



# **MASTER'S THESIS**

## **Modeling Mode Choice Behavior After the Introduction of New Railway Connections to Munich Airport**

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## **Abstract**

The demand for air travel has grown steadily over the last few years and consequently increased the number of trips to the airport made by air travelers and airport employees. As a result, ground access to the airport has become an essential factor in airport attractiveness. This study intends to investigate the mode choice behavior of airport workers and airport passengers after the introduction of new railway connections to Munich Airport.

The assessment of the effect of these transportation links will be based on the revealed preference surveys of passengers and employees of Munich Airport. Discrete choice models are estimated with R software to analyze the sensitivity of airport users to changes in the railway service. The research considers six transport modes – private car, rental car, car sharing, taxi, bus and train; later, they are merged into auto and transit alternatives. The estimation results confirm the assumption that the reduction of travel time and a number of transfers makes transit services more attractive for airport users. Gender, age, number of accompanying people and monthly household income also have an impact on mode choices of air passengers.

The parameters determined for each model are applied to assess various scenarios involving railway projects in the area of Munich Airport and study their impact on the travel behavior of airport users. The spatial analysis defined areas affected by the modifications in the railway network proposed by each scenario and compared changes in transit shares. The findings of this research create a foundation for ground transportation planning in the area of Munich Airport that takes into account factors influencing travel behavior of air passengers and airport employees.

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# 1. Introduction

Munich Airport is the second-largest airport in Germany and plays an important role in the Munich region (Flughafen München GmbH, 2017). Increasing demand for air travel is represented by the steadily growing airport passenger turnover. The airport is no longer just a transportation node – it facilitates economic growth in the region, provides space for business and innovation activities, and simply serves as a recreational area. At this point, ground accessibility becomes one of the key factors in airport attractiveness for all its users and visitors.

People use various means of transport to reach Munich Airport. According to the research made in 2017 by its authorities, 50% of departing passengers' trips were made by taxis, private and rental cars (Flughafen München GmbH, 2017, p. 15). The passenger surveys conducted in other airports reveal an even higher proportion of trips made by car. In particular, their shares in 2005 comprised 63%, 67%, 61% and 72% in Heathrow, Gatwick, London Stansted, and London Luton airports respectively (National Academies of Sciences, Engineering, and Medicine [NASEM], 2008, p. 137). With the growing number of air travelers, the number of trips to Munich Airport will continue to rise. This can result in obstructed traffic, heavy road congestion during peak hours and an increasing level of emissions in the airport area.

Similarly, airport employees use private vehicles as the major mode to access their workplace. In the overview of modal shares among workers of Frankfurt International and Hamburg Airports transit comprises only 15% (Leigh Fisher Associates, Coogan & MarketSense, 2000, p. 38). The peculiarities of work at the airport contribute to the low popularity of transit. The shifts are done also at night and early in the morning, including weekends and holidays, when the public transport service may be limited or absent. At the same time, the deficiency of public transport connections to the airport is one of the key factors that influence the decision of airport workers to use private vehicles (Leigh Fisher Associates et al., 2000, p. 21). Thus, it is important to improve ground access to the airport and support sustainable modes of transport not only from the passengers' but also from the airport employees' perspective.

One of the ways to promote public transport access to the airport is the provision of rail connections. Birolini et al (2019, p. 122) stated in their work that a direct railway service to the airport is a competitive transport option, which will be capable of attracting a significant share of travelers. The authors also mentioned that the airport's express train has a much higher potential to increase the use of the railway services than a simple extension of the existing regional commuter service (Birolini et al, 2019, p. 113). Moreover, Murakami (2016, p. 97) revealed the

relation between airports with rail links and economic development. His research demonstrates that cities around the world with a rail connection to the airport and with urban rail investments are respectively 22% and 14.7% more productive than those without any rail systems. This means that, in addition to improved transport connectivity of the airport, rail links can promote the economic development of a region.

In the chosen study area a large-scale railway project Erdinger Ringschluss is scheduled to be executed until 2029, followed by another massive railway connection Walpertskirchener Spange. This study as well considers several other projects developed for the Munich Airport area to improve its rail connectivity with surrounding regions. NASEM (2008, p. 14) emphasized that changes in airport ground access systems (for instance, the establishment of a new rail link to the airport) are likely to have an outcome in the relative attractiveness of different modes, and thus in shares of travelers using each mode. That is why it is essential to be able to predict the travel behavior of airport passengers and their modal choices in response to changes in the range of existing options (NASEM, 2008, p. 14). Given these facts, this thesis aims to estimate the effect of new rail connections to Munich Airport on the travel behavior of airport workers and airport passengers. The resulting mode choice decisions will be predicted using a discrete choice model and compared with actual modal shares to evaluate the effects of these changes in the airport ground access.

## **1.1. Outline of Paper**

This thesis is subdivided into eight chapters. An overview of the relevant literature that specifies the academic and research activity in the field of mode choice models for airport users is provided in Chapter 2. Chapter 3 describes the proposed methodology and specifies the research objective. In Chapter 4 various stages of the data collection, processing (Section 4.4) and analysis (Section 4.5) are presented. Chapter 5 explains the process of model estimation and Chapter 6 focuses on the estimation results. In Chapter 7 various scenarios incorporating railway projects in the area of Munich Airport are tested. In the same chapter, the predicted modal shares of airport passengers and employees are compared to the base scenario and spatially analyzed. Finally, Chapter 8 completes the thesis with conclusions, limitations of this study and suggestions for future research.

## 2. Literature Review

### 2.1. Four-Step Model

With the help of transportation forecasting, the future need for transportation and the capabilities of the transport system can be evaluated. The forecasting models can determine the impact of modifications in the transport system. For example, a forecast can demonstrate the changes in a modal split of the region due to the construction of a new railway line or estimate its effect on the public transport ridership. Such predictions are widely used for transportation planning, traffic engineering studies, as well as the design of new transport infrastructure.

A traditional approach to transportation forecasts is a four-step model. This model is used to study various transport systems and to predict the behavior of its users. For the first time the model was applied to the full extent in 1955 for the Chicago Area Transportation Study travel forecasting (Weiner, 1997, p. 18). Rosenbaum and Koenig (1997, pp. 10-11) described the four steps of a travel demand model:

- 1) Trip generation – in the beginning, a study area is divided into traffic zones, where a number of trips is generated and attracted by each zone. The calculation of generated and attracted trips in each zone is based on the information about households, the number of working places and the population of each zone;
- 2) Trip distribution – the origin and destination of each trip are matched and the number of trips from and to each zone is calculated. Traditionally, this is done with the help of gravity, or spatial interaction model, travel time is used as an accessibility measure;
- 3) Mode choice – in this step trips are split by transport mode, and as a result, it is possible to estimate modal shares. Mode choice models can also consider the travel cost, the relative travel time and the trip purpose;
- 4) Trip assignment – in the final step the trips between origins and destinations are loaded in the transportation network. Traffic assignment defines the route that is chosen by each user to reach their destination points and is usually based on the assumption that individuals attempt to minimize their travel time. This process continues until all trips are loaded into the network.



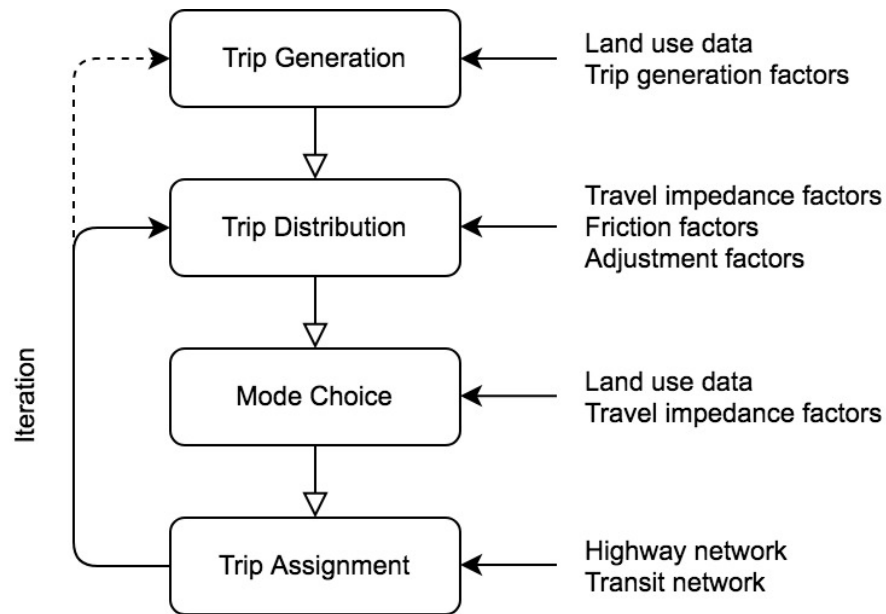


Figure 1. Four-Step Model (adapted from Rosenbaum & Koenig, 1997, p. 11)

Figure 1 is a schematic representation of the traditional four-step travel demand model. This research focuses on the third step of the estimation process – mode choice. NASEM highlighted in their review of airport ground access mode choice models that the possibility to predict mode choices of airport workers and air passengers is “a key analytical component of airport landside planning, as well as airport system planning” (2008, p. 11).

