from multiple sources and use word embeddings, convolutional layers, and attention mechanisms to increase prediction accuracy. The first to use a gravity model to forecast long-term consumer demand for UAM was used (Becker et al., 2018). They found 26 possible high-demand markets for UAM implementation worldwide based on eight socioeconomic variables. This research can be combined with other research, such as Uber Elevate, to evaluate additional criteria, such as potential customers or cost, to obtain more accurate results regarding potential markets. A multi-task deep learning (MTDL) model (Luo et al., 2020) is proposed to predict the demand for a short-distance taxi at the different zones, which can predict the volume of demand in numerous traffic zones in real-time. This model outperforms other prediction models by comparing the following evaluation metrics, i.e., MAPE, RMSE, R2, and MAE, due to its ability to dig the spatiotemporal characteristics in a large data sample. This research is only useful while predicting short-distance taxi demand; it does not apply for long-distance real-time taxi demand. To predict short and long-distance demand for air taxis, (Rajendran & Zack, 2019) proposed a generalized model based on standard taxi trip data. The first step is to estimate demand for air taxi services using two methodologies by selecting a small number of frequent taxi customers who want to use this service. The second method is to classify potential sites for locating air taxi infrastructure using a clustering approach combined with a multimodal transportation-dependent warm start technique.

Results show an effect of commuters' willingness to travel rates, demand contentment rates, and time-cost tradeoffs. The percentage of saved time and the rate of "willingness to fly" had no substantial effect on location decisions or the number of locations and suggested a thorough market study is needed to assess on-demand travel. Any service provider interested in entering the air taxi business might utilize the findings of this study as a decision-making tool. One of the study's limitations is the unavailability of data from other demand sources, i.e., Uber, Lyft, and other transport modes, e.g., buses, trains, and other transit services (Metro, tram, etc.). A discrete event simulation model was proposed by (Rajendran & Shulman, 2020), leveraging the six sigmas Define, Measure, Analyze, Design, and Verify (DMADV) methodology. The results show that the number of air taxis required to meet the demand for urban air mobility in New York City and all indicators has a linear impact on vehicle usage. Still, other indicators, particularly the seating capacity, are stable. The main failing of the study is the lack of data, and the latent demand that would emerge from the mature air taxi system was not considered. Machine learning algorithms (Rajendran et al., 2021) are used to predict the demand for air taxis at different times of the day in different traffic zones of New York City. There are two data sets used in this study. The first is ride-related and includes features like a month, weekday, and time. The second is weather-related, including temperature, wind, and visibility. Demand is predicted using machine learning algorithms such as logistic regression, artificial neural networks, random forests, and gradient boosting. The experiments show that the gradient boosting algorithm provides better prediction accuracy performance. In this study, MLAs are delimited to four well-known algorithms available in the literature. Based on these limitations, we will implement a deep neural network model in this research work to improve prediction performance.

3.2. DATASET OF THE CASE STUDY

We analyze our proposed approach using an expected potential demand because air taxi services are currently in the experimental stage and have yet to be launched in megacities. Therefore, we use a percentage of present normal taxi demand using the land taxi-based benchmark dataset to predict future demand for air taxi services. The Uber Elevate white paper information was used to create this demand segment (Holden & Goel, 2016), whereby the company discovered after conducting extensive market research. We examined 150,000 of the New York City (NYC) Taxi and Limousine Commission data records available online for our investigation.

3.2.1. Dataset Description

This section presents a detailed description of the datasets used in our experimental study. We used the New York City Taxi and Limousine Commission Trip Record Data dataset. This dataset contains records for each taxi journey, comprising pick-up and drop-off, date and time, pick-up and drop-off locations, trip lengths, categorized prices, rate kinds, payment methods, and driver-reported passenger counts (See Table 3.2).

Table 3.2 Dataset description

Feature variable	Value examples
Id : A unique identifier for each trip	1,2, ...
Vendor id : A code indicating the provider associated with the trip record	1, 2
Pickup date-time : Date and time when the meter was engaged	12/1/2020 0:07
Dropoff date-time : Date and time when the meter was disengaged	12/1/2020 0:18
Store and forward flag : This indicates whether the trip record was held in-vehicle memory before sending it to the vendor. Y=store and forward; N=not a store and forward trip	N or Y
PU Location ID : The pick-up location id	138
DO Location ID : The drop-off location id	263
Payment type : Card, Cash, etc. Numeric code indicating how the passenger paid for the trip. 1 = Bank card; 2 = Cash; 3 = No charge; 4 = Dispute; 5 = Unknown; 6 = Trip canceled.	1, 2, 3
Fare amount : Amount of charges in dollars	21.5
MTA tax : A tax of 0.50 USD MTA has triggered automatically according to the tariff displayed on the meter.	0.5 or -0.5
Tip amount : Amount to pay in terms of TIP	2.5
Tolls amount : Toll tax amount depends on the distance	6.12 or 0
Improvement surcharge : Constant surcharge amount	0.3
Total amount : fare amount+extra+mta tax+tip amount+toll amount+improvement surcharge	33.92
Passenger count : The number of passengers in the vehicle (driver entered value)	2
Trip distance : Duration of the trip in minutes	7.6

It should be noted that our case study is based on supervised learning. To that end, we should define, among the available variables, the one representing the output (y). The concerning output, in this study, is the “demand” that we need to predict. But, in the raw data, no information regarding demand is provided. Therefore, we should define one, which is explained in the next section.

3.2.2. Demand Calculation

In literature (Rajendran et al., 2021) uses the density of passengers requesting air taxi rides to travel to a specific location to calculate demand level.

Therefore, we use the same columns to calculate the demand ratio based on *passenger count* and *distance* (See Equation 3.2). The high ratio indicates high demand, and the low ratio indicates low demand.

$$Ratio = Passenger\ Count * Distance \quad (3.2)$$

In the next section, we prepare a detailed analysis of UAM demand prediction using different State-of-the-art Deep Learning (DL) approaches.

3.3. DEEP LEARNING-BASED IMPLEMENTED MODELS

Deep learning is a subfield of machine learning that deals with "artificial neural networks," which are algorithms inspired by the structure and function of the brain. In other words, it mirrors how human brains work. Deep learning algorithms are structured similarly to the nervous system, with each neuron connecting and passing information. Deep learning models work in layers, and a typical model at least has three layers. Each layer accepts the previous information and passes it on to the next one. Deep learning models tend to perform well with the amount of data, whereas old machine learning models stop improving after saturation.

In this section, we use three State-of-the-art deep learning-based approaches, including Long-Short Term Memory (LSTM) (Hochreiter & Schmidhuber, 1997), Gated Recurrent Unit (GRU) (Jozefowicz et al., 2015), and Transformer (Vaswani et al., 2017) for the UAM demand prediction task. We will also consider these as baseline classifiers to compare and use these networks as an input (transfer-learning) to a new model.

3.3.1. Long Short-Term Memory (LSTM)

We implement the Long Short-Term Memory (LSTM) network, an improved variant of recurrent neural networks, to remembrance previously-stored information. This method was used to solve the RNN gradient problem. The LSTM method is well-suited for identifying, processing, and predicting time series with unknown time lags. We trained LSTM via backpropagation and reduced the network loss. An LSTM network has three gates see (Figure 3.2).

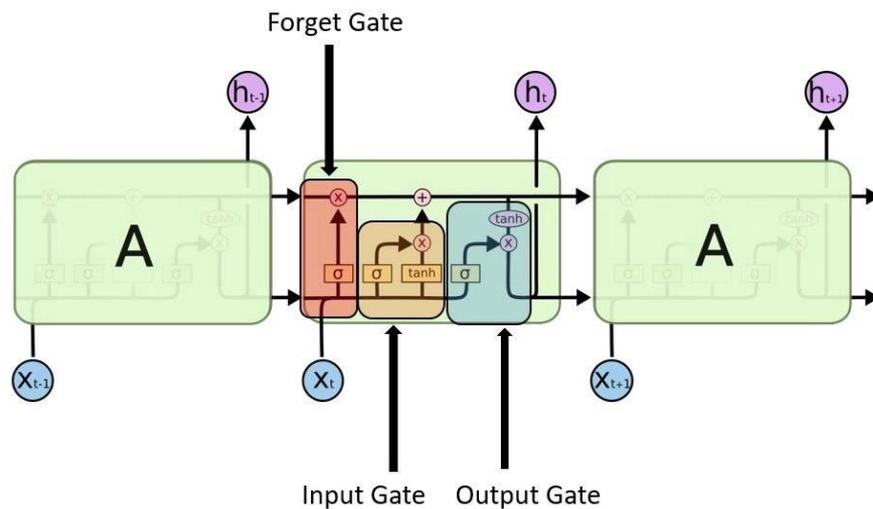


Figure 3.2 Long Short-Term Memory (LSTM) gates

Input gate: Discover which value to change memory from the input. The sigmoid function determines what values $[0,1]$ should be moved. The tanh function, on the other hand, assigns weight to the values passed to assess their importance on a scale of $[-1$ to $1]$.

$$i_t = \sigma(W_i * [h_{t-1}, x_t] + b_i) \quad (3.3)$$

$$\tilde{C}_t = \tanh(W_c * [h_{t-1}, x_t] + b_c) \quad (3.4)$$

Forget gate: Discover what blocks discarding information. The sigmoid function is defined as it examines the previous state and content inputs and returns a number ranging from 0 (omit this) to 1 (keep this) for each of the inputs C_{t-1} cell state number.

$$f_t = \sigma(W_f * [h_{t-1}, x_t] + b_f) \quad (3.5)$$

Output gate: Block input and memory to evaluate output. Sigmoid function defines 0,1 values. And tanh function gives weighting to pass values to determine their level of importance from -1 to 1 and multiplied with Sigmoid output.

$$O_t = \sigma(W_o * [h_{t-1}, x_t] + b_o) \quad (3.6)$$

$$h_t = O_t * \tanh(C_t) \quad (3.7)$$

3.3.2. Gated Recurrent Unit (GRU)

We used the GRU network, the enhanced version of the regular recurrent neural network (Cho et al., 2015). GRU employs gate updates and resets to solve the vanishing gradient problem of a standard RNN. These two vectors determine the information that should be transferred to the output. They are unique in that they can be trained to remember information from the past without it being washed away over time or information unrelated to prediction being eliminated. Figure 3.3 demonstrates detailed Gated Recurrent Unit (GRU) architecture.

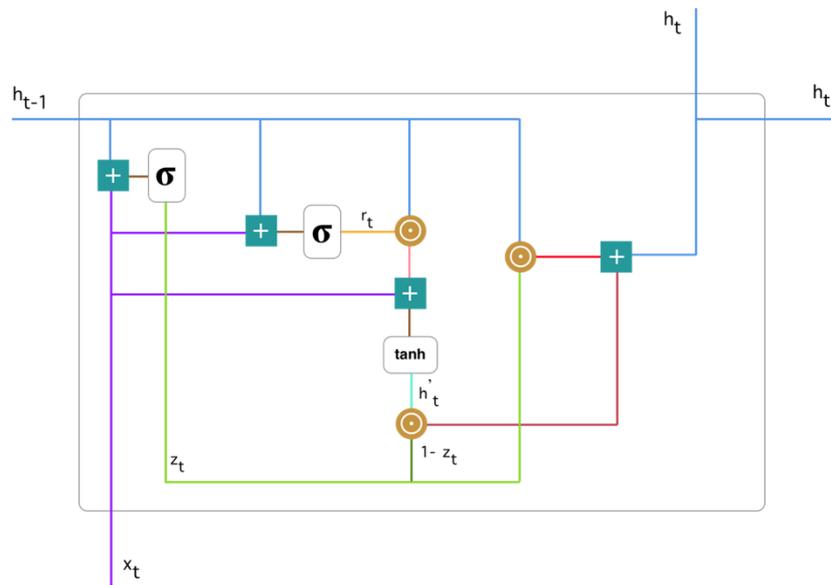


Figure 3.3 Gated Recurrent Unit

Update Gate: For time step t the formula for calculating the update gate z_t is:

$$z_t = \sigma(W^{(z)}x_t + U^{(z)}h_{t-1}) \quad (3.8)$$

Next x_t is connected to the network unit, it is multiplied by its weight $W^{(z)}$. Similarly for h_{t-1} stores data for the preceding $t - 1$ units then multiplied by its weight $U^{(z)}$. All outcomes are entered, and the number is squashed between 0 and 1, applying a sigmoid activation feature. Figure 3.4 follows the schema as mentioned earlier.

