Linköping University | ITN
Master's Thesis | Intelligent Transport Systems & Logistics
Autumn 2024 | LiU-ITN-TEK-A--24/046--SE

Analysis of Passenger Demand for Electric Air Transportation in Sweden

Master's Thesis by
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2024/10/21

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Abstract

The air transport industry is constantly looking for solutions to reduce its significant contribution to global warming. Electrification of aircraft is a result of such attempts and presents a promising solution that could revolutionize the future of air transportation. While the technical development of all-electric aircraft is ongoing it is also crucial to understand the customer acceptance of this new mode. In this context, this study aims to investigate the factors that influence traveller choices and perceptions towards all-electric air transportation and to construct a small-scale demand model incorporating those factors, to predict the passenger demand for selected airport pairs in Sweden. The methodology consists of a comprehensive literature review, expert workshop, stated preference survey, and model development and analysis. Binary logit models were developed to understand the passenger choices for both leisure and business travellers, based on the primary data collected by the survey. The model results demonstrated that ticket price, travel time, environmental concerns when choosing a transport mode, and safety concerns regarding new modes have an impact on the choice of electric aircraft with high statistical significance for both traveller groups. A scenario analysis using the developed models revealed the market dynamics that could be more favourable for implementing EA operations. The results obtained by this study can be utilized by industry stakeholders such as airlines, airport operators, policymakers, and manufacturers to assist in their decision-making process.

Keywords: All-electric Aircraft, Factors of Demand, Demand Modeling, Binary Logit Model, Passenger Choice.

Acknowledgement

I would like to extend my sincere gratitude to my supervisor for the master's thesis, Professor Tobias Andersson Granberg for his immense guidance and support throughout this journey of completing the thesis. It is a great pleasure to work under his supervision.

Next, my deepest gratitude goes to my examiner for the master's thesis Assistant Professor Valentin Polishchuk. Your comments, feedback and insight were extremely valuable in improving my study to this level

I would also like to thank Yunhe Wang, for being my opponent for the thesis.

Finally, I wish to thank my husband, my parents and my friends for their support and encouragement throughout this study period.

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Abbreviations

CA	Conventional Aircraft
CPI	Consumer Price Index
EA	Electric Aircraft
EV	Electric Vehicles
eVTOL	Electric Vertical Takeoff and Landing Vehicle
GDP	Gross Domestic Product
MLA	Machine Learning Algorithms
MNL	Multinomial Logit Model
OD	Origin-Destination
PPP	Purchasing Power Parity
SP	Stated Preference
UAM	Urban Air Mobility
VTOL	Vertical Takeoff and Landing Vehicle

1. Introduction

The world is on the verge of a climate crisis and the global concerns over climate change and reduction of carbon emissions are escalating. Numerous industries are collectively and individually addressing this critical issue, making substantial transformations toward sustainability through technological advancements. Aviation is one such industry that has a significant contribution to the global carbon footprint. According to the International Energy Agency, in 2022, the aviation industry accounted for 2% of the global energy-related CO2 emissions and the trends show that it has grown faster than the other transport modes in recent decades (Kim & Teter, 2023). The overall global warming impact of the industry is even higher about 3.5%, due to the non-CO2 effects such as the emission of NOx, water vapour and its effect on the concentration of other gases in the atmosphere (Ritchie, 2024).

Though progress comes at a significant environmental cost, the aviation industry is still considered to be a major enabler of global economic expansion providing crucial networking for international trade as well as cultural exchange. Hence it is imperative to find a balance to maintain the economic benefits while at the same time minimizing the negative externalities. This sensitive trade-off has compelled the stakeholders of the aviation sector to explore innovative solutions to mitigate its environmental impact. One such initiative is the International Civil Aviation Organization (ICAO) and its member states setting a main objective to achieve net zero carbon emissions from international aviation by 2050 (Kim & Teter, 2023). Simultaneously, several other organizations have initiated research to identify sustainable solutions with the integration of technological advancement especially focusing on the possibility of using alternatives to fossil fuel.

Within this context, the potential introduction of electric air transportation emerges as an innovative approach, offering a promising solution to achieve this mission. The related technology has been improving through continuous research and development, and by 2030 electric aircraft are expected to provide a 49% to 88% reduction in CO2 emissions relative to fossil-fueled reference aircraft (Mukhopadhya, 2022). In addition to the emission reduction, the benefits are also realized in terms of noise reduction, and operational and maintenance cost reductions (Schäfer et al., 2019).

While the concept of electric aviation introduces numerous benefits, it is not without its challenges due to its novelty and evolving technology. The requirement of larger capital funds for the development of technologies and testing, the energy density of battery packs, the requirement of infrastructure improvements to facilitate charging, limited range and passenger capacity in the initial stage can be drawn as examples of the associated challenges (Doctor et al., 2022; Schäfer et al., 2019; Steele, 2022). Despite these challenges, the field of study appears to be expanding with continuous research conducted at a global scale and in a multitude of aspects related to electric aviation.

Considering the above, it can be understood that electric aviation will become a significant player in the passenger transport sector in the near future. Hence, while ensuring the technical prerequisites to pave the path towards electric aviation, it is also equally important to assess the passengers' demand for travelling in electric aircraft. The increasing environmental consciousness among passengers seems like a driving factor of interest in electric aviation, yet the challenges may lie in their willingness to accept new aircraft technology. The existing body of knowledge related to electric air transportation also reveals a notable absence of studies specifically addressing demand analysis in the realm of electric aviation. This highlights a potential research gap to be addressed in future studies.

In this context, this study dives into the details of passenger demand for air travel using electric aircraft. It thoroughly examines the factors that influence the demand for air travel, in fact, the general demand factors applicable to all types of air travel as well as the specific demand factors unique to air travel using electric aircraft. Subsequently, the most significant factors identified are then incorporated into modelling the passenger demand for electric aviation. A profound understanding of the passenger demand together with the quantitative modelling of the demand will be vital for the relevant stakeholders in a country in estimating the future market dynamics. Hence, this research aims to fill this gap by providing an in-depth analysis of passenger demand for travelling by all-electric aircraft aiding the prediction of future trends.

1.1. Aim & Research Questions

This research aimed to comprehensively analyze the passenger demand characteristics for air travel using all-electric aircraft while investigating the factors that influence traveller choices and perceptions towards all-electric air transportation. The insights discovered were then applied to construct a small-scale demand model which could predict the passenger demand between selected airport pairs in Sweden. The findings of this study serve as a proof-of-concept for potential data collection, model development, and analysis methods that capture the unique features of demand for electric aviation. This lays a foundation for future research and practical applications in estimating demand, benefiting industry stakeholders such as airlines, airports, and policymakers in supporting the successful integration of electric aviation in Sweden.

Research Questions

- What factors determine passenger demand for electric air transportation in Sweden, and how do they impact that demand?
- How can these factors be incorporated into demand modelling?

1.2. Scope

The passenger demand analysis for electric aviation consists of a wide range of study matters. Thus, the following limitations will be introduced to define the scope of the study. The primary focus of the study will pertain to Sweden, while considering the circumstances of neighbouring countries, particularly in the Nordics, as necessary. Despite the existence of various applications related to electric air transportation such as electric vertical take-off and landing vehicles (eVTOLs) and unmanned aerial systems (UAS), this study will exclusively investigate the demand for passenger transportation via all-electric aircraft, specifically all-electric piloted fixed-winged aircraft.

1.3. Methodology

The research methodology follows a mixed approach combining qualitative insights together with quantitative modeling in order to deliver robust findings that are representative of real-world scenarios in a way that can be easily applicable to support decision-making. This methodology builds upon a stepwise completion of four stages, namely a literature review, an expert workshop, a stated preference survey and mathematical model development.

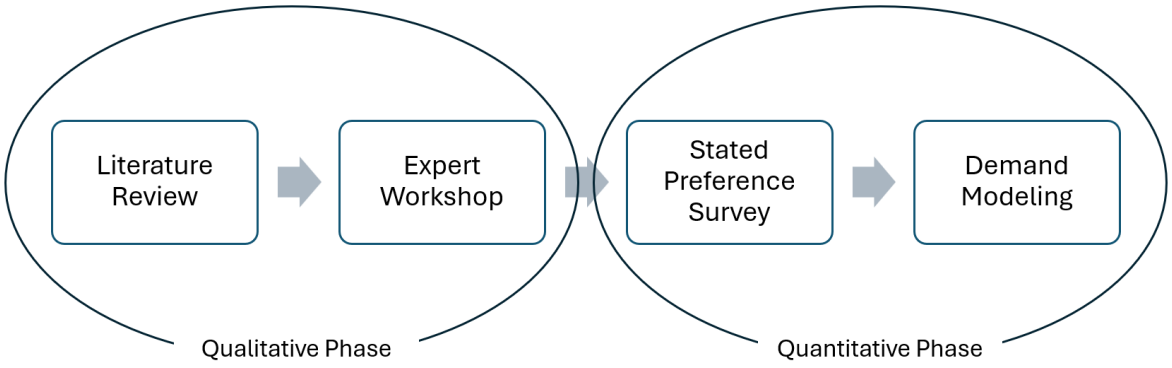

Figure 1.1 – Research Methodology Diagram

An extensive literature review was conducted to identify potential factors that influence the demand for electric aviation. This phase also helped to establish the theoretical framework for the study, guiding the selection of variables, modeling approaches and data collection.

The expert workshop was targeted at gathering additional insights on demand drivers, demand models and data collection methods. It also provided validation of already obtained results from the previous stage. This involved a diverse panel of industry experts including academics, researchers, professionals working in airlines, airport operators and transport authorities. The findings were analyzed in a deductive qualitative approach.

The stated preference survey was designed based on the findings of the above methods and aimed at collecting primary data on demand-driving factors found from previous stages. Data such as personal preferences, demographic characteristics and stated preference between conventional aviation and electric aviation under different circumstances were collected in this survey. This survey was developed on an online surveying platform and was shared among a representative sample of potential air travellers. The output was analyzed descriptively and used as input to the model development.

The most crucial component of the thesis was the development of a small-scale binary logit model to estimate the demand for electric aviation. This model incorporated trip-related factors such as travel time, ticket price, number of transfers and the trip purpose, attitudinal factors such as environmental awareness, openness to new technology and perceived safety of a new mode of transport, and demographic factors such as age, gender and income. The model fit was ensured using traditional goodness-of-fit measures used in discrete choice modeling. The model performance was tested using scenario analysis of three air travel market segments in Sweden.

Each of the above methodologies is explained in detail in their respective chapters in this thesis.

1.4. Thesis Outline

This research thesis consists of five chapters which comprehensively elaborate the research framework. The contents of these chapters are briefly described below.

Chapter 1 – Introduction

Provides an introduction to the research work with a brief explanation of the cause, aim and research questions, scope, and an outline of the research methodology.

Chapter 2 – Background & Motivation

Discusses in detail where the current state of electric aviation is at, its possible uses and the motivation for conducting demand studies focusing on electric aviation.

Chapter 3 – Literature Review

Delves deeper into reviewing the existing knowledge in the field of electric aviation and related transport modes.

Chapter 4 – Expert Workshop

Explains the methods used for the expert workshop conducted and the contents of the workshop.

Chapter 5 – Stated Preference Survey

Explains in detail the development of a stated preference survey as a primary data collection method.

Chapter 6 – Development of the Demand Model

Elaborates on the theoretical framework on which the model is based and the model-building approach using statistical software.

Chapter 7 – Data Analysis & Results

Comprehensively analyzes the results obtained by following the methodology and tests the model output.

Chapter 8 – Research Findings & Discussion

Demonstrates a discussion of the findings of the research study and how these findings can be utilized as support in decision-making. Summarizes the work done in the research and presents the conclusions drawn based on the results obtained along with the limitations and suggestions for future work.

2. Background & Motivation

2.1. Electric Aviation

The primary reason for the aviation industry to shift towards sustainable energy solutions as an alternative to fossil fuel is the negative impacts of conventional aviation on the environment and climate change. The combustion of jet fuels not only contributes to CO2 emission but also generates non-CO2 pollutants such as contrails and contrail cirrus clouds formation. These non-CO2 emissions have a similar magnitude of impact as the CO2 emissions which in turn lead to roughly double the impact on climate (Gnadt et al., 2019; Schäfer et al., 2019). Moreover, the release of NOx and the noise of the aircraft are found to result in adverse health effects and premature mortality of affected groups, turning this into a social concern (Schäfer et al., 2019).

The industry has been on the lookout for several different fuel alternatives such as biofuels, liquid hydrogen fuel and liquid natural gas as potential solutions to minimize the environmental impact of aviation. Although these alternatives provide significant reductions in CO2 emissions, they still fall behind in eliminating the non-CO2 component. In fact, hydrogen and natural gas fuels result in increased levels of contrails and cirrus cloud formation due to their high content of hydrogen (Gnadt et al., 2019; Schäfer et al., 2019).

In this context, electric aviation could be considered a promising remedy to mitigate the downsides of the above-mentioned alternatives. Electric aviation simply refers to the use of electric propulsion engines instead of the traditional fossil-fueled engines. The emergence of electric aviation was initiated with the concept of “More-electric Aircraft (MEA)” in which the existing aircraft propulsion systems such as hydraulic, mechanical and pneumatic are replaced by electric systems (Gnadt et al., 2019; Steele, 2022). The technology further emerged in the recent past and several different forms of electric propulsion have been introduced to the market namely Turboelectric, Hybrid-electric and All-electric based on the topology of the power train (Adu-Gyamfi & Good, 2022; Gnadt et al., 2019).

The turbo-electric and hybrid-electric systems, however, still rely on the combustion of some type of fuel causing emissions to an extent. In contrast, all-electric aircraft which are powered entirely by batteries, have the potential to reduce in-flight emissions to zero, making it superior to conventional fuels, alternative fuels as well as other electric propulsion systems. In addition to the

elimination of direct CO2 and non-CO2 emissions, the technology accommodates noise reduction and provides a more sustainable solution for the future of aviation that is deemed to be more socially acceptable. Nevertheless, it is noteworthy that though the in-flight emissions are eliminated, the total emissions reduction should be realized considering the ground-level source of power generation (Eaton et al., 2023; Gnadt et al., 2019; Schäfer et al., 2019).

In addition to the environmental benefits mentioned, the potential to achieve a higher on-board energy conversion efficiency, higher propulsion efficiency in electric propulsion provides efficient energy consumption (Gnadt et al., 2019) leading to significant savings in energy cost. Furthermore, the maintenance costs are expected to be lower than those of a conventional aircraft, for instance, due to the light weight of the aircraft and the relative mechanical simplicity of the engines (Adu-Gyamfi & Good, 2022; Schäfer et al., 2019). Together, the higher efficiency and lower maintenance costs result in notable reductions in operational costs making the technology attractive to the potential stakeholders (Hellesund, 2022; NEA, 2023).

Despite all the above-discussed positive aspects, it can be understood that there still remain several major challenges. The most prominent limitation at hand currently is battery technology. The energy and power of the battery are crucial enablers of the feasibility of an all-electric aircraft flight (Gnadt et al., 2019; Schäfer et al., 2019). Adu-Gyamfi & Good (2022) state in their study that the required level of sophistication of the battery pack technology has not yet been achieved to conquer the ranges of jet-fuel-powered engines. However, research related to the capacity expansion of the batteries has continued and within the past years has demonstrated a rapid development in battery technology owing to the increasing tendency towards using electric vehicles (Gnadt et al., 2019).

Due to this limitation, the first-generation all-electric aircraft designs are small, lightweight, low in capacity, and have only short distance ranges. Additionally, according to Gnadt et al. (2019), the focus on smaller aircraft sizes is driven by several other reasons such as the lower costs and risks for aircraft manufacturers from investing in small-scale projects, reduced cooling system requirements due to lower power and waste heat levels, and greater efficiency gains in transitioning to electric propulsion for small aircraft compared to larger ones with turbofan engines.

At present, this technology has been applied to a wide variety of aerial vehicles including vertical takeoff and landing vehicles (VTOL), light aircraft such as ultra-light (ULA) and light-sport

(LSA), and narrow-bodied aircraft (Adu-Gyamfi & Good, 2022; Gnadt et al., 2019) Companies like Heart Aerospace, Airbus, Pipistrel, Yuneec, Aviation Alice, etc., are spearheading this innovation, introducing electric regional aircraft aimed at reducing carbon emissions and operating costs for short-haul flights. Other innovators, such as Volocopter and Lilium, are developing electric VTOL aircraft to transform urban air mobility. These advancements demonstrate the diverse applications of electric propulsion ensuring sustainability in future air travel.

2.2. Initiatives in Nordics & Sweden

The Nordic countries are well-known for being pioneers of innovation, and collaboration for innovations is their key strategy. Sustainable development is a prime consideration in the region, and they continuously work in order to achieve this goal together. The Nordics Council of Ministers' vision, also known as the "Vision 2030" is set to make the Nordics the most sustainable and integrated region in the world by 2030. The action plan towards this vision consists of the objective of promoting solutions that support carbon neutrality and climate adaptation. In alignment with this objective, efforts are made to develop climate-friendly energy technologies, to become the most sustainable electricity market, to accelerate the green transition of the transport sector and to increase the research and development to combat climate change. In this sense, the focus of the region has naturally been directed towards electric aviation (Nordic Co-operation, n.d.).

Unlike in many other parts of the world, air transportation is a particularly important mode of transport to the Nordics. The most prominent reason for this is the geographical barriers present in the region that restrain the use of other modes of transport such as cars and trains. Geographical characteristics such as long coastal lines, mountains and fjords, lakes, forests, archipelagoes and the extreme winter weather pose as a hindrance in the construction of road and rail infrastructure and travelling around these barriers is considerably time-consuming. This limits the accessibility of cars and public transport, in most cases, leaving air travel the only option for the residents to access public services, work opportunities and other necessities (Lundberg, 2023; NEA, 2023). In these rural areas where commercial operations are not viable, Public Service Obligations (PSO) routes are positioned by the authorities to serve the commuters and to maintain the transport network (Hellesund, 2022; Kinene et al., 2020, 2022; Lundberg, 2023; NEA, 2023).

This predominant role aviation plays in the region combined with the region's commitment to achieving carbon neutrality, has brought electric aviation and related research into the spotlight. Electric aviation acts as an ideal candidate to be implemented in Nordics due to several reasons. First, the short distance range of electric aircraft is well suited and functional for destinations which are geographically closer yet obstructed by water bodies, forests or other geographic features enabling within as well as cross-border connections (Brandt, 2021; Lundberg, 2023; NEA, 2023; Voll, 2023). Next, the Nordics currently own infrastructure to generate the world's cleanest energy mix, leading the electric aircraft powered by those energy sources to have close to zero net emissions (Brandt, 2021; NEA, 2023; Voll, 2023). Moreover, the significantly lower electricity prices in Nordic countries compared to other countries in the EU further accommodates the feasibility of implementation (Eurostat, 2024).

Conversely, the countries in the Nordics will also be able to realize the benefits of implementing electric aviation in several ways. Primarily this will enable increased accessibility to the residents connecting urban and rural areas by introducing new routes. Lundberg (2023) in his study investigated the feasibility of short-haul routes to implement electric flights and the study revealed 203 potential routes that have significant travel time benefits from electric flights than the existing transport options. The time benefits were also observed between urban destinations which were separated by large water bodies. Another crucial advantage is cross-border collaborations, which is the possibility of connecting urban destinations through open waters. Each of these benefits could be understood as largely impactful on the economic and social development of the region.

Recognizing these potential benefits in every aspect, the members of the region have found various initiatives to facilitate innovations for electric aviation. The Nordic Network for Electric Aviation (NEA) is one such collaborative effort involving Sweden, Norway, Denmark, and Finland. The initiative is a collective of stakeholders such as airlines, airport operators, aircraft manufacturers, researchers and governing authorities aiming to create a platform for sharing knowledge and developing joint projects towards rapid and steady advancement of electric aviation in the region. The network focuses on infrastructure development, standardization, and regulatory issues to ensure the smooth integration of electric aircraft into the existing air transport system (Nordic Innovation, n.d.).