There are two main approaches in modeling the travel behavior – aggregate and disaggregate. In the first case, the modeling is made for a group of individuals, clustered by their socio-economic attributes, while modeling the travel choices for each individual is known as a disaggregate approach (Koppelman & Bhat, 2006, p. 1). The essential advantages of the disaggregate approach over the aggregate approach were defined by Koppelman and Bhat (2006). According to the authors, this approach explains the choice of each individual in given conditions, and thus better reflects changes in choice behavior if attributes of individuals or alternatives are changed. The second advantage is the causal nature of the disaggregate approach that increases the likelihood of predicting in a different time and geographic context (Koppelman & Bhat, 2006, p. 2). Third, the author stated that aggregation results in a substantial loss in variability, thus having a lower level of model precision than with the disaggregate approach. Finally, Koppelman and Bhat (2006, p. 2) pointed out that the proper specifications of disaggregate models produce unbiased parameter estimates. Due to these advantages of the disaggregate approach, discrete choice models are extensively used in travel demand modeling.

## 2.2. Discrete Choice Models

Discrete choice models explain decision-makers' choices among a finite number of mutually exclusive alternatives (Train, 2009, p. 11). These models calculate the utility for each of the alternatives. According to NASEM (2008, p. 22), utility is a function of measurable (observable) characteristics of both the decision-maker (e.g. income, age, education) and the alternative (e.g. travel time, travel cost). It is assumed that the individual will always choose the alternative with the highest utility.

However, it is not possible to perfectly model human behavior in the real world. The decision made by an individual does not only depend on certain characteristics of the alternative but also some unobservable parameters – a lack of information about another alternative, specific circumstances in the process of decision making (e.g. weather conditions, national holidays), personal preferences and perceptions, etc. Train (2009, p. 34) stated that these parameters are also included in the utility function and considered by the researcher as random. A decision-maker  $n$  has  $j$  alternatives and the utility  $U$  obtained from alternative  $j$  has two components – the known observable parameters  $V$  and the unknown part  $\varepsilon$  (Train, 2009, p. 34):

$$U_{nj} = V_{nj} + \varepsilon_{nj} \quad (1)$$

The random component  $\varepsilon$  in Equation 1 takes into account all unobserved variations in taste and preferences that influence a person's decision. Train (2009, p. 34) noted that by assuming that each  $\varepsilon_{nj}$  is identically and independently distributed extreme value, the logit choice model is derived. Depending on the number of alternatives, there are binomial (with two alternatives) and multinomial (with three or more alternatives) logit models.

The probability of choosing a certain alternative is always between 1 and 0 – the higher is the utility of the alternative, the more likely the individual is to choose it. A common mathematical form to express it is the logistic function that has been widely used for airport access mode choice studies (NASEM, 2008, p. 4). For a model that considers more than two alternatives the probability that the individual  $n$  chooses the alternative  $i$  equals:

$$P_{ni} = \frac{e^{V_{ni}}}{\sum_j e^{V_{nj}}} \quad (2)$$

where  $V_{ni}$  represents observable variables related to alternative  $i$  and  $j$  is the number of alternatives (Train, 2009, p. 37).

The problem of logit models is the independence of irrelevant alternatives (IIA). Train (2009, p. 45) claims that for any two alternatives the ratio of logit probabilities does not depend on any other alternatives. This means that the relative chances of choosing one alternative over another are the same, regardless of other available alternatives and their attributes (Train, 2009, p. 45). But this IIA property is not applicable in all situations. Train (2009, p. 46) demonstrates it on the well-known example of the red-bus-blue-bus problem. A new alternative is introduced to a model with equal choice probabilities between a car and a blue bus (exactly like a blue bus, just in red color), so the choice probabilities will be equally distributed among alternatives ( $P_{car} = P_{bluebus} = P_{redbus} = \frac{1}{3}$ ); however, in real life, the original probability of taking the bus would be split between the two buses (Train, 2009, p. 46). To overcome the IIA problem of the multinomial logit model, a nested logit (NL) model can be used.

### 2.3. Nested Logit Model

According to Train (2009, p. 77), the NL model is suitable when the most similar to each other alternatives faced by an individual can be subdivided into sets, called nests. A tree diagram below demonstrates an example of a nested structure for the decision maker's mode choices.

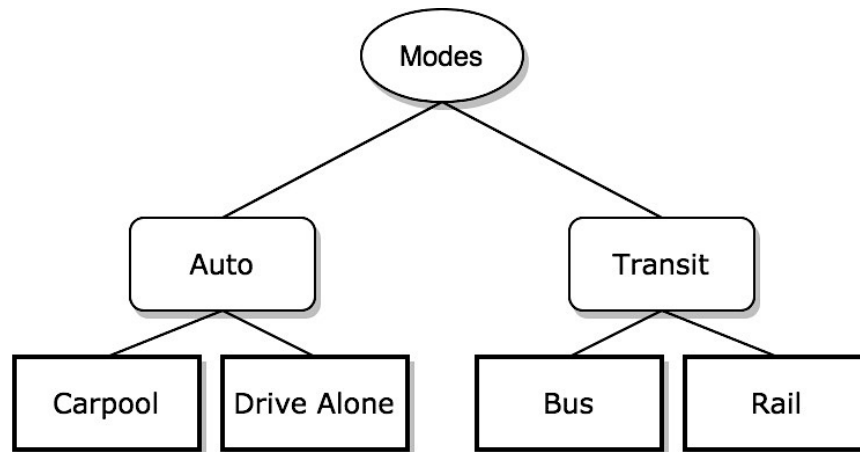


Figure 2. Tree Diagram of Mode Choice (adapted from Train, 2009, p. 83)

In Figure 2 the alternatives were grouped into auto and transit nests. This division can be affected by vehicle ownership that in this case forms two transport subsets. Regardless of the chosen structure, the one pattern will be applicable for NL models: the IIA problem remains within each nest but not across nests (Train, 2009, p. 78). Caused by the similarity of the alternatives in one nest, the cross-elasticities between them will be higher than between nests – in this way, an increase in the travel cost for rail will have a bigger impact on transit modes as they are more correlated. With a nesting structure, the red-bus-blue-bus problem from MNL models is omitted.

For instance, if the bus alternative is removed from this sample structure, the probability of individual driving by rail increases more than the probability of a carpool or driving the car alone.

According to Train (2009, p. 79), if alternatives are grouped into  $k$  nests ( $B_1, B_2, \dots, B_k$ ), the utility that a person obtains from alternative  $j$  in nest  $B_k$  can be expressed by Equation 1. However,  $\varepsilon_{nj}$ s are correlated within nests, so for any two alternatives  $j$  and  $m$  in nest  $B_k$ ,  $\varepsilon_{nj}$  is correlated with  $\varepsilon_{nm}$  (Train, 2009, p. 79).

If the utility has to be calculated on the deeper level of the structure, the formula changes. Let us consider the tree diagram with a two-level nesting structure as an example, so the  $B_k$  nest will stand for “Transit” and the alternative  $j$  will stand for “Bus” in the  $k$  nest. Then the utility equation for the “Bus” alternative is:

$$U_{nj} = W_{nk} + Y_{nj} + \varepsilon_{nj} \quad (3)$$

where  $W_{nk}$  depends only on variables that describe nest  $k$  and  $Y_{nj}$  depends on variables that describe the alternative  $j$  (Train, 2009, p. 82). The part named  $Y_{nj}$  will be different for the “Rail” alternative in the “Transit” nest, while the  $W_{nk}$  part will remain the same for both the “Bus” and the “Rail” alternatives. However, for the nest “Auto” the  $W_{nk}$  component will be different.

The probability of selecting the alternative  $i$  in nest  $B_k$  can be expressed as the product of two probabilities:

$$P_{ni} = P_{ni|B_k} \cdot P_{nB_k} \quad (4)$$

where  $P_{ni|B_k}$  is the conditional probability of choosing the alternative  $i$  if nest  $B_k$  is chosen, and  $P_{nB_k}$  is the marginal probability of selecting an alternative in nest  $B_k$  (Train, 2009, p. 82). In this equation  $P_{ni|B_k}$  can be expressed as:

$$P_{ni|B_k} = \frac{e^{\frac{Y_{ni}}{\lambda_k}}}{\sum_{j \in B_k} e^{\frac{Y_{nj}}{\lambda_k}}} \quad (5)$$

where  $\lambda_k$  is the logsum coefficient (Train, 2009, p. 82). The values of this parameter denote how similar are the pairs of alternatives in the nest, where  $\lambda_k = 0$  implies that pairs of alternatives in the nest are perfectly correlated and  $\lambda_k = 1$  states that there is no correlation among mode pairs in the nest, so the NL model turns into the multinomial logit (MNL) model (Koppelman & Bhat, 2006, p. 163).