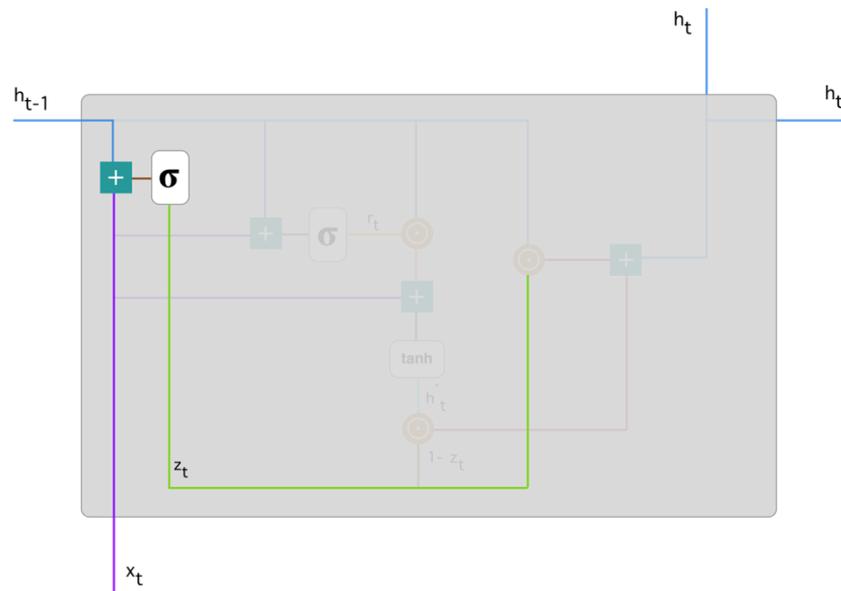


Figure 3.4 Illustrate the schema of the update gate

The model can use the update gate to determine how much previous knowledge (from earlier steps in time) should be transferred into the future. This is extremely useful because the model will decide to copy all previous data and eliminate the possibility of gradient fading.

Reset Gate: Basically, the model uses this gate to determine how much past knowledge to forget. To measure, we applied :

$$r_t = \sigma(W^{(r)}x_t + U^{(r)}h_{t-1}) \quad (3-9)$$

This formula is the same for update gates. The difference is in weights and gate use. Figure 3.5 below indicates where the gate is:

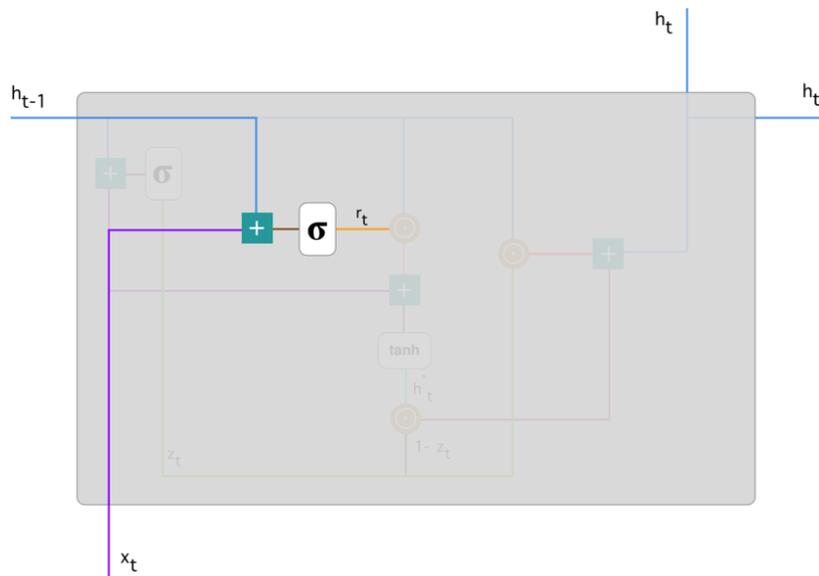


Figure 3.5 Illustrate the schema of the reset gate

As previously, we plug in h_{t-1} *blue line*, and x_t *purple line*, multiply with their respective weights, add the outcomes, and use the sigmoid function.

Current Memory Content: The effect of the gates on the final product is demonstrated in this example. Then, we start using the reset gates. The reset gate stores past data and adds new memory content. The following is how it was calculated:

$$h'_t = \tanh(Wx_t + r_t \odot Uh_{t-1}) \quad (3-10)$$

Step 1. The input x_t multiply by a weight W and h_{t-1} by a weight U .

Step 2. Hadamard (element-wise) calculate among the reset gate r_t and Uh_{t-1} .

It resolves to decide what measures should be removed from the previous ones. Assume we are dealing with a sentiment analysis issue to determine someone's feelings for a book review. After a few paragraphs, the text begins with "This is a fantasy novel that explains..." and ends with "I didn't like the book

because I think it captures so many specifics." We only need the last section of the review to determine the book's overall satisfaction level. A neural network gets closer to the conclusion of the text; this will be learning to allocate r_t vector near to 0, trying to erase previous sentences and concentrating only on the ending sentences.

Step 3. Steps 1 and 2 should be added together.

Step 4. Use the tanh nonlinear activation function.

Figure 3.6 illustrates the steps.

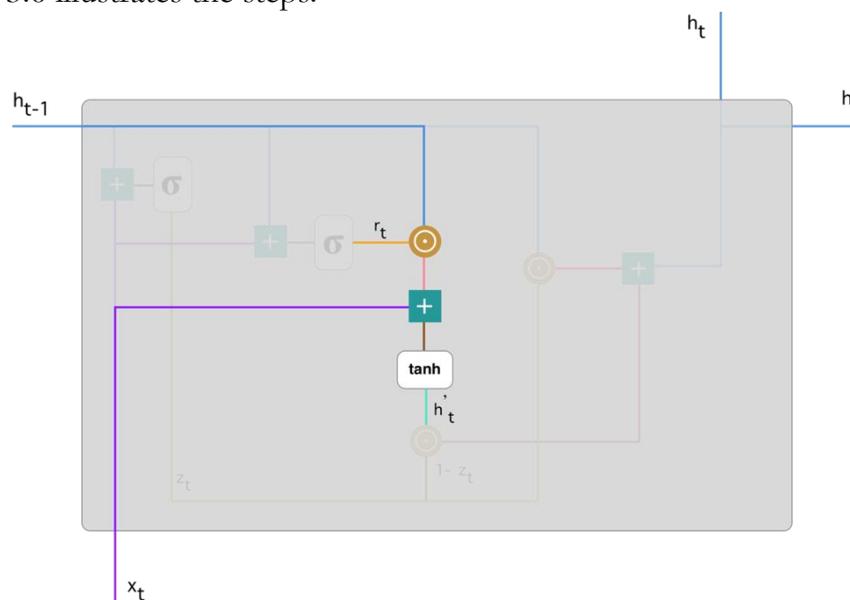


Figure 3.6 Illustrate the current memory content

we ensure an element-wise multiplication of h_{t-1} *blueline*, and r_t *orange line* and then add the result *pink line* by the input x_t *purple line*. Lastly, *tanh* is used to produce h'_t *bright green line*.

Final Memory at Current Time Step: Lastly, the network, represented by the, h_t vector is measured. This vector contains information about the current unit and transfers it to the network. Therefore, the upgrade gate is required. Defines what

should be collected from present memory substance h'_t and what should be collected from prior steps h_{t-1} . This is how it's done:

$$h_t = z_t \odot h_{t-1} + (1 - z_t) \odot h'_t \quad (3-11)$$

To update the gate, element-wise multiplication should be used z_t and h_{t-1} .

1. Use element-wise multiplication to $1 - z_t$ and h'_t .
2. Add the outcomes from steps 1 and 2

The most critical information is now at the start of the document. It will learn vector environment, z_t near to 1 and hold the most previous details. After that, z_t approximately 1 at this time stage, $1 - z_t$ approximately 0 would disregard a significant percentage of the remaining content (in this scenario, the last section of the analysis describing the book plan), insignificant to our prediction.

Figure 3.7 highlights the above equation:

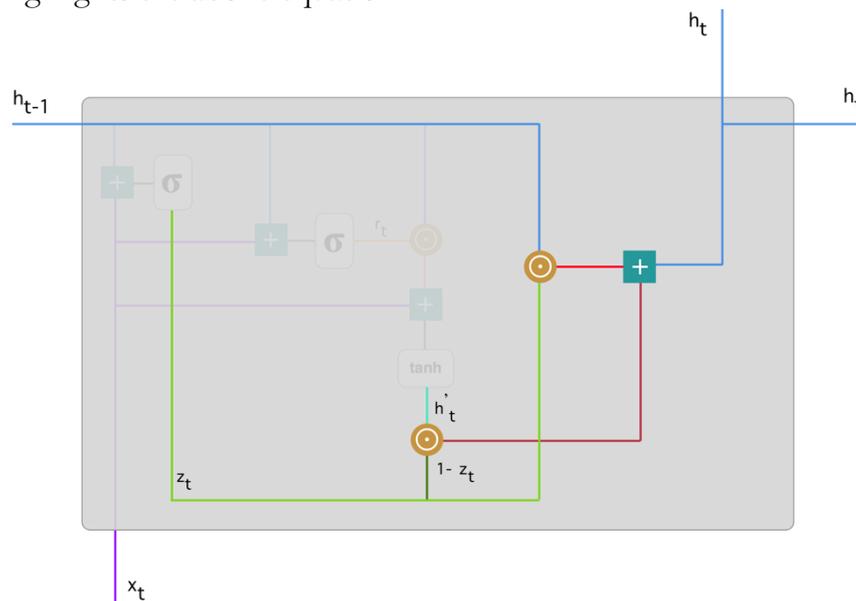


Figure 3.7 Illustrate the final memory content

As a result of this, z_t the green line was used to compute $1 - z_t$ and combined with h'_t the bright green line produces a result as a dark red line. z_t is used with h_{t-1} blue line for element-wise multiplication. Lastly, h_t the blue line results from the summation of the outputs equivalent to the bright and dark red lines.

Hence, we can see how GRUs can store and filter data through their gates.

The vanishing gradient problem is no longer an issue because the model does not wash out the new input every time it is run. In its place, it saves the relevant data and forwards it to the next network step. They can perform exceptionally well in complex situations if they have received the proper training and preparation.

3.3.3. Transformer

“Attention Is All You Need” article introduces a new architecture known as "Transformer" (Vaswani et al., 2017). Similar to the LSTM, Transformer is a two-part architecture for transforming sequences used in machine learning (encoder and decoder). Since it does not imply recurrent networks, it differs from previous sequence-to-sequence models (GRU, LSTM, etc.). Using recurrent networks to capture sequence dependencies is one of the most effective methods available (See figure 3.8).

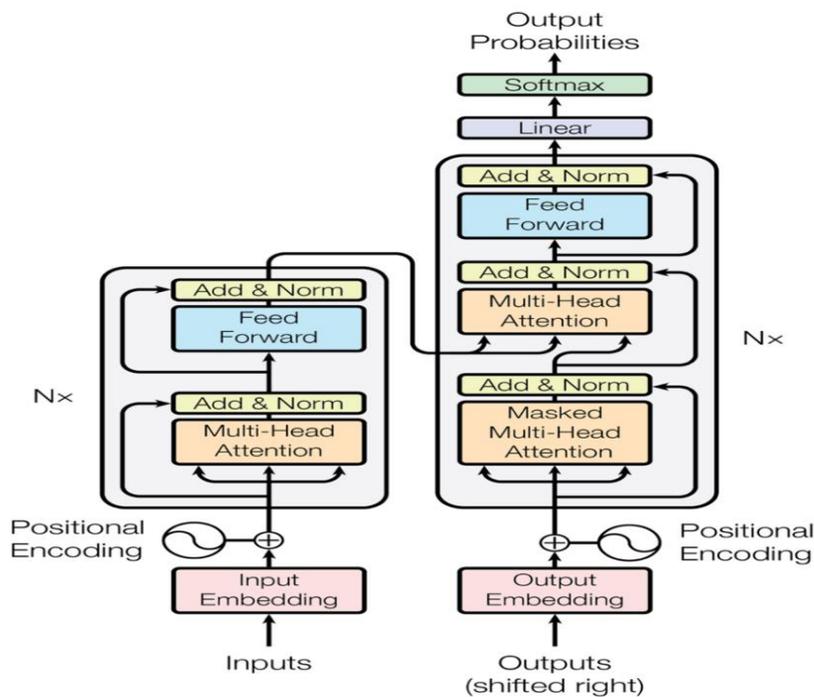


Figure 3.8 Transformer model architecture (Vaswani et al., 2017)

Architecture is shown that on the left is the encoder, and on the right is the decoder. In the diagram, N_x shows the encoder and decoder as stackable modules. Each module is comprised of feed-forward and multi-head attention layers. Because we can't use strings directly, we have to embed the inputs and outputs in an n -dimensional space first.