Supplementing the collective efforts, the member countries also contribute individually to the common goal. Sweden, for instance, has launched the "Fossil-Free Aviation 2045" initiative, which aims to make all domestic air travel fossil-fuel-free by 2030, and all international flights departing from Swedish airports by 2045. This goal is part of a much larger national strategy to reduce greenhouse gas emissions and promote sustainable transportation solutions (Fossilfritt Sverige, 2018; NEA, 2023). The initiative includes significant investments in electric aircraft infrastructure, research and development, and partnerships with industry leaders to facilitate the transition to electric aviation. Moreover, industry pioneer Heart Aerospace based in Gothenburg further contributes to the country's goal by conducting continuous development of the technology and manufacturing aircraft.

Similarly, Norway has also taken notable actions in promoting electric aviation. The country has set targets to operate its first domestic scheduled routes by electric aircraft by 2030 and by 2040, all civilian domestic flights in Norway are expected to be operated by electric aircraft. Norway's extensive network of short-haul routes, combined with strong governmental support for green technologies, makes it an ideal testing ground for electric aircraft. Elfly Group is spearheading the electric aircraft manufacturing based in Norway by introducing their seaplane which is much more suitable to be operated on Norwegian coastal flight routes (NEA, 2023). Similar efforts are made by Denmark, Finland and Iceland as other member countries of the Nordics to contribute to the advancement of electric aviation.

2.3. Importance of Demand Studies in Aviation

While the development of the technical stability of electric aircraft progresses, and the nations provide the required policy support to implement electric aviation, it is equally important to understand the user acceptance of this new technology. Hence the need for demand studies comes into play. Proper estimation of demand is a crucial component of the decision-making process related to economic viability, reliable operations, resource planning, and regulation and policy-making for stakeholders such as airlines, airport operators, policy makers and manufacturers. (Karlaftis et al., 1996; Long et al., 2023; Wang & Gao, 2021; Zachariah et al., 2023). Moreover, it is a paramount step in planning research where it lays a foundation to provide decision support to

the above stakeholders in decision-making related to market analysis, network and infrastructure planning and joint planning with existing other modes.

Considering the literature related to conventional air transportation, it is apparent that demand estimation is involved at all three levels of their decision-making process: namely strategic, tactical and operational. Karlaftis et al., (1996) explain that demand forecasting is at the core of the planning and design process of an airport and that the capacity of the important characteristics in it such as the terminals, runways, road networks, parking lots, and storage facilities are largely decided based on the demand forecasts. For airlines, demand forecast is involved in fleet planning, manpower planning, resource allocation, and network planning in the long-term strategic planning, and for flight scheduling, revenue management, marketing, and rostering in short-term tactical level planning. The demand forecast is a benchmark for the policy makers to set budgets for air transportation, and for manufacturers demand acts as a baton for the development of technology and equipment manufacturing (Wang & Gao, 2021).

In addition to the above-mentioned, demand can be considered as a representation of the consumer's willingness to pay for a certain good or service. If the commodity is priced above the level of the consumers' willingness to pay, it will not be chosen by a certain group of consumers and that would affect the demand for that commodity (Anand et al., 2021; Mayakonda et al., 2020). Demand estimates depict a picture of consumers' willingness to pay for an air ticket, hence understanding this theory would help the airlines to set the ticket prices for different market segments.

It is fair to assume that the importance of demand estimation related to electric air transport operations could be similar to an extent to that of conventional air transportation due to the similarities in the operations. Given the specific characteristics of all-electric air transportation such as short-haul operations, charging requirements and less capacity, it can be understood that the requirements for planning new flight routes, identifying charging port locations, deciding flight frequencies and fleet planning may arise anew (Voll, 2023). Moreover, given the novel nature of technology, the manufacturers have to bear massive risk in investing in technology without guaranteed market success. These critical concerns highlight the need for accurate demand forecasts that can guide the decision-making process for the above-mentioned aspects specific to electric air transport operations. Further, the demand estimation will also be pivotal in assessing

passenger acceptance and a willingness to pay mainly to position this new mode of transportation among the other competitors.

Overall, it can be identified that demand estimation plays a major role in supporting the growth and commercialization of both conventional aviation and electric aviation. However, even though the literature is enriched with demand studies on conventional aviation, there seems to be a significant lack of studies that target the demand for electric aviation. Therefore, as an emerging area of technology and most importantly an industry which is highly sensitive to passenger demand, the continuous attention to research and development of the demand studies for electric aviation is of utmost importance.

3. Literature Review

This section consists of a systematic review of literature relevant to demand analysis of electric air transportation. As the novelty of the study area and the absence of sufficient studies related to demand analysis of all-electric aviation, this systematic review lays a foundation for the whole study by the identification of necessary factors that influence the demand for electric air transportation which will later be used as inputs to the demand model. The review will also examine different demand modeling approaches used in transport studies and discuss the suitability of those models in terms of their applicability to this specific study.

3.1. Search Strategy

When searching the studies related to electric air transportation, it was understood that a variety of study areas cover a whole topic. However, these studies can clearly be separated into two main areas, one focusing on the technical aspects of the aircraft and the other focusing on the operational and planning aspects of the mode. Since the technical development has been continued over a long period of time there exists an extensive number of studies on the technical aspects yet the operations & planning studies fall behind. This effect could be easily identified from the initial search for studies.

The initial search was conducted in February 2024 using renowned scientific research databases namely Scopus and Google Scholar. The keywords used were “electric”, “aviation”, “demand”, and “models”. The search results of this initial search were limited to studies that fall into the technical aspects mentioned above. Therefore, further attempts were made to search using new keywords such as “air transportation”, “modeling approaches”, “demand factors”, “battery powered”, “battery electric” etc. This directed the results towards the studies on urban air mobility which is one area of electric aviation that looked into the implementation of electric VTOLs in urban settings.

While the studies on urban air mobility created the groundwork, further search was conducted at different stages as the research progressed. As there is ample literature found on conventional air transportation, the next search direction was to find demand modeling studies related to conventional air transportation. Moreover, studies on the demand modeling of electric vehicles

were reviewed as they are closely related to electric aviation in terms of the technology used. A manual search was also carried out using the reference lists contained in the already-found relevant literature. Apart from this, the literature search was also executed to identify the data collection methods and analysis methods of workshop outputs at later stages of the research.

Following this framework resulted in compiling a rich set of literature to put a sound base to the study. However, it is noteworthy that in spite of the extensive search strategy, only a handful of studies that directly discuss the demand factors or demand modeling of all-electric air transportation were found in both databases. This further justified the significance of this research study.

3.2. Factors Influencing the Demand for All-electric Aviation

This section discusses one of the most critical aspects of this study, which is the identification of factors that influence the demand for all-electric aviation. The findings of this section laid a bedrock to build the rest of the parts of this study.

Demand studies are known to be a fundamental research area in any type of transport mode. Literature provides examples of a great number of studies related to transport demand. These studies have been continuing over a long period of time and have achieved a good level of maturity at present. Yet this area of study seems to be expanding due to the introduction of novel trends aided by the advancement of technology and growing concerns over the environmental impact of transportation (Profillidis & Botzoris, 2019c). Air transportation, being one of the branches of the global transportation system, follows similar trends as the other modes and the studies pertaining to its demand hold significant importance in the area of research (Wang & Gao, 2021; Zachariah et al., 2023).

In this context, Electric aviation can be identified as one of the youngest study areas in the field, which is still emerging to set its presence in the community of demand studies. When considering electric aviation, the concept of Urban Air Mobility (UAM) can be recognized as a well-established research area and consequently, the demand for studies for UAM can be frequently found in the literature (Long et al., 2023). In contrast, only a handful of studies have targeted the demand for flights by other means of electric aviation such as fixed-winged aircraft. Hence in order to

understand broader aspects of the demand it was decided to investigate studies not only based on electric aviation but also demand studies on conventional aviation.

Identifying the factors that drive the demand was observed to be a paramount step conducted in many demand studies for air transportation in literature. This feature was common for both conventional aviation studies and electric aviation studies. It was also realized that different researchers have used different terminologies to introduce these factors influencing the demand in their studies, such as drivers of demand (Jorge-Calderón, 1997; Zachariah et al., 2023), predictor variables of demand (Wang & Gao, 2021) and explanatory variables of demand (Karlaftis et al., 1996). Further, a contrasting presentation of such demand factors was seen in different studies. For instance, authors like Long et al. (2023), Wang & Gao (2021) and Zachariah et al. (2023) presented these factors in their systematic review studies as a compilation of outputs of several studies while some other authors demonstrate the influence of these factors on demand using their demand model outputs (Becker et al., 2018; Dayioglu & Alnipak, 2023; Jorge-Calderón, 1997; Karlaftis et al., 1996).

3.2.1. Demand Factors Discussed in Conventional Aviation Studies

In view of conventional aviation, the study done by Karlaftis et al. (1996) introduces personal consumption expenditure per capita (PCE), gross domestic product (GDP) per capita, gross national product (GNP) per capita and disposable income per capita as the demand factors and has used them as inputs to the model described in the study and showed that these factors have an impact on the demand. In a similar study, Jorge-Calderón (1997) proved that income, population, distance, ticket price, departure frequency and the size of the aircraft influence the air travel demand while Wei & Hansen (2005) explain the roles of aircraft size, service frequency, seat availability and fare in total air passenger demand. Dayioglu & Alnipak (2023) experiments with a demand model using population, consumer prices for transport, purchasing power parities (PPP), exchange rates, fleet size, GDP per capita, net direct investment, urban population rate, tourism enterprises as input variables and the model identified the GDP, population, net direct investment and exchange rates as the most effective factors. GDP, public policies, consumer price index, open skies agreements and low-cost carrier operations are significant findings of Valdes (2015) in terms of the demand factors.

Moreover, the literature analysis conducted by Wang & Gao (2021) demonstrates a summary of frequently used demand predictor variables based on 87 air transport demand studies. The authors elaborate on the different variants of GDP, income, population and airfare utilized by the different studies analyzed. For instance, GDP is found in the forms of GDP per capita, state/provincial GDP and GDP of city pairs while income can be seen in the forms of income per capita, personal income per capita, household income, monthly salary and disposable income in different studies. In a similar manner, the population has its variants such as national population, regional population, origin-destination population and population growth, and airfare is found as average airfare, airline yield, and airfare for flight segment/leg. Moreover, a great variety of other factors have also been explored relating to socio-economic, airline operational and other settings such as tourism-related factors, employment/unemployment rates, inflation rates, agricultural and manufacturing production, education level, fuel price, flight frequency, flight connectivity, on-time performance, flight duration, special events (such as military conflicts, terrorism attacks, sports events, public health crisis) national borders/barriers, transport policies, spatial factors (such as geographical locations and distance) and alternative transport modes.

Apart from the above, interestingly Zachariah et al. (2023) present that the demand is influenced by customer characteristics. The study explains that customer travel preferences are important in forecasting travel demand for airlines as well as aviation-related industries like airport design, supplier requirements, and tourism-related firms. In addition, the study explains that travel decisions are aided by personal instincts. A customer's spending capacity has also been given as an example that drives demand where they found a relationship between high income and lower ticket prices significantly impacting aviation demand.

3.2.2. Demand Factors Discussed in UAM Studies

When compared to conventional aviation, the concept of UAM is distinct in terms of functionalities as UAM is meant to be operated in urban settings parallel to other urban transport modes as opposed to conventional point-to-point operations. However, looking at the demand studies, similarities could be seen in the identified demand factors. For instance, some of the most frequently discussed demand factors in the previous section such as GDP, population, income, distance and ticket price/airfare have been explored as demand drivers related to UAM demand

studies (Anand et al., 2021; Becker et al., 2018; Boddupalli, 2019; Mayakonda et al., 2020; Mayor & Anderson, 2019). Yet it has been observed that the researchers have unveiled new insights with regard to demand drivers.

Travel time and travel cost are two significant factors identified from the UAM studies which have not been discussed much in conventional aviation studies. Anand et al. (2021), Boddupalli (2019), Haan et al. (2021), Jafer & Mi (2017), Mayakonda et al. (2020) and Mayor & Anderson (2019) have used both of these factors in their demand analysis models. Anand et al. (2021) and Mayakonda et al. (2020) in their study have constructed a demand estimation based on the travellers' willingness to pay derived using a function of travel time and travel cost. Additionally, the value of travel time saving (VTTS), also known as the value of time (VOT) and the purpose of the trip have also been considered in this function which in turn can be explained as drivers of UAM demand. The same authors also have incorporated the range and cruising speed of the VTOL and access and egress time to and from the vertiports as decisive factors of passenger demand.

The study by Haan et al. (2021) examined the travel time impact using two distinct measures, namely the in-vehicle travel time (IVTT) and out-of-vehicle travel time (OVTT) which is similar to access/egress time. The existing vertiport locations have also been considered as a result of using the OVTT. The interesting additional factors presented in this study would be the autonomous vehicle ownership and the ride guarantee provided by the UAM service that has a positive impact on the demand as suggested by the model output obtained in the study. Apart from these, factors such as land use (Wai et al., 2021), surface traffic condition (Boddupalli, 2019; Mayor & Anderson, 2019), alternative transport modes available (Mayakonda et al., 2020; Mayor & Anderson, 2019) and number of households (Haan et al., 2021) are also exhibited as demand influencing factors.

As opposed to the mainstream factors frequently seen, Long et al. (2023) discuss safety and security, and noise as demand influencers. The study elaborates on different aspects of safety that attract users towards the services such as the consideration of personal safety, operational safety and physical security of the users. The efficient noise reduction expected in electrification has also been identified as a demand driver as public acceptance can be closely tied to low noise emissions.

On another point of note, Karami et al. (2024) have unravelled a different perspective of UAM demand which relates to the behaviour of the users. Their study examines how the consumers'

usage intention of UAM is influenced by 10 behavioural factors namely attitude, compatibility, ecological awareness, enjoyment, perceived usefulness, personal innovativeness, price evaluation, safety concern, subjective norm and trust. The results demonstrate that the usage intentions are positively influenced by the subjective norms, perceived usefulness and attitude which are the basic determinants of the theory of planned behaviour (Ajzen, 1991). Trust, personal innovativeness and ecological awareness positively influence the perceived usefulness and enjoyment, and price evaluation positively influence the attitude towards usage of UAM while safety has a negative influence on the same. In a similar study, Winter et al. (2020) explore the human emotions impacting the willingness to fly in UAM. This study analyzed the emotional factors such as familiarity, value, fun factor, wariness of new technology, fear, and happiness and understood that the wariness of new technology and fear relate negatively to the willingness to fly while the other factors relate positively to the same. The findings of these studies have revealed some hidden aspects of demand such as the impact of human behavioural factors which can be found to be more relevant for a novel transport mode that is relatively eco-friendly and technologically advanced yet has not been familiar to the general public.

3.2.3. Demand Factors Discussed in Studies on Electric Aircraft

While conventional aviation and UAM studies lay a groundwork for demand factors identification it is also worthwhile to investigate the same that has been discussed in studies related to electric aviation. Though it is not common to see such demand studies in the field of electric aviation some presence could be observed related to demand factor identification.

The recent study conducted by Veisten et al. (2024) investigates the decisive factors influencing passengers to choose all-electric aircraft using stated preference methods, and whether the passengers are willing to pay a price premium. The results elaborate that the choice is impacted by the ticket price of electric aircraft, in fact, the people who are willing to choose this mode are motivated at low levels of price premium, yet the choice drops sharply at higher levels whereas the people who are not willing to choose the mode are motivated to do so when provided discounts. The study further explains the relationship between age and education level, and electric aircraft demand where the young and/or highly educated have a high likelihood to choose electric aircraft. In a similar manner, a positive association is observed between technology innovativeness and

technology optimism of an individual and flying electric. On the contrary, a negative influence has been observed in safety and range factors.

One of the main theoretical frameworks recurrently used in user preference studies related to electric aviation is the theory of planned behaviour which was also mentioned previously in the UAM section (Ajzen, 1991). Similarly, the same theory is seen applied in many instances related to electric aircraft studies in order to describe behavioural aspects. Developed by Ajzen (1991), the theory of planned behaviour "permits prediction and understanding of particular behaviours in specified contexts". It describes that the attitudes toward the behaviour, subjective norms with respect to the behaviour, and perceived control over the behaviour are expected to predict behavioural intentions with a high degree of accuracy and that these intentions together with the perceived behavioural control led to control behaviour of human beings. Due to the nature of electric aircraft as a new transport mode, it is naturally required to study these aspects of user acceptance hence many authors have looked into a variety of believes, values and attitudes of people based on this theory (Han, Lee, et al., 2019; Han, Yu, et al., 2019a, 2019b; Steele, 2022).

For instance, Han, Yu, et al. (2019b) examine how environmental value, environmental awareness green image and injunctive social norms impact the personal norms of airline passengers which in turn influence the green intentions. Further, the impact of age and gender has also been considered here. In a similar study, Han, Yu, et al. (2019a) investigate the impact of perceived risk, trust, attitudes and new product knowledge on users' intention to adopt electric aircraft. Meanwhile, Han, Lee, et al. (2019) demonstrate that the sense of obligation to take pro-environmental actions affects the intention to use and recommend electric aircraft. These studies further confirm that user characteristics are a prominent factor in the demand for electric aircraft.

3.2.4. Demand Factors related to Electric Vehicle Demand

The studies related to the demand for electric vehicles (EVs) can be seen to display a close relationship to electric aircraft in some respects. One most obvious is the fact that both modes use the same energy technology that is commonly accepted as environmentally friendly. Secondly, literature can be found related to EVs which discuss their demand not only by qualitative or hypothesis testing studies but using the ones with mathematical modeling that considers demand

factors. Hence, demand factors related to EVs might provide a picture of the contribution of similar attributes on all-electric aircraft.

Similar to all the other modes discussed above, EV demand studies can be found that incorporate the most frequent type of factors: socioeconomics. Hamed & Al-Eideh (2018) and Huang & Qian (2021) revealed the impact of socioeconomic factors such as age, gender, household income and household size on the intention to buy EVs.

In terms of the operational factors, the reduced driving range is one of the commonly identified factors in the related literature that hinders the customer demand for EVs (Dimatulac & Maoh, 2016; Domarchi & Cherchi, 2023; Hamed & Al-Eideh, 2018; Huang & Qian, 2021; Jin et al., 2020). This is due to the inconveniences that the users have to face such as the time they have to spend on recharging. Reduced range is also a known technical characteristic to expect in all-electric aircraft and from the results related to EV demand it can be assumed that the same effects may be realized for all-electric aircraft.

EV demand studies have also given massive importance to understanding the behavioural factors of the users. The study by Jin et al. (2020) identified that attitudinal factors such as awareness about the mode, environmental consciousness, and self-image created by using EVs have a positive impact on EV demand. Domarchi & Cherchi (2023) in their literature analysis study have discovered that much research had considered phycological factors such as pro-environmental attitudes and user anxiety about the safety, and knowledge of innovative technology when modeling the demand for EVs. These factors further justify the importance of considering behavioural demand factors when defining all-electric aircraft demand factors.

3.2.5. Identification of Factor Categories

One significant property identified from observing the drivers of demand presented in each of the above modes is that they can be clearly divided into different groups. For instance, considering the conventional aviation demand studies, factors like GDP, PPP and CPI can be categorized into one group as economic factors. Correspondingly, the factors such as environmental awareness, safety concerns, values and attitudes present in electric aviation demand studies can be grouped into one

as personal factors. This property has been observed by authors who studied demand, and the different categorizations introduced by them exist in literature.

Jorge-Calderón (1997), introduces several factors of demand and divides them into two main categories from an airline's point of view as geo-economic factors and service-related factors. The author describes that the geo-economic factors are determined by the economic activity and geographical or locational characteristics of the area where transportation takes place which fall outside the control of airlines. Income, population, percentage of university degree holders, percentage of full-time employees and distance are drawn as examples for this category. On the other hand, service-related factors are determined by both the quality and money price components of the airline, and this includes the price, frequency of departures, load factor, size of aircraft and public policies.

Wang & Gao (2021) elaborate that the factors found in air transport demand studies can be categorized into three groups namely, socioeconomic factors, airline operational factors and other factors. The socioeconomics category includes GDP, income, population, tourism-related measures, and labour-related factors while the airline operational factors include airfare, flight connectivity, flight frequency, flight duration and low-cost carrier operations. Further, factors such as the existence of special events, national borders, policies, spatial factors and alternative transport modes fall into the other factors category. Similar factors are studied by Zachariah et al. (2023) and those are classified into categories as economic, geographical, service quality, airfare, and market factors.