To express the marginal probability  $P_{nB_k}$ , Train (2009, p. 82) uses the following equation:

$$P_{nB_k} = \frac{e^{W_{nk} + \lambda_k I_{nk}}}{\sum_{l=1}^K e^{W_{nl} + \lambda_l I_{nl}}} \quad (6)$$

The author explains that the probability of choosing nest  $B_k$  depends on the expected utility that the individual obtains from the nest. This expected utility consists of  $W_{nk}$  – the utility that the person gets regardless of which alternative is chosen in the nest, and  $\lambda_k I_{nk}$  – an additional utility that the decision-maker  $n$  gets by being able to select the best alternative in nest  $B_k$  (Train, 2009, p. 83).

$I_{nk}$  is the log of the denominator in conditional probability formula:

$$I_{nk} = \ln \sum_{j \in B_k} e^{\frac{Y_{nj}}{\lambda_k}} \quad (7)$$

and represents the expected utility for the choice of alternatives within nest  $B_k$  and is the log of a sum of the nested utility exponents (Train, 2009, p. 83).

Referring to the tree diagram that was taken as an example, the conditional probability that the decision-maker uses “Rail” if the nest “Transit” is chosen will be:

$$P_{Rail|Transit} = \frac{e^{\frac{Y_{Rail}}{\lambda_{Transit}}}}{e^{\frac{Y_{Rail}}{\lambda_{Transit}}} + e^{\frac{Y_{Bus}}{\lambda_{Transit}}}} \quad (8)$$

and the marginal probability of choosing an alternative in the “Transit” nest will be:

$$P_{Transit} = \frac{e^{(W_{Transit} + \lambda_{Transit} I_{Transit})}}{e^{W_{Auto}} + e^{(W_{Transit} + \lambda_{Transit} I_{Transit})}} \quad (9)$$

The tree diagram in Figure 2 considered as an example is one of many possible nested structures that can be created from four alternatives (carpool, drive-alone, bus, train). Different structures of NL models create different results and thus change model interpretation. The subsequent changes in travel forecast may be significant enough to influence decisions regarding transportation planning and capital investments. To select a suitable nesting structure, a combination of judgment about reasonable nesting structures and statistical hypothesis testing is needed (Koppelman & Bhat, 2006, p. 166).

## 2.4. Airport Mode Choice Models

This study is initiated because at the moment there is a lack of insights into the current condition of ground access to Munich Airport and its influence on the travel mode choice behavior of airport users. Discrete choice models are widely used for travel demand modeling due to their ability to analyze the decision-making behavior of users who have to choose between mutually exclusive modes of transport. Such models are a powerful tool for forecasting the changes in travel behavior due to the modifications in mode attributes (new tariffs, faster connection, increased capacity), transportation network (new road or railway), or socioeconomic characteristics of an individual (increase in income, age changes). There are numerous examples of discrete choice models used in both air passenger and airport workers mode choice models.

In his book, Train (2009, p. 71) provided an example of a successful implementation of a logit model for forecasting travel behavior of commuters after the launch of a new rail system in the San Francisco Bay area. Mode choice models were estimated on the commuters' sample before the system launch and provided valuable information about factors that influence commuters' decisions (Train, 2009, p. 71). After the Bay Area Rapid Transit system was open for service, the mode choices of the commuters were observed and the predicted share of new rail system users was compared with the observed share (Train, 2009, p. 71). Train (2009, p. 71) highlighted that the models' prediction was good and far more precise than the forecasts that did not use discrete choice models.

The discrete choice modeling was also used in the research for the new Athens International Airport. Psaraki and Abacoumkin (2002, p. 93) classified travelers in twelve types by characteristics that affected their modal choice – residence, trip purpose and destination. In the research they used a logit model to define ground access choices for each type of passenger at the existing airport. The resulting choice probabilities were applied to forecast the modal split for the new airport, so the proper planning of ground facilities could be done (Psaraki & Abacoumkin, 2002).

Birolini et al (2019) evaluated in their research a new direct rail connection to Milan-Bergamo Airport, considering five modes of transport (private car, drop-off, taxi, bus and train) and two market segments (business and non-business air travelers). The authors used a mixed multinomial logit model to study the behavior of outgoing passengers, to estimate their sensitivity to travel cost and travel time and to quantify access mode choice preferences of air passengers.

Later, Birolini et al (2019, p. 117) simulated the introduction of new rail service and used the estimated model coefficient to calculate the potential share of each transport alternative.

Miyoshi and Rietveld (2014) used another type of discrete choice model to test the hypothetical carbon charge on car commuters that produce carbon dioxide emissions to access Manchester Airport. The authors researched the impact of this charge on travel behavior with the help of the two-level nested multinomial logit model, with one nest for car users (car alone, car with a passenger, passenger in a car and taxi) and another for alternative mode choices (bus, metro, walking and bicycle). The modal shares of commuters were calculated taking into account the travel time and travel cost and then were compared to the modal shares after the introduction of carbon charges (Miyoshi & Rietveld, 2014). The authors highlighted that there is a great effect of shifting from private to public transport on the overall damage costs of CO<sub>2</sub>.

NASEM (2008) provided a comprehensive review of eight airport ground access mode choice models. The study includes information about the data used for modeling, the structure of the model, its explanatory variables, the market (air passengers or airport workers) and its segmentation. Some of these models are reviewed in more detail below.

Based on an air passenger survey conducted in the Boston Logan International Airport in 1993, two models with separate coefficients for business and non-business trips were created – NL for residents and MNL for visitors (NASEM, 2008, p. 109). The broad list of considered variables included the travel time (in-vehicle and out-of-vehicle), the access time to the public modes by car, the travel cost, the number of transfers, the residence, the number of luggage pieces, the air party size, the number of air trips in the last year and whether travel expenses were covered by the employer (NASEM, 2008, p. 109). The resulting model was a part of the regional transportation planning in the Boston metropolitan area and was used to predict car trips to and from Boston Logan International Airport (NASEM, 2008, p. 112).

The Chicago Airport Express Ridership Forecasting study was conducted in 2004 to understand how air passengers might change their mode choice behavior after the opening of an express train connection between the Chicago city center and O'Hare International and Midway (NASEM, 2008, p. 113). Based on the results of revealed preference and stated preference surveys, two NL models with nine transport modes were created for travelers on business and non-business journeys (NASEM, 2008, p. 114). The utility function included the total travel time with different weights for the access, transfer and waiting time, travel cost with separate coefficients for two traveler income groups and two dummy variables – the availability of baggage check-in at the downtown terminal and the use of an intermediate station (NASEM, 2008, p. 114). Several

scenarios were tested to forecast the ridership and the revenue for the Airport Express train, including different fares, the availability of a free shuttle and various travel time assumptions (NASEM, 2008, p. 119).

Another airport access mode choice model described by NASEM (2008, p. 124) was developed in 2001 to evaluate the effect of a new transport link between bus rapid transit and Oakland International Airport on ridership compared with an existing shuttle bus connection. The multinomial logit model considered not only air passenger trips (subdivided by trip purpose and residence) but also trips of the airport employees, and included six explanatory variables – the travel cost, the household income, the waiting time, the walking distance and travel times by bus, rail and car (NASEM, 2008, p. 125).

The described above studies suggest that the topic of airport access mode choice models is well studied. They also provide evidence that discrete choice modeling is a suitable and appropriate method for the problem considered in this research. However, there is no general approach to model the alterations in the mode choice behavior of airport users after changes in the transportation system (e.g. new transport connections) or transport service (e.g. new tariff). The researchers use different model structures, market segmentation, transport modes and explanatory variables in models for certain regions and even for airports in the same area. This conclusion suggests that there are all preconditions to create separate mode choice models for air travelers and employees of Munich Airport. The estimation results of these models will identify the attributes that play a role in travel decisions of airport users. The insights of this research can be used to create ground access strategies and evaluate transportation projects that can motivate passengers and employees of Munich Airport to switch from private vehicles to more sustainable modes of transport.



### 3. Methodology and Aim of the Thesis

Over the last couple of decades, there were numerous studies in the field of airport transport accessibility, described in detail in Section 2.4. Nevertheless, the ground access at every airport is unique because of the airport's location, passenger volumes and their socio-economic characteristics and even the economic development of the country. Comprehensive research made by NASEM (2008) is questioning the transferability of airport ground access models due to their wide-ranging specifications. Although the behavior of airport users seems to be similar in different regions, "after taking into account differences in air passenger or airport employee characteristics and transportation system service levels, it appears unlikely that current airport access mode choice models do this correctly" (NASEM, 2008, p. 70). That is why the case of Munich Airport has to be addressed individually to increase the accuracy of forecasting.

Another important aspect considered in this study is the travel behavior of airport employees. Most of the studies mentioned in Chapter 2 do not examine this group of travelers during the development of mode choice models. However, their trips can comprise a significant share of the trips to and from the airport. It is essential to model mode choices of airport employees since their trips are performed regularly and create a high demand for airport ground access services.

Based on the previous findings and practices, this research aims to estimate the impact of various railway projects on the mode choice behavior of passengers and workers of Munich Airport. The objectives are to create a discrete choice model for a part of the Munich metropolitan area and to confirm the assumption that the improvement in the existing railway service will increase the attractiveness of railway connections to the airport. The designed models can be used for future surface transport strategies and planning procedures in the area of Munich Airport. In the furtherance of this goal, a methodology described in Figure 3 will be implemented.