The model's positional encoding of words is a minor but crucial component. We must assign a relative position to each word or part because the order of the elements in a sequence is important. Each word contains these positions (n -dimensional vector) (See figure 3.9).

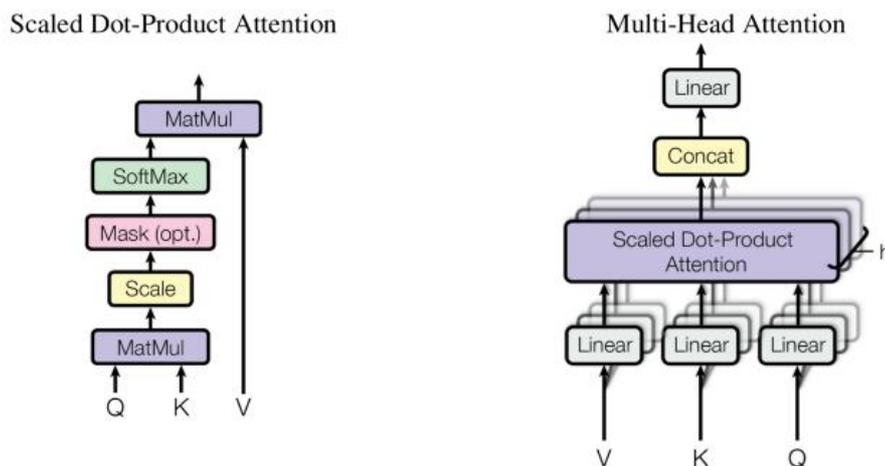


Figure 3.9 Scaled Dot-Product Attention and Multi-Head Attention

Let's start with the attention mechanism's description. It's simple and can be described by the equation:

$$Attention(Q, K, V) = \sigma\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (3-11)$$

Q is a matrix containing the query (vector representation of one word in the sequence), K is a matrix containing all the keys (vector representations of all words in the sequence), and V is a matrix containing all the values. V and Q are

the same word sequences for multi-head attention modules in encoders and decoders. V is different from Q because it is used in the attention module, which considers encoder and decoder sequences. So, we multiply and add the values in V together with certain attention-weights specified as follows:

$$a = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right) \quad (3-12)$$

The weights are based on how each word (Q) influences the others (represented by K). Weights between 0 and 1 are also applied to the SoftMax function. Those weights are used for all words in V . When compared to Q , the encoder and decoder vectors are the same, but they are different compared to the module with both encoder and decoder inputs. It is possible to parallelize this attention mechanism into multiple mechanisms, as illustrated in the right image. The attention mechanism is recurrent, having the types Q , K , and V linear projections. As a result, the model may learn from dissimilar Q , K , and V representations. The variables Q , K , and V are multiplied by learned weight matrices W in these linear representations.

Q , K , and V of the attention modules differ dependent on whether they are located in the encoder, decoder, or somewhere between these two locations. We need to focus on also the entire encoder input sequence or a subset of it for this analysis.

A multi-head attention module is used to ensure that an encoder input sequence and the decoder input sequence are considered up to a certain point in the decoding process. A pointwise feed-forward layer follows the encoder and decoder's multi-attention heads. Using the same parameters for each position in the sequence, this small feed-forward network performs a linear transformation on each element in the given sequence.

3.4. EXPERIMENTAL RESULTS AND DISCUSSION

In this section, we first share the execution environment configuration before presenting the results of the implemented models, namely LSTM, GRU, and transformer, and discussing some key implementation insights.

3.4.1. Execution Environment

We set up the following execution environment to implement the aforementioned deep learning models:

- Python 3 was used as a programming language.
- System characteristics used an Intel Core i5 processor at 2.67GHz and 8GB of memory.
- Libraries used for implementation are TensorFlow (Dean & Monga, 2015), Scikit-learn (Varoquaux et al., 2017), and Keras (Chollet, 2015).

3.4.2. Results and Discussions

In this section, the results of each step of the machine learning pipeline discussed earlier in section 3.1.1 are presented in detail.

Step 1. Data Acquisition

The data acquisition is the first step in the machine learning pipeline. Since air taxi services are currently in the testing phase, we don't have the actual data for demand prediction. As a result, we predict future demand for air taxi services using a percentage of current normal taxi demand from the land taxi-based benchmark dataset. Therefore, we use the New York City Taxi, and Limousine Commission Trip Record Dataset in this study discussed earlier in section 3.2 with a detailed

description of each field of the dataset. This dataset contains records for each taxi journey, comprising pick-up and drop-off, date and time, pick-up and drop-off locations, trip lengths, categorized prices, rate kinds, payment methods, and driver-reported passenger counts.

Step 2. Data Preprocessing

The data preprocessing is the second step and critical step in the machine learning pipeline. We discussed the case study dataset and the description of each dataset column in section 3.2. Since this dataset is a raw dataset, we found many data anomalies that need to be fixed in this step, e.g., few columns with zero, negative, and illogical values. We also eliminate some columns in this data preprocessing steps that are no longer useful for demand prediction (rate_code id, congestion surcharge, etc.)

Step 3. Models Implemented

In this step, we implement three deep learning-based models (LSTM, GRU, and Transformer) were tested in our experiment, and the results were as follows:

1. LSTM trained on train dataset and tested on the test dataset.
2. GRU trained on train dataset and tested on the test dataset.
3. Transformer trained on train dataset and tested on the test dataset.

Step 4. Models Training

In this step, we trained and tested the models mentioned earlier by using different hyperparameter to tune the performance of the methods discussed above in step 3.

Table 3.3, 3.4, and 3.5 shows the hyperparameters for the LSTM, GRU, and transformer network.

Table 3.3 Hyperparameters for LSTM Network

Hyperparameters	Values
Embedding Size	128
LSTM Layers	04
Batch size	64
Learning rate	0.0001
Epochs	100

Table 3.4 Hyperparameters for GRU Network

Hyperparameters	Values
Embedding Size	128
GRU Layers	03
Batch size	64
Learning rate	0.0001
Epochs	100

Table 3.5 Hyperparameters for Transformer Network

Hyperparameters	Values
Hidden_Size	16
Attention_Head_Size	1
Dropout	0.1
Hidden_Continues_Size	8
Loss	QuantileLoss
Learning rate	0.03
Output_Size	7
Epochs	100

Step 5. Models Evaluation

As previously discussed in section 3.1.1, we used various evaluation metrics to assess the performance of the implemented models, including Mean Absolute Error (MAE), Mean Square Error (MSE), and Root Mean Square Error (RMSE). To evaluate performance in this experiment, we used RMSE as an evaluation metric.

For regression tasks, the RMSE is the most commonly used metric. The square root of the average squared distance between the actual and predicted scores are used to calculate this. As a result, we achieved a root-mean-square error of 2.06 for the LSTM network and 2.11 for the GRU network, and 0.64 for the Transformer network. The experimental results show that the transformer outperformed on GRU and LSTM networks. The detailed results are summarized in Table 3.6.

Table 3.6 Performance comparison between LSTM, GRU, and Transformer

Method	RMSE
LSTM	2.06
GRU	2.11
Transformer	0.64

Our empirical study presented the evidence to support the demand prediction with relatively high predictive performance. Our experimental result shows that a Transformer was applied to analyse urban mobility demand and highly predictive performance.

Since the transformer method performs better than GRU and LSTM, we will analyze some key insights in detail in the next section.

3.4.3. More Results Of The Best Model

As previously demonstrated, that transformer model outperformed LSTM and GRU. More transformer results, specifically attention loss, learning curve, and variable importance, are examined in this section.

Attention Loss.

Regarding attention loss for training and testing steps, we have seen in Figures 3.10 and 3.11 that values are overlapping. It shows that the loss is relatively minimal between observed and predicted values.

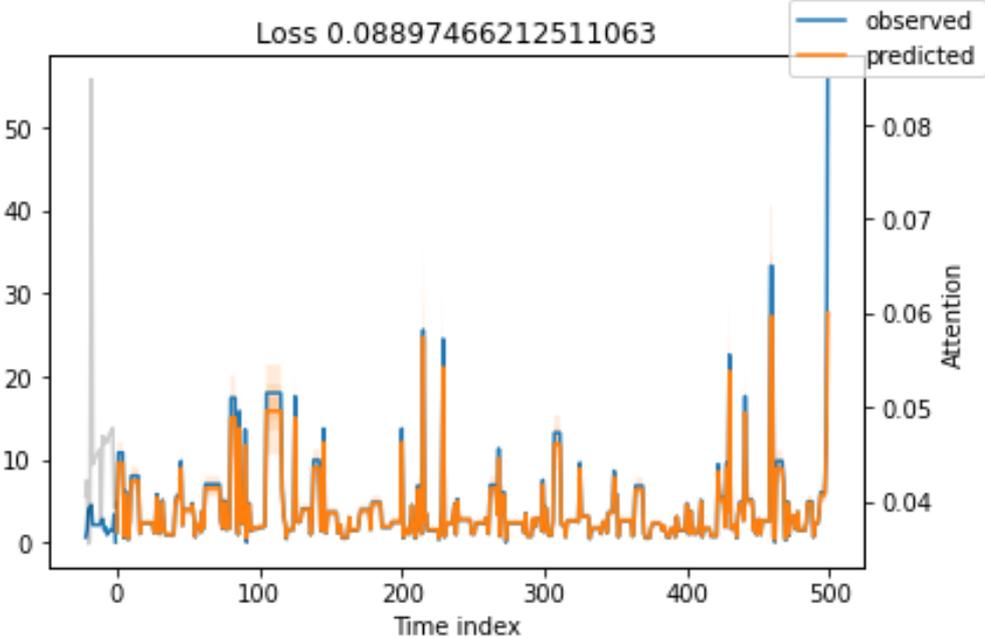


Figure 3.10 Shows the testing loss

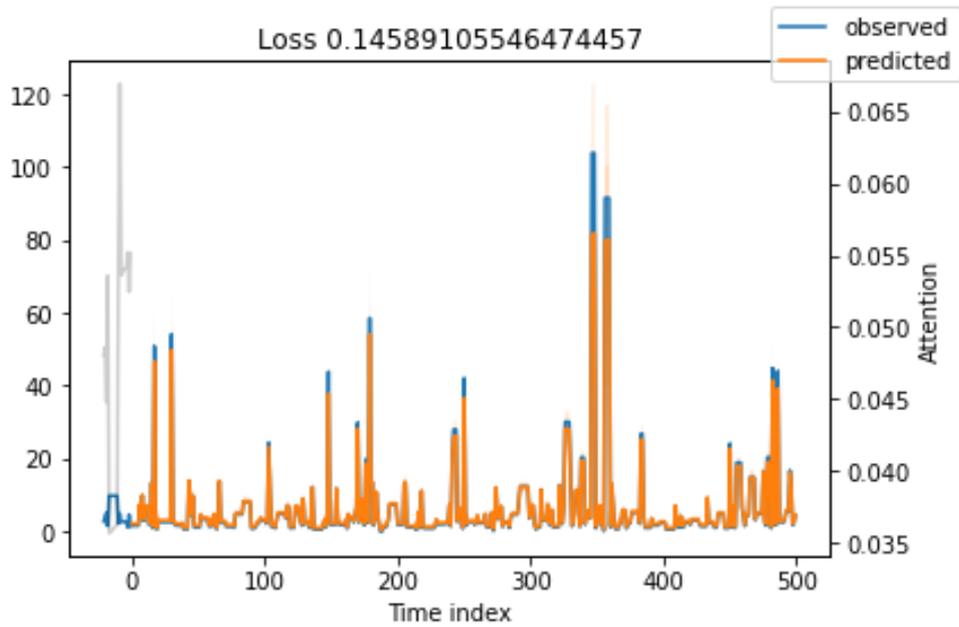


Figure 3.11 Shows the training loss

Learning Curve.

We ran multiple experiments with different values to find the optimal learning rate and found that a 0.035 learning rate was the best (see figure 3.12).