It was observed that the UAM demand factors have also been categorized as the above. Long et al. (2023) discovered the factors they identified can be classified into three categories namely, trip-related factors, motivating factors and acceptance-related factors which is a slightly different categorization than usual. The trip-related factors category consists of time, cost, and distance while surface traffic congestion and capacity of vehicles are categorized as motivating factors. Acceptance-related factors include safety and security, privacy, and noise.

While these categorizations can be found in the literature for conventional aviation and UAM studies, it is not common to see such classifications related to electric aircraft demand. The key reason for this could be the lack of extensive research on the topic and the existing research being

mostly narrowed to cover the behavioural aspect of users, leading to an absence of incorporating other categories.

Table 3.1 provides a summary of the factors discussed in the above sections.

3.3. Demand Estimation Approaches

When looking into the literature a great number of demand estimation approaches can be recognized. These estimations are seen to have been conducted from the perspectives of different actors involved in the process. For instance, analysis can be made for countries, airlines, airports, specific air routes or city-pairs (Dayioglu & Alnipak, 2023; Jorge-Calderón, 1997; Profillidis & Botzoris, 2019a) and even from the user perspective. They can also be introduced as aggregated and disaggregated where the aggregated approaches are commonly utilized in estimating the passenger demand for aggregated settings such as countries, cities, airlines or airports (Karlaftis et al., 1996; Profillidis & Botzoris, 2019a) while the disaggregated approach is focused on understanding the individual choice of a user for particular service (Anas, 1983). Hence, the type of estimation method and the inputs used are seen to be chosen based on the level of aggregation a particular researcher expects to work on.

The literature provides examples for the different types of estimation approaches used to analyze aviation demand. Considering the conventional aviation field, one of the methods utilized very often by researchers is the econometric models in which the model predicts future events based on discovering relationships between economic variables (Dayioglu & Alnipak, 2023; Karlaftis et al., 1996; Profillidis & Botzoris, 2019a; Zachariah et al., 2023). Econometric models are used to determine which economic factors such as GDP, income, population, etc., have an influence on aviation demand. These are used in aggregated settings such as for regions, countries, city pairs, etc., and often depend on the existence of historical statistical data. Profillidis & Botzoris (2019a) explain that the input data for these models are found in three forms namely time series data, cross-sectional data and panel data. They also explain that if the set of data used is not based on the same or comparable measurement process over time and for all the measurement organizations or recorders, such data would not fully represent the problem and hence only provide a qualitative assessment. This implies that econometric models can be highly dependent on the availability of

Authors & year	Mode	Analysis Method Equipped	Factors discussed or used as model inputs																														
			GDP	Population	Income	Travel time	Travel cost	Distance	Ticket price/airfare	Service Frequency	Aircraft size	Congestion	Alternative modes	Employment rate	Age	Gender	Land use	Public policies	Number of households	Range	Cruise speed	Fleet Size	Access/egress time	Trip purpose	Value of time	Willingness to pay	Airport location	Vehicle ownership	Env. Awareness	Safety	Tech. awareness	Personal factors	Other economic	Other Factors
Smith et al., 2012	eVTOL	NASA's own model					■													■	■						■							■
Becker et al., 2018	UAM	Gravity Model	■					■	■																									■
Mayor & Anderson, 2019	UAM	Not disclosed	■	■	■	■						■	■																					■
Boddupalli, 2019	eVTOL	SP Survey Multinomial Logit			■	■		■				■																■						■
Winter et al., 2020	UAM	Survey Hypothesis testing																													■	■		■
Mayakonda et al., 2020	UAM	Top-down Approach			■	■	■	■	■				■								■		■	■	■	■								
Anand et al., 2021	UAM		■	■	■	■	■	■	■											■	■		■	■	■	■								
Haan et al., 2021	UAM /eVTOL	Multinomial Logit			■	■	■	■											■	■	■				■		■	■						■
Wai et al., 2021	UAM	OD matrix & Fare-Time				■	■	■									■																	■
Karami et al., 2024	UAM	Interviews Hypothesis testing																											■	■		■		■
Karlaftis et al., 1996	CA	Time series models	■		■																												■	■
Jorge-Calderón, 1997	CA	Regression		■	■			■	■	■	■																							
Wei & Hansen, 2005	CA	Nested Logit Model							■	■	■																							■
Valdes, 2015	CA	Panel data analysis (Regression)	■															■															■	■
Dayioglu & Alnipak, 2023	CA	Panel data analysis (Regression)	■	■																		■											■	■
Han, Yu, et al., 2019a	EA	Survey Hypothesis testing																											■			■		
Han, Yu, et al., 2019b	EA	Survey Hypothesis testing													■	■													■			■		
Han, Lee, et al., 2019	EA	Survey Hypothesis testing																												■		■		■
Brandt, 2021	EA	Case Study Interviews																											■	■	■	■		■
Steele, 2022	EA	Survey Hypothesis testing												■	■	■																■		■
Veisten et al., 2024	EA	Survey Logistic Regression			■				■						■	■												■	■		■			■

Table 3.1 – Summary of Demand Influencing Factors

historical data and the quality of data. Regression is a common application of econometric models using the ordinary least square method (OLS) as the estimating method. However, a drawback of this model is the reverse causality meaning one or more variables correlating with the error term. This problem is addressed by using instrumental variables and applying three-staged least square regression (Wang & Gao, 2021; Zachariah et al., 2023).

In the arena of conventional aviation, another frequently found demand estimation method is time series forecasting. It is a powerful demand analysis method for predicting future trends and values using time-series data. Wang & Gao (2021) demonstrate the different types of time series methods used in air transportation demand studies like error correlation model (ECM), vector error correlation model (VECM), Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA), Autoregressive Integrated Moving Average with Explanatory Variable (ARIMAX) and Seasonal Autoregressive Integrated Moving Average (SARIMA) in their study. This study further explains that a common practice is to mix these methods and that these mixed models usually outperform other methods. Zachariah et al. (2023) claim that these models can be identified in two forms named univariate and multivariate where univariate forecasting is used when only one variable changes over time while the other is used when multiple variables change over time. It can also be understood that these types of models require data stationarity and that it should be checked before the modeling as the statistical variables such as mean and variance, do not change over time. The high uncertainty and irregularities in passenger movements pertaining to the aviation industry pose difficulties in applying this forecasting method in this context (Zachariah et al., 2023).

In the recent past, the popularity of machine learning techniques has driven every industry to find more efficient solutions. Simliarly, the applications of machine learning have been applied in demand estimation for air transportation. Long et al. (2023), Wang & Gao (2021) and Zachariah et al. (2023) provide evidence for different approaches of machine learning applied in both conventional and electric aviation demand studies. They include artificial neural networks, linear regression, gradient boosting, random forests, deep neural networks, recurrent neural networks, decision trees, generic algorithms and greedy algorithms. Rajendran et al. (2021) have incorporated machine learning algorithms (MLAs) namely logistic regression, artificial neural networks, random forests, and gradient boosting in their study out of which they conclude the gradient boosting algorithm as the best performing among others. All the above authors have agreed upon the fact that MLAs display great potential in improving the

accuracy and efficiency of the estimates and that it is a promising future path for demand studies.

Considering the UAM demand studies, the study by Long et al. (2023) demonstrate ample insight into the demand estimation methods employed in this area. The study separates the models utilized in UAM-related demand methods into two groups; qualitative and quantitative. Qualitative methods mainly utilize survey-based approaches while the quantitative approaches utilize data-based estimation. According to the authors of the study, the most common method of surveying is the stated-preference surveys (Ahmed et al., 2021; Al Haddad et al., 2020; Boddupalli, 2019; EASA, 2021; Ilahi et al., 2021). In terms of modeling, the application of a variety of modeling approaches can be seen including gravity models for city pairs (Becker et al., 2018), discrete choice models, agent-based models and machine learning models (Rajendran et al., 2021; Rajendran & Zack, 2019). In addition to these, some unique approaches have also been found such as the top-down methodology that is influenced by the traditional 4-steps transport model employed by Anand et al. (2021) & Mayakonda et al. (2020) and the fare-distance-time matrix and OD matrix analysis by Wai et al. (2021). However, calibrated mode choice models followed by stated preference surveys, are understood to be the predominant methods for UAM demand estimation. Long et al. (2023) also explain that the absence of historical data is a great challenge in demand estimation yet stated preference surveys can be used to overcome this challenge.

As Long et al. (2023) proclaim, in general, most of the studies that exist in UAM literature focus on estimating passenger quantities and fleet sizes at an aggregated level. Nevertheless, it is also pivotal to concentrate on the disaggregated aspect as it explains why an individual makes a particular choice given their circumstances hence, better reflects the changes in choice behavior due to changes in individual characteristics and attributes of alternatives (Koppelman & Bhat, 2006). Given the close relationship electric aviation has with the behavioural characteristics of humans, the role of discrete choice models comes into play in this context. It has been seen that the discrete choice models are being increasingly used to understand user behavior in transport studies (Koppelman & Bhat, 2006). In UAM demand studies, discrete choice models are frequently employed to analyze the relationship between travel time and travel cost with the market demand. There exist different forms of discrete choice models. Multinomial logit model (MNL), mixed logit model (MXL), random parameter multinomial logit model (RPML), ordered logit models (OLMs) and binary logit model (BLM) are some of the examples (Koppelman & Bhat, 2006; Long et al., 2023). It can also be understood that in

the event of no historical data available, discreet choice models can be effectively used after being calibrated by the data from a stated preference survey.

In terms of the electric aircraft demand studies, a major variation of models is not observed yet, possibly owing to the fact that the study area is new and emerging. However, it has been observed that studies primarily use some method of surveying (Han, Lee, et al., 2019; Han, Yu, et al., 2019a, 2019b; Steele, 2022; Veisten et al., 2024) such as stated preference if not a qualitative method such as interviews (Brandt, 2021) to gather required data. Analysis methods have been limited to either qualitative analysis of interviews or hypothesis testing calibrated by survey results. Though the study area seems promising it still displays a significant lack of quantitative and data-based demand modeling research.

3.4. Data Collection Methods for Demand Modeling

As the previous sections in the literature review provide a solid foundation for demand modeling it is also crucial to understand suitable data collection methods required for demand modeling. The most common practice in the field of transportation to assess and understand traveler preferences or choices is conducting a survey. There are two main surveying methods used in these transport studies namely, revealed preference (RP) and stated preference (SP) (Hensher et al., 2015; Johnston et al., 2017; Long et al., 2023; Profillidis & Botzoris, 2019b; Sanko, 2001). The study by Sanko (2001) states that in revealed preference surveys, respondents are asked about something they actually did hence their behaviour is revealed, while in stated preference surveys, respondents are asked what they would do if they faced a particular situation that they have not actually faced, hence stated. Despite this difference, both methods are based on the underlying paradigm of the utility maximization theory considering a rational consumer (Hensher et al., 2015; Profillidis & Botzoris, 2019b).

Revealed preference surveys are based on the assumption that the individual's response may not change over time, which gives rise to an inconsistency. Due to this factor of inconsistency, though the revealed preference surveys are suitable in the evaluation of consumer preference for a new transport mode, they cannot directly be used to evaluate demand under conditions which do not yet exist. This is because naturally, the consumer preference can change later when the said situation arises than when they expressed it initially. When the scenario considered in the survey is hypothetical (i.e. if the mode does not exist) it is even more difficult to capture the inconsistencies in revealed preference surveys as there is no previous experience

obtained by the individual (Profillidis & Botzoris, 2019b). Hence stated preference surveys can be understood as a preferable method to capture the choices of individuals towards a nascent and emerging mode such as all-electric aviation.

The literature provides ample evidence for the application of stated preference surveys in transport studies for both existing and hypothetical modes. For instance, Ahmed et al., (2021), Al Haddad et al., (2020), Boddupalli, (2019), EASA, (2021) and Ilahi et al., (2021) have employed stated preference methods in their studies pertaining to the demand analysis of UAM while Björklund, (2018), Dimatulac & Maoh, (2016), Huang & Qian, (2021) and Jin et al., (2020) used it for the same for electric vehicles. Similar studies could be found related to ground transportation modes as well (Puan et al., 2019).

Stated preference surveys come in different types according to the need of the analysis. One of the most common methods is the stated choice experiments (CE) where the respondents are asked to choose one out of two or more multi-attribute alternatives (Johnston et al., 2017; Profillidis & Botzoris, 2019b). Another method is the contingent valuation (CV) where the respondents are asked to choose a proposed change at a specified cost (Johnston et al., 2017). The study by Profillidis & Botzoris, (2019) presents another method named stated ranking where the respondents are required to rank, order or scale various attributes of one or more transport alternatives. Examples of all three types being used in different demand studies can be found in the literature (Björklund, 2018; Boddupalli, 2019; EASA, 2021; Veisten et al., 2024). However, Sanko (2001) argues that the ranking method was applied in the earlier ages of stated preference surveys and that the stated choice experiment method is the most popular method used in transport studies.

4. Expert Workshop

Though the preliminary knowledge about the general background, demand factors and modeling approaches were obtained from the thorough literature review, there still existed some ambiguity given the lack of maturity of available literature related to the subject area. This in turn led to realizing the need to have a different perspective on the study. Hence, it was decided to get expert opinions on the overall project and to get the findings validated. A panel of experts including industry professionals and academics with expertise in aviation, electric transportation, and demand analysis was invited to share their ideas and opinions on these matters. This section explains the methodology of the expert workshop.

4.1. Workshop Purpose & Objectives

As explained above, the ambiguity in the output from the literature study was the primary motivation for organizing this workshop. The major concerns arising from these ambiguities were the questions of how to capture the increase in demand due to the introduction of a new mode of transportation and how to incorporate electric aviation specific demand factors into the model. Further, the absence of historical data posed a major challenge, hence it was also important to realize how to address the issue of not having historical data and how to gather it. In addition, the factors identified to be influencing the demand for electric aviation needed to be validated and the number of factors should be reduced if they are to be used as model inputs. Further, the usability of the demand models identified relevant to UAM and conventional aviation on electric aviation should be confirmed.

In order to achieve these outcomes at the end of the workshop, it was pivotal to have a clear set of objectives established. These objectives were targeted at gathering insights into what was missing in the literature, and they should be aligned with the overall objectives of this particular research. In this context, the following were the objectives set for the workshop:

- Identify specific factors influencing the demand for electric air transportation.
- Determine the input data and data sources required for modeling the demand.
- Discuss suitable modeling approaches to capture the demand for a new mode of transport.

4.2. Participants

An open invitation was sent to a set of professionals including academics, researchers, professionals working in airlines, airport operators and transport authorities, and they were asked to further share the invitation with relevant colleagues. The workshop consisted of a panel of 6 participants from diverse professional backgrounds representing SAS airline, Swedish Regional Airports (SRF), Norrköping Airport, VTI (the Swedish National Road and Transport Research Institute) and Linköping University.

4.3. Workshop Structure

The workshop was conducted over a single day in an online format allowing the participation of experts from different regions. It consisted of four sessions; an initial presentation to introduce participants and outline the research objectives, followed by three discussions. The discussions were moderated by a facilitator who ensured balanced participation and kept the flow focused on key questions related to the study. Data collection during the workshop included audio and video recordings of the full session, detailed notes, and participants' submissions via the online platforms used.

The first discussion was a facilitated discussion focused on the first objective which is to identify the specific factors influencing the demand for electric air transportation. The participants were provided with a list of demand factors (Table 7.1 presented in Chapter 7) for electric aviation and each of the participants was asked to reflect on the provided list based on the following questions:

1. What is the relevance/importance of each factor?
2. What factors can be considered most influential in identifying demand for electric air transportation?
3. What factors might be unique to electric aviation compared to conventional aviation?
4. Are there any new factors to be considered?
5. Any factors that can be eliminated?

Then the participants were directed to an online spreadsheet where each had their private sheet in which they were instructed to select the ten most influential factors and the ten least

influential factors from the provided list as per their opinion. They were also asked to list the additional factors they believe the author should consider as well as the factors to be eliminated from the given list. Once the provided time passed, the participants were encouraged to provide explanations for each of their choices and later to brainstorm together with other participants.

The second discussion was aimed at determining the input data and data sources required for modeling the demand. The discussion was provided with discussion points as guidance to maintain the flow of the discussion as follows:

1. What are the potential input data for modeling the demand based on the factors discussed earlier?
2. What input data can be used to describe EA-specific factors?
3. What are the sources of data (Ex: surveys, databases, government census, etc.)?
4. What are the data collection methods and potential challenges in sourcing data?
5. What is the requirement to conduct a Stated Preference Survey?
6. What is the relevance/importance of a SP survey to the study?
7. What are the data gaps and limitations and what strategies can be used to address the gaps?

The participants were allowed to discuss, brainstorm and present their own opinions on the above points.

The third discussion was to find suitable modeling approaches to capture the demand for a new mode of transport. The participants were informed of the different types of modeling approaches available in transport research studies and aviation-related research by providing a brief introduction drawing the pros and cons of each approach. Then the participants were advised to discuss based on the points presented below.

- Suitability of the models to address the challenges explained.
    1. How to capture the increase in demand due to the introduction of a new mode of transportation?
    2. How to incorporate EA-specific demand factors into the model as model parameters?

3. How to address the issue of not having historical data?

- Consider aspects such as model complexity, and data availability.
- What are your ideas on the pros and cons of the presented models and their suitability?
- Any suggestions for new modeling approaches?

4.4. Analysis Approach

The expert workshops are a qualitative research approach to gather the required knowledge. Hence the analysis would also follow a qualitative approach. For the analysis of this workshop, the deductive qualitative analysis approach was selected (Pearse, 2019). The reason for selecting this approach was that this workshop was conducted under already established themes and the objective of the workshop analysis was to identify the data under those defined themes. The video recording and the transcripts were studied to understand the recurring topics and keywords, and out of them what was most relevant to the scope of this study had been focused.

Apart from this, the analysis was also conducted on the outputs obtained such as the different lists of factors created by the participants.

5. Stated Preference Survey

From the output obtained from the literature review and the expert workshop, it was concluded that a Stated Preference (SP) survey would be used as the data collection method in this study. This section explains the methodology of creating the survey questionnaire and the collection of data using the survey.

5.1. Survey Questionnaire Structure

The survey questionnaire comprised four main sections. The first section included questions related to the previous air travel experience of the respondents. The second section consisted of personality/attitude-related questions. The choice scenarios were presented in the third section and the fourth and final section consisted of demographic questions.

The section dedicated to previous travel experience consisted of four questions. Questions in this section examine the familiarity of a respondent with air travel. The questions cover areas such as travel frequency, trip purpose, factors they consider important when traveling by air and the frequency of paying for climate compensation when buying an air ticket. These questions here are for the general understanding of how people view air travel. The question for factors they think are important when traveling by air was given as a ranking of the most important to least important while the other three questions were single-choice questions.

It was understood that the personal behaviour or attitudes of a person have a direct impact on the demand for all-electric air travel as a transport mode. From the results of the literature review and the expert workshop, it was clear that a person's attitudes toward environmental awareness, technological awareness and the perceived safety of the mode have the potential to drive the demand. Hence, questions to gather data on these aspects were an integral part of the survey. Three questions covering environmental awareness, technological awareness and safety were presented and each question had options of a five-point Likert scale ranging from "Strongly Disagree" to "Strongly Agree". Figure 5.1 depicts the three questions along with the Likert scale.