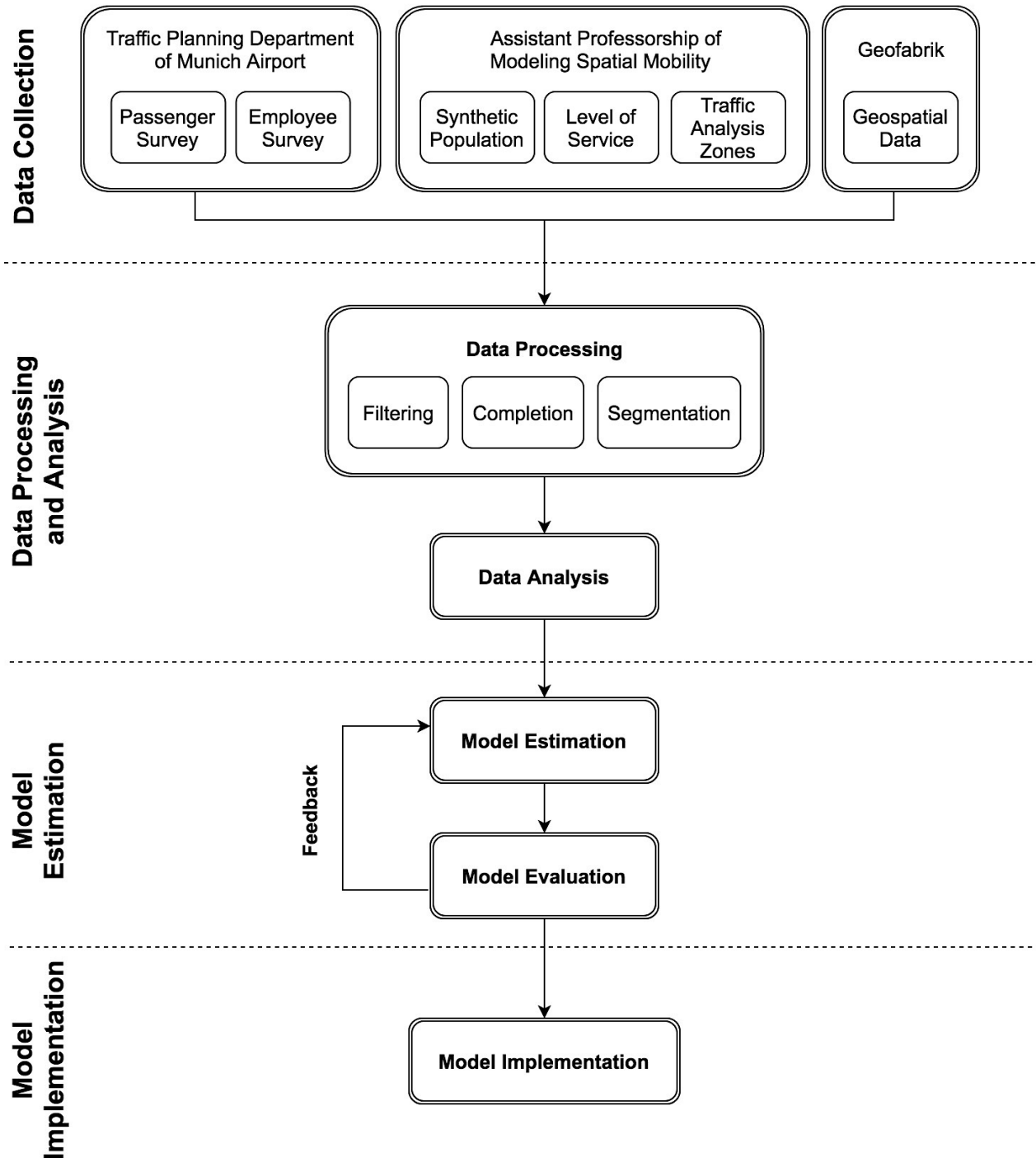


Figure 3. Research Methodology

A process map in Figure 3 distinguishes four main steps: Data Collection, Data Processing and Analysis, Model Estimation and Model Implementation. During the first step, three main data sources are involved:

1. Traffic Planning Department of Munich Airport – provided results of passenger and employee surveys;

2. Assistant Professorship of Modeling Spatial Mobility – shared the attributes of a synthetic population, a map of traffic analysis zones and level of service for each transport mode;
3. Geofabrik – a download server of Openstreetmap for geospatial data that was used for spatial analysis in this research.

After the collection of necessary data, all information went through certain processing stages. First, irrelevant trip records are filtered out and the data are structured for further analysis and merged into bigger data frames if necessary. Later, the missing information about the travel cost is added to a dataset. Then, the airport passengers' data are subdivided into four groups by residence and travel purpose to create a separate sub-model for each of them. The processed data is later analyzed by socio-economic and trip characteristics.

In the following step datasets for passengers and employees are transformed into a shape suitable for statistical processing with R software. The models are iteratively estimated with mlogit package for R to develop a utility function with explanatory variables and coefficients that have the closest match to the input data. The output of each model is evaluated until the function that results in the highest goodness of fit is defined for each group of airport users. During this stage, the significance and plausibility of all explanatory variables in the selected models are confirmed.

Finally, the models are implemented to predict the impact of various railway projects on the modal shares of employees and passengers of Munich Airport. Construction projects are subdivided into four scenarios and compared to the base scenario, the variances in modal shares are analyzed spatially and by groups of the airport users. With this approach, the railway projects that wield major influence on the travel behavior of Munich Airport users can be identified.

## 4. Data Collection

To conduct travel forecasting, prior data collection is necessary. Modeling mode choice behavior can be based on the information obtained by conducting a revealed or stated preference survey. The stated preference survey is used to examine choices that individuals will make among hypothetical alternatives. For example, the survey might describe a set of future public transport connections to the city center and ask an interviewee to choose one of the alternatives.

In contrast, the revealed preference survey collects the data about actual choices that were made by individuals. In terms of mode choice modeling, the information obtained from the survey will describe the actual trip and its attributes – the origin, destination, trip purpose, travel time and mode of transport used. Additionally, it can also include information about decision-makers that is believed to affect their choices (such as age, gender, income, education, occupation, etc.). There are numerous examples of revealed preference surveys applied in other travel behavior researches. For instance, Birolini et al (2019) used the results of the survey conducted in Milan-Bergamo Airport to evaluate the new rail service. To understand the mode choices made by commuters, Miyoshi and Rietveld (2014) used the data from a revealed preference survey of Manchester Airport staff. Finally, Psaraki and Abacoumkin (2002) studied access modal split with the help of a passenger survey conducted in the existing Athens Airport.

This study uses two revealed preference surveys, conducted by the Traffic Planning Department of Munich Airport in 2018. The first one is a sample of almost 20,000 departing passengers and provides individual characteristics of each traveler, together with the mode that was used to reach the airport. The second one is a mode choice survey of around 3,000 Munich airport workers and contains information about the transport means used by employees to commute to their workplace.

Another data that is used for model estimation is the synthetic population provided by the research group Modeling Spatial Mobility (MSM) led by Prof. Dr. Rolf Moeckel at the Technical University of Munich (<https://www.msm.bgu.tum.de>) free of charge. Moeckel and Moreno (2018) developed an algorithm that generated around 4.5 million individuals for the greater Munich metropolitan area. The attributes of the synthetic population created in their research are applied in this study since no other information on the personal level is available due to privacy reasons. The detailed overview of data used in this research is provided further in Sections 4.1-4.3 and Section 4.4 explains how different datasets were merged and processed before model estimation.

## 4.1. Synthetic Population

The development of the synthetic population was done in the study area that covered the cities of Munich, Augsburg, Landshut, Ingolstadt and Rosenheim, together with their suburbs (Moeckel & Moreno, 2018, p. 4). This area contains a population of 4.5 million persons, 2.1 million households and 444 municipalities (Moeckel & Moreno, 2018, p. 4). Later, Moeckel and Moreno (2018) divided municipalities into traffic analysis zones (TAZs) using a gradual raster-based zone system. The resulting 4,953 TAZs are used for further analysis and define the study area of this research since the personal attributes essential for further modeling are only available for this territory. Figure 4 demonstrates the map of counties and cities in Bavaria (in color) divided into TAZs, with a red line delineating the study area.



Figure 4. Study Area With TAZs. Adapted from data provided by MSM

The attributes of the synthetic population generated during the research of Moeckel and Moreno (2018) were provided in CSV format. The file contains 4,424,760 records with demographic characteristics of each individual. The variables relevant for this study and their description are listed in Table 1. Additionally, the MSM research group provided the aggregated travel times and the number of transfers for car, bus and train from each postal code zone in the study area.