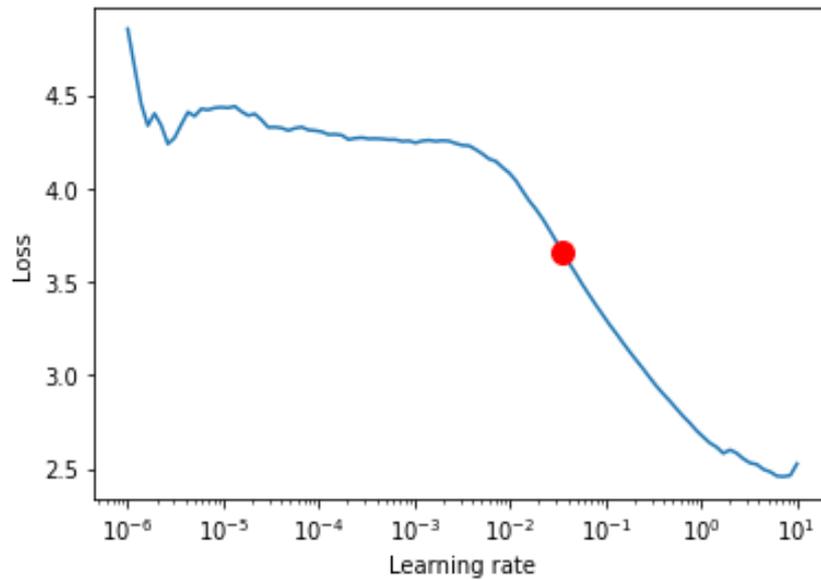


Figure 3.12 Shows the learning rates

Variable Importance.

Since we have many variables in our dataset and they don't influence demand equally, that's why we use variable importance to identify the most important variables.

Figure 3.13 depicts important variables that are more useful and influential for forecasting demand, such as trip distance, passenger count, and pickup and dropoff locations.

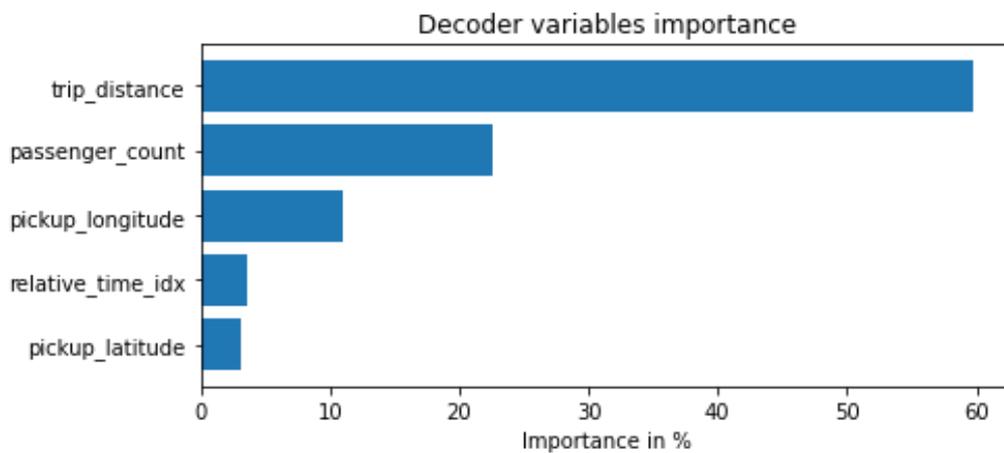


Figure 3.13 Shows the importance of the decoder features

It is interesting for decision-makers who want to deploy or implement UAM. It is critical to understand and achieve optimal values for these variables when investing. For example, a high passenger count indicates a high demand for long enough distances. Pick-up and drop-off locations are also important for decision-makers when deciding on new UAM infrastructure deployment, such as vertiports, etc.

These significant findings indicate the possibility of utilizing an approach such as transfer learning to propagate knowledge from previously trained models to a new UAM dataset, as outlined in the following section.

3.5. KNOWLEDGE TRANSFER FROM LAND TO AIR MOBILITY DOMAIN

Transfer learning is the process of transferring the knowledge using parameters of a neural network trained on a single dataset and to a new domain with a different dataset (Özbulak et al., 2016). An interesting phenomenon is observed in several deep neural networks trained on numerical data. They learn general features on the first layers of the network, which do not appear restricted to a single dataset but apply to a wide range of datasets.

Transfer learning should allow us to apply knowledge from previously learned tasks to newer, related ones. If we have more data for task T1, we can use it to learn and apply this knowledge (features, weights) to task T2 (which has significantly less data). The main motivation, particularly in the context of deep learning, is that most models that solve complex problems require a large amount of data, and obtaining large amounts of labeled data for supervised models can be extremely difficult, given the time and effort needed to label data points. Conventional machine learning and deep learning algorithms have traditionally been designed to work in isolation, which is still the case today. These algorithms are developed over time to perform specific tasks. When the source dataset shifts to reflect the new dataset, the models must be rebuilt from scratch. When it comes to transfer learning, the concept refers to overcoming the isolated learning paradigm and applying knowledge gained from one task to solve related tasks. Transfer learning can be a powerful tool for training a large target network without over-fitting it when the target dataset is significantly smaller than the base dataset.

In the light of the above result, we can use the transfer knowledge from the above well-trained architecture such as transformer to the new model and train with the UAM dataset. This approach will boost the learning curve of the new model for UAM demand prediction and reduce the under and overfitting problems. Figure 3.14 shows the high-level architecture of the new model with a transfer learning approach.

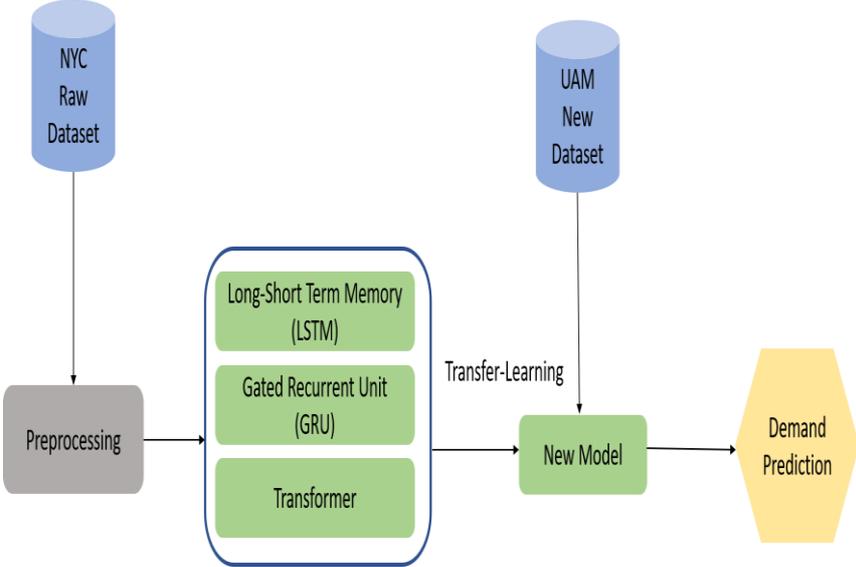


Figure 3.14 UAM demand prediction using transfer learning

CONCLUSION

This chapter investigated the demand prediction of a taxi UAM use case to provide policymakers and service providers with in-depth knowledge of the return on the investment required for UAM deployment. A benchmark dataset of 150,000 records was used for this purpose. Our experiments used different state-of-the-art DL models: LSTM, GRU, and Transformer for UAM demand prediction. The transformer showed a high performance with an RMSE of 0.64, allowing decision-makers to analyze the feasibility and viability of their investments. This valuable result demonstrates the potential for leveraging an approach such as transfer learning by propagating knowledge from previously trained models to a new UAM dataset. We believe this will improve prediction results compared to other basic networks trained on raw data. The problems of deploying UAM will be addressed in the next chapter.

4. DATA-DRIVEN FRAMEWORK FOR MULTIDIMENSIONAL URBAN MOBILITY

INTRODUCTION

In Chapter 3, we discussed the prediction of UAM demand to facilitate decision-making by comparing different state-of-the-art deep learning models. Our experiments showed the possibilities of leveraging transfer learning by propagating the knowledge resulting from a model trained on a benchmark dataset to any model trained on new data. Prior to deployment, decision-makers can thus analyze the return on their investment. In this chapter, to assess the feasibility of deployment, we propose a data-driven framework for UAM operation. To this end, Section 4.1 explores the different decision levels for the deployment. Section 4.2 summarizes the MaaS paradigm, a traditional urban mobility framework on top of which our proposed solution is defined. Section 4.3 describes a data-driven framework we propose for multidimensional urban mobility. Section 4.4 highlights the interoperability issues of its main components. The idea behind this study is to investigate the communication between the different components of the proposed framework. Finally, we conclude the chapter with a summary of the analyses carried out.

4.1. DECISION MAKING IN MULTIDIMENSIONAL URBAN MOBILITY

Regardless of the legal and regulatory framework, several decisions must be made to implement and deploy the MUM framework. It is widely understood that decision-making between stakeholders may be separated into hierarchically ordered activities that can be distinguished based on the extent of the issue addressed. It determines the strategic, tactical, and operational levels of decision-making.

Figure 4.1 briefly explains the service's scope and the MUM decision-making aspects assigned to different levels.

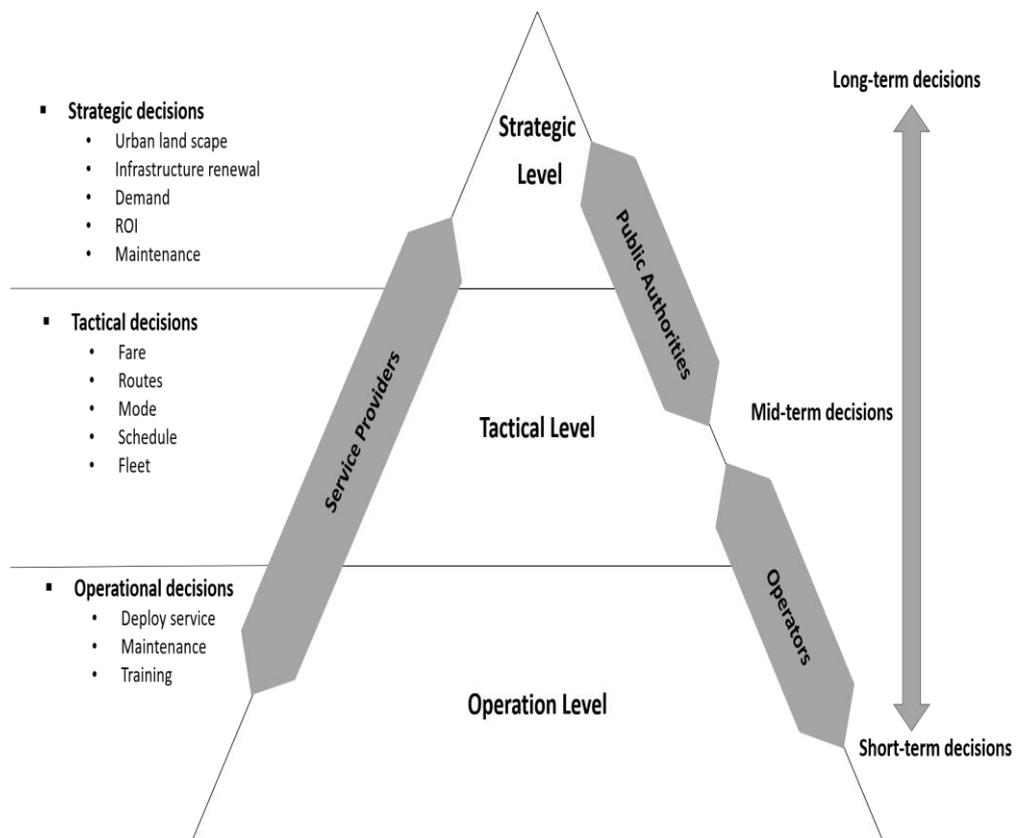


Figure 4.1 The pyramidic view of decision levels of MUM

- (1) Strategic level:** Strategic decision-making is engaged in forming broad objectives and the wide selection of the strategies that can be utilized to achieve them. Decision-making activities at the strategic level thereby answer the question, 'What do we wish to achieve?' Aspects such as the fundamental aims of the system, such as urban landscape, infrastructure renewal, maintenance, profit, demand, and supply areas, may be found at the strategic level. These broad service features and goals also dictate the amount of integration and intermodality.
- (2) Tactical level:** At the tactical level, choices are made on the acquisition of means that can aid in the achievement of the overall goals and the most efficient use of these means. Therefore, activities at the tactical level of decision-making strive to answer the question, 'What solution can assist achieve the strategic goals? The tactical level transforms the overall purposes stated during the strategic decision-making process into particular service needs. It establishes the foundation for the actual design of services to be provided. Specific services such as the fare route network, mode, schedules, and fleet should be designed within this level.
- (3) Operational level:** The operational decision-making ensures the efficient performance of the service concerning the orders specified in the decision-making levels above. Aspects at the operational level address the question, "How do you make the product?" The tactical components are integrated into day-to-day practice, which includes human management in the form of employees training, deployment services, and maintenance of the system based on the objectives and constraints of the tactical planning level.