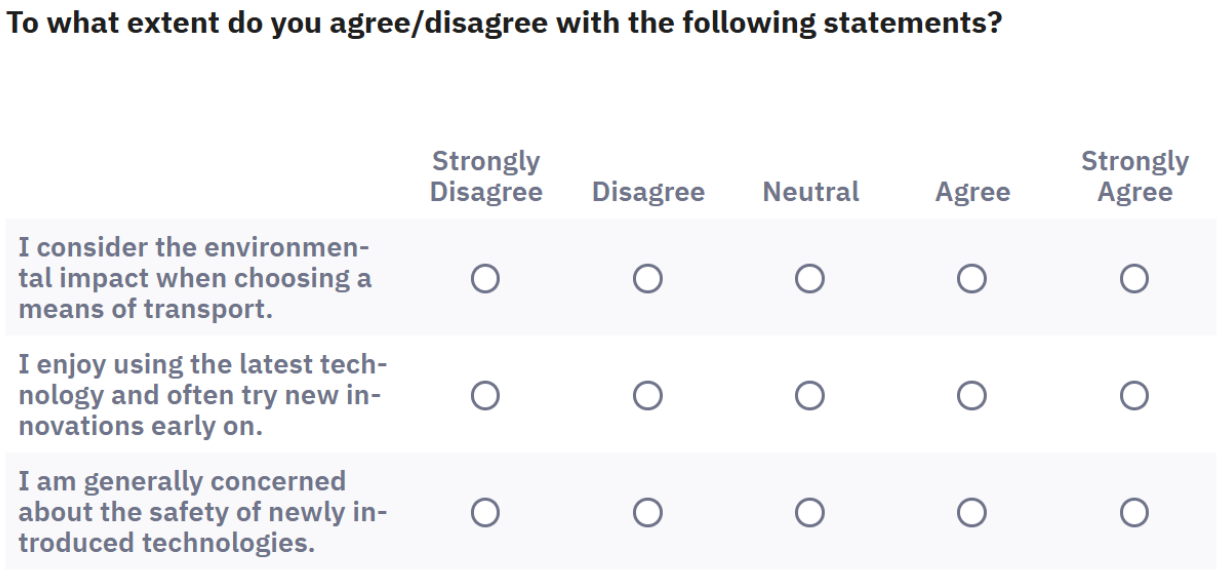

Figure 5.1 – Questions with Likert Scale used in Personality/attitude questions.

The most critical section of the whole questionnaire was the section that contained choice scenarios as this is the foundation for the discrete choice demand model. Each respondent was presented with ten choice questions, each having two alternatives: the conventional aircraft option and the all-electric aircraft option. At the beginning of the section, a brief description of all-electric aircraft was given as the concept might not be familiar to many of the respondents. The attributes for each alternative were also presented and the respondent was expected to select one out of the two alternative options based on their preference. The creation of the choice questions is explained in detail in the next section. An example of a choice question presented in the actual survey is demonstrated in Figure 5.2.

The last section included questions to gather a respondent's demographic data such as age, gender, income, highest education level and employment status. These data would be analyzed descriptively in order to understand the sample and some of them such as age, gender and income would later be used as inputs to the model.

Apart from the four main sections explained above, a screening question was presented in the beginning in order to screen-out the participants who are under 18 years of age. At the end of the questionnaire, another question was added as suggestions for improvements to obtain feedback and ideas from the participants to further improve the survey for future work.

Assume you are planning a one-way flight for you, considering the following details. If both flight alternatives below are available to you, which would you choose?

Flight Alternatives	 Conventional Aircraft	 All-electric Aircraft
Origin & Destination	Stockholm to Gothenburg	Stockholm to Gothenburg
Purpose of your trip	Business	Business
Ticket Price	1800 kr	1800 kr
Travel Time	60 min	1hr 30 min
No. of Transfers	0	0
Personal Carbon Footprint	61 kg	5 kg
	○	○

Figure 5.2 – Example of a Choice Scenario Question.

5.2. Choice Experiment Design

As mentioned in the previous section, choice questions were the most critical part of the survey, and these questions had to be carefully constructed in order to obtain the desired results from the survey. As Figure 5.2 depicts, each choice question consists of two alternatives: Conventional Aircraft and All-electric Aircraft, and under each alternative presented are the attributes related to that alternative. When creating these types of questions, a researcher should typically take various considerations into account. These include the number of alternatives required, the attributes that need to be considered, the range of values for each attribute and the number of choice questions directed per each respondent (Garrow et al., 2019). The methodology of constructing the choice questions considering the above is called the Choice Experiment Design (Sanko, 2001).

5.2.1. Alternatives

At the beginning of the choice experiment design process, it is required to decide the alternatives that are going to be studied by the survey. Here in this study, the focus was given to identifying the demand for all-electric aircraft, therefore it was automatically considered to be an alternative. After considering the outputs from the literature study and the expert

workshop it was concluded that the mode choice between all-electric aircraft and conventional aircraft would be interesting to study hence conventional aircraft was chosen as the other alternative.

5.2.2. Attributes & Attribute Levels

Next, was to select the attributes of the alternatives. The attributes were chosen after careful consideration of the demand factors that needed to be included in the choice model together with the characteristics of an all-electric aircraft. The cost and travel time of transport modes are commonly included attributes in transport-related stated preference surveys (Garrow et al., 2019; Sanko, 2001). The ticket price was considered as the cost as the comparison here was between two air transportation alternatives traveling from one airport to another. Travel time for an all-electric aircraft largely depends on the distance between the origin and destination (OD) it flies. Due to the battery capacity constraint, these aircraft can only fly about 200-300 km in one stretch (Hellesund, 2022) and have to be recharged to fly longer. Therefore, the longer the distance between the origin and destination the more stops must be made, resulting in longer travel times.

Owing to this situation, it was understood that instead of including travel time as an attribute when creating choice experiments, it was preferable to use distance and Number of transfers as two different attributes. The distance was represented in terms of OD pairs. Three attribute levels for OD pairs were defined based on short-distance, medium-distance and long-distance routes relative to the distance capacity of the electric aircraft and for each distance category an OD was assigned. For short-distance Arlanda – Visby (A-V), for medium-distance Arlanda – Gothenburg (A-G), and for long-distance Arlanda – Lycksele (A-L) were chosen. For transfers having one transfer or no transfers were chosen as two attribute levels.

When it comes to the cost of air travel, it is known that the airlines do not have fixed ticket prices for any flight rather it fluctuates due to many reasons such as the seasonal demand. Taking this nature of air travel into account, it was decided to include cost attributes with the attribute levels High and Low. Furthermore, the trip purpose was also introduced as an attribute with Business and Leisure as its two attribute levels. Table 5.1 presents a summary of the attributes and the levels discussed above.

5.2.3. Design of Experiments

Once the attributes and levels are finalized then next was to design the choice experiments. This simply refers to designing a number of choice questions as demonstrated in Figure 5.2 with different attribute combinations. The total number of such questions to be created and the number of questions presented to each respondent depends on the methodology that is being followed.

Attribute	Levels		
	1	2	3
OD	Arlanda to Visby	Arlanda to Gothenburg	Arlanda to Lycksele
Ticket price	Low	High	-
Purpose	Business	Leisure	-
Transits	0	1	-

Table 5.1 – Attributes and Attribute Levels

The initial design involves only one alternative and then is expanded into the other alternatives. Factorial designs are used to develop these combinations for one alternative (here it was for conventional aircraft). Given there are only four attributes in this study where only one having three levels and the other three having two levels each, a Full Factorial design is applicable. A Full Factorial design is when every possible combination of attribute levels is used to design one alternative. The number of combinations obtained from this method is the result of the number of levels raised to the power of the number of attributes and if there are attributes with differing numbers of levels the raised values are simply multiplied together (Sanko, 2001). Thus, all the combinations possible for conventional aircraft alternative had been $3^1 \times 2^3$ that is 24 combinations which was not computationally difficult to obtain.

Scenarios	Conventional Aircraft			
	O-D	Purpose	Ticket Price	Transits
1	A-V	Business	Low	0
2	A-G	Business	Low	0
3	A-L	Business	Low	0
4	A-V	Business	High	0
5	A-G	Business	High	0
6	A-L	Business	High	0
7	A-V	Leisure	Low	0
8	A-G	Leisure	Low	0
9	A-L	Leisure	Low	0
10	A-V	Leisure	High	0
11	A-G	Leisure	High	0
12	A-L	Leisure	High	0
13	A-V	Business	Low	1
14	A-G	Business	Low	1

15	A-L	Business	Low	1
16	A-V	Business	High	1
17	A-G	Business	High	1
18	A-L	Business	High	1
19	A-V	Leisure	Low	1
20	A-G	Leisure	Low	1
21	A-L	Leisure	Low	1
22	A-V	Leisure	High	1
23	A-G	Leisure	High	1
24	A-L	Leisure	High	1

Table 5.2 – Full Factorial Design for Conventional Aircraft

The full factorial for conventional aircraft was then needed to be expanded to all-electric aircraft. In order to do this several factors were considered. Usually in transport studies when creating choice sets it is recommended to change all the attribute values of the initially designed alternative to obtain different combinations. However, in this study, the two modes that are compared have some unique and similar operational characteristics. For instance, it is not fair to assess the two modes based on two different OD pairs as attributes such as the travel times, cost and number of transits required are not alike across the different OD pairs. Similarly, it is not practical to compare the modes based on different trip purposes. Hence, it was decided to create the scenarios for electric aircraft by only changing the ticket price and number of transits attributes while the OD and purpose attributes remain unchanged.

Further, considering the distances used here, though they were identified as short, medium and long distances relative to the technical and operational performance of all-electric aircraft, and require stops in between the OD pairs, for conventional aircraft such transits are not required in real-life scenarios. Hence it was understood that having one transit for conventional aircraft could be disregarded. Owing to this reason the expansion was only conducted using zero transits for conventional aircraft, reducing the number of combinations for the initial alternative. Each of the remaining choice scenarios was extended to four choice games as shown in Table 5.3 resulting in 48 different choice games.

Choice Set No.	CA				EA			
	OD	Purpose	Ticket Price	Transits	OD	Purpose	Ticket Price	Transits
1	A-V	Business	Low	0	A-V	Business	Low	0
2	A-V	Business	Low	0	A-V	Business	High	0
3	A-V	Business	Low	0	A-V	Business	Low	1
4	A-V	Business	Low	0	A-V	Business	High	1
5	A-V	Leisure	Low	0	A-V	Leisure	Low	0
6	A-V	Leisure	Low	0	A-V	Leisure	High	0

7	A-V	Leisure	Low	0	A-V	Leisure	Low	1
8	A-V	Leisure	Low	0	A-V	Leisure	High	1
9	A-V	Business	High	0	A-V	Business	Low	0
10	A-V	Business	High	0	A-V	Business	High	0
11	A-V	Business	High	0	A-V	Business	Low	1
12	A-V	Business	High	0	A-V	Business	High	1
13	A-V	Leisure	High	0	A-V	Leisure	Low	0
14	A-V	Leisure	High	0	A-V	Leisure	High	0
15	A-V	Leisure	High	0	A-V	Leisure	Low	1
16	A-V	Leisure	High	0	A-V	Leisure	High	1
17	A-G	Business	Low	0	A-G	Business	Low	0
18	A-G	Business	Low	0	A-G	Business	High	0
19	A-G	Business	Low	0	A-G	Business	Low	1
20	A-G	Business	Low	0	A-G	Business	High	1
21	A-G	Leisure	Low	0	A-G	Leisure	Low	0
22	A-G	Leisure	Low	0	A-G	Leisure	High	0
23	A-G	Leisure	Low	0	A-G	Leisure	Low	1
24	A-G	Leisure	Low	0	A-G	Leisure	High	1
25	A-G	Business	High	0	A-G	Business	Low	0
26	A-G	Business	High	0	A-G	Business	High	0
27	A-G	Business	High	0	A-G	Business	Low	1
28	A-G	Business	High	0	A-G	Business	High	1
29	A-G	Leisure	High	0	A-G	Leisure	Low	0
30	A-G	Leisure	High	0	A-G	Leisure	High	0
31	A-G	Leisure	High	0	A-G	Leisure	Low	1
32	A-G	Leisure	High	0	A-G	Leisure	High	1
33	A-L	Business	Low	0	A-L	Business	Low	0
34	A-L	Business	Low	0	A-L	Business	High	0
35	A-L	Business	Low	0	A-L	Business	Low	1
36	A-L	Business	Low	0	A-L	Business	High	1
37	A-L	Leisure	Low	0	A-L	Leisure	Low	0
38	A-L	Leisure	Low	0	A-L	Leisure	High	0
39	A-L	Leisure	Low	0	A-L	Leisure	Low	1
40	A-L	Leisure	Low	0	A-L	Leisure	High	1
41	A-L	Business	High	0	A-L	Business	Low	0
42	A-L	Business	High	0	A-L	Business	High	0
43	A-L	Business	High	0	A-L	Business	Low	1
44	A-L	Business	High	0	A-L	Business	High	1
45	A-L	Leisure	High	0	A-L	Leisure	Low	0
46	A-L	Leisure	High	0	A-L	Leisure	High	0
47	A-L	Leisure	High	0	A-L	Leisure	Low	1
48	A-L	Leisure	High	0	A-L	Leisure	High	1

Table 5.3 - Choice Games

Out of the 48 choice sets, there could be identified some trivial games that could be excluded from the survey such as having transits in the Arlanda – Visby which is a short-distance route and having zero transits in the Arlanda – Lycksele which is a long-distance route. Moreover,

for the same OD pair, trip purpose and number of transfers having two scenarios with the same price levels seemed to be trivial (for example see the highlighted rows in Table 5.3), hence of such pairs only one scenario was retained.

After the removal of trivial games, the resulting table consisted of 30 final choice set combinations. Yet 30 questions directed per one respondent increases the cognitive burden of the respondent. Therefore, it was decided to develop a block design in which the choice sets are divided into subsets known as blocks. 30 choice sets were assigned to 3 blocks, each block having 10 questions. This way the cognitive burden posed on the respondents will be reasonable. A block will be randomly assigned to the respondent when the survey is conducted. The final choice sets with the blocks are presented in Table 5.4.

Once the choice sets were finalized, the required values for attributes were defined as per Table 5.5. The travel time and the CO2 emissions were dependent on the distance and number of transfers required. These choice sets were then transferred into questions as depicted in Figure 5.2.

Block	OD	Purpose	Ticket Price	Transits	OD	Purpose	Ticket Price	Transits
1	A-V	Business	Low	0	A-V	Business	Low	0
	A-V	Leisure	Low	0	A-V	Leisure	High	0
	A-G	Business	Low	0	A-G	Business	Low	0
	A-G	Leisure	High	0	A-G	Leisure	Low	0
	A-G	Business	Low	0	A-G	Business	High	1
	A-G	Leisure	Low	0	A-G	Leisure	Low	1
	A-L	Business	Low	0	A-L	Business	High	1
	A-L	Leisure	Low	0	A-L	Leisure	Low	0
	A-L	Business	Low	0	A-L	Business	High	0
	A-L	Leisure	Low	0	A-L	Leisure	Low	1
2	A-V	Business	High	0	A-V	Business	Low	0
	A-V	Leisure	Low	0	A-V	Leisure	Low	0
	A-G	Business	Low	0	A-G	Business	High	0
	A-G	Leisure	Low	0	A-G	Leisure	Low	0
	A-G	Business	High	0	A-G	Business	Low	1
	A-G	Leisure	Low	0	A-G	Leisure	High	1
	A-L	Business	Low	0	A-L	Business	Low	0
	A-L	Leisure	Low	0	A-L	Leisure	High	1
	A-L	Business	High	0	A-L	Business	Low	1
	A-L	Leisure	High	0	A-L	Leisure	Low	0
3	A-V	Business	Low	0	A-V	Business	High	0
	A-V	Leisure	High	0	A-V	Leisure	Low	0
	A-G	Business	Low	0	A-G	Business	Low	1
	A-G	Leisure	Low	0	A-G	Leisure	High	0

	A-G	Business	High	0	A-G	Business	Low	0
	A-G	Leisure	High	0	A-G	Leisure	Low	1
	A-L	Business	Low	0	A-L	Business	Low	1
	A-L	Leisure	Low	0	A-L	Leisure	High	0
	A-L	Business	High	0	A-L	Business	Low	0
	A-L	Leisure	High	0	A-L	Leisure	Low	1

Table 5.4 – Final Choice Sets with Blocks

OD	CA						EA					
	Arlanda to Visby		Arlanda to Gothenburg		Arlanda to Lycksele		Arlanda to Visby		Arlanda to Gothenburg		Arlanda to Lycksele	
Ticket Price	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low
Leisure	1100	700	1000	600	1900	1100	1100	700	800	600	1900	1100
Business	3300	2100	3000	1800	5700	3300	3300	2100	2400	1800	5700	3300
Travel Time	50min		60min		1hr 25min		55min		1hr 30min		2hr	
TT with 1 Tr	-		-		-		-		2hr 05min		2hr 30min	
CO2	45kg		61kg		75kg		2.8kg		5kg		7kg	
CO2 with 1 Tr							-		5.2kg		7.2kg	

Table 5.5 – Attribute Values Used in the Survey

5.3. Survey Responses Collection

The finalized choice questions were then compiled with the questions in the other sections into a complete questionnaire. The questionnaire consisted of a total of 22 questions per respondent which approximately takes about 5 minutes to complete. The survey was developed on a web-based surveying platform named LimeSurvey. The link to access the survey and QR code was shared with participants through emails and other methods in July 2024. Survey responses were collected between July to August 2024 and received 105 responses out of which only 84 could be extracted to make a valid and testable data set.

However, a potential problem identified with the survey distribution was that the survey was distributed among an audience consisting of students, academics and professionals in the aviation industry where this community, in general, could be understood as enthusiasts for new trends in aviation. This might have caused selection bias in the survey results.

6. Development of the Demand Model

One of the research objectives of this thesis is to develop a demand model that involves the demand factors identified in the previous stages of the study. Hence the development of this model holds critical importance in the whole study. This section explains the process of developing the model in terms of the theoretical framework behind it and the stages of actual model development.

6.1. Theoretical Framework

The literature review conducted in the earlier stages of the study demonstrated several types of demand modeling approaches found related to conventional aviation and UAM. However, to the best of the author's knowledge, no studies have been found to understand what approaches might be fit for the modeling of all-electric aircraft demand. Hence it was decided to experiment with a discrete choice model considering the existing market for conventional aviation. An explanation for this selection is provided later in this thesis in Chapter 7. A key assumption made in selecting this model is that the electric aircraft would be introduced to the existing conventional aviation market and that a certain amount of modal shift from CA to EA would be expected. As there are only two alternatives considered, the binary logit model was selected out of the varieties of discrete choice models. However, the underlying theoretical framework is the same for any of such models.

An individual decides to make choices based on different elements associated with their decision-making process. Koppelman & Bhat (2006) explain that in the context of transportation, these elements would be the decision maker, the alternatives, the attributes of alternatives and the decision rule. Out of these, one such decision rule named utility maximization is what the theoretical framework of discreet choice theory is built upon. Utility is derived from the attributes of a particular alternative or a set of alternatives and the utility maximization rule claims that an individual will select the alternative that maximizes his or her utility from a set of alternatives available to them (Koppelman & Bhat, 2006). This rule implies that there exists a function that contains attributes of alternatives and characteristics of decision-makers that demonstrate the utility valuation of a certain individual for each of the alternatives available to them. An alternative is said to be chosen by the individual if the utility of that alternative is greater than that of all the other alternatives.

This utility function can be expressed as follows in Equation 6.1. The true utility of alternative i to the decision maker t ($U_{i,t}$) consists of two parts: one being the deterministic component, also known as the systematic utility, which describes the observable behaviour of decision-makers ($V_{i,t}$) and the other being the probabilistic portion that describes the error or the utility unknown to the analyst ($\varepsilon_{i,t}$) .

$$U_{i,t} = V_{i,t} + \varepsilon_{i,t}$$

Equation 6.1 – Utility Function

The systematic portion of the utility function includes the parameters that are to be estimated in the model and are often formulated additively to simplify the model estimation. The components in this function can be of three sorts. They can be related to the attributes of alternatives such as travel time, travel cost, number of transfers, etc. or related to the characteristics of the decision maker such as gender, age, income, household size, etc. It can also be interactions between the attributes of alternatives and the characteristics of the decision maker.