*Table 1. Relevant Synthetic Population Data*

Variable	Description
<b>Household ID</b>	Identification number of individual's household
<b>Age</b>	Age of the individual in years
<b>Gender</b>	Male / female
<b>Occupation</b>	Toddler / student / employed / unemployed / retiree
<b>Income</b>	The annual income of an individual in Euro
<b>Home zone</b>	Number of TAZ where individual lives

## 4.2. Mode Choice Survey of Munich Airport Workers

In 2018, the Traffic Planning Department of Munich Airport examined what transport modes the employees of Munich airport and subsidiaries use to arrive at their workplace. The survey defines the current transport choices of the workers and their modal preferences. For the estimation of the model, only two variables extracted from the survey results are used: the postal code of the worker's permanent residence and the chosen transport mode. The modes mentioned by employees include private car (used as driver or passenger), train, bus, motorbike and bicycle. Additionally, the total number of workers in each postal code area was provided.

## 4.3. Passenger Survey of Munich Airport

The same year Munich Airport carried out an investigation and questioned almost 20,000 departing passengers. The survey contains personal attributes of passengers, information about their flight (such as travel purpose, destination country, whether the flight is outward or return) and the characteristics of their trip to the airport. Table 2 provides the variables chosen for modeling, together with the detailed description.

Table 2. Relevant Data From the Passenger Survey

Variable	Description
<b>Origin</b>	Postal code of travel origin
<b>Residence</b>	The trip to the airport starts from the place of residence
<b>Travel purpose</b>	Business / private
<b>Trip length</b>	Duration of a trip in days
<b>Age</b>	Age of the individual in years
<b>Gender</b>	Male / female
<b>Companion</b>	Number of accompanying persons in the trip to the airport terminal
<b>Income group</b>	1. under 500 €
	2. 500 – 1,000 €
	3. 1,000 – 1,500 €
	4. 1,500 – 2,000 €
	5. 2,000 – 2,500 €
	6. 2,500 – 3,000 €
	7. 3,000 – 3,500 €
	8. 3,500 – 4,000 €
	9. 4,000 € and more
<b>Mode</b>	Mode of transport used to arrive at the airport

There are seven modes of transport in the passenger survey – private car, rental car, car sharing, taxi, shared taxi, bus and train. The taxi and shared taxi are later merged into taxi mode.

#### 4.4. Data Processing

The subsequent procedure in the research is the preparation of data for the modeling process. The survey results are represented in the form of a table, where each record corresponds to the individual's response. During the data processing, the records that meet one of these conditions are eliminated:

- The transport mode is not specified;
- The transport mode used for the trip is bicycle or motorbike (in airport workers survey);
- The study area does not cover the postal code of the individual's permanent residence.

When the irrelevant records are filtered out from the surveys, two data frames are created with 2,736 trip records of the airport employees and 13,858 trip records of the airport passengers. As the next step, the data frames have to be completed with variables that are essential to understand the transport choices.



#### 4.4.1. Transfers, travel time and travel cost

The distances, number of transfers and travel time for each TAZ are provided by the MSM research group. These variables are available for three modes (private car, bus and train) and are aggregated by postal codes. In the passenger survey, the travel time and distances for rental car, car sharing, taxi and shared taxi are the same as for the private car. The number of transfers for the mentioned above modes is set to zero. The resulting variables are matched with the corresponding postal code in each data frame record. If there is no connection by public transport from a certain postal code area, the travel time is specified as 10,000 minutes. This is done to minimize the utility of such transport connections, so the individual is not likely to choose this route to the airport.

#### Travel cost for public transport

Both surveys for passengers and workers do not contain the travel cost for all origin-destination pairs. There is no platform or service that allows gathering this information automatically, so it was decided to collect this data manually. Due to the considerable number of records that have to be processed, the travel cost was aggregated at the county and city level. In fact, the travel cost is not uniform since the public transport fares vary depending on distance, time of the day, travel party size and age of the individual; also, some people have season tickets or special fares. Altogether, the study area covers five cities (Ingolstadt, München, Landshut, Rosenheim and Augsburg) and 24 counties (Aichach-Friedberg, Augsburg, Bad Tölz-Wolfratshausen, Dachau, Dillingen, Dingolfing-Landau, Donau-Ries, Ebersberg, Eichstätt, Erding, Freising, Fürstenfeldbruck, Kelheim, Landsberg am Lech, Landshut, Miesbach, Mühldorf am Inn, München, Neuburg-Schrobenhausen, Neumarkt, Pfaffenhofen an der Ilm, Rosenheim, Starnberg, Weilheim-Schongau).

The fares for the long-distance railway trips are collected from the Deutsche Bahn AG (DB) website and for the short-distance trips from the Münchner Verkehrs- und Tarifverbund (MVV) website. Since ticket prices on the DB website can change depending on the time of the day, day of the week and the time interval before the planned trip, for more consistent results it was decided to collect all data at once under the following conditions:

- The trip is planned one month in advance;
- The trip will be made during the off-peak hours in a workday;
- Among the trips with the same duration and number of transfers, the trip with the lowest



fixed fare is chosen.

Taking into consideration that the surveys were conducted in 2018, the costs for short-distance trips correspond to the MVV tariffs in the fourth quarter of 2018, before the entry into force of the new tariffs related to the completion of the Neufahrn rail link on December 9th, 2018 and the MVV tariff reform on December 15th, 2019.

The available bus connections to the airport were checked through the route planner of Google Maps, the costs were obtained from the Flixbus, Lufthansa Express Bus, Ingolstädter Verkehrsgesellschaft and MVV websites. For the area covered by MVV, tariffs from the fourth quarter of 2018 are applied. During the data collection, the same conditions as for the train ticket fares were applied. It must be noted that 10 counties and one city do not have a bus connection even to the city of Munich, so the 1,000 Euros fare was applied to minimize the utility of traveling by bus from these areas.

### **Travel cost for private car**

The travel cost for cars is subdivided into two parts. The first one represents compulsory costs that are based on the average fuel consumption per kilometer and petrol prices. According to the German online portal for statistics Statista, cars with petrol engines used on average 7.8 liters of petrol per 100 kilometers in 2018 (Ahlswede, 2020). The same source mentions the average annual price for a liter of premium gasoline: 145.6 cents (Hohmann, 2020). Thus, fixed costs of 0.015 Euro per kilometer are included for modes like private car, rental car, car sharing, taxi and shared taxi.

The second part takes into account additional costs that can be time-related (such as payments for parking, car rental and car sharing services) or distance-related (taxi rates). For travelers that drive to the airport by car, these costs are a parking charge. The passenger survey distinguishes five types of car users:

- 1) Car passengers;
- 2) Parked at the airport terminal;
- 3) Parked in other parking spaces;
- 4) Parked in an unspecified location;
- 5) Parked in the airport surrounding.

The parking fee is neglected for people that were brought to the airport and for the airport workers. For other Munich Airport passengers, there are two types of parking tariffs – terminal and

budget (Flughafen München GmbH, 2020, p. 1). Terminal parking lots are located right in between Terminal 1 and Terminal 2, so the departure gates are within walking distance. In contrast, budget parking spaces are positioned outside the airport, and passengers have to use S-Bahn (suburban rail) or bus transfer to reach the terminals. However, the fee for this parking area is lower. The parking rates in different areas of Munich Airport are provided in Table 3.

Table 3. Parking Rates at Munich Airport

Duration of parking	Budget parking rate	Terminal parking rate
1 day	26 €	36 €
2 days	36 €	72 €
3 days	46 €	108 €
4 days	56 €	144 €
5 days	68 €	175 €
6 days	76 €	187 €
7 days	87 €	199 €
8 - 13 days	26 € per day + 5 €	36 € per day + 15 €
14 days	122 €	299 €
15-21 days	26 € per day + 5 €	36 € per day + 15 €
22 days	162 €	419 €
Every next day	+ 5 €	+ 10 €

Note. Reprinted from “*Parken am Flughafen München*”, by Flughafen München GmbH, 2020, p. 1, Munich: Author. Copyright 2020 by Flughafen München GmbH

The price for travelers that did not specify their parking location is calculated according to the budget tariff, assuming that individuals tried to pay less. For those who are not willing to park at the airport premises, there are numerous parking areas nearby. It was decided to choose the one with the highest number of reviews on the website for parking space comparison (Ravenhorst, n.d.). It turned out to be Pfiffing Parken located in Schweig, five kilometers away from Munich Airport (Oslislo, 2018). With all that said, three parking tariffs (terminal, budget, outside the airport) are calculated based on the duration of the passenger’s trip – the number of days abroad defines the parking time and the corresponding price.

### Travel cost for car sharing and car rental

The varying costs for car sharing are calculated based on the tariffs of SHARE NOW. It is the oldest and most significant car sharing service provider in the market that in 2019 united two other companies – car2go and DriveNow (SHARE NOW GmbH, 2019). Since the rental price per

minute varies from 20 to 36 cents, the average of 28 cents is taken, together with an additional 13.99 Euros fee for dropping off the car at Munich Airport (SHARE NOW GmbH, n.d.).

Car rental costs are usually calculated per day. The well-known German car rental company Sixt SE is one of the Munich Airport contractors and taken as a reference. The prices for their services are obtained from the Munich Airport car rental webpage (Sixt). The average fee per day is calculated among 20 different sedan models (as this is the most common vehicle type) excluding outliers in the price range. It results in 105 Euros and since the rental period is unknown, the rental costs are considered for one full day only.