However, alternative organizational forms can be decided depending on the distribution of different strategic, tactical, and operational roles among public and

private stakeholders within the MUM system and the design of the contractual linkages between these stakeholders.

As shown in figure 4.1, stakeholders involved in defining the decision-making process have different overlapping phases of involvement. Public authorities, service providers, and operators pass through varying decision-making process abstraction between generic long-term goal setting, the intermittent level of tactical levels and solutions, and the executive (instruments) level of work. The public authority must connect the strategic and operational levels by translating strategic goals (what') and resources (with what') through the tactical level of how' to specify the plan to achieve these goals, which must be linked to the operational status of deployment of the means' to enable the essential services.

The following section will discuss the traditional framework for urban mobility, such as MaaS.

4.2. TRADITIONAL FRAMEWORK FOR URBAN MOBILITY

This section will discuss the traditional framework for urban mobility, such as MaaS, and highlight core characteristics and implementation examples.

4.2.1. Mobility as a Services (MaaS)

MaaS is a multimodal transportation service that is integrated and smooth and supplied through a digital end-user interface in which diverse mobility providers are encouraged to collaborate and interconnect to work as an Eco-system(M Kamargianni & Matyas, 2017).

In the vision of a city, MaaS is globally a new way of structuring urban mobility that meets sustainability requirements since its intended purpose is to prevent individuals from using their vehicles. They offer a wide range of services (See figure. 4.2).

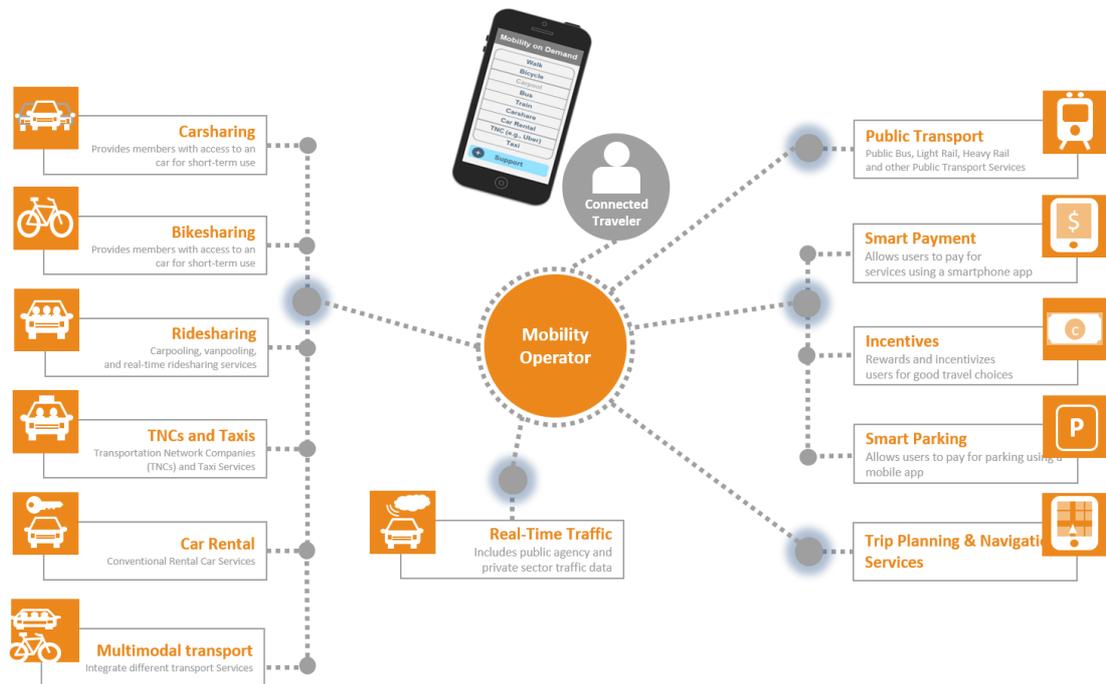


Figure 4.2 Mobility as a service (MaaS)

Indeed, it is based on a wide use of digital technologies to guarantee access to information for users and invoicing the services used within the frame of sustainable development. It allows end-users to find the most cost-effective route, price, and multimodal transport option along with a wide range of end-to-end services quickly (through convenient tools such as recommender systems or routing planners) real-time information such as traffic condition time of day and demand. MaaS also organizes the relationships of the urban mobility stakeholders and ensures that their respective priorities are met: (i) the end-user prioritizes speed and cost for their travel, without sacrificing comfort and reliability; (ii) the transport authority must ensure accessibility to the city's various attractions while reducing costs to make the best use of public funds, in a context where environmental concerns and their impact on health (pollution) and climate (carbon footprint) are becoming increasingly important; (iii) mobility operators, public and private, highlight the need for the profitability of the services they offer to be able to invest

and pursue the development of services that are increasingly in line with users' expectations (Hietanen, 2014).

Virtuous cycle with these stakeholders' priorities can then occur: (i) services provided to end-users motivate them to leave their private cars for public modes; (ii) the city-center is then relieved of congestion, which also reduces the carbon footprint, while (iii) users switch to high-performance services whose costs are controlled, taking into consideration this mass modal shift; (iv) operators, in turn, can continue their development and investments.

4.2.2. MaaS Core Characteristics

According to (Jittrapirom et al., 2017), the following features can characterize MaaS: (See figure. 4.3)

Integration of transport modes	• Encourage the use of public transport services through multimodal transport, and to facilitate intermodal travel.
Tariff option	• Offer different types of fare, "mobility package" and "pay-as-you-go";
Single platform	• User can use various services such as travel planning, booking, ticketing, e-payment and real-time traffic information via single platform.
Multiple Actors	• Interaction between different actors such as Public authorities, Mobility service providers, Operators and Users.
Use of ICT	• Internet network (Wi-Fi, 4G, LTE, GPS) e-ticketing and e-payment systems, database management systems and infrastructure integrated technology (Internet of Things)
Registration	• The aim is to enable the end-user to join the platform and benefit from access to services, including personalized services;
On-demand services	• The purpose is to facilitate the satisfaction of end-user requirements and expectations;
Personalization	• This allows end-users to change service options according to their preferences.

Figure 4.3 MaaS core characteristics

- **Integration of transport modes.** The objective is to motivate people to use public transportation by using multimodal transportation and making intermodal travel easier;

- **Tariff option.** It is made up of two types of fares: "mobility packages" and "pay-as-you-go"; the first includes packages of different modes of transportation and several kilometres/minutes/points that can be used in exchange for a monthly payment, whereas the second charges users based on their actual use of the service;
- **Single platform.** It is based on the digitalization of content through which users can easily access (including from their smartphone) various services such as booking, travel planning, ticketing, real-time traffic information, and e-payment;
- **Multiple actors.** Interaction occurs through a digital platform between different stakeholders within the MaaS ecosystem, including individual or corporate customers, transport service providers (private or public), platform owners (third parties, public transport providers or metropolitan authorities), e-payment, e-ticketing, telecommunications, and data management companies;
- **Use of Internet technologies.** It is mainly based on the combination of devices such as smartphones or computers, mobile Internet network (Wi-Fi, 4G, LTE, GPS), e-ticketing, and e-payment systems, database management systems, and infrastructure integrated technology (Internet of Things);
- **Obligation to register.** The aim is to enable the end-user to join the platform and benefit from access to services, including personalized services;
- **On-demand services.** The purpose is to facilitate the satisfaction of end-user requirements and expectations;
- **Personalization.** Allows end-users to change service options according to their preferences, hence the possibility of freely

composing related trips or building their mobility package, with a different volume of use for specific modes of transport;

The following section provides an overview of some MaaS applications. These applications are implemented in terms of the fundamental MaaS core characteristics.

4.2.3. MaaS Implementation Examples

MaaS is mainly infused by Information and Communication Technologies (ICT). MaaS is used in both backward and forward applications to support the optimization of traffic fluxes and gather citizens' views about livability in cities or the quality of local public transport facilities (Clara Benevolo, 2016). With these new technologies, the need arises to introduce new services such as car sharing, bike sharing, ride-sharing. (Jittrapirom et al., 2017). Several MaaS-based platforms have been developed: for example, BeMobility at Berlin, EMMA at Montpellier, OptiMod at Lyon, STIB at Brussels, SHIFT at Las Vegas, SMILE at Vienna, UbiGo at Gothenburg. (Jittrapirom et al. 2017; Kamargianni et al. 2016). However, most of them have succeeded in implementing the integration of e-ticketing, e-payment, several mobility modes, and the development of practical solutions for users such as itinerary recommendations, a proposal of multimodal solutions, real-time traffic information.

Table 4.1 summarizes the few well-known MaaS applications, country, and offering services adopted from (Maria Kamargianni et al., 2016) and (Jittrapirom et al., 2017).

Table 4.1 Well-known MaaS applications

Application Name	Country	Services
Whim	Helsinki/Finland	Pay-per-ride, bike-sharing, car rental, and public transport mobility planner
TransitApp	USA, UK, Canada, Europe, Australia.	Car-sharing, bike-sharing, and pay-per-ride for public transport

Optymod	Lyon/France	Bike-sharing, parking, Transport planner, and regional trains schedule
Mobility2.0 Services	Palma/Spain	Car-sharing, bike-sharing, and pay-per-ride for public transport
Ustra	Hannover/Germany	Car-sharing, pre-reserve taxi, and integrated mobility bill
UbiGo	Gothenburg/Sweden	Bike-sharing, car rental, public transport mobility planner and pay-per-ride
Mobility Mix	Netherlands	The monthly travel budget, transport planning
Moovel	Berlin/Germany	Pay-per-ride, car-sharing, and bike-sharing
Smile	Vienna/Austria	Trip planning, booking shared modes, service alerts, and real-time traffic info

However, the MaaS framework concentrated solely on users from urban mobility stakeholders, rather than other stakeholders such as service providers and government agencies, and mainly developed user-centric applications. Therefore, in the following section, we propose a methodology to create the novel data-driven framework that supports all urban mobility stakeholders' requirements and helps develop some decision-centric and system-centric applications in the context of multidimensional urban mobility. These applications help decision-makers to make decisions accordingly.

4.3. PROPOSED DATA-DRIVEN FRAMEWORK FOR MULTIDIMENSIONAL URBAN MOBILITY

This section proposes a data-driven framework and its essential components for multidimensional urban mobility. As shown in Figure 4.4, several specific framework components must be considered to provide and implement multidimensional urban mobility.