The error term, on the other hand, by definition is considered unobserved and unmeasured. However, by introducing assumptions to this error term, the mathematical formation of the discrete choice models can be done. These assumptions are that the error components are Gumbel distributed, are identically and independently distributed across alternatives, and are identically and independently distributed across individuals (Koppelman & Bhat, 2006). By considering these three assumptions together, the multinomial logit model (MNL) is obtained. The MNL model generates a choice probability for each of the available alternatives considering their systematic utilities. Equation 6.2. demonstrates the general expression of the model where P_i denotes the probability of choosing alternative i and V_i denotes the systematic utility of alternative i.

$$P_i = \frac{e^{V_i}}{\sum_{j=1}^{J} e^{V_j}}$$

Equation 6.2 – General Expression for Choice Probability

The systematic utility will generally look like what is presented in Equation 6.3. Here the X_{ni} depict the attributes of the utility function of alternative i such as travel time, cost, income, etc., mentioned above and the betas represent the parameters of respective variables.

$$V_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} \ldots + \beta_n X_{ni}$$

Equation 6.3 – Function of Systematic Utility

β_0 is the bias and it is generally referred to as the alternative specific constant. In order to obtain the choice probabilities, it is required to first estimate the parameters. The process of obtaining values for these is called model estimation and it is conducted based on the observed choice data which contains an indicator explaining the choice made and the values for variables for each chosen alternative. One of the most commonly utilized techniques for model estimation is the maximum likelihood estimation. This method uses the maximum likelihood function (Equation 6.4), and the parameter values are derived by maximizing this likelihood function. The likelihood function $L(\beta)$ for a sample of T individuals each with J alternatives is derived using P_{jt} that represents the probability that individual t chooses alternative j, and δ_{jt} that represents whether the individual t chooses alternative j or not (it becomes 1 if is chosen, 0 otherwise).

$$L(\beta) = \prod_{\forall t \in T} \prod_{\forall j \in J} (P_{jt}(\beta))^{\delta_{jt}}$$

Equation 6.4 – Maximum Likelihood Function

However, Koppelman & Bhat (2006) explain the log of the above function can be used due to the convenience and ease of differentiation and that can be maximized since the log value of a function delivers the same maximum. This is called the log-likelihood function and can be expressed as Equation 6.5. By maximizing this function, the parameters are estimated, and by applying those parameters in Equation 6.2 the choice probabilities of each alternative are computed.

$$LL(\beta) = Log\big(L(\beta)\big) = \sum_{\forall t \in T} \sum_{\forall j \in J} \delta_{jt} \times \ln\left(P_{jt}(\beta)\right)$$

Equation 6.5 – Log-likelihood Function

6.2. Logit Model for Electric Aviation Demand

The development of the model was conducted in Biogeme, which is a software specialized in estimating parameters of discrete choice models using maximum likelihood estimation (Bierlaire, 2018). The data required for the development of the model was acquired from the stated preference survey which was explained in Chapter 5. Biogeme requires a specific format of data named IDCASE where all the attributes of all the alternatives available are presented in separate columns while an individual's choice is recorded in rows. As per the stated preference survey in this study one respondent is presented with 10 choice games hence 10 rows will be created per respondent. An example of such a data set is presented in Table 6.1.

Case	Respondent ID	Age	Gender	Income	Conventional Aircraft			Electric Aircraft			Choice
					Price	Time	CO2 Emission	Price	Time	CO2 Emission	
1	1	2	2	4	2100	50	45	2100	55	2.8	1
2	1	2	2	4	700	50	45	1100	55	2.8	1
3	1	2	2	4	1800	60	61	1800	90	5	1
4	1	2	2	4	1000	60	61	600	90	5	1
5	1	2	2	4	1800	60	61	3000	125	5.2	0
6	1	2	2	4	600	60	61	600	125	5.2	0
7	1	2	2	4	3300	85	75	5700	150	7.2	0
8	1	2	2	4	1100	85	75	1100	120	7	1
9	1	2	2	4	3300	85	75	5700	120	7	0
10	1	2	2	4	1100	85	75	1100	150	7.2	0

Table 6.1 – IDCASE Data Type Example Data Table

Once the dataset was prepared it was fed into the software. The model building involves the development of utility functions for both alternatives. Numerous different models can be obtained by changing the use of alternative attributes, however, identifying the best model is a trial-and-error process.

Koppelman & Bhat (2006) introduce several instructions reviewing the performance of the developed model including judgement-based informal methods, goodness-of-fit measures and statistical methods. Informal methods include the checking of parameter signs where some of the attributes have the traditionally accepted signs. For instance, time and cost parameters are traditionally considered a disutility, hence if the results show negative signs for parameters of these attributes the model may be considered correct based on the signs. Another informal method is to check the differences of signs for alternative specific variables. This means that some variables applied in different alternatives could represent different utilities. For instance, we can assume that a person's environmental awareness can be a positive drive for the utility of electric aircraft while a disutility for conventional aircraft. Therefore, if the alternative

specific parameter for environmental attribute has obtained a positive sign in electric aircraft utility function while the same was negative in conventional aircraft utility this may be a sign of accuracy based on this judgement-based method.

The goodness-of-fit test is conducted by comparing the log-likelihood (LL) measures of a model. The LL measures used in this method are the LL(0): the LL with zero coefficients (also known as the null log-likelihood), LL(C): the LL of the constants only model, LL($\hat{\beta}$): the LL of the estimated model, and LL(*) = 0 the LL of an ideal estimation model that exactly represents the real world. The values of these different LL measures will always be in the order shown in Figure 6.1. Based on the relationship of these measures a value called "rho-squared" is computed as in Equation 6.6.

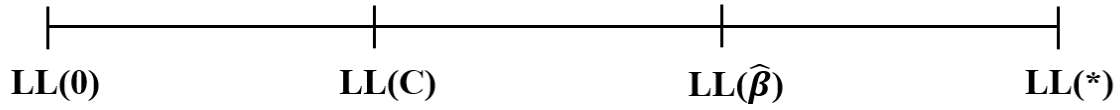

Figure 6.1 – Relationship Between Different Log-likelihood Measures

$$\rho_0^2 = 1 - \frac{LL(\hat{\beta})}{LL(0)}$$

Equation 6.6 – Equation for Rho-squared

The ρ_0^2 value usually lies between 0 and 1, however there exists no threshold value that can certify that a particular model is a good model. Rather, this value is used to compare two models to understand which is better.

For the analysis of parameter values the t-test is used. Hypothesis testing is done where a null hypothesis is defined as an estimated value of certain parameter k, $\hat{\beta}_k = 0$. It is observed that if the test statistic $|t| > 1.96$, the null hypothesis can be rejected with 95% confidence which means that $\hat{\beta}_k \neq 0$ and the parameter k has a significant effect on the choice. One can also use a 90% confidence level where the null hypothesis is rejected if $|t| > 1.645$ (Koppelman & Bhat, 2006).

Nonetheless, Koppelman & Bhat (2006) elaborates that having an insignificant t-test value does not necessarily mean that the corresponding parameter should be removed from the model. It makes sense to keep the variable in the model if the analyst has a reasonable cause to

think that it is significant, and the parameter sign is accurate. Furthermore, the study advises that one should be cautious when eliminating variables that seem important based on the low t-test value as those same variables may become significant when other factors are added to or removed from the model. Hence it can be understood that the intuition of the analyst is also important in deciding a model's accuracy.

The values required for the above-mentioned tests, namely the LL values and the t-test values for each parameter estimated are computed by Biogeme as one of the model outputs where an analyst can make decisions based on them. Under these conditions, different models were tested, and the results of models built are presented in Chapter 7.

7. Data Analysis & Results

The logical flow of methodologies explained in Chapters 3-6 provided a framework to achieve the research objectives set at the beginning of the study and this section discusses how the results are obtained by applying the methodology. This section describes the results obtained at each stage of the research including the literature review, expert workshop, stated preference survey and the binary logit demand model.

7.1. Output of the Literature Study

The literature study conducted covered a diverse range of topics directly or closely related to electric air transportation. It provided in-depth knowledge of the factors that could be identified as influential to the EA demand and a path to identify the demand modeling approach suitable as well as the data collection method that could aid the study.

In terms of factor identification, the literature suggested a great number of factors relevant to all-electric aircraft demand based on other closely connected modes such as conventional aviation, UAM and EVs. These factors identified displayed a clear classification into different categories. Considering these factors along with their respective categories, a preliminary list was created as one of the outputs from this stage. This preliminary list of factors is depicted in Table 7.1.

Category	Factors	Category	Factors
Economic	1.Gross Domestic Product (GDP) 2.Consumer Price Index (CPI) 3.Other (Exchange rate, PPP, FDI, fuel price)	Operational	20.Ticket price/airfare 21.Frequency 22.Size of the aircraft 23.Cruising speed 24.Range 25.Existing airport/vertiport location 26.Fleet size
Demographic	4.Population 5.Age 6.Gender 7.Income 8.Vehicle ownership 9.Land use 10.Number of households 11.Employment rate	Personal	27.Beliefs 28.Values 29.Attitudes 30.Subjective Norms 31.Perceived behavioural control 32.Value of travel time saving 33.Willingness to pay 34.Environmental awareness 35.Technological awareness 36.Safety
Trip-related	12.Travel time 13.Travel cost 14.Distance 15.Alternative transport modes 16.Congestion 17.Trip purpose 18.Access/egress time 19.Waiting time	Other	37.Public policies/agreements

Table 7.1 – Preliminary List of Demand Factors and Categories

This identified preliminary list included factors which were raw and unfiltered. Most of them were seemingly correlated. Some of the direct correlations between the factors could be identified from the literature itself, for instance, the value of travel time saving is correlated to income and purpose and the willingness to pay is correlated to the value of travel time saving, travel time and travel costs. These findings of literature together with a further investigation of factors resulted in a correlation map as depicted in Figure 7.1. It demonstrated that most of the personal factors such as attitude and travel time are correlated with many other factors.

The dominant factors discussed in most of the electric aviation studies including UAM were the personal behaviour-related or attitudinal factors, specifically, a person's environmental concern, openness to new experiment with new technologies and perceived safety of a new transport mode. A clear distinction was observed between these studies and conventional aviation studies as this personal aspect was not taken into much consideration in such studies. Instead, they elaborated more on the demand based on the other factor categories.

From the knowledge gained on the demand modeling approaches in the literature, it could be understood that there exist two perspectives of demand modeling, namely, aggregated and disaggregated. As evident in the literature review chapter, the aggregated models were developed concerning how the demand is seen at an aggregated level such as national level, airport, city pair, etc. The models as such utilized demand factors like GDP and other economic factors, population, public policies, number of households and operational factors such as frequency, range, size of the aircraft, fleet size and distance as inputs. When looking at these input factors, it could be seen that they usually explain a general or aggregated feature commonly applied to a large scale, for example, to describe a population. On the contrary, the disaggregated models were built based on the individual perspective, therefore, more individual choice-centric factors such as gender, age, income, travel time, travel cost, willingness to pay, and personal factors were often selected as inputs to these models.

In addition to these observations, some other key concerns were also observed regarding these factors and their suitability to be incorporated in demand modeling. One was that some of these factors could be quantified while others were qualitative. All the factors listed under the personal category which were suggested in the literature to have a strong impact on the demand were qualitative factors. This led to the question of how these qualitative factors were to be incorporated into demand modeling. In addition, it was also important to recognize the positive

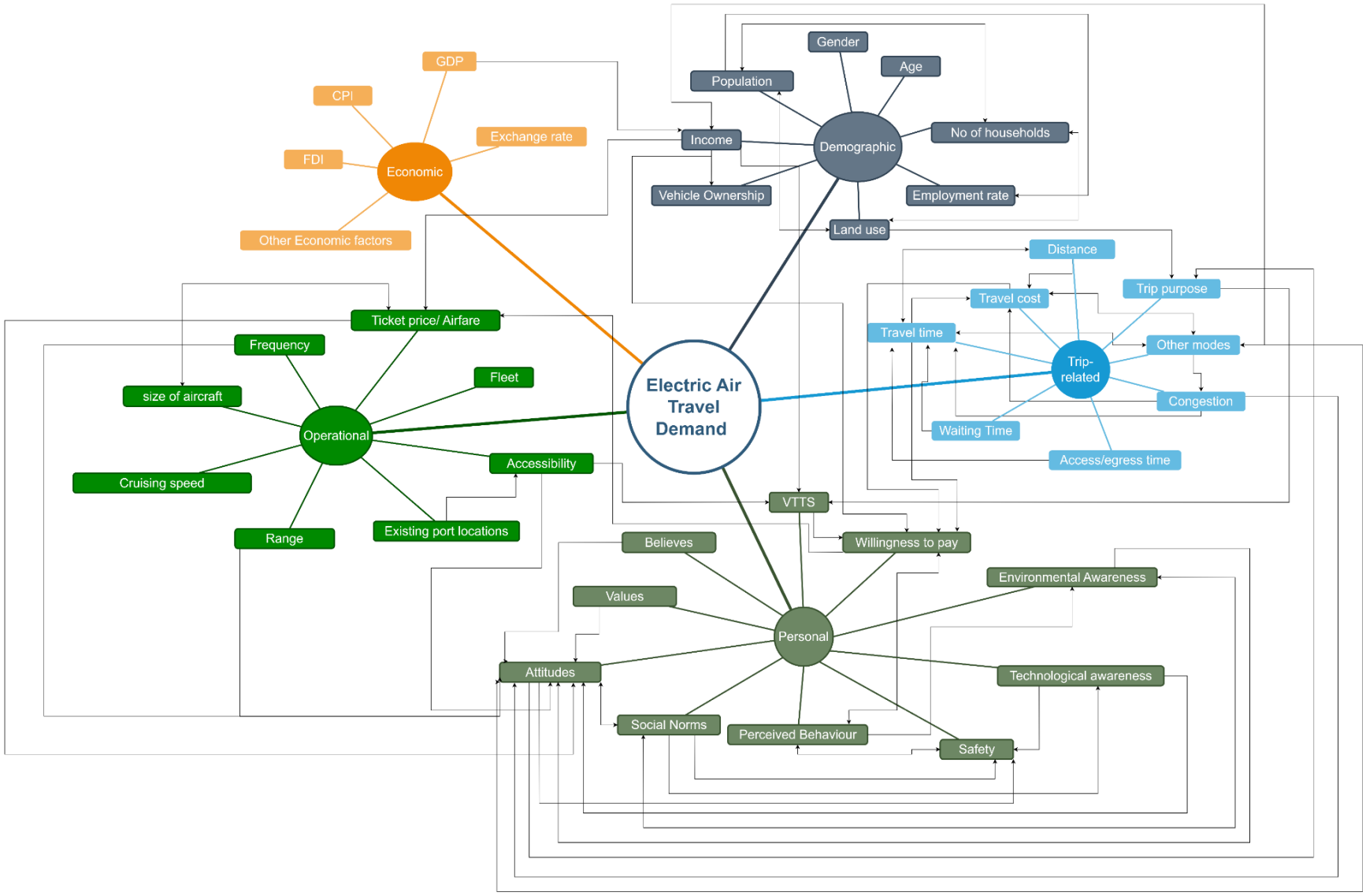

Figure 7.1 –Correlation Map of Demand Factors

or negative effects of the factors on demand. These concerns were highlighted in the discussions in the expert workshop.

With respect to the demand models, one prominent observation was the categorization of them based on their usability and applicability on different levels of aggregation. Mode choice models are commonly recognized as disaggregated models in literature, and these were mostly used related to UAM. This is owing to the fact that UAM is a newly introduced mode as an alternative to urban transportation hence the market share or user choice probability is important to compute. On the other hand, conventional aviation commonly utilizes aggregated demand analysis approaches such as econometric and time series models as they were usually focused on estimating the demand from an aggregated perspective, for instance, for an airport or for a certain geographical area rather than comparing it with other transport modes. Table 7.2 demonstrates a summary of a few types of models found in the literature.

Regardless of the type, one common element affecting all these models was the unavailability of historical data. Due to this reason, the usability of some of the models such as time series models, and machine learning models, were restrained. In addition, quantification and integration of electric aviation specific personal behavioural factors into these models seemed to pose a significant challenge.

In terms of the data collection methods, owing to the unavailability of empirical data as electric aviation is a new mode, a suitable method for data collection understood through literature was the stated preference survey method. Due to its unique characteristic where it can be used to collect data under hypothetical scenarios or in a situation that does not exist in the present, this method appeared to be more viable in applying in the context of electric aviation.

Econometric Models		Discrete Choice Models		Gravity Models		Time Series Models		Machine Learning Models	
• Use statistical techniques to estimate relationships between variables based on economic theory and empirical data. • Can analyze the determinants of demand for electric aviation based on factors such as price, income, and travel costs. • Output – Predicted demand values		• Analyze individual decision-making processes by modeling the probability that individuals choose one alternative from a set of mutually exclusive alternatives. • Can predict travelers' choices among different transportation modes, including electric aviation. • Output – Choice probabilities		• Gravity models estimate transportation flows between origin-destination pairs based on the "mass" of the origin and destination locations and the "distance" between them. • Estimate the demand for air travel between different locations based on population, economic activity, and distance. • Output – Predicted flow between OD pairs		• Analyze historical demand data to identify patterns and trends over time, allowing for forecasting future demand. • Useful for capturing seasonality, trends, and cyclical patterns in demand for electric aviation. • Output – Forecasted demand values		• Use advanced algorithms to model complex relationships between multiple factors affecting demand. • Can handle large datasets with many variables, uncovering hidden patterns in demand for electric aviation. • Output – Predicted demand with variable importance	
Pros	Cons	Pros	Cons	Pros	Cons	Pros	Cons	Pros	Cons
• Can be used to assess the impact of policy interventions, such as pricing schemes or subsidies.	• Explanatory variables can be correlated with unobserved factors, leading to biased estimates. • Limited flexibility in capturing complex interactions and nonlinear relationships.	• Simple and widely used. • Has the ability to capture personal preferences. • Can accommodate a wide range of choice scenarios and attributes.	• Suitable for analyzing mode choice. • Data collection can be challenging.	• Provides demand values between OD pairs. • Can be applied to different spatial scales, from local to regional or global, making them versatile.	• Assumes homogeneity of travelers or goods across origin-destination pairs, which may not accurately reflect real-world variations in travel behavior.	• Effective in capturing and forecasting demand trends over time. • Can handle large datasets and is relatively easy to implement.	• Requires extensive historical data for accurate predictions. • May not fully account for sudden shifts or external disruptions.	• Can model non-linear relationships and interactions between variables. • Offers high predictive accuracy and the ability to learn from new data.	• Requires historical data • Model interpretability can be challenging, making it difficult to understand the underlying factors driving demand. • Requires extensive computational resources and expertise in algorithm tuning.

Table 7.2 – Summary of Demand Models Identified

7.2. Output of the Expert Workshop

The expert workshop consisted of three main sessions and the output of the workshop was obtained in different forms. One is using the direct outputs of the online material used to obtain answers from the participants during the sessions, and the other is the identification of recurring themes of the discussion under the themes of demand factors, demand models and data collection methods.

The participants were allowed to select the most and least relevant factors according to their personal opinions from the list in Table 7.1. Considering the selections of all the participants, a summary of output was created, and it is shown in Table 7.3. This summary was prepared considering the factors which were mentioned as most or least relevant by three or more participants. In their explanations for the selection, five out of six participants demonstrated that the distance factor was automatically considered when choosing the travel time as the travel time depends on the distance. Another interesting point of view shared was that though people's attitudes are important, they could be subjective to whatever resources are at hand. It was explained using an example where a participant mentioned that they consider themselves environmentally conscious but considering the ticket price they would choose the cheapest option regardless of its environmental impact.

Most Relevant Factors	Least Relevant Factors
Travel time	Age
Alternative transport modes	Cruising Speed
Income	Gender
Ticket price	Vehicle Ownership
Existing airport locations	Beliefs
Population	
Range	
Frequency	
VTTS	
WTP	
Environmental Awareness	

Table 7.3 – Workshop Output – Most & Least Relevant Factors

The participants were able to recognize that several factors had correlations. These correlations were pointed out by them and the suggestion was to refine the list by avoiding having such correlations so that it would lead to a shorter list to consider in modeling. The correlated factors identified were as follows:

- Travel time, waiting time and value of travel time saving
- Waiting time and frequency
- Travel time and cruise speed
- Willingness to pay and trip purpose
- Ticket price and willingness to pay
- Travel cost and ticket price
- Distance and Travel time

In addition, the participants were asked to provide a list of new factors that they might think need to be included in the list. This list includes the following factors.

- Incentives and subsidies introduced by government policies
- New routes
- Airport "readiness"
- Airport infrastructure
- Operational cost
- Attractions of destination Ex: events
- Number of transfers
- Flight shame

The discussions were carried out on how the operational cost components such as the cost of the aircraft and the electricity price, could be major constraints considering electric aviation. However, counterarguments were made that these factors are related to the supply aspect and that they are usually represented in the price of a ticket. Another interesting aspect of the discussion was how the policies, policy incentives and subsidies can drive demand towards these new sustainable modes. Participants discussed that if the governments were to amend the policies in favour of something, the public would likely follow. Thus, it would be important to have policy support so that people would be more interested in using electric aircraft.