### **Travel cost for taxi and shared taxi**

In contrast to the mentioned costs, the taxi tariffs are based on the distance traveled. In Munich city, the price includes a minimum fare of 3.70 Euros, an order fee of 1.40 Euro and the price per kilometer – 2 Euros for distances up to five kilometers, 1.80 Euro for 5-10 kilometers range and 1.70 Euro for trips over 10 kilometers (Taxi Munich, 2008). Since no rates for the shared taxi services were found, this mode is treated as taxis and the travel cost is calculated accordingly.

#### **4.4.2. Personal attributes of the airport workers**

The data provided by the Traffic Planning Department of Munich Airport does not contain personal attributes of airport workers due to privacy reasons. It was decided to combine the results of the mode choice survey of the airport workers with the synthetic population data using R software. The following methodology was applied:

- 1) The total number of airport workers is summarized by postal code;
- 2) The travel time to the airport is added to each of the postal codes;
- 3) TAZs from the synthetic population are overlapped with the postal code areas in Bavaria using QGIS software;
- 4) TAZs are matched with each postal code to define the number of workers in every TAZ;
- 5) The employed people are extracted from the synthetic population, their number in each TAZ equals the number of airport workers living there;
- 6) The annual income of every person is recalculated to the total monthly household income;
- 7) Personal attributes of the employed people from the synthetic population are added to the survey results by pairing the TAZs.

As a result, 24,884 records with individual characteristics of airport workers and the travel time of

their home-based-work trips were created. However, during the model estimation process, this approach resulted in a low significance of personal attributes such as age, gender and household income. The explanation behind it is a disadvantage of the matching procedure – the only parameter that could join the personal attributes from the synthetic population with the results of the airport workers survey was the TAZ identification number. Consequently, the chance that personal characteristics added to each employee do not correspond to reality is very high. For further research, it was decided to use only the findings derived from the airport workers survey and to estimate the model for airport workers based on the mode-specific variables only. Another attempt was made to estimate air passenger models with the synthetic population data, however, the number of relevant records with trips ending at the airport was insufficient.

## 4.5. Data Analysis

Content removed due to data usage restrictions

## 5. Model Estimation

The models applied in this research are specified before the estimation process. This stage includes denoting the choice set, selecting explanatory variables and determining the model structure. As described in Section 4.5, the choice set for airport passengers includes private car, car sharing, rental car, taxi, bus and train while the choice set for employees is limited to three modes – private car, bus and train. The model for passengers of Munich Airport will be split into four sub-models: two for residents traveling for business (BR) or leisure (LR) purpose and two for visitors that have a business (BV) or private trip (LV).

### 5.1. Variables and Correlations

Table 4 provides an overview of the variables used during model estimation. The marks in the last two columns indicate which variables are considered in Air Passenger Models (APMs) and the Airport Employee Model (AEM). Note that the value of dummy variables could only be 0 or 1; usually, 1 stands for the presence of an attribute and 0 for the absence. For instance, if the person is living in the study area, the dummy variable takes on the value of 1 and 0 otherwise.

Table 4. Variables Considered in Model Estimation

Variable	Type of variable	APM	AEM
<b>Individual-specific</b>			
Residence	Dummy	✓	
Travel purpose	Dummy	✓	
Age	Discrete	✓	
Gender	Dummy	✓	
Number of accompanying people	Discrete	✓	
Monthly household income	Discrete	✓	
<b>Trip-specific</b>			
Travel time	Continuous	✓	✓
Travel cost	Continuous	✓	✓
Number of transfers	Continuous	✓	✓
Travel distance	Continuous	✓	✓

The correlation between the explanatory variables is checked before model estimation, as the discrete choice models can include only exogenous variables. The correlation matrices for the variables in APMs and AEM are shown in Figure 5 and Figure 6 respectively. Both were created with the help of the R package corrplot. The transfers for automotive vehicles, as well as the car rental costs, are excluded from the list of variables since their values are constant and a correlation can't be calculated.

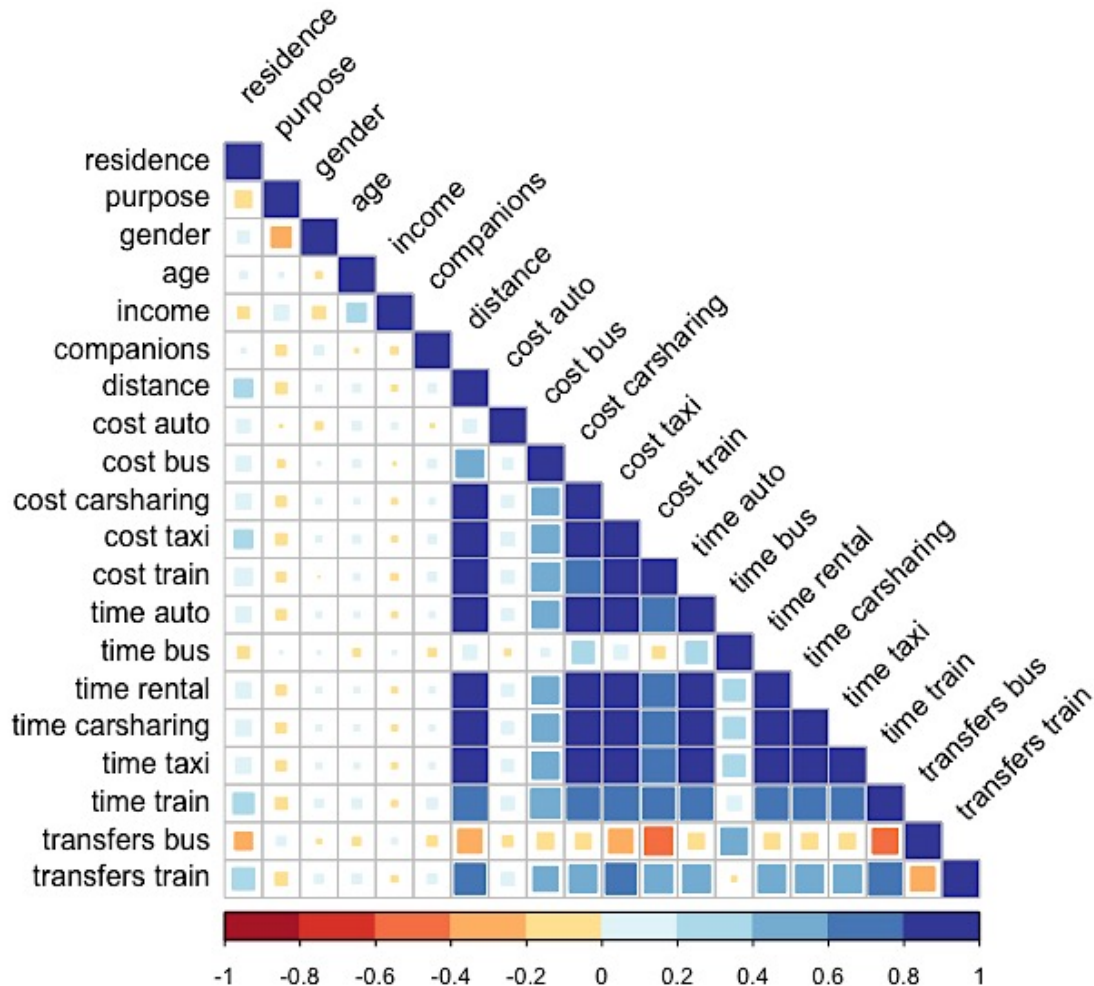


Figure 5. Correlation Matrix for APMs

All individual-specific variables in Figure 5 have low correlation coefficients. At the same time, there is a very strong correlation between distance, travel time and travel cost for all modes of transport. This is explained by the distance-related nature of costs that was discussed in Section 4.4.1, and the same principle is applied in the structure of public transport costs – people traveling over short distances pay a lower tariff. A high correlation is also present between the

travel time and the number of transfers for bus and train. There is a minimal relation between the car travel cost and the distance since costs include a parking fee paid by the traveler.

The same relation between distance, travel time and travel cost is observed in the correlation matrix for variables of the airport employee model. The costs of a trip by bus, train and car are directly proportional to the duration of the trip and the distance traveled, longer trips by public transport have a higher number of transfers.