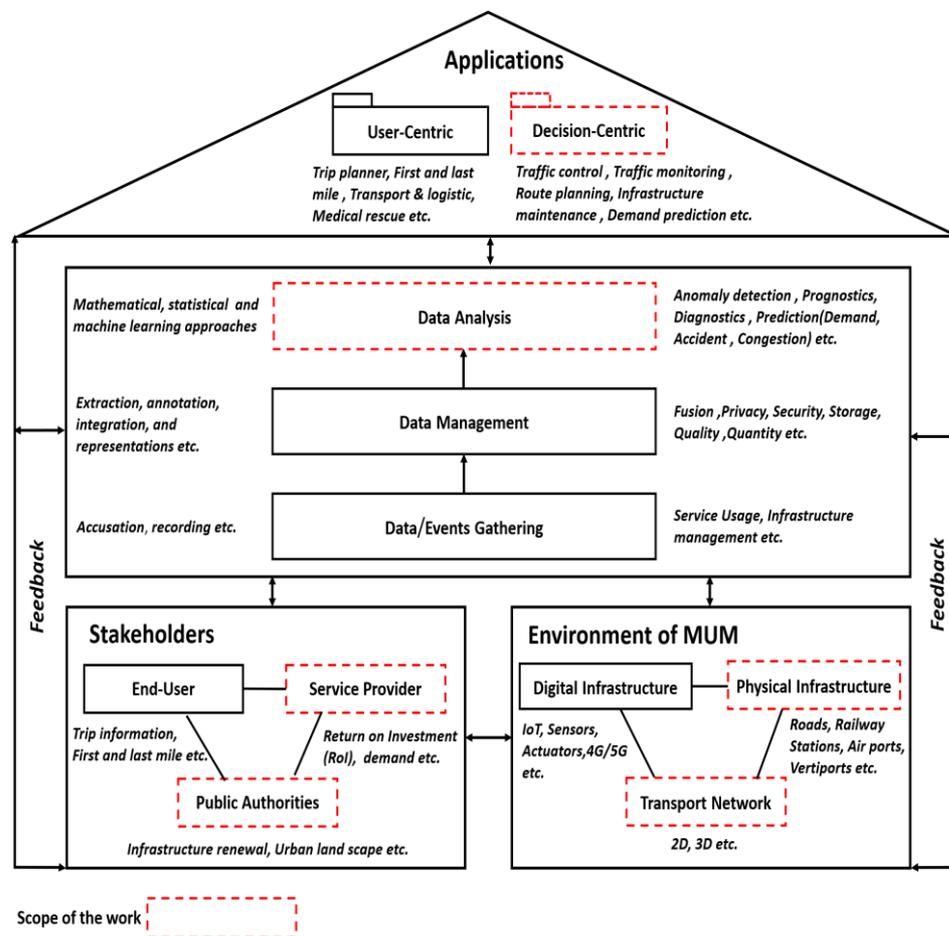


Figure 4.4 Data-driven framework for multi-dimensional urban mobility

From the perspective of a framework, stakeholders and the environment of MUM are the framework's pillars. The data-driven framework components are derived from multidimensional urban mobility key stakeholders, including (End-users, Service Providers, and Public Authorities) and the environment of MUM, which provides for (Physical Infrastructure, Digital Infrastructure, and Vehicle Network) data. The main objective of this framework is to gather data/events from these fundamental pillars and manage this data to discover meaningful data patterns and characteristics to develop different MUM applications, i.e. (and User-centric, Decision-centric).

In the following subsection, we will go through each component of the data-driven framework for MUM in detail.

4.3.1. Stakeholders

Stakeholders are the primary component of the framework. Key stakeholders of the urban mobility system are end-users, public authorities, and service providers.

End-users: The end-user inputs data to the framework, e.g., trip information, first and last-mile application, etc. End-users put pressure on public authorities to avail the above needs with higher satisfaction.

Public authorities: As a regulatory and supervisory body, the public authorities must determine which partnerships and regulations to implement which services to provide and in what manner to end-users and service providers. The framework receives data from public authorities, including information, e.g., Urban landscape utilization (scarcity), infrastructure renewal and maintenance, etc.

Service providers: Mobility operators (public or private) and solution providers (technology companies). These service providers input data related to operating strategies, e.g., return on investment (ROI), demand, etc. The service providers also pressure public authorities to gain such financial benefits.

4.3.2. Environment of MUM

Another primary component of the framework is the environment for MUM, which contains IoT devices, e.g., sensors and actuators, physical infrastructure (roads, bridges, railway stations, airports, and vertiports), digital infrastructure (IoT, sensors, and telecommunication 4G/5G) and vehicle network, i.e. (2D and 3D).

4.3.3. Data/Events Gathering

This framework component gathers the data and events generated by stakeholders and the environment of MUM. Service usage and complaints are examples of end-user related data. Like infrastructure management, city footprints

and incidents data are allied to public authorities. E-ticketing and demand of new transport mode data, i.e., UAM, is more interrelated with service providers.

4.3.4. Data Management

This framework component manages and integrates data collected from different heterogeneous data sources. While managing data, we will consider various aspects, such as data fusion, privacy, security, storage, quality, and quantity. However, there are several issues associated with this data management process, such as:

Real-time Data: This issue comes when dealing with a huge amount of contextual data (Xiao et al., 2015). The data treatment of real-time data is a critical issue, which is significantly affected by the large amounts of data coming from multiple sources. The nature of data is time-sensitive, so a reflection of unpredictability and predictability in the data flow is difficult to manage. Because physical processes do not always correspond to the results of analyses, it is critical to use computations in a practical and timely manner. When an online stream handles information, the information can frequently change in response to changing circumstances (Abbasi et al., 2020).

Data Heterogeneity: It poses a threat to the integrity of communication while also having a negative impact on the established protocols. Systems must be robust enough to ensure that a wide range of devices and applications operate without interruption. Considering the studies that have been reviewed, We can conclude that dealing with multiple data sources and presenting that data in several formats is a significant challenge. Interoperability is difficult to achieve due to the diversity of innovative space communication technologies. Because of the heterogeneity of these technologies, achieving interoperability between innovative space communication technologies is difficult. (Abbasi et al., 2020).

Data Privacy and Security: The addition of a social component to the framework may result in more or slightly more sensitive data being collected and

used. Privacy is critical in maintaining the user's right to remain anonymous on the internet. Other issues, such as this one, go unnoticed regularly. Consequently, it is necessary to raise public awareness of the problem. Users will almost certainly stop using systems that do not adequately protect their data, such as financial transactions. The general public would despise such systems. As a result, keeping those systems secure is exceptionally hard(Abbasi et al., 2020).

4.3.5. Data Analysis

In the data analysis component of the framework, some analytic techniques are applied for data treatment to analyze the data pattern and its characteristics to reveal meaningful insights, such as anomaly detection, prognostics, diagnostics, and prediction (demand, accident, and congestion). From a stakeholder point of view, they need to exchange and share data by using some services. For instance, public authorities need services data from different mobility providers linked to existing city infrastructure to make policies and regulations to improve the quality of existing infrastructures. From a mobility provider perspective, they need to integrate booking and payment processing systems built separately by different solution providers. Mobility providers are always looking for an opportunity to generate new business models from the existing model or add a new business model on top of the current model. For example, the pay-as-you-go model is a new way of payment, and it must be interoperable with traditional payment systems. From an environment of MUM perspective, the data is utilized to analyze the environment to collect information with the help of sensors and initiate actions to impact the environment and give a response back to systems (Fukuda et al., 2016). In operating infrastructures, we have different IoT devices, i.e., sensors and actuators, to collect data from various heterogeneous sources to make them interoperable for analysis and appropriate decisions, i.e., infrastructure renewal.

The results of this data analysis support decision-makers in developing various decision-support tools or applications that help in decision-making and

policy design. Stakeholders can utilize the data patterns and characteristics and provide their responses accordingly. Even the MUM environment can take some actions based on these analyses, e.g., the state of the infrastructure.

4.3.6. Applications

The last roof of the framework is the application component, which recommends different application types according to the stakeholders' needs. For example, end user-centric applications are, i.e. (trip planner, first and last mile, transport & logistic, and medical rescue). Decision-centric applications examples are, i.e. (traffic control, traffic monitoring, route planning, infrastructure maintenance, and demand prediction.

The proposed framework aims to create decision-support applications that will allow city policymakers to effectively manage the earlier issues while considering models provided by existing mobility solutions. The decision support system necessitates dealing with multiple levels of interoperability issues between stakeholders' information systems, which are discussed in the next section in detail.

4.4. INTEROPERABILITY CONCERNS BETWEEN PROPOSED FRAMEWORK COMPONENTS

This section investigated the interoperability concerns of the main components in our proposed framework to facilitate communication between the existing solutions (which are mostly user-centric) and the components designed specifically for UAM operation.

4.4.1. A brief overview of interoperability concerns and approaches

To make framework components interoperable, different interoperability concerns, such as data, services, process, and business, and different

interoperability implementation approaches, such as integrated, unified, and federated, must be considered. (Chen et al. 2017). We have adopted the concept of Framework for Enterprise Interoperability (FEI) provided by (Chen et al. 2017) to identify the different levels of interoperability in our proposed framework components and approaches to solve them accordingly (See figure 4.5).

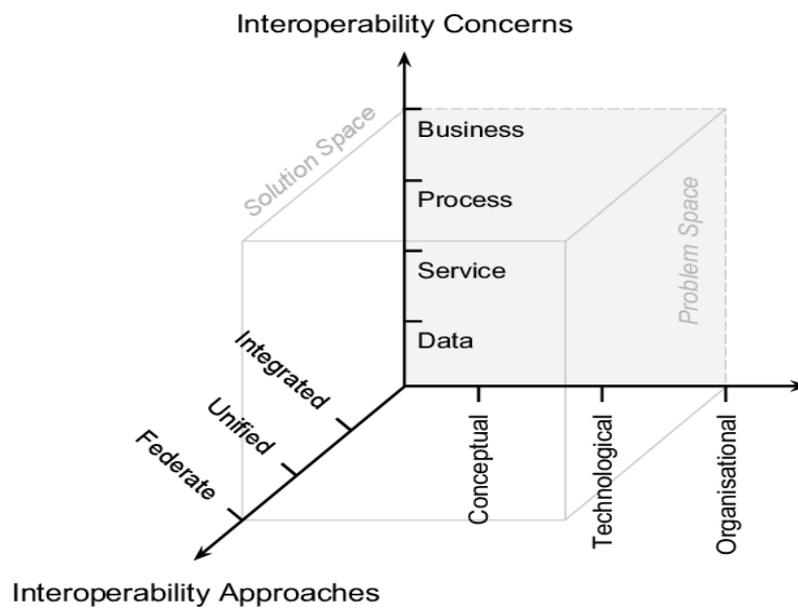


Figure 4.5 Framework for Enterprise Interoperability (Chen et al. 2017)

The data interoperability. Generally, consider the main interoperability concern related to data access, aggregation, and reasoning. It is about finding and sharing information from cross-domain sources, i.e., databases, operating systems, and database management systems.

Interoperability of services. It is referred to as services independently developed by different vendors and running parallel to solve syntactic and semantic issues.

Interoperability of processes. It is referred to as a combination of the different services. Process defines in which order services will run according to user needs. Several processes function collaboratively within an organization to validate specific tasks.

Interoperability of business. The interoperability of business refers to the system's workflows in a consistent way for business-to-business integration.

Following are approaches to address the above concerns.

Integrated approach. Different models use the same template when using an integrated approach to implement interoperability. The common format does not have to be an international standard, but all stakeholders must agree before developing models and systems.

Unified approach. It indicates a standard format between systems but only at a high level of abstraction. This format is not executable, which is valid for an integrated approach.

Federated approach. In this approach, there is no shared format between all the systems. To make systems interoperable at run time. It means the federated approach suggests that no partner enforces their models, languages, and work methods and must share an ontology (Chen et al. 2017).

In the following subsection, we will discuss which interoperability concerns and levels will occur between the proposed framework in the context of the above-highlighted levels and approaches.

4.4.2. Interoperability concerns between different components of the framework

This section discussed different building blocks of the framework and different interoperability concerns associated with these blocks. As discussed above, the framework comprises stakeholders, MUM environment, and Services (user and decision centric).

Stakeholders. Potential stakeholders of the framework are users, providers, and public authorities. End-User used different services provided by various mobility providers and public authorities. The government needs to make new policies and regulations to address MUM concerns like traffic congestion, infrastructure, safety, and pollution to create a sustainable green, and user-friendly environment (Clara Benevolo et al. 2016). From a stakeholder point of view, they need to exchange and share data by using some services. For instance,

public authorities need services data from different mobility providers linked to existing city infrastructure to make policies and regulations to improve the quality of existing infrastructures. From a mobility provider perspective, they need to integrate booking and payment processing systems built separately by different solution providers. Mobility providers are always looking for an opportunity to generate new business models from the existing model or add a new business model on top of the existing model. For example, the pay-as-you-go model is a new way of payment, and it must be interoperable with traditional payment systems.

MUM Environment. It consists of physical objects such as Internet of Things devices, such as sensors and actuators, as well as infrastructures such as roads, bridges, railway stations, airports, and vehicle networks such as 1D, 2D, or 3D, and which are used to analyze the environment, collect information with the help of sensors, and initiate actions to impact the environment and provide a response back to systems, among other things. (Fukuda et al., 2016). In operating infrastructures, we have different IoT devices, i.e., sensors and actuators, to collect data from various heterogeneous sources to make them interoperable for analysis and appropriate decisions, i.e., infrastructure renewal.

Services. The new mobility paradigm is changing the core mobility services like public transport, car rental, parking, taxis, and shuttle into new smart services such as car sharing, bike sharing, integrated mobility, on-demand mobility (Bellini et al., 2019). Since all these services are developed by autonomous solution providers, to use all these services on a single platform needs to be integrated and interoperable. The user of the services needs to adopt the different processes to use a particular service like first he registers then pay. So, these processes are also interoperable for smooth access to the service.