In terms of the demand modeling approaches, one of the main concerns the author had before the workshop was how the increase in demand due to the introduction of a new mode of transportation could be captured. The experts suggested that it is best to treat the demand either just as it already exists, or it is diverted from existing modes. For example, if the PSO routes would be replaced by

electric aircraft the demand already existing for conventional aircraft would still be there. Similarly, a modal shift from trains and cars could be expected. Therefore, it was recommended to not treat the demand as it would spontaneously generate. Furthermore, it was suggested to begin the modeling process with a simple and completely unconstrained perspective.

Concerning the problem of unavailability of historical data, the experts pointed out options such as using reference data with decent assumptions, using a growth factor on existing flight data, adopting the approaches used in similar situations in other transport modes like in the situation of a new train route, and to consider general movement data which can be captured by telecommunication data.

Data collection approaches were also discussed during the workshop and the experts were introduced to the concept of stated preference surveys as a methodology to collect required data. However, based on their experiences, the experts elaborated that the surveying methods could not be reliable. They pointed out that people would usually be willing to use something before it exists yet when it actually happens most people would change their earlier preference. This same theory was explained by Profillidis & Botzoris (2019b) as a common occurrence in surveying practices.

7.3. Output Analysis of Literature Review & Expert Workshop

The analysis of outputs of the literature review combined with the outputs obtained from the expert workshop portrayed a clear understanding of the demand factors related to electric aviation and guided towards the path to be taken to achieve the main objective of this study which was to build a basic demand model that could represent the factors found important in the context of electric aviation.

It was realized that the relevance of most of the factors was based on the model that a particular analyst uses. For instance, for the aggregated models, factors that explain the features of a large population were used and for disaggregated models, more personal factors were considered. However, given the electric aviation-specific context, personal factors such as environmental awareness, technology awareness and perceived safety demonstrated a prominent significance as the unique explanatory variables that drive the electric aviation demand.

Moreover, the identification of demand factors as model inputs and the data collection method was mostly dependent on the selection of a suitable demand model. Given the requirement to begin at a simple and unconstrained situation and the perspective of demand, as it is generated from the modal shift instead of spontaneously rising anew, it was understood that the application of discreet choice modeling was preferable. Discreet choice modeling demonstrated its relevance in this context in many other aspects of usability. These models enable modeling personal choice and allow the incorporation of the user's personal preferences. Thus, electric aviation specific factors can be incorporated into the model. It also allows the analysts to combine other types of factors such as trip-related and demographics. Further, the plus or minus effect of each factor considered in the model can simply be obtained and this together with the different factor combinations resulted in realizing more diverse impacts on the demand. The quantification of EA-specific factors can be achieved using a stated preference survey and discreet choice models can easily be paired with SP surveys.

Upon the selection of the model, suitable alternatives and input parameters should also be decided. The alternatives were chosen to be all-electric aircraft and conventional aircraft, and the model was decided to apply to the existing conventional aviation passenger movements between origins and destinations. In terms of the factors to be applied as inputs, it was understood that the traditional trip-related factors played a major role in electric aviation as they usually do in other modes of transportation. Hence the travel time, travel cost and trip purpose were selected. However, it was understood that given the application of the model is expected between two airports and that only the two air transport alternatives were considered the air ticket price could be considered as the passenger's travel cost. In addition, since the discussions of expert workshops highlighted the importance of the number of transits when it came to the all-electric aircraft due to its limited range, number of transfers was also chosen. The significance of the personal/attitudinal factors had also been understood in this context, hence the three aspects of concerns: environment, technology and safety were also decided to be included. Moreover, demographic factors were also considered to be applied.

Based on the above, the data collection method was developed using stated preference methods as explained in Chapter 6. Though the surveying method was found to have the disadvantage of less reliability, it demonstrated more relevance to be used in the context of this study by solving the

issues arising from not having historical data and quantification of qualitative personal factors. The factors curated above were carefully placed in the survey in a way that can provide a meaningful data set to build the discrete choice model.

7.4. Descriptive Analysis of the Survey Data

The online survey was distributed among an audience consisting of students, academics and aviation professionals. Within the period of data collection, 105 responses were received. A data cleaning methodology was carried out to identify inconsistent entries, missing values and entries with nonsensical values, and such entries were removed. After the cleaning, the dataset was reduced to 84 data points that could be used for descriptive analysis and model development.

While this survey distribution approach permitted to obtain valuable insights, it also posed certain limitations. The audience appeared to be particularly enthusiastic about the topic and, in general, about new trends. Furthermore, the composition of the audience, predominantly students, academics and aviation professionals, resulted in a less demographically diverse sample. Consequently, the results might have been somewhat skewed, reflecting the perspectives of a specialized group rather than a broader population.

7.4.1. Demographic Statistics

The demographic statistics of the survey respondents are summarized in Table 7.4 below.

The gender distribution among respondents seemed fairly balanced, slightly skewed towards males. This closely aligned with the Swedish national census data from 2023, indicating a representative sample in terms of gender. The respondents' age distribution shows a higher concentration in the age range of 25-44, particularly in the 25-34 category, which suggested that the younger and middle-aged adults were more represented in the survey, while older age groups (55+) were underrepresented. This, however, was slightly deviated from the Swedish census data for 2023.

The income distribution showed that a significant portion of respondents earn between 30,000 and 60,000kr per month, with a notable percentage earning less than 20,000kr which could be

explained by the high number of students in the sample. Higher-income respondents (60,000+ kr) were less represented, which might indicate that the survey had attracted more respondents from middle-income groups.

Variable	Respondents %	Census % (2023)
Gender		
Female	48.81%	49.65%
Male	51.19%	50.35%
Age		
18-24	9.52%	9.93%
25-34	38.10%	16.99%
35-44	28.57%	16.37%
45-54	16.67%	15.58%
55-64	5.95%	15.16%
65-74	1.19%	12.64%
75+	0.00%	13.33%
Monthly Personal Income		
<20000 kr	22.62%	-
20000 kr - 29999 kr	3.57%	-
30000 kr - 39999 kr	25.00%	-
40000 kr - 49999kr	15.48%	-
50000 kr - 59999 kr	15.48%	-
60000 kr - 69999 kr	1.19%	-
70000 kr +	9.52%	-
I don't know	7.14%	-
Highest Education Level		
Primary School	0.00%	-
Secondary School	1.19%	-
High School Diploma	2.38%	-
Bachelor's Degree	23.81%	-
Master's Degree	47.62%	-
Doctoral Degree	22.62%	-
Other	2.38%	-
Employment Status		
Employed - Full Time	63.10%	-
Employed - Part Time	5.95%	-
Self-employed	2.38%	-
Unemployed	5.95%	-
Student	21.43%	-
Retired	1.19%	-
Other	0.00%	-

Table 7.4 – Demographic Statistics of Survey Respondents (Census Source: https://www.scb.se/)

The majority of respondents held a master's degree or higher, demonstrating that the survey sample was predominantly well-educated. As explained at the beginning of the section, this might affect the attitudes and opinions expressed in other parts of the survey, particularly those related to technological adoption and environmental concerns.

The employment status data indicated that the majority of respondents were in full-time employment. However, a significant proportion of the respondents were students explaining the higher concentration of respondents in the 25-34 category, the income less than 20,000kr, and holding a master's degree. Similarly, the low percentage of retirees corresponds with the younger age distribution observed earlier.

7.4.2. Previous Air Travel Experience Related Statistics

The survey gathered data on the previous travel experience of respondents in terms of their air travel frequency within the past year, their trip purpose, important factors they consider when booking a flight and their frequency of buying climate-compensated air tickets. Table 7.5 depicts the survey statistics related to those questions.

Most respondents (88.1%) had taken a flight within the past year, and 1-5 times was the most common frequency. The majority of air travel among respondents is for family or leisure purposes, followed by business. Considering the climate-compensated ticket purchases, a significant portion of respondents stated that they never or rarely pay for climate compensation. This indicated a potential area of low engagement with the environmental initiatives of the sample.

Table 7.6 summarizes the rankings of important factors the respondents consider when purchasing an air ticket. According to the table, the majority of the respondents ranked the ticket price as the first priority while travel time was selected as the second most prioritized factor. Direct vs. transit flights and airport location took the third and fourth priorities, and the environmental impact was selected as the least prioritized. This indicated that in this sample, cost was the most important factor for most respondents when making travel decisions, while environmental impact was generally considered less important. This interestingly confirmed the same concern raised at the expert workshop.

Variable	Respondents %
Air Travel Frequency within the past year	
Never	11.90%
1-5 times	48.81%
5-10 times	23.81%
More than 10 times	15.48%
Most Common Purpose of Air Trips	
Business	28.57%
Family/ Leisure	64.29%
Home to Work	1.19%
Other	5.95%
Frequency of Paying for Climate Compensated Tickets	
Never	40.48%
Rarely	25.00%
Sometimes	15.48%
Often	2.38%
Always	0.00%
I don't know	16.67%

Table 7.5 – Previous Air Travel Experience Related Survey Statistics

	Ticket Price	Total Travel Time	Direct vs transit	Airport Location	Env. Impact
1st Ranked Option	55.95%	15.48%	21.43%	4.76%	2.38%
2nd Ranked Option	26.19%	40.48%	22.62%	4.76%	5.95%
3rd Ranked Option	9.52%	33.33%	28.57%	17.86%	10.71%
4th Ranked Option	4.76%	4.76%	17.86%	50.00%	22.62%
5th Ranked Option	3.57%	5.95%	9.52%	22.62%	58.33%

Table 7.6 – Statistics on Ranking of Important Factors Considered When Purchasing Air Tickets

7.4.3. Personal/Attitudinal Related Statistics

Three questions were directed at the respondents to understand their attitudes towards concern over the environmental impact of transport modes, openness to new technology and their perceived safety using a new mode of transport. The response rates received are shown in Table 7.7. Considering the environmental concern when choosing a mode, though a majority of respondents agreed/strongly agreed (42.85%), it appeared somewhat scattered among all the options. Nevertheless, a majority could be considered open to new technologies and there was a significant level of concern regarding their safety when experimenting with a new mode of transportation.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I consider the environmental impact when choosing a means of transport.	11.90%	19.05%	26.19%	32.14%	10.71%
I enjoy using the latest technology and often try new innovations early on.	1.19%	10.71%	35.71%	39.29%	13.10%
I am generally concerned about the safety of newly introduced technologies	1.19%	26.19%	22.62%	36.90%	13.10%

Table 7.7 – Statistics of Personal/Attitudinal Questions

7.5. Output of the Demand Model

The Binary choice model was developed based on data obtained from $n \times 10$ (n =84) choice games from the survey. As explained in Chapter 6, the choice model was built in the Biogeme discreet choice modeling software. Primarily the trip purpose was considered to be a major concern when building the models as the other explanatory variables such as the time, cost, income, etc. tend to differ across trip purpose (Koppelman & Bhat, 2006). Therefore, it was decided to develop two separate binary logit models considering the main trip purposes stated in the survey, namely, leisure and business.

As was found in many empirical studies, the common practice of choice modeling to identify the best model was by developing multiple models and choosing the best out of them comparing their performance. Therefore, several models were tested for each trip purpose, by including and excluding different explanatory variables in order to identify the best-performing model among the tested. Table 7.8 demonstrates the models, with only the alternative specific constants (Model 1 & Model 3) and final models which obtained consistent parameter values (Model 2 & Model 4) for both types of trip purposes. Model 1 and Model 3 are shown in the table in order to explain the relative performance improvements in Model 2 and Model 4 respectively in terms of the model fit.

In all models, conventional aircraft (CA) was kept as the reference alternative. Initially, constants-only models were tested where only the alternative specific constant of electric aircraft (EA) was considered (Model 1 & Model 3). The positive parameter coefficients with high significance in both models here demonstrated a positive baseline preference for EA. In simple terms, it meant when all other variables were disregarded, the passengers would have a positive utility towards EA. However, considering the trip purpose, the leisure traveller model (Model 1) demonstrated higher statistical significance and higher impact compared to the business traveller model (Model 3) explaining that the leisure travellers were more inclined towards choosing EA than business

Variable	Alternative	Leisure Purpose				Business Purpose			
		Model 1 Constant Only		**Model 2** Trip-related, Personal & Demographic Variables		**Model 3** Constant Only		**Model 4** Trip-related, Personal & Demographic Variables	
		Beta	t-test	Beta	t-test	Beta	t-test	Beta	t-test
Alternative Specific Constant	EA	0.614	5.81	-2.29	-1.56	0.45	4.64	-2.12	-1.82
Ticket Price	CA, EA	-	-	-0.00261	-7.82	-	-	-0.000746	-6.8
Travel Time	CA, EA	-	-	-0.0443	-1.65	-	-	-0.0396	-1.78
Number of transits	CA, EA	-	-	0.4	0.375	-	-	-0.226	-0.276
CO2 emission in CA	EA	-	-	0.0383	1.35	-	-	0.0374	1.7
Environmental Awareness	EA	-	-	0.643	5.6	-	-	0.53	5.42
Openness to Technology	EA	-	-	0.185	1.2	-	-	0.104	0.691
Safety Concern	EA	-	-	-0.292	-2.15	-	-	-0.368	-2.73
Income	EA	-	-	0.0278	0.313	-	-	0.044	0.558
Gender - Male	EA	-	-	0.438	1.55	-	-	0.386	1.55
Age	EA	-	-	0.146	0.977	-	-	0.371	2.71
Null Log Likelihood		-272.407		-272.407		-309.837		-309.837	
Log-likelihood of the estimate		-254.724		-180.584		-298.782		-214.6518	
ρ^2		0.065		0.337		0.036		0.307	

Table 7.8 – Binary Logit Model Outputs for the Two Types of Models

travellers. It could also be observed that their significance decreased as more factors were included in later models (Model 2 & Model 4), suggesting that preferences for EA were influenced by the attributes and factors introduced in these later models.

Model 2 and Model 4 included explanatory variables related to trip-related attributes: travel time, ticket price, number of transits, CO2 emission, personal/attitudinal attributes: environmental, technological and safety concerns, and demographic attributes: age, gender and income. The set of trip-related attributes namely, travel time, ticket price and the number of transits were considered generic to both alternatives while the others were specific to the EA alternative.

Considering the travel time and ticket price, the parameter signs were negative in both Model 2 and Model 4 demonstrating a disutility. According to the judgement-based informal method explained in Chapter 6, the parameter sign for these two variables aligned with the common norms in multinomial logit modeling (Koppelman & Bhat, 2006). The ticket price was significant and had negative parameter values in both models. Showing consistency with the economic theory, this explained that the passengers were less likely to prefer EA when it was expensive. The parameter value for ticket price in the leisure traveller model depicted a higher impact on choosing EA than that of the business traveller model suggesting the leisure travellers were more price sensitive than business travellers. This explained the general behaviour of business and non-business travellers where business trips are usually sponsored by employers and have higher budgets as opposed to leisure trips. These results showed the importance of employing different pricing strategies for EA in different markets in order to be more attractive to the passengers in each market.

While travel time was marginally significant (0.1 significance level) in both models, its negative sign in both cases suggested that longer travel times discouraged passengers from choosing EA. The parameter values indicated that business travellers were somewhat more sensitive to travel time than leisure travellers, which aligns with the general understanding that business travellers tend to value time more highly. This finding highlights the importance of considering travel time when targeting different market segments, particularly for business travellers.

The number of transits is generally seen as a disutility as having more transits leads to inconveniences such as longer travel times and waiting times. In align with this, the parameter sign for the business traveller model demonstrated a negative, however, for the leisure traveller model

it remained positive demonstrating counterintuitive results. In addition, the parameter value was not significant in either of the models, indicating that the number of transfers only had little to no impact on the passenger choice based on the sample studied. One reason behind these unexpected results could have been the very small sample size. Another reason could have been that the OD pairs used for the choice sets in the survey only have direct CA flights which in turn led to having zero transits for CA as model input for all the scenarios. This could potentially be avoided in future work by incorporating long-distance OD pairs with more transits in choice scenarios in the survey to understand the impact of having transfers more accurately.

The CO2 emissions associated with conventional aircraft demonstrated a positive yet marginally significant parameter value in both Model 2 & Model 4. This indicated that the higher personal carbon footprint of a CA flight had a positive influence on passengers choosing EA over CA. Parameter values having a similar magnitude in both models explained that CO2 emissions had a similar impact on the choice of EA in both instances.

The environmental concern showed a positive parameter value with a high significance in both models elaborating that the people who tend to consider the environmental impact when choosing a transport mode are highly likely to choose EA over CA. The value in the leisure traveller model was slightly higher than that of the business traveller model indicating that the leisure travellers with high environmental concern were more likely to choose EA over CA than the business travellers with the same concern. The results could be understood intuitively as leisure travellers who are more environmentally conscious would be inclined to support greener options like electric aircraft.

The parameter values for technological openness were positive yet not significant in both models. The leisure travellers who were open to new technologies were more inclined to choose EA over CA than the business travellers. Safety concern on the other hand displayed a significant and negative parameter value demonstrating that the perceived safety of a new mode hinders the people's choice of EA considering both leisure and business travellers. Nonetheless, business travellers showed comparatively higher sensitivity to the perceived safety than leisure travellers.

Considering the gender, the models (Models 2 & 4) suggested that the males showed a higher preference for EA in both types of models with a high statistical significance value compared to other demographic variables. The income variable obtained a positive parameter value, however,

with a low significance which might suggest that income does not play a major role in the choice of EA in this sample. Age depicted unusual results in both Model 2 and Model 4, indicating a positive influence on the choice of EA, suggesting that the older population is more likely to choose EA. This finding however contradicted the findings by Han, Yu, et al., (2019b) and Veisten et al., (2024) which explain that the younger generations are more likely to choose EA. Furthermore, the parameter value was highly significant in the business traveller model while in the leisure traveller model, it was not significant.

With regard to the model fit and the performance, the final models of both purposes (Model 2 and Model 4) showed significant improvement in the log-likelihood value compared to that of their respective constant-only models (Model 1 & Model 3), and the zero-variables model (null log-likelihood). This denoted that the model fit had greatly improved with the addition of new factors. Moreover, the ρ_0^2 value had also improved in a similar manner. This further explained that the overall goodness-of-fit of the model had been improved with the introduction of these factors.

It is noteworthy that the results presented in this section are based on the dataset used and reflect the behaviour of the sample used rather than the entire population. Hence, it is important to acknowledge that the behaviour and preferences observed here may differ when applied to a larger or more diverse population. Despite this limitation, the results demonstrate that the basic model is feasible and serves as a valuable proof of concept. The outcomes show that the methodology is sound and that similar models could be successfully implemented at a larger scale. However, the limitations encountered in this study such as the small sample size and its impact on the results highlight the need for more comprehensive data. In future work, these issues can be mitigated by employing a larger and more representative sample, enabling the model to perform more accurately across different demographic groups.

7.5.1. Scenario Analysis

The discreet choice models usually explain the behaviour of an individual. However, it is equally important to predict the collective behaviour when these individuals are considered as a group and when the demographic attributes and trip attributes change. In order to observe this group-

behaviour and to check the performance of the developed model, it was decided to conduct a scenario analysis.

As Koppelman & Bhat (2006) mention, micro-simulation of an entire population using a synthetic sample is a widely used practice, especially in instances where the variable values for each individual in the population are practically impossible to obtain. Generally, when such a model is applied to analyze a real population and obtain its demand for a particular alternative, the synthetic population is generated through the census related to the particular region. However, here in this study, the aim was to observe the performance of the model and in turn prove the concept. Thus, the synthetic population was generated in a way that mimicked the demographic and personal/attitudinal data of the sample dataset obtained through the SP survey.

Three flight OD pairs where conventional air travel currently functions were selected for the simulation experiment, namely, Arlanda-Visby (A-V), Arlanda-Gothenburg (A-G) and Arlanda-Lycksele (A-L). The actual total demand values of existing conventional aircraft operations (air trips) in each of the three OD pairs for the year 2023 were obtained from Trafikverket. This total number of passengers was divided into leisure and business trips based on the percentages calculated considering the frequency of travel and the most common trip purpose obtained from the survey.

Based on the number of passengers, synthetic populations were generated for each of the two travel purposes using the following method. First, the survey data was categorized based on unique combinations of variables environmental concern, technology openness, safety perception, age, gender, and income. Each unique combination represents a distinct category of respondents with similar preferences and characteristics and 80 such different combinations were identified in the dataset. The synthetic population was then designed to reflect the characteristics of these 80 categories. For each category, a proportionate number of individuals, calculated as n/80 (where n is the total number of passengers), was assigned to ensure that the population distribution retained the characteristics of the survey data.