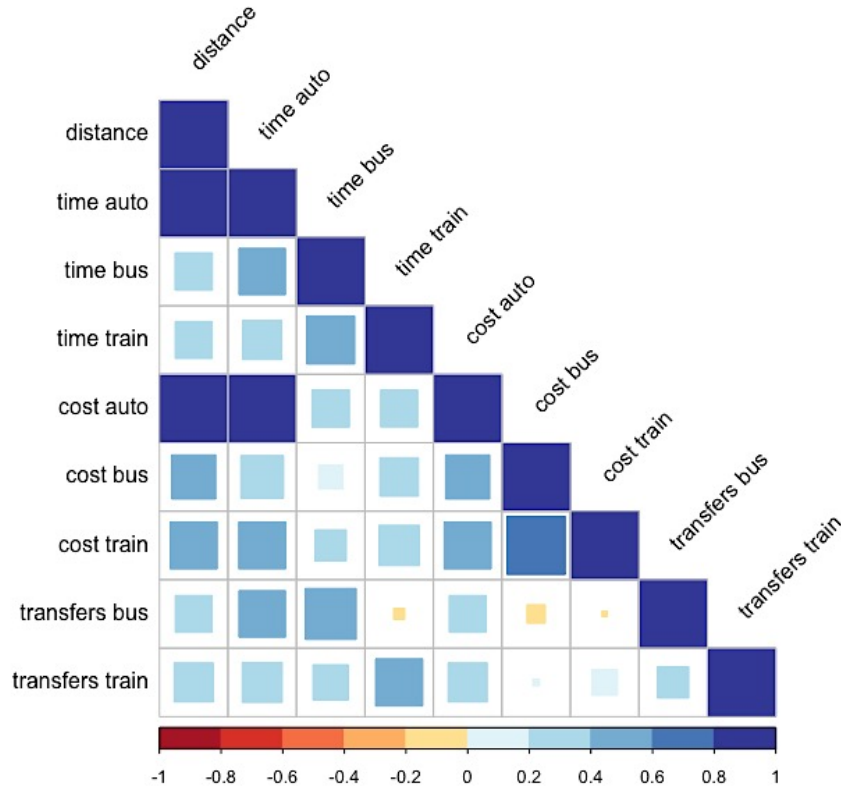


Figure 6. Correlation Matrix for the AEM

## 5.2. Utility Function

Once the choice sets and explanatory variables are defined for both models, the utility functions can be formulated. They are represented in the form of linear equations with different combinations of explanatory variables for every group of airport users. The utility function for each alternative consists of the known observable parameters  $V$  and the unknown part  $\varepsilon$ :

$$U_{nj}^P = V_{nj}^P + \varepsilon_{nj}^P \quad (10)$$

where  $U_{nj}^P$  is the utility of  $j$  alternative (private car, car sharing, rental car, taxi, bus or train) for a decision-maker  $n$  that is traveling for  $p$  purpose (business, non-business and work). The observable part of the utility contains individual-specific and trip-specific variables:

$$V_{nj}^P = V_{individual}^P + V_{trip}^P \quad (11)$$

In the AEM only trip-specific variables are included since there are no personal attributes of airport workers available. The observable part consists of explanatory variables  $x_i$  that are multiplied by parameters  $\beta_i$  defined in the stage of model estimation:

$$V_{trip}^P = \beta_{1j}^P \cdot x_{1j}^P + \beta_{2j}^P \cdot x_{2j}^P + \dots + \beta_{mj}^P \cdot x_{mj}^P \quad (12)$$

Additionally, every mode has an alternative-specific constant  $\beta_0$ , which addresses mode attributes that are not explained by the other variables. The resulting utility function of alternative  $j$  for an individual  $n$  traveling for  $p$  purpose is:

$$U_{nj}^P = \beta_{0j}^P + V_{individual}^P + V_{trip}^P + \varepsilon_{nj}^P \quad (13)$$

The private car is chosen as the base alternative for both models and thus its alternative-specific constant  $\beta_0$  is set to 0.

### 5.3. Model Estimation with R Software

R is a programming tool used for statistical processing and graphical visualization of data. The mlogit package for R was developed by Yves Croissant to estimate the multinomial logit models with the individual- and/or alternative-specific variables (n.d., p. 1). According to the author, the package also allows extending the standard MNL model to nested, heteroscedastic, or random parameter models.

Prior model estimation the datasets for passengers and employees are converted into a suitable shape. The mlogit function has two types of the data format: wide and long. The long shape is used, if each row of a data frame represents one alternative (mode) for each observation and wide shape is applied if each row is a choice (Croissant, n.d., p. 3). In this thesis, the wide data format is used, with separate columns for mode- and individual-specific variables.

After reshaping the data, the mlogit formula is used for the estimation of the MNL or the NL model. The author describes three parts of the formula (2019, p. 17):



1. The alternative-specific variables with a generic coefficient (e.g. travel cost);
2. The individual-specific variables (e.g. age, income, gender, size of a household, etc.);
3. The alternative-specific variables with alternative specific coefficients (e.g. travel time).

In the models for airport passengers and employees, the travel cost is considered as the generic parameter – it makes no difference to a traveler whether 10 Euros are spent for a bus or train ticket. The travel times are included in the third part of the formula under the assumption that changes in travel time are perceived differently in every mode of transport.

Model estimation is an iterative process aimed at the development of function with explanatory variables and coefficients that have the closest match to the input data. The model estimation results were improved using the following approaches:

- Merging alternatives into clusters;
- Gradually addition of variables, starting from trip-specific to individual-specific ones;
- Transformation of selected variables using quadratic polynomial function, logarithmic and quadratic forms of variables, intercept removal;
- Comparison of the output after introducing a variable with alternative-specific or generic coefficients.

The MNL and NL models for airport passengers and workers were created with the help of R software. Various combinations and forms of explanatory variables were tested. The statistical validity of every model was assessed using log-likelihood function value and McFadden  $R^2$ . The next sections describe the consecutive process of the model estimation aimed at the development of the model with the highest predictive performance.

## 5.4. Multinomial Logit Model

At first, each model was estimated with the six and three modes of transport for the airport's passengers and employees respectively. However, the outcome revealed very low maximum likelihood values, since there are modes with very few observations. Based on the mode characteristics, the alternatives were merged into different combinations of clusters until the highest predictive performance of the model was achieved. Table 5 provides a comparison of two models for airport employees. While the utility equation remains the same, two merging approaches were tested. In the first one, the model is estimated with bus and train as separate modes, while the second one has only auto and transit groups.

Table 5. Comparison of the AEM with Three and Two Modes

AEM with 3 modes				AEM with 2 modes			
Mode	Parameter	Estimate	Significance	Mode	Parameter	Estimate	Significance
Bus	Intercept	-1.70157	***	Transit	Intercept	-0.747848	***
Train	Intercept	-1.33983	***	Auto	Total travel time	-4.902949	***
Car	Total travel time	-4.24663	***	Transit	Total travel time	-1.756742	***
Bus	Total travel time	-1.69311	***				
Train	Total travel time	-1.52012	***				***
Log-likelihood		-1487.6		Log-likelihood		-1118.5	
McFadden's $R^2$		0.12682		McFadden's $R^2$		0.20418	

Note. Significance code: \*\*\* 99.9% significance level, \*\* 99% significance level, \* 95% significance level

When the values of log-likelihood and McFadden's  $R^2$  are compared, the model performance improves with the lower number of alternative groups. As a result, it was decided to make further estimations of APMs and the AEM with auto and transit mode clusters only. Since the number of alternatives is reduced to two, the MNL model turns into a binomial logit model. The estimation results for models with three modes that have the best fit to the input data can be found in Appendix A for each group of passengers.

After defining the alternative groups, the structure of the model has to be determined. Figure 5 and Figure 6 in Section 5.1 reveal a strong correlation between the number of transfers and the travel time – therefore, these variables cannot be introduced into the model simultaneously. To overcome this limitation, the value of time and transfer penalties are involved in the estimation process.

#### 5.4.1. Transfer Penalty

The number of transfers is one of the attributes that represent the level of service offered by each mode. It is important to include this variable into the models since the reduction in the number of transfers or provision of direct connections is one of the transit service improvement indicators that will be used to evaluate the new railway connections in Chapter 7. Moreover, transfers play an essential role in modal choices of airport passengers – they increase the likelihood of a missed connection and make a trip more complex for travelers that are not familiar with the public transport network.

Transfers have a certain disutility for the traveler and are comparable to the out-of-vehicle waiting time. It was decided to include the number of transfers into the model by converting this variable into time with the help of transfer penalties. The review of the relevant literature reveals different values of the equivalent in-vehicle minutes (EIVM) for every transfer, represented in Table 6.

Table 6. Transfer Penalties in Other Studies

Study	Country	Transfer penalty	
Garcia-Martinez, A., Cascajo, R., Jara-Diaz, S. R., Chowdhury, S., & Monzon, A. (2018). Transfer penalties in multimodal public transport networks	Spain	1 transfer	15.2 EIVM
		2 transfers	17.7 EIVM
Toronto Transit Commission. (2008, April). Service Improvements for 2008	Canada	Each transfer	10 EIVM

Since the values in the first study are available for a maximum of two transfers, the values for the higher number of transfers were calculated by estimating the percentage difference between EIVM for one and two transfers. The time penalty for each transfer was sequentially increased by 15% (e.g. penalty for 5 transfers equals penalty for 4 transfers \* 1.15).

Later, the transfer penalty values obtained in the Spanish research resulted in a better fitness of APMs and the AEM during the estimation process. Therefore, these penalties were used to transform the number of transfers into EIVM and create a new variable – the total travel time, which is the sum of the travel time and the transfer penalty. In the case of direct connections, travel time equals the total travel time. The measures of models' fit (represented by log-likelihood and McFadden's  $R^2$ ) with different values of transfer penalties are compared in Appendix B. The values used in the Spanish and Canadian researches are referred to as “progressive” and “uniform” respectively.