Thus, there is a need to provide standards to make blocks interoperable with each other to ensure that the interfaces, data flows, and message content allow for the open exchange of communications and collaboration among framework building blocks.

CONCLUSION

It's important to understand the various levels of decision-making before implementing a multidimensional urban mobility framework. The global MaaS framework, which represents a new way of thinking about the transportation system, was discussed in this chapter. Based on this development, it is possible to integrate various innovative mobility services into a single platform. Using real-time data such as traffic conditions, time of day, and demand, it would be possible for users to quickly find the best route and best price across a wide range of end-to-end services. Since, MaaS is solely concerned with users and not with the other urban mobility stakeholders involved, such as service providers and public authorities. It is a "user-centric" approach to urban mobility. Therefore, we proposed a methodology as a first step toward developing a data-driven framework to understand better data and event gathering, the data management process, and the issues associated with data interoperability, i.e., managing data, heterogeneous data, including real-time data, security, and data privacy. Following, we conduct some data analysis to uncover meaningful information that will assist decision-makers in developing user-centric and decision-centric applications.

CONCLUSION AND FUTURE PERSPECTIVE

This thesis addresses the general issue for deploying a UAM in megacities, taking into consideration some critical constraints related to the barriers and obstacles to efficient implementation: for instance, market viability, integration of air and land modes, interoperability between user-centric urban mobility platforms such as MaaS and decision-centric information system dedicated to public authorities and urban mobility service providers. To answer the scientific challenges behind this general issue and its deployment constraints, we first performed a systematic survey which allowed us to find meaningful insights to provide guidance to decision-makers: vehicle design (for example, eVTOL), manufacturing and regulation, infrastructure and operations, public acceptance, simulation and modelling, demand prediction, dynamic routing, integration of ground and UAM transportation scheduling, pilot and pilotless training, etc. We then considered the case of taxi-based air transportation to analyze the market viability through the demand prediction issue. For that purpose, we have proposed and implemented three deep learning temporal models and compared their respective results: the Transformer architecture exhibited the highest performance (with an RMSE of 0.64), as compared to LSTM (with an RMSE of 2.06) and GRU (2.11). Next, we assessed the feasibility of deploying a UAM system of systems through a data-driven framework we have proposed, which explains the critical components to be considered and allows for integrating multiple components of multidimensional urban mobility, including (land and air modes). Finally, the analyzed interoperability issues permitted us to efficiently combine user-centric features with decision-making features in a single system, as requested by the proposed framework.

Future work aims to combine a discrete event modeling approach with artificial intelligence to simulate each component of the proposed framework and model different real-life scenarios. For generalization purposes, we also intend (1) to define a transfer deep learning model to propagate the knowledge gathered from the land taxi benchmark dataset we have used into a realistic scenario of air

mobility, (2) make the proposed framework available in the Digital Twin to leverage the decision-making features implemented.

BIBLIOGRAPHY

- Airbus, 2017. Rethinking Urban Air Mobility. [Online] Available at: <https://www.airbus.com/newsroom/stories/rethinking-urban-air-mobility.html>
- Abbasi, F. A., Karray, M. H., Houe, R., Memon, M. A., & Archimède, B. (2020). Towards a Knowledge-Driven Framework of Cyber-Physical Social System for Multidimensional Urban Mobility. *Advances in Data Science and Adaptive Analysis*, 12(03n04), 2041005. <https://doi.org/10.1142/s2424922x20410053>
- Al Haddad, C., Chaniotakis, E., Straubinger, A., Plötner, K., & Antoniou, C. (2020). Factors affecting the adoption and use of urban air mobility. *Transportation Research Part A: Policy and Practice*, 132(January), 696–712. <https://doi.org/10.1016/j.tra.2019.12.020>
- Balac, M., Vetrella, A. R., Rothfeld, R., & Schmid, B. (2018). Towards the integration of aerial transportation in urban settings. *BRISK Binary Robust Invariant Scalable Keypoints*. <https://doi.org/10.3929/ethz-a-010025751>
- Balac, M., Vetrella, A. R., Rothfeld, R., & Schmid, B. (2019). Demand Estimation for Aerial Vehicles in Urban Settings. *IEEE Intelligent Transportation Systems Magazine*, 11(3), 105–116. <https://doi.org/10.1109/MITS.2019.2919500>
- Becker, K., Terekhov, I., Niklaß, M., & Gollnick, V. (2018). A global gravity model for air passenger demand between city pairs and future interurban air mobility markets identification. *2018 Aviation Technology, Integration, and Operations Conference, September*. <https://doi.org/10.2514/6.2018-2885>
- Bellini, F., Dulskaija, I., Savastano, M., & D'Ascenzo, F. (2019). Business Models Innovation for Sustainable Urban Mobility in Small and Medium-Sized European Cities. *Management and Marketing*, 14(3), 266–277. <https://doi.org/10.2478/mmcks-2019-0019>
- Boddupalli, S. S. (2019). *Estimating demand for an electric vertical landing and takeoff (eVTOL) air taxi service using discrete choice modeling*. August. <http://hdl.handle.net/1853/61811>
- Chee, W. L., & Fernandez, J. L. (2013). Factors that Influence the Choice of Mode of Transport in Penang: A Preliminary Analysis. *Procedia - Social and Behavioral Sciences*, 91(225), 120–127. <https://doi.org/10.1016/j.sbspro.2013.08.409>
- Chen, D. (2017). Framework for enterprise interoperability. *Enterprise Interoperability: INTEROP-PGSO Vision*, 1–18. <https://doi.org/10.1002/9781119407928.ch1>
- Cho, K., van Merriënboer, B., Bahdanau, D., & Bengio, Y. (2015). *On the Properties of Neural Machine Translation: Encoder–Decoder Approaches*. <https://doi.org/10.3115/v1/w14-4012>
- Clara Benevolo, R. P. D. and B. D. (2016). Smart Mobility in Smart City Action. *Springer International Publishing Switzerland 2016*, 11, 241–256. <https://doi.org/10.1007/978-3-319-23784-8>
- Clara Benevolo, R. P. D. and B. D., & Abstract. (2016). Smart Mobility in Smart City

- Action Taxonomy, ICT Intensity and Public Benefits. *Adhyayan: A Journal of Management Sciences*, 4(1), 13–29. <https://doi.org/10.21567/adhyayan.v4i1.10200>
- Cohen, M. M. (1996). The vertiport as an urban design problem. *SAE Technical Papers*. <https://doi.org/10.4271/965523>
- D.Little, A. (2018). *The Future of Mobility 3 . 0. March*.
- Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. *Journal of Business Research*, 133(March), 285–296. <https://doi.org/10.1016/j.jbusres.2021.04.070>
- Eker, U., Fountas, G., Anastasopoulos, P. C., & Still, S. E. (2020). An exploratory investigation of public perceptions towards key benefits and concerns from the future use of flying cars. *Travel Behaviour and Society*, 19(December 2019), 54–66. <https://doi.org/10.1016/j.tbs.2019.07.003>
- Fadhil. (2018). A GIS-based Analysis for Selecting Ground Infrastructure Locations for Urban Air Mobility. *Bgu.Tum.De, May*. www.msm.bgu.tum.de
- Farahani, R. Z., SteadieSeifi, M., & Asgari, N. (2010). Multiple criteria facility location problems: A survey. *Applied Mathematical Modelling*, 34(7), 1689–1709. <https://doi.org/10.1016/j.apm.2009.10.005>
- Fukuda, A., Hisazumi, K., Ishida, S., Mine, T., Nakanishi, T., Furusho, H., Tagashira, S., Arakawa, Y., Kaneko, K., & Kong, W. (2016). Towards sustainable information infrastructure platform for smart mobility - Project overview. *Proceedings - 2016 5th IIAI International Congress on Advanced Applied Informatics, IIAI-AAI 2016*, 211–214. <https://doi.org/10.1109/IIAI-AAI.2016.110>
- Garrow, Binder, L. A., German, B. J., Mokhtarian, P. L., Daskilewicz, M. J., & Douthat, T. H. (2018). If you fly it, will commuters come? Predicting demand for evtol urban air trips. *2018 Aviation Technology, Integration, and Operations Conference*, 1–41. <https://doi.org/10.2514/6.2018-2882>
- Hietanen, S. (2014). ‘ Mobility as a Service ’ – the new transport model? *Eurotransport*, 12(2), 2–4.
- Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. *Neural Computation*. <https://doi.org/10.1162/neco.1997.9.8.1735>
- Holden, J., & Goel, N. (2016). *Fast-Forwarding to a Future of On-Demand Urban Air Transportation*. 1–98. <https://www.uber.com/elevate.pdf>
- Horni, A., Nagel, K., & Axhausen, K. W. (2016). *The Multi-Agent Transport Simulation Title of Book : The Multi-Agent Transport Simulation MATSim*.
- Inac, H., & Oztemel, E. (2022). An assessment framework for the transformation of mobility 4.0 in smart cities. *Systems*, 10(1), 1–20. <https://doi.org/10.3390/systems10010001>

- Jiang, S., Chen, W., Li, Z., & Yu, H. (2019). Short-term demand prediction method for online car-hailing services based on a least squares support vector machine. *IEEE Access*, 7, 11882–11891. <https://doi.org/10.1109/ACCESS.2019.2891825>
- Jittrapirom, P., Caiati, V., Feneri, A.-M., Ebrahimigharehbaghi, S., González, M. J. A., & Narayan, J. (2017). Mobility as a Service: A Critical Review of Definitions, Assessments of Schemes, and Key Challenges. *Urban Planning*, 2(2), 13. <https://doi.org/10.17645/up.v2i2.931>
- Jozefowicz, R., Zaremba, W., & Sutskever, I. (2015). An Empirical Exploration of Recurrent Network Architectures. *JMLR*. <https://doi.org/10.1109/CVPR.2015.7298761>
- Kamargianni, M., & Matyas, M. (2017). The Business Ecosystem of Mobility-as-a-Service. *96th Transportation Research Board (TRB) Annual Meeting, Washington DC, 8-12 January 2017*, January, 8–12. http://discovery.ucl.ac.uk/10037890/1/a2135d_445259f704474f0f8116ccb625bdf7f8.pdf
- Kamargianni, Maria, Li, W., Matyas, M., & Schäfer, A. (2016). A Critical Review of New Mobility Services for Urban Transport. *Transportation Research Procedia*, 14. <https://doi.org/10.1016/j.trpro.2016.05.277>
- Kiba-Janiak, M., & Witkowski, J. (2019). Sustainable urban mobility plans: How do they work? *Sustainability (Switzerland)*, 11(17). <https://doi.org/10.3390/su11174605>
- Lascara, B., Spencer, T., DeGarmo, M., Lacher, A., Maroney, D., & Guterres, M. (2018). *Urban Air Mobility Landscape Report: Initial Examination of a New Air Transportation System*. 17. <https://www.mitre.org/publications/technical-papers/urban-air-mobility-landscape-report>
- Mayakonda, M. P., Justin, C. Y., Anand, A., Weit, C. J., Wen, J. T., Zaidi, T. A., & Mavris, D. N. (2020). A top-down methodology for global urban air mobility demand estimation. *Aiaa Aviation 2020 Forum, 1 PartF*(January 2021). <https://doi.org/10.2514/6.2020-3255>
- Mingrone, L., Pignataro, G., & Roscia, M. (2015). Smart urban electric transport system: An innovative real model. *2015 International Conference on Renewable Energy Research and Applications, ICRERA 2015*, 1457–1462. <https://doi.org/10.1109/ICRERA.2015.7418649>
- Moreira-Matias, L., Gama, J., Ferreira, M., Mendes-Moreira, J., & Damas, L. (2013). Predicting taxi-passenger demand using streaming data. *IEEE Transactions on Intelligent Transportation Systems*, 14(3), 1393–1402. <https://doi.org/10.1109/TITS.2013.2262376>
- Mudumba, S. V., Chao, H., Maheshwari, A., Delaurentis, D. A., & Crossley, W. A. (2021). Modeling co2 emissions from trips using urban air mobility and emerging automobile technologies. *Transportation Research Record*, 2675(9), 1224–1237. <https://doi.org/10.1177/03611981211006439>