The utility functions were then applied to the two sets of trip purposes separately. The utility function values were derived using Model 2 and Model 4 above, for each OD pair and the values for each variable in the utility functions had to be defined to simulate the individual decisions for the entire population. The trip-related variable values required for utility calculation were based

on the OD pair and were common for the whole population. The personal/attitudinal attributes and demographic variable values, on the other hand, had to be unique to each individual in the population and they were assigned based on the survey data as explained above.

The trip-related variable values used in the base-case scenario for the leisure traveller model and the business traveller model are shown in Table 7.9.

	Leisure Traveller Model						Business Traveller Model					
	A-V		A-G		A-L		A-V		A-G		A-L	
	CA	EA	CA	EA	CA	EA	CA	EA	CA	EA	CA	EA
Ticket Price (kr)	700	840	600	720	1100	1320	2100	2520	1800	2160	3300	3960
Travel Time (min)	50	55	60	125	85	150	50	55	60	125	85	150
Number of Transits	0	0	0	1	0	1	0	0	0	1	0	1
CO2 emission of CA (kg)	45		61		75		45		61		75	

Table 7.9 – Base Case Scenario - Input Values for Trip-related Variables for the Two Models

The ticket prices for CA in the base case scenario were set as the "low" price levels considered in the SP survey choice scenarios. EA prices were set 20% higher than the CA prices. The number of transfers for CA was kept at zero as the CA operations between the ODs considered here are direct flights. However, considering the technical characteristics of the EA, A-G and A-L ODs were assigned with one transfer.

Table 7.10 depicts the results obtained from the simulation for both models.

		Leisure Trips			Business Trips		
OD	Total Demand	Total	CA	EA	Total	CA	EA
A-V	90000	65342	8170 12.50%	57172 87.50%	24658	3080 12.49%	21578 87.51%
A-G	500000	363014	231438 63.75%	131576 36.25%	136986	104432 76.24%	32554 23.76%
A-L	17200	12488	6396 51.22%	6092 48.78%	4712	3304 70.12%	1408 29.88%

Table 7.10 – Base Case Scenario Results

The results illustrated that in the A-V OD pair, EA dominated both leisure and business markets despite the higher price. On the contrary, in A-G and A-L, CA still dominated both the markets. From the results, it could be understood that in shorter routes such as A-V where the travel times for both alternatives were similar and no transfers needed, EA demonstrated a high adoptability even with slightly higher prices. The high CA demand in A-G and A-L pairs could be explained by the longer travel time taken by EA compared to CA due to the charging stops (transfers). In the

same OD pairs, the larger market share of CA in business trips than the leisure trips explained that there could be higher resistance for the adoption of EA from business travellers in these OD pairs than from leisure travellers. Considering the same two pairs, A-L demonstrated a higher EA market share compared to A-G despite its long distance and longer travel time, which seemed slightly counterintuitive as the longer travel times usually increase the disutility. One possible reason for this could be the survey responses having a selection bias for EA regardless of the distance or travel time.

Based on the results of the base case, a sensitivity analysis was conducted to observe how the model generated results under a change in variable values. Two scenarios were defined in order to understand the price sensitivity of the passengers and the sensitivity to travel time.

In order to understand the price sensitivity, a scenario was developed assuming an instance where the price of CA had been increased due to an introduction of a new environmental policy by the Swedish government where the EA prices are subsidized, and a carbon tax is imposed on CA. CA ticket prices were now 10% higher than the EA ticket prices. The trip-related variable values applied in this simulation are shown in Table 7.11.

	Leisure Traveller Model						Business Traveller Model					
	A-V		A-G		A-L		A-V		A-G		A-L	
	CA	EA	CA	EA	CA	EA	CA	EA	CA	EA	CA	EA
Ticket Price (kr)	924	840	792	720	1452	1320	2772	2520	2376	2160	4356	3960
Travel Time (min)	50	55	60	125	85	150	50	55	60	125	85	150
Number of Transits	0	0	0	1	0	1	0	0	0	1	0	1
CO2 emission of CA (kg)	45		61		75		45		61		75	

Table 7.11 – CA Price Increase Scenario Input Values for Trip-related Variables

		Leisure Trips			Business Trips		
OD	Total Demand	Total	CA	EA	Total	CA	EA
A-V	90000	65342	1634 2.50%	63708 97.50%	24658	924 3.75%	23734 96.25%
A-G	500000	363014	154292 42.50%	208722 57.50%	136986	83888 61.24%	53098 38.76%
A-L	17200	12488	2808 22.49%	9680 77.51%	4712	2006 42.57%	2706 57.43%

Table 7.12 - CA Price Increase Scenario Results

The simulation results obtained from this scenario are illustrated in Table 7.12 and revealed that the 10% increase in CA ticket prices was sufficient to shift all leisure travellers from CA to EA demonstrating that the leisure travellers were highly sensitive to the price changes of the alternatives. However, for the business travellers, while the A-L OD pair showed a shift towards EA, the A-G OD pair retained its high CA market share despite the price increase. This suggested that the business travellers in the A-G OD pair were not highly sensitive to the price increase. A possible explanation for this could be that the ticket prices in the A-G sector were relatively lower to begin with, making the price increase still affordable for business travellers.

The next scenario was developed, assuming an instance where the technical characteristics of the EA are improved, and the aircraft range is increased. The aircraft are now able to fly directly between the origins and destinations of the considered three pairs without having transits. This was represented in the simulation by reducing the number of transits to zero in A-G and A-L pairs and in turn reducing the travel time. The rest of the variables were kept unchanged. This set of input values for the trip-related variables is shown in Table 7.13.

	Leisure Traveller Model						Business Traveller Model					
	A-V		A-G		A-L		A-V		A-G		A-L	
	CA	EA	CA	EA	CA	EA	CA	EA	CA	EA	CA	EA
Ticket Price (kr)	700	840	600	720	1100	1320	2100	2520	1800	2160	3300	3960
Travel Time (min)	50	55	60	90	85	115	50	55	60	90	85	115
Number of Transits	0	0	0	0	0	0	0	0	0	0	0	0
CO2 emission of CA (kg)	45		61		75		45		61		75	

Table 7.13 – Zero Transits Scenario Input Values for Trip-related Variables

		Leisure Trips			Business Trips		
OD	Total Demand	Total	CA	EA	Total	CA	EA
A-V	90000	65342	8170 12.50%	57172 87.50%	24658	3080 12.49%	21578 87.51%
A-G	500000	363014	81684 22.50%	281330 77.50%	136986	29104 21.25%	107882 78.75%
A-L	17200	12488	2340 18.74%	10148 81.26%	4712	590 12.52%	4122 87.48%

Table 7.14 – Zero Transits Scenario Results

Table 7.14 demonstrates the results of the simulation and revealed that with this change in variables, all the markets were now shifted from CA to EA. As the variable values were not changed in A-V, the market shares remained the same as the base case for this OD pair. The other two OD pairs demonstrated a clearly high market share for EA in both traveller groups. The A-L OD pair showed an increase in the market share in response to the lowered travel time and the number of transits. The salient output in this was the market shift displayed by the business travellers in the A-G OD pair. While this group previously showed low sensitivity to price changes, this market shift highlighted that they were more responsive to reduced travel time and fewer transits than to ticket prices, emphasizing the importance of the value of time and convenience for this segment.

The output of the scenario analysis unravelled key insights that could be drawn from the suggested models by offering insight into how these findings might act in favour of the adoption of EA when its operation is implemented. Although these insights were mainly based on a sample that may not fully represent the broader population, however, demonstrated the potential of EA for certain markets, one of such being the short-distance flight routes. The short-distance ODs demonstrated a higher adoption possibility, considering the output of both leisure and business traveller models. This aligns with the operational limitations of first-generation EA, which are better suited for shorter distances due to their limited range and cruising speed.

From an operational point of view, short-distance ODs could be connected by EA with almost similar travel times as CA and with no transits reducing the inconveniences that the passengers have to face while at the same time reducing the environmental impact. Additionally, the short-distance market appeared to be less sensitive to the price, suggesting that the travellers were willing to choose EA for short distances even with a slightly higher price than CA. Hence it can be understood that short distances are ideal candidates for early-stage EA operation implementation.

Another important finding was the behavioural differences between leisure and business travellers, which suggested the requirement for distinct and sophisticated approaches to cater for each market. The leisure traveller segment generally seemed to be more enthusiastic about choosing EA over CA than the business traveller segment. Furthermore, the leisure travellers were more sensitive to the change in price of the alternatives while the business travellers were more sensitive to the change in travel time and the number of transits. This indicated that leisure travellers would be

more prone to adopt EA during the early phases of implementation than business travellers. However, in order to increase the demand from business travellers the authorities prioritize reducing travel times and minimizing the need for charging stops, which directly affect operational efficiency and convenience.

In conclusion, the findings highlighted the importance of tailoring operational strategies to the distinct preferences of different traveller groups. Moreover, these initial insights provide a foundation for more extensive research and real-world testing, demonstrating that the proposed model is a viable proof of concept.

8. Research Findings & Discussion

8.1. General Discussion

This research study primarily focused on understanding the dynamics of passenger demand for electric air transportation in Sweden by developing a small-scale demand model considering passenger choices and preferences. The study employed a mixed-method approach consisting of both qualitative and quantitative elements. In the qualitative phase of the study, a thorough literature study followed by an expert workshop was conducted as the background study. The quantitative phase included a stated preference survey followed by the development of the mathematical model to derive demand values between airport pairs.

The findings of the qualitative stage prominently highlighted that a passenger's preference to use all-electric aircraft was influenced by traditional factors such as travel time, travel cost, trip purpose and number of transits, and in addition, the personal/attitudinal factors such as a person's awareness about the environmental impact of a certain transport mode, openness to new technology and innovations, and perceived safety of a new transport mode along with the demographics of the passenger such as age, gender and income. These preliminary results were then utilized to develop the survey, and the data obtained were fed to the model as input parameters.

The output of the two main models established the impact of each of the above factors on the passenger's choice of all-electric aircraft over conventional aircraft, and in turn, influenced the total demand for EA considering each traveller group: leisure and business. In both types of models, travel time, travel cost and safety consideration obtained negative parameter values displaying that these as negative drivers of passenger choice of EA. On the contrary, the parameter values for environmental and technology concerns, CO2 emission amount of CA, age, income and gender were derived positively in both models explaining them as a positive driver for a passenger's choice of EA for the two traveller groups. However, the number of transits presented mixed results, particularly for leisure travellers, where an unexpected positive parameter sign was observed. Among these variables, ticket price, travel time, environmental awareness, and safety concerns were statistically significant in both the leisure and business traveler models, while age achieved statistical significance only in the business traveler model. The models displayed model

fit in terms of the informal judgement-based methods as well as the goodness-of-fit tests confirming the theoretical validity of the model.

The statistical significance and the negative parameter value of the ticket price and travel time across the two models indicated the predominant role of these factors in a passenger's decision-making process. These parameter values being generic to both alternatives further demonstrated the dominance regardless of the alternative they chose. This highlighted that a reduction in travel time and ticket prices is needed in order to attract more passengers for electric aviation. This theory was further confirmed by the results obtained from the scenario analysis where the leisure travellers displayed high sensitivity to price while the business travellers were more sensitive to the travel time. These findings implied the importance of drawing the attention of EA operators and other relevant authorities to apply distinct strategies to different market groups to acquire larger market shares. More particularly in this case, introducing competitive pricing into leisure markets while reducing travel times and other inconveniences caused due to having transfers (charging stops) in business markets.

While the above two factors act as fundamental drivers, the output of the models also suggested that there still exists plenty of room for influencing passenger demand through environmental awareness and safety aspects. The highly positive influence seen of people being more conscious of the environmental impact of a mode and the less significant yet positive influence of CO2 emissions quantity of existing conventional aircraft on the demand for all-electric aircraft meant that when the public was more environmentally conscious the tendency to use electric aircraft was risen with it. This in turn illustrated the importance of making the public more aware and responsible of the impact of air transportation on the environment. This not only would be an approach in driving people towards electric aviation but also would serve the purpose of environmental awareness in general.

In terms of safety concerns, the negative impact of how people perceived the safety of a new mode posed a potential barrier to the adoption of electric aircraft. This revealed the importance of thorough safety assurance from the phase of manufacturing to operation. Furthermore, the general awareness of the usability of electric aircraft seems crucial in order to reduce passenger resistance based on safety concerns.

Another aspect that the model output demonstrated was the impact of demographic factors. The demographics of the market are generally crucial to consider when looking at the adoption possibility of any given commodity. Considering the gender, males showing a significant preference for choosing electric aviation was highlighted as an interesting finding of the model. This in a way could be a result of the higher proportion of male participants in the dataset, yet, given the differences in the decision-making process between males and females this might also reflect differences in the perceiving risk or technology adoption. Age could be understood as another main demographic factor which, in general, might affect the demand for technology-related commodities. The general perception of age is that the new technologies usually are easily adopted by younger generations. Han, Lee, et al. (2019) & Veisten et al. (2024) claim that it is same for electric aviation. However, contradictory to the above, the model results demonstrated a positive impact on the demand implying the older generation prefers to select electric aviation more. These impacts identified in different demographic groups on electric aviation demand emphasized the importance of developing different marketing strategies for electric aviation that target these specific demographic groups.

In general, the model provided a thorough understanding of the behaviour of each factor from a theoretical standpoint.

The scenario analysis conducted using the developed model provided valuable insights into the dynamics of different market segments. The results highlighted the relatively easy market share acquisition possibility on shorter distance routes even in the instances where the prices for all-electric aircraft trips were higher than that of conventional aircraft trips. This high adoption possibility of electric aircraft in shorter routes was offered as they have similar travel times as conventional aircraft travel. Further, the shorter routes ideally aligned with the technical limitations of the first-generation all-electric aircraft such as limited range and cruising speed. In contrast, for medium and long-distance routes, where more charging stops are needed, EA would likely face challenges in maintaining competitive travel times. In such situations, alternative approaches should be explored such as ticket price reduction and targeting certain demographic groups in order to gain market share.

This scenario analysis further revealed how the model output can be incorporated in decision-making, particularly in understanding the market adoption possibility of the electric aircraft in

terms of how the different market characteristics may affect the demand and what adjustments to be made in markets to acquire more share. For instance, as the travel times could not be reduced in the early stages of EA implementation due to technical limitations, focusing on lowering ticket prices would be essential, particularly in the leisure market where price sensitivity is higher. As EA technology matures and travel times become more competitive compared to CA travel times, the focus could be shifted to targeting business travellers on medium and long-distance routes, where time is a more critical factor.

In this context, several recommendations can be made on how the model output could be applied in favour of boosting the demand expected for electric aviation by the time of its implementation within Sweden. As the model suggested and the scenario analysis clearly depicted, the ticket price of electric aviation can be a critical decisive factor of demand for electric aviation. Thus, recommendations can be provided for policymakers to incentivize electric aviation, for instance by applying subsidies or introducing price regulations for the markets where the ticket price is a significant barrier such as the leisure traveller market. Further, the imposition of environmental regulations concerning the promotion of sustainable fuel and demotivating fossil fuel, for instance by imposing a CO2 tax or surcharge on conventional aviation prices, could also be recommended to drive demand towards EA by making CA less attractive.

Taking the impact of people's environmental concerns on the demand for electric aviation into account, environmental regulations as mentioned above could also be useful in driving the public's attention towards being more conscious of the environment hence seeking more sustainable transport options which in turn might result in people's tendency to choose electric aviation.

The findings also suggested recommending marketing strategies targeted at certain demographic groups. For example, based on the results, the markets which have a higher male population or are notably tech-savvy or considered more environmentally concerned are highly likely to adopt electric aviation and gain a higher market share than others. Comprehensive market research to analyze the demographic composition of various regions would allow the relevant authorities to identify the markets where the most favourable demographics for EA adoption exist and implement operations in such markets to maximize the economic benefits. Such demographic groups should be prioritized in marketing campaigns emphasizing unique attractive points of each market such as the environmental benefits and technological innovations of electric aircraft.

Apart from these recommendations, this study holds greater significance in the study area. The study was based on thorough background research where a considerable amount of time and effort has been invested in exploring and understanding the fundamentals of demand modeling of electric aviation in terms of factors, models and data collection methods. Furthermore, this study is among the early efforts to model passenger demand for electric aviation using a mathematical approach and incorporating diverse factors such as operational, attitudinal and demographic factors. Given the novelty of this field, the study serves as a foundational piece of research, providing a framework for future studies. The insights gained from this research can guide policymakers, EA operators, airlines, and other industry stakeholders in making informed decisions about the development and implementation of electric aviation operations.

8.2. Limitations & Future Research

While the study offers valuable insights it is equally important to recognize its limitations.

Initially, considering the developed model, though it displayed the applicability from a theoretical point of view, the model was developed based on a survey where the sample size was small. This restricts the generalizability of the model. Therefore, this model can be considered as a base model for proof of the concept. The model can be refined and revalidated using a large-scale survey which is more representative and diverse. This enables performance enhancement of the model by including more variables such as more in-depth attitudinal factors by combining methodologies like factor analysis.

Another limitation was the assumption that the factors identified have an equal impact across all demographics and regions in Sweden, which may not be the case in reality. Further research can be introduced to explore regional variations and the impact of other potential factors on demand based on the regions.

In addition, the binary logit model developed in the study assumed a linear relationship between the variables and the choice which in theory is correct yet in reality might underestimate the decision complexities of humans. Hence, studies can be conducted in the future to expand the model to capture more complex elements of passengers' decision-making.

The sample size limitation greatly affected the accuracy of the performance of variables, such as age and income. The initial plans of the study included experimenting with age and income using their respective value ranges in order to capture their effects on the choice behaviour better. However, when these variables were categorized into distinct ranges, the model results became inconsistent and unrealistic, likely due to the small sample size which further diminished when subdivided into multiple age and income groups. To address this issue in future work, a larger and more representative sample should be collected to ensure that sufficient data points are available for each age and income category. This would allow for a more granular-level analysis without compromising the models' reliability.

In addition to the above, this study will also lead the way to a great number of new research areas that incorporate the results of this study. These will possibly look at the infrastructure planning for providing necessary support infrastructure for the functioning of electric aviation, the network and route planning, and integrated operational possibilities of electric aviation with other transport modes.

8.3. Concluding Remarks

In conclusion, this thesis aimed to develop a small-scale demand model incorporating the electric aviation specific demand factors to obtain demand values for certain airport pairs within Sweden. The study employs a mixed methodology consisting of a qualitative assessment to understand the demand factors and a quantitative modeling to incorporate those identified factors into a demand model and generate results. The results of the binary logit models for leisure and business travellers commonly demonstrated that ticket price, travel time, environmental awareness and safety concerns have an impact on the choice of electric aircraft with high statistical significance. A scenario analysis was conducted using the model to understand the market dynamics revealed by the model. The results of the study can be applicable in diverse settings such as policymaking, in developing targeted marketing, and for future research. Further, the results can generally be useful for industry stakeholders such as airlines, airport operators, and manufacturers as an assistance in their operational decision-making.

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Appendices

Survey on Air Travel Using Electric Aircraft

Introduction

Dear Participant,

Thank you for taking the time to participate in our survey. We are conducting research to understand public preferences and opinions on all-electric air transportation. Electric air transportation uses electric engines powered entirely by batteries, instead of traditional jet engines that rely on fossil fuels.

Purpose & Structure of the Survey

(Click here to see more)

Confidentiality

Your responses will be kept confidential and will only be used for research purposes. Your participation is completely voluntary, and you can withdraw from the survey at any time without any consequences.

Eligibility

To participate in this survey, you must be 18 years of age or older. Please answer the following question to confirm your eligibility:

Are you 18 years of age or older?

*

Choose one of the following answers
Please choose **only one** of the following:

◯ Yes
◯ No

Previous Air Travel Experience

How many times have you taken air trips (international and/or domestic) within the last year?

*

Please choose **only one** of the following:

◯ Never
◯ 1-5 times
◯ 5-10 times
◯ More than 10 times

What is the most common purpose of your air trips?

*

Please choose **only one** of the following:

- ◯ Business
- ◯ Family/ Leisure
- ◯ Home to work
- ◯ Other

Rank the following factors in order of which you think is the most important to you when booking a flight.

*

Please number each box in order of preference from 1 to 5

- ☐ Ticket price
- ☐ Total Travel time
- ☐ Direct vs. flights with transits
- ☐ Airport locations
- ☐ Environmental impact of the trip

How often do you use climate-compensated air tickets when you travel by air?

*

Please choose **only one** of the following:

- ◯ Never
- ◯ Rarely
- ◯ Sometimes
- ◯ Often
- ◯ Always
- ◯ I don't know/ Other

Buying climate-compensated flight tickets helps offset your flight's carbon emissions by funding projects that reduce greenhouse gases, aiming to make your travel carbon-neutral.

To what extent do you agree/disagree with the following statements?

*

Please choose the appropriate response for each item:

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I consider the environmental impact when choosing a means of transport.	○	○	○	○	○
I enjoy using the latest technology and often try new innovations early on.	○	○	○	○	○
I am generally concerned about the safety of newly introduced technologies.	○	○	○	○	○

Choice Scenarios

Introduction to Electric Aviation

Electric air transportation may use electric engines powered entirely by batteries, instead of traditional jet engines that use fossil fuels. This can greatly reduce carbon emissions, noise, and fossil fuel use. Many companies and researchers are working on electric aircraft prototypes aiming to make electric air travel available soon. Initially, these aircraft will be able to carry a limited number passengers and fly shorter distances than fossil-fueled aircraft.

As you move on to the choice scenarios in this survey, think about the benefits and trade-offs of electric air travel.

Assume you are planning a one-way flight for you, considering the following details. If both flight alternatives below are available to you, which would you choose?

Flight Alternatives	Conventional Aircraft	All-electric Aircraft
Origin & Destination	Stockholm to Visby	Stockholm to Visby
Purpose of your trip	Business	Business
Ticket Price	2100 kr	2100 kr
Travel Time	50 min	55 min
No. of Transfers	0	0
Personal Carbon Footprint	45 kg	2.8 kg

*

Please choose the appropriate response for each item:

a	b
○	○

Assume you are planning a one-way flight for you, considering the following details. If both flight alternatives below are available to you, which would you choose?

Flight Alternatives	Conventional Aircraft	All-electric Aircraft
Origin & Destination	Stockholm to Visby	Stockholm to Visby
Purpose of your trip	Leisure	Leisure
Ticket Price	700 kr	1100 kr
Travel Time	50 min	55 min
No. of Transfers	0	0
Personal Carbon Footprint	45 kg	2.8 kg

*

Please choose the appropriate response for each item:

a	b
○	○

Assume you are planning a one-way flight for you, considering the following details. If both flight alternatives below are available to you, which would you choose?

Flight Alternatives	Conventional Aircraft	All-electric Aircraft
Origin & Destination	Stockholm to Gothenburg	Stockholm to Gothenburg
Purpose of your trip	Business	Business
Ticket Price	1800 kr	1800 kr
Travel Time	60 min	1hr 30 min
No. of Transfers	0	0
Personal Carbon Footprint	61 kg	5 kg

*

Please choose the appropriate response for each item:

	a	b
	○	○

Assume you are planning a one-way flight for you, considering the following details. If both flight alternatives below are available to you, which would you choose?

Flight Alternatives	Conventional Aircraft	All-electric Aircraft
Origin & Destination	Stockholm to Gothenburg	Stockholm to Gothenburg
Purpose of your trip	Leisure	Leisure
Ticket Price	1000 kr	600 kr
Travel Time	60 min	1hr 30 min
No. of Transfers	0	0
Personal Carbon Footprint	61 kg	5 kg

*

Please choose the appropriate response for each item:

	a	b
	○	○

Assume you are planning a one-way flight for you, considering the following details. If both flight alternatives below are available to you, which would you choose?

Flight Alternatives	Conventional Aircraft	All-electric Aircraft
Origin & Destination	Stockholm to Gothenburg	Stockholm to Gothenburg
Purpose of your trip	Business	Business
Ticket Price	1800 kr	3000 kr
Travel Time	60 min	2 hr 05 min
No. of Transfers	0	1
Personal Carbon Footprint	61 kg	5.2 kg

*

Please choose the appropriate response for each item:

	a	b
	○	○

Assume you are planning a one-way flight for you, considering the following details. If both flight alternatives below are available to you, which would you choose?

Flight Alternatives	Conventional Aircraft	All-electric Aircraft
Origin & Destination	Stockholm to Gothenburg	Stockholm to Gothenburg
Purpose of your trip	Leisure	Leisure
Ticket Price	600 kr	600 kr
Travel Time	60 min	2 hr 05 min
No. of Transfers	0	1
Personal Carbon Footprint	61 kg	5.2 kg

*

Please choose the appropriate response for each item:

	a	b
	○	○

Assume you are planning a one-way flight for you, considering the following details. If both flight alternatives below are available to you, which would you choose?

Flight Alternatives	Conventional Aircraft	All-electric Aircraft
Origin & Destination	Stockholm to Lycksele	Stockholm to Lycksele
Purpose of your trip	Business	Business
Ticket Price	3300 kr	5700 kr
Travel Time	1hr 25min	2 hr 30 min
No. of Transfers	0	1
Personal Carbon Footprint	75 kg	7.2 kg

*

Please choose the appropriate response for each item:

	a	b
	○	○

Assume you are planning a one-way flight for you, considering the following details. If both flight alternatives below are available to you, which would you choose?

Flight Alternatives	Conventional Aircraft	All-electric Aircraft
Origin & Destination	Stockholm to Lycksele	Stockholm to Lycksele
Purpose of your trip	Leisure	Leisure
Ticket Price	1100 kr	1100 kr
Travel Time	1 hr 25 min	2 hr
No. of Transfers	0	0
Personal Carbon Footprint	75 kg	7 kg

*

Please choose the appropriate response for each item:

	a	b
	○	○

Assume you are planning a one-way flight for you, considering the following details. If both flight alternatives below are available to you, which would you choose?

Flight Alternatives	Conventional Aircraft	All-electric Aircraft
Origin & Destination	Stockholm to Lycksele	Stockholm to Lycksele
Purpose of your trip	Business	Business
Ticket Price	3300 kr	5700 kr
Travel Time	1 hr 25 min	2 hr
No. of Transfers	0	0
Personal Carbon Footprint	75 kg	7 kg

*

Please choose the appropriate response for each item:

	a	b
	○	○

Assume you are planning a one-way flight for you, considering the following details. If both flight alternatives below are available to you, which would you choose?

Flight Alternatives	Conventional Aircraft	All-electric Aircraft
Origin & Destination	Stockholm to Lycksele	Stockholm to Lycksele
Purpose of your trip	Leisure	Leisure
Ticket Price	1100 kr	1100 kr
Travel Time	1 hr 25 min	2 hr 30 min
No. of Transfers	0	1
Personal Carbon Footprint	75 kg	7.2 kg

*

Please choose the appropriate response for each item:

	a	b
	○	○

Choice Scenarios

Introduction to Electric Aviation

Electric air transportation may use electric engines powered entirely by batteries, instead of traditional jet engines that use fossil fuels. This can greatly reduce carbon emissions, noise, and fossil fuel use. Many companies and researchers are working on electric aircraft prototypes aiming to make electric air travel available soon. Initially, these aircraft will be able to carry a limited number passengers and fly shorter distances than fossil-fueled aircraft.

As you move on to the choice scenarios in this survey, think about the benefits and trade-offs of electric air travel.

Assume you are planning a one-way flight for you, considering the following details. If both flight alternatives below are available to you, which would you choose?

Flight Alternatives	Conventional Aircraft	All-electric Aircraft
Origin & Destination	Stockholm to Visby	Stockholm to Visby
Purpose of your trip	Business	Business
Ticket Price	3300 kr	2100 kr
Travel Time	50 min	55 min
No. of Transfers	0	0
Personal Carbon Footprint	45 kg	2.8 kg

*

Please choose the appropriate response for each item:

	a	b
	○	○

Assume you are planning a one-way flight for you, considering the following details. If both flight alternatives below are available to you, which would you choose?

Flight Alternatives	Conventional Aircraft	All-electric Aircraft
Origin & Destination	Stockholm to Visby	Stockholm to Visby
Purpose of your trip	Leisure	Leisure
Ticket Price	700 kr	700 kr
Travel Time	50 min	55 min
No. of Transfers	0	0
Personal Carbon Footprint	45 kg	2.8 kg

*

Please choose the appropriate response for each item:

	a	b
	○	○

Assume you are planning a one-way flight for you, considering the following details. If both flight alternatives below are available to you, which would you choose?

Flight Alternatives	Conventional Aircraft	All-electric Aircraft
Origin & Destination	Stockholm to Gothenburg	Stockholm to Gothenburg
Purpose of your trip	Business	Business
Ticket Price	1800 kr	3000 kr
Travel Time	60 min	1 hr 30 min
No. of Transfers	0	0
Personal Carbon Footprint	61 kg	5 kg

*

Please choose the appropriate response for each item:

	a	b
	○	○

Assume you are planning a one-way flight for you, considering the following details. If both flight alternatives below are available to you, which would you choose?

Flight Alternatives	Conventional Aircraft	All-electric Aircraft
Origin & Destination	Stockholm to Gothenburg	Stockholm to Gothenburg
Purpose of your trip	Leisure	Leisure
Ticket Price	600 kr	600 kr
Travel Time	60 min	1 hr 30 min
No. of Transfers	0	0
Personal Carbon Footprint	61 kg	5 kg

*

Please choose the appropriate response for each item:

	a	b
	○	○

Assume you are planning a one-way flight for you, considering the following details. If both flight alternatives below are available to you, which would you choose?

Flight Alternatives	Conventional Aircraft	All-electric Aircraft
Origin & Destination	Stockholm to Gothenburg	Stockholm to Gothenburg
Purpose of your trip	Business	Business
Ticket Price	3000 kr	1800 kr
Travel Time	60 min	2 hr 05 min
No. of Transfers	0	1
Personal Carbon Footprint	61 kg	5.2 kg

*

Please choose the appropriate response for each item:

	a	b
	○	○

Assume you are planning a one-way flight for you, considering the following details. If both flight alternatives below are available to you, which would you choose?

Flight Alternatives	Conventional Aircraft	All-electric Aircraft
Origin & Destination	Stockholm to Gothenburg	Stockholm to Gothenburg
Purpose of your trip	Leisure	Leisure
Ticket Price	600 kr	1000 kr
Travel Time	60 min	2 hr 05 min
No. of Transfers	0	1
Personal Carbon Footprint	61 kg	5.2 kg

*

Please choose the appropriate response for each item:

	a	b
	○	○

Assume you are planning a one-way flight for you, considering the following details. If both flight alternatives below are available to you, which would you choose?

Flight Alternatives	Conventional Aircraft	All-electric Aircraft
Origin & Destination	Stockholm to Lycksele	Stockholm to Lycksele
Purpose of your trip	Business	Business
Ticket Price	3300 kr	3300 kr
Travel Time	1 hr 25min	2 hr
No. of Transfers	0	0
Personal Carbon Footprint	75 kg	7 kg

*

Please choose the appropriate response for each item:

	a	b
	○	○

Assume you are planning a one-way flight for you, considering the following details. If both flight alternatives below are available to you, which would you choose?

Flight Alternatives	Conventional Aircraft	All-electric Aircraft
Origin & Destination	Stockholm to Lycksele	Stockholm to Lycksele
Purpose of your trip	Leisure	Leisure
Ticket Price	1100 kr	1900 kr
Travel Time	1 hr 25 min	2 hr 30 min
No. of Transfers	0	1
Personal Carbon Footprint	75 kg	7.2 kg

*

Please choose the appropriate response for each item:

	a	b
	○	○

Assume you are planning a one-way flight for you, considering the following details. If both flight alternatives below are available to you, which would you choose?

Flight Alternatives	Conventional Aircraft	All-electric Aircraft
Origin & Destination	Stockholm to Lycksele	Stockholm to Lycksele
Purpose of your trip	Business	Business
Ticket Price	5700 kr	3300 kr
Travel Time	1 hr 25 min	2 hr 30 min
No. of Transfers	0	1
Personal Carbon Footprint	75 kg	7.2 kg

*

Please choose the appropriate response for each item:

	a	b
	○	○

Assume you are planning a one-way flight for you, considering the following details. If both flight alternatives below are available to you, which would you choose?

Flight Alternatives	Conventional Aircraft	All-electric Aircraft
Origin & Destination	Stockholm to Lycksele	Stockholm to Lycksele
Purpose of your trip	Leisure	Leisure
Ticket Price	1900 kr	1100 kr
Travel Time	1 hr 25 min	2 hr
No. of Transfers	0	0
Personal Carbon Footprint	75 kg	7 kg

*

Please choose the appropriate response for each item:

	a	b
	○	○

Choice Scenarios

Introduction to Electric Aviation

Electric air transportation may use electric engines powered entirely by batteries, instead of traditional jet engines that use fossil fuels. This can greatly reduce carbon emissions, noise, and fossil fuel use. Many companies and researchers are working on electric aircraft prototypes aiming to make electric air travel available soon. Initially, these aircraft will be able to carry a limited number passengers and fly shorter distances than fossil-fueled aircraft.

As you move on to the choice scenarios in this survey, think about the benefits and trade-offs of electric air travel.

Assume you are planning a one-way flight for you, considering the following details. If both flight alternatives below are available to you, which would you choose?

Flight Alternatives	Conventional Aircraft	All-electric Aircraft
Origin & Destination	Stockholm to Visby	Stockholm to Visby
Purpose of your trip	Business	Business
Ticket Price	2100 kr	3300 kr
Travel Time	50 min	55 min
No. of Transfers	0	0
Personal Carbon Footprint	45 kg	2.8 kg

*

Please choose the appropriate response for each item:

	a	b
	○	○

Assume you are planning a one-way flight for you, considering the following details. If both flight alternatives below are available to you, which would you choose?

Flight Alternatives	Conventional Aircraft	All-electric Aircraft
Origin & Destination	Stockholm to Visby	Stockholm to Visby
Purpose of your trip	Leisure	Leisure
Ticket Price	1100 kr	700 kr
Travel Time	50 min	55 min
No. of Transfers	0	0
Personal Carbon Footprint	45 kg	2.8 kg

*

Please choose the appropriate response for each item:

	a	b
	○	○

Assume you are planning a one-way flight for you, considering the following details. If both flight alternatives below are available to you, which would you choose?

Flight Alternatives	 Conventional Aircraft	 All-electric Aircraft
Origin & Destination	Stockholm to Gothenburg	Stockholm to Gothenburg
Purpose of your trip	Business	Business
Ticket Price	1800 kr	1800 kr
Travel Time	60 min	2 hr 05 min
No. of Transfers	0	1
Personal Carbon Footprint	61 kg	5.2 kg

*

Please choose the appropriate response for each item:

	a	b
	○	○

Assume you are planning a one-way flight for you, considering the following details. If both flight alternatives below are available to you, which would you choose?

Flight Alternatives	 Conventional Aircraft	 All-electric Aircraft
Origin & Destination	Stockholm to Gothenburg	Stockholm to Gothenburg
Purpose of your trip	Leisure	Leisure
Ticket Price	600 kr	1000 kr
Travel Time	60 min	1 hr 30 min
No. of Transfers	0	0
Personal Carbon Footprint	61 kg	5 kg

*

Please choose the appropriate response for each item:

	a	b
	○	○

Assume you are planning a one-way flight for you, considering the following details. If both flight alternatives below are available to you, which would you choose?

Flight Alternatives	 Conventional Aircraft	 All-electric Aircraft
Origin & Destination	Stockholm to Gothenburg	Stockholm to Gothenburg
Purpose of your trip	Business	Business
Ticket Price	3000 kr	1800 kr
Travel Time	60 min	1 hr 30 min
No. of Transfers	0	0
Personal Carbon Footprint	61 kg	5 kg

*

Please choose the appropriate response for each item:

	a	b
	○	○

Assume you are planning a one-way flight for you, considering the following details. If both flight alternatives below are available to you, which would you choose?

Flight Alternatives	 Conventional Aircraft	 All-electric Aircraft
Origin & Destination	Stockholm to Gothenburg	Stockholm to Gothenburg
Purpose of your trip	Leisure	Leisure
Ticket Price	1000 kr	600 kr
Travel Time	60 min	2 hr 05 min
No. of Transfers	0	1
Personal Carbon Footprint	61 kg	5.2 kg

*

Please choose the appropriate response for each item:

	a	b
	○	○

Assume you are planning a one-way flight for you, considering the following details. If both flight alternatives below are available to you, which would you choose?

Flight Alternatives	 Conventional Aircraft	 All-electric Aircraft
Origin & Destination	Stockholm to Lycksele	Stockholm to Lycksele
Purpose of your trip	Business	Business
Ticket Price	3300 kr	3300 kr
Travel Time	1 hr 25 min	2 hr 30 min
No. of Transfers	0	1
Personal Carbon Footprint	75 kg	7.2 kg

*

Please choose the appropriate response for each item:

	a	b
	○	○

Assume you are planning a one-way flight for you, considering the following details. If both flight alternatives below are available to you, which would you choose?

Flight Alternatives	 Conventional Aircraft	 All-electric Aircraft
Origin & Destination	Stockholm to Lycksele	Stockholm to Lycksele
Purpose of your trip	Leisure	Leisure
Ticket Price	1100 kr	1900 kr
Travel Time	1 hr 25 min	2 hr
No. of Transfers	0	0
Personal Carbon Footprint	75 kg	7 kg

*

Please choose the appropriate response for each item:

	a	b
	○	○

Assume you are planning a one-way flight for you, considering the following details. If both flight alternatives below are available to you, which would you choose?

Flight Alternatives	Conventional Aircraft	All-electric Aircraft
Origin & Destination	Stockholm to Lycksele	Stockholm to Lycksele
Purpose of your trip	Business	Business
Ticket Price	5700 kr	3300 kr
Travel Time	1 hr 25 min	2 hr
No. of Transfers	0	0
Personal Carbon Footprint	75 kg	7 kg

*

Please choose the appropriate response for each item:

	a	b
	○	○

Assume you are planning a one-way flight for you, considering the following details. If both flight alternatives below are available to you, which would you choose?

Flight Alternatives	Conventional Aircraft	All-electric Aircraft
Origin & Destination	Stockholm to Lycksele	Stockholm to Lycksele
Purpose of your trip	Leisure	Leisure
Ticket Price	1900 kr	1100 kr
Travel Time	1 hr 25 min	2 hr 30 min
No. of Transfers	0	1
Personal Carbon Footprint	75 kg	7.2 kg

*

Please choose the appropriate response for each item:

	a	b
	○	○

Demographics and Background

Please state the zip code of your residential area.

*

Please write your answer here:

Age

*

Please choose **only one** of the following:

- ○ 18 -24
- ○ 25 -34
- ○ 35 - 44
- ○ 45 - 54
- ○ 55 - 64
- ○ 65 - 74
- ○ 75+

Gender *

Please choose **only one** of the following:

- ◯ Female
- ◯ Male
- ◯ Other

Your monthly personal income. *

Please choose **only one** of the following:

- ◯ Less than SEK 20,000
- ◯ SEK 20,000 - SEK 29,999
- ◯ SEK 30,000 - SEK 39,999
- ◯ SEK 40,000 - SEK 49,999
- ◯ SEK 50,000 - SEK 59,999
- ◯ SEK 60,000 - SEK 69,999
- ◯ SEK 70,000 and above
- ◯ I don't know/ Other

What is your highest completed education level? *

Please choose **only one** of the following:

- ◯ Primary School
- ◯ Secondary School
- ◯ High School Diploma
- ◯ Bachelor's Degree (Ex: BSc, BA, BEng)
- ◯ Master's Degree (Ex: MSc, MBA, MA)
- ◯ Doctoral Degree (Ex: PhD, EdD)
- ◯ Other

What is your current employment status? *

Please choose **only one** of the following:

- ◯ Employed - Full Time
- ◯ Employed - Part Time
- ◯ Self-employed
- ◯ Unemployed
- ◯ Student
- ◯ Retired
- ◯ Other

Suggestions for Improvement

We appreciate your participation in this survey! As we strive to enhance our research, we value your insights. Please take a moment to share any suggestions or ideas you may have for improving the survey.

Is there anything you think we could improve in this survey? Please share any suggestions or ideas you may have.

Please write your answer here:

You are all done!