- Mueller, E., Kopardekar, P., & Goodrich, K. (2017). Enabling airspace integration for high-density on-demand mobility operations. *17th AIAA Aviation Technology, Integration, and Operations Conference, 2017, June, 1–24*.
<https://doi.org/10.2514/6.2017-3086>
- NASA. (2018). *NASA Urban Air Mobility URBAN AIR MOBILITY (UAM) MARKET STUDY Contents. November*.
- Nneji, V. C., Stimpson, A., Cummings, M., & Goodrich, K. H. (2017). Exploring Concepts of Operations for On-Demand. *17th AIAA Aviation Technology, Integration, and Operations Conference, 1–12*.
- Ortego, A., Valero, A., & Abadías, A. (2017). Environmental impacts of promoting new public transport systems in urban mobility: A case study. *Journal of Sustainable Development of Energy, Water and Environment Systems, 5(3), 377–395*.
<https://doi.org/10.13044/j.sdewes.d5.0143>
- Özbulak, G., Aytar, Y., & Ekenel, H. K. (2016). How transferable are CNN-based features for age and gender classification? *Lecture Notes in Informatics (LNI), Proceedings - Series of the Gesellschaft Fur Informatik (GI)*.
<https://doi.org/10.1109/BIOSIG.2016.7736925>
- Patrick M. Condon, K. D. (2009). A Cost Comparison of Transportation Modes. *Nephrologie et Therapeutique, 16(1), 1S13-1S14*. [https://doi.org/10.1016/S1769-7255\(20\)30072-9](https://doi.org/10.1016/S1769-7255(20)30072-9)
- Ploetner, K. O., Al Haddad, C., Antoniou, C., Frank, F., Fu, M., Kabel, S., Llorca, C., Moeckel, R., Moreno, A. T., Pukhova, A., Rothfeld, R., Shamiyeh, M., Straubinger, A., Wagner, H., & Zhang, Q. (2020). Long-term application potential of urban air mobility complementing public transport: an upper Bavaria example. *CEAS Aeronautical Journal, 11(4), 991–1007*. <https://doi.org/10.1007/s13272-020-00468-5>
- Qiao, F. (2021). *Modelling and simulation of urban traffic systems : present and future Feng Qiao * and Tao Liu Haochen Sun Lingzhong Guo Yifan Chen. 1(1), 1–32*.
<http://hdl.handle.net/1853/61811>
- Rajendran, S., & Shulman, J. (2020). Study of emerging air taxi network operation using discrete-event systems simulation approach. *Journal of Air Transport Management, 87(June), 101857*. <https://doi.org/10.1016/j.jairtraman.2020.101857>
- Rajendran, S., & Zack, J. (2019). Insights on strategic air taxi network infrastructure locations using an iterative constrained clustering approach. *Transportation Research Part E: Logistics and Transportation Review, 128(January), 470–505*.
<https://doi.org/10.1016/j.tre.2019.06.003>
- Rothfeld, R., Straubinger, A., Fu, M., Al Haddad, C., & Antoniou, C. (2019). Urban air mobility. In *Demand for Emerging Transportation Systems: Modeling Adoption, Satisfaction, and Mobility Patterns*. Elsevier Inc. <https://doi.org/10.1016/B978-0-12-815018-4.00013-9>

- Rothfeld, R., Straubinger, A., Fu, M., Al Haddad, C., & Antoniou, C. (2020). Urban air mobility. In *Demand for Emerging Transportation Systems*. Elsevier Inc. <https://doi.org/10.1016/b978-0-12-815018-4.00013-9>
- Saharan, S., Bawa, S., & Kumar, N. (2020). Dynamic pricing techniques for Intelligent Transportation System in smart cities: A systematic review. *Computer Communications*, 150(November 2019), 603–625. <https://doi.org/10.1016/j.comcom.2019.12.003>
- Samuels, J. M. (2018). Critical issues in transportation 2019. In *TR News* (Vol. 2019, Issue 217). <https://doi.org/10.17226/25314>
- SESAR Joint Undertaking. (2017). *U-space*. 68–70. <https://doi.org/10.2829/614891>
- Shamiyeh, M., Rothfeld, R., & Hornung, M. (2018). A performance benchmark of recent personal air vehicle concepts for urban air mobility. *31st Congress of the International Council of the Aeronautical Sciences, ICAS 2018*, 1–12.
- Sivasubramaniyam, R. D., Charlton, S. G., & Sargisson, R. J. (2020). Mode choice and mode commitment in commuters. *Travel Behaviour and Society*, 19(May 2019), 20–32. <https://doi.org/10.1016/j.tbs.2019.10.007>
- Straubinger, A., & Rothfeld, R. (2018). Identification of Relevant Aspects for Personal Air Transport System Integration in Urban Mobility Modelling. *Transport Research Arena TRA*.
- Thipphavong, D. P., Apaza, R. D., Barmore, B. E., Battiste, V., Belcastro, C. M., Burian, B. K., Dao, Q. V., Feary, M. S., Go, S., Goodrich, K. H., Homola, J. R., Idris, H. R., Kopardekar, P. H., Lachter, J. B., Neogi, N. A., Ng, H. K., Oseguera-Lohr, R. M., Patterson, M. D., & Verma, S. A. (2018). Urban air mobility airspace integration concepts and considerations. *2018 Aviation Technology, Integration, and Operations Conference*. <https://doi.org/10.2514/6.2018-3676>
- Tomaszewska, E. J., & Florea, A. (2018). Urban smart mobility in the scientific literature - Bibliometric analysis. *Engineering Management in Production and Services*, 10(2), 41–56. <https://doi.org/10.2478/emj-2018-0010>
- Tyrinopoulos, Y., & Antoniou, C. (2013). Factors affecting modal choice in urban mobility. *European Transport Research Review*, 5(1), 27–39. <https://doi.org/10.1007/s12544-012-0088-3>
- Uber. (2018). *Uber Air Vehicle Requirements and Missions*. <https://s3.amazonaws.com/uber-static/elevate/Summary+Mission+and+Requirements.pdf>
- Uber Copter to Offer Flights From Lower Manhattan to J.F.K.* - *The New York Times*. (n.d.). Retrieved July 1, 2021, from <https://www.nytimes.com/2019/06/05/travel/uber-helicopter-nyc-jfk.html>
- UN-Habitat. (2020). *Unpacking the Value of Sustainable Urbanization*. <https://doi.org/10.18356/c41ab67e-en>

- UN, 2020. (2020). Economic and Social Council. *International Organization*, 17(2), 488–492. <https://doi.org/10.1017/s0020818300033877>
- Vascik, P. D., & Hansman, R. J. (2017). *EVALUATION OF KEY OPERATIONAL CONSTRAINTS AFFECTING ON-DEMAND MOBILITY FOR AVIATION IN THE Evaluation of Key Operational Constraints Affecting*. June. <https://doi.org/10.2514/6.2017-3084>.Report
- Vascik, P. D., & Hansman, R. J. (2019). Development of Vertiport Capacity Envelopes and Analysis. *ALAA SciTech 2019 Forum in San Diego, CA, January*.
- Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., & Polosukhin, I. (2017). Attention is all you need. *Advances in Neural Information Processing Systems, 2017-Decem(Nips)*, 5999–6009.
- Verma, S., & Gustafsson, A. (2020). Investigating the emerging COVID-19 research trends in the field of business and management: A bibliometric analysis approach. *Journal of Business Research*, 118(June), 253–261. <https://doi.org/10.1016/j.jbusres.2020.06.057>
- Wang, J., Lim, M. K., Zhan, Y., & Wang, X. F. (2020). An intelligent logistics service system for enhancing dispatching operations in an IoT environment. *Transportation Research Part E: Logistics and Transportation Review*, 135(August 2019), 101886. <https://doi.org/10.1016/j.tre.2020.101886>
- Wu, Z., & Zhang, Y. (2021). Integrated Network Design and Demand Forecast for On-Demand Urban Air Mobility. *Engineering*, xxxx. <https://doi.org/10.1016/j.eng.2020.11.007>
- Ye, R., & Titheridge, H. (2017). Satisfaction with the commute: The role of travel mode choice, built environment and attitudes. *Transportation Research Part D: Transport and Environment*, 52, 535–547. <https://doi.org/10.1016/j.trd.2016.06.011>
- Yedavalli, P., & Mooberry, J. (2019). *An Assessment of Public Perception of Urban Air Mobility (UAM)*.

SUMMARY OF RESEARCH

A data-driven framework for the deployment of urban air mobility

Nowadays, mobility in cities is becoming difficult due to demographic growth and the increasing need for on-demand services. As a response, megacities are looking into the possibility of introducing air mobility to reduce traffic congestion, provide quick answers to crises situations, etc. However, even though the key enabling technologies are mature (thanks to advances in energy efficiency, unmanned air engines, information and communication technologies, and other developments), some critical issues remain unresolved, placing additional pressure on public authorities to renew the existing solutions:

- When it comes to implementing urban air mobility, what are the most significant obstacles and valuable insights to keep in mind (how to integrate air and land modes of transportation; are the current infrastructures ready to accommodate the air mode, etc.)?
- Can the market viability sustain the required investments for the deployment?
- What are the critical components of the resulting mobility system of systems?

To answer these questions and facilitate the implementation of urban air mobility (UAM), in this thesis, we first conducted a bibliometric analysis to identify primary research areas and associated obstacles related to its implementation. Due to the lack of data on this hot research topic, we proposed a deep learning method to predict the UAM demand using a taxi-based benchmark dataset. The proposed solution is a hybridization of the transfer learning method with the transformer architecture. In order to assess the feasibility of the deployment, we proposed a data-driven framework that allows us to explain the critical components using a system engineering methodology. It can later assist decision-makers in developing decision-centric applications, such as predictions, infrastructure maintenance, service renewal, etc. Finally, we investigated the interoperability concerns of the main components in our proposed framework to facilitate communication between the existing solutions (which are mostly user-centric) and the components designed specifically for UAM operation. Future work intends to

Summary Of Research

combine a discrete events-based method with artificial intelligence to simulate each component of the proposed framework and model different real-life scenarios.

Développement d'un cadre de référence guidé par l'utilisation des données pour le déploiement de la mobilité urbaine aérienne

De nos jours, la mobilité dans les villes est de plus en plus difficile, notamment en raison de la croissance démographique et du besoin croissant de services à la demande. En réponse, les mégapoles étudient la possibilité d'introduire la mobilité aérienne pour réduire la congestion du trafic, apporter des réponses rapides aux situations de crise, etc. Cependant, même si les technologies clés sont matures (grâce aux progrès scientifiques dans les domaines de l'efficacité énergétique, des drones, des technologies de l'information et de la communication, etc.), certains problèmes critiques sont toujours sans solution, exerçant ainsi une pression supplémentaire sur les pouvoirs publics pour le renouvellement des solutions de mobilité existantes :

- Lorsqu'il s'agit de mettre en œuvre la mobilité aérienne urbaine, quels sont les freins les plus significatifs et les enseignements précieux à retenir (autrement dit, comment intégrer les modes de transport aérien et terrestre ; les infrastructures actuelles sont-elles prêtes à accueillir le mode aérien, etc.) ?

- La viabilité du marché peut-elle soutenir les lourds investissements nécessaires au déploiement ?

- Quels sont les composants critiques du système des systèmes de mobilité résultant ?

Pour répondre à ces questions et faciliter la mise en œuvre de la mobilité urbaine aérienne (MUA), dans cette thèse, nous avons d'abord mené une analyse bibliométrique afin d'identifier les principaux domaines de recherche et les obstacles associés liés à sa mise en œuvre. En raison du manque de données sur ce nouveau sujet de recherche, nous avons ensuite proposé une méthode d'apprentissage profond pour prédire la demande du marché de la MUA à partir d'un ensemble de données de référence basé sur les taxis terrestres. La solution proposée est une hybridation de la méthode d'apprentissage par transfert avec une architecture de type transformeur. Afin d'évaluer la faisabilité du déploiement, nous avons également proposé un cadre de référence guidé par l'utilisation de données qui permet d'expliquer les composants critiques à l'aide d'une méthodologie d'ingénierie système. Celui-ci peut aider les décideurs à développer des applications d'aide à la décision, telles que celles fournissant des

prévisions, la maintenance des infrastructures, le renouvellement des services, etc. Enfin, nous avons étudié les problèmes d'interopérabilité des principaux composants du cadre de référence proposé pour faciliter la communication entre les solutions existantes (qui sont principalement centrés sur l'utilisateur, comme les planificateurs d'itinéraires) et les composants conçus spécifiquement pour le fonctionnement de la MUA. Les travaux futurs visent à combiner une méthode de l'approche basée sur la modélisation des événements discrets avec l'intelligence artificielle pour simuler chaque composant du cadre proposé et modéliser différents scénarios de la vie réelle.