#### 5.4.2. Value of Time

Value of time (VOT) is a factor that reflects the individual's willingness to pay for the time saving. Since both the travel time and cost are important factors in the evaluation of the airport ground access improvement, the VOT is used to estimate the travel time as monetary costs. There are two approaches to introduce the VOT to the model. The first one is a so-called “implied value of time” that can be obtained from the  $\beta$ -coefficients of the model, where the travel time (TT) and the travel cost (TC) are independent variables:

$$U = \beta_{time} \cdot TT + \beta_{cost} \cdot TC \quad (14)$$

The ratio of the travel time and travel cost parameters define the VOT:

$$VOT = \frac{\beta_{time}}{\beta_{cost}} \quad (15)$$

However, due to the high correlation of time and costs for certain modes of transport (e.g. car sharing, car rental, private car and taxi), their coefficients resulted in implausible values – the estimate for a cost usually had a positive sign that is not consistent with the utility maximization rule. Thus, it was decided to use another approach and use the asserted VOT from the previous researches.

The guidance for the valuation of travel time made by the U.S. Department of Transportation (2016) provides different values of travel time savings for business and leisure passengers. For intercity personal travel by surface modes, the VOT is estimated at 70% of the hourly median household income, while the VOT for intercity business travel and transfer time is valued at 100% of the hourly income (U.S. Department of Transportation, 2016). In the guidance of the U.S. Department of Transportation (2016, p. 11), the nationwide median annual household income in the U.S. comprised 56,516 USD in 2015 and was divided by 2,080 to yield an income of 27.20 USD per hour.

The same calculations are made to obtain an hourly income for this research. According to the Federal Statistical Office of Germany (Statistisches Bundesamt, 2020), the median monthly gross household income in 2018 was 4,846 Euros. In the same year, the mean working time for full-time workers in Germany was 41 hours per week (Statistisches Bundesamt, 2019), which makes it approximately 2,140 hours per year.

The income per hour  $I_h$  can be calculated by multiplying the monthly income  $I_m$  by 12 months and dividing the obtained value by the annual working time  $WT_y$  in hours:

$$I_h = \frac{I_m \cdot 12}{WT_y} = \frac{4,846 \text{ Euros} \cdot 12}{2,140 \text{ hours}} = 27.2 \text{ [Euros/hour]} \quad (16)$$

Consequently, the VOT for private trips comprises 70% of the hourly income and equals 19 Euros per hour, while the VOT for business travelers and the transfers equals 27.2 Euros per hour. The value of 27.2 Euros per hour is also used for the airport employees' work trips. The results of the VOT calculations for each group of the airport users are demonstrated in Table 7.

Table 7. Time Values in Euros per Hour for APMs and the AEM

Time value	Model				
	APM-BR	APM-LR	APM-BV	APM-LV	AEM
VOT	27.2	19	27.2	19	27.2
$VOT_{tr}$	27.2				

Another set of VOT in the context of travel distance was considered during this research. In the study focused on the estimation of values of time and reliability, Axhausen et al. (2015) created a non-linear model based on the German population survey and calculated the time values based on the distance, mode of transport and travel purpose. The VOT values for leisure and work trips by auto and transit modes are represented in Table 8.

Table 8. Distance Related Time Values in Euros per Hour by Purpose and Transport Mode

Purpose	Mode	Distance, km										
		<10	10-20	20-30	30-40	40-50	50-60	60-70	70-80	80-90	90-100	100-125
Business	Auto	3.68	5.01	6.72	7.72	8.60	9.16	9.67	10.08	10.49	10.76	11.25
	Transit	4.10	4.50	5.51	6.10	6.62	6.95	7.26	7.50	7.74	7.90	8.19
Leisure	Auto	3.44	5.01	6.29	7.04	7.70	8.13	8.51	8.81	9.12	9.33	9.69
	Transit	3.97	4.22	5.22	5.81	6.32	6.66	6.95	7.19	7.43	7.59	7.88

Note. Reprinted from “Ermittlung von Bewertungsansätzen für Reisezeiten und Zuverlässigkeit auf Basis der Schätzung eines Modells für modale Verlagerungen im nicht-gewerblichen und gewerblichen Personenverkehr für die Bundesverkehrswegeplanung”, by Axhausen et al., 2015, pp. 94-95, Zürich: ETH Zürich, Institut für Verkehrsplanung und Transportsysteme. Copyright 2015 by ETH

The models were estimated twice using income- and distance-related values of time to choose VOT that improve the model performance. The  $VOT$  for travel time and the  $VOT_{tr}$  for transfers were used to calculate the generalized cost  $GC$  by converting the travel time  $TT$  and the transfer penalty  $TP$  into the monetary values:

$$GC = VOT \cdot TT + VOT_{tr} \cdot TP + TC \quad (17)$$

The VOT can be also used to transform the travel cost into time and thus, calculate the generalized time  $GT$ :

$$GT = TT + TP + \frac{TC}{VOT} \quad (18)$$

Table 9 provides an overview of the estimation results for the AEM and four sub-models for air passengers, with auto and transit modes and generalized cost or generalized time as a variable. In Option 1 the VOT is based on the hourly income, while for Option 2 it depends on the distance.

Table 9. Log-likelihood and McFadden's  $R^2$  Values in APMs and the AEM with Different VOT

Model	Generalized cost		Generalized time	
	Option 1	Option 2	Option 1	Option 2
<b>Log-likelihood</b>				
APM-BR	<b>-734.4</b>	-808.67	-734.4	<b>-708.9</b>
APM-LR	<b>-2527.7</b>	-2898.2	<b>-2531.7</b>	-2621.9
APM-BV	<b>-628.8</b>	-681.64	-628.8	<b>-529.18</b>
APM-LV	<b>-975.35</b>	-1179.5	-977.95	<b>-942.58</b>
AEM	<b>-1247.5</b>	-1376.1	<b>-1247.5</b>	-1371.7
<b>McFadden's <math>R^2</math></b>				
APM-BR	<b>0.49677</b>	0.44588	0.49677	<b>0.51425</b>
APM-LR	<b>0.33494</b>	0.23747	<b>0.33388</b>	0.31015
APM-BV	<b>0.67304</b>	0.64556	0.67304	<b>0.72484</b>
APM-LV	<b>0.57197</b>	0.48239	0.57084	<b>0.58636</b>
AEM	<b>0.11241</b>	0.021704	<b>0.11241</b>	0.024029

Table 9 shows that in the case of generalized cost the log-likelihood and McFadden's  $R^2$  values improve with the VOT based on the income and travel purpose (marked in bold). At the same time, the model with generalized time has a better fit when using Option 2 of VOT. However, models for airport passengers with utility function based on generalized cost or generalized time were not demonstrating the plausible signs for the auto alternative and therefore, were rejected.

## 5.5. Nested Logit Model

In a multinomial logit model, all the alternatives are mutually exclusive. Since some of the alternatives considered in the model are more similar than others, nested structures are tested to consider the correlation within groups of alternatives. Examining different clustering patterns identified the most appropriate and reasonable nesting structure of models:

1. Private car, taxi, car rental and car sharing in *Auto* nest, bus and train in *Transit* nest;
2. Taxi, car rental and car sharing in *Hire* nest, bus and train in *Transit* nest and *Auto* as an independent mode on the level of two mentioned above nests;
3. Private car, taxi, car rental and car sharing in *Auto* nest; *Bus* and *Train* as independent modes;
4. Taxi, car rental and car sharing in *Hire* nest, *Auto*, *Bus* and *Train* as independent modes.

Created nested structures are evaluated by the logsum parameter or nesting coefficient. It is a function of the correlation between the unobserved portions for alternative pairs; if its values fall outside the range between 0 and 1, the NL model is rejected (Koppelman & Bhat, 2006, p. 163). However, the values of this parameter estimated for each group of airport users are not consistent with the theory.

Further researches of the NL models for Munich Airport should be done with the help of other software for statistical analysis due to R limitations – the nesting coefficient cannot be adjusted in the mlogit package. For instance, the Python package Biogeme is focused on discrete mode choice models and includes necessary tools for NL model estimation. Other alternative software for the estimation and analysis of NL models include the NLOGIT 6 package by Econometric Software and the GAUSS DC application by Aptech Systems. After the exclusion of NL models due to the inconsistent output, the estimation results in Chapter 6 are provided for MNL models.

## 6. Estimation Results

The best fit of the model to the survey data is achieved by introducing the total travel time and personal attributes (for APMs only) to the utility equation. All estimated parameters in the selected models have at least a 95% level of significance, shown in the Sig column of Table 10, and plausible signs that are in line with the theory. The values of the parameters are discussed in more detail further in this chapter. For the complete output of the mlogit function please refer to Appendix C.

Table 10. Estimation Results for APMs and the AEM

Mode	Parameter	APM-BR		APM-LR		APM-BV		APM-LV		AEM	
		Estimate	Sig	Estimate	Sig	Estimate	Sig	Estimate	Sig	Estimate	Sig
Transit	Intercept	3.2802258	***	4.0262908	***	5.06111	***	5.476835	***	-0.747848	***
Transit	Age	-0.0183097	**	-0.0076957	**						
Transit	Gender	0.4435049	**					-0.303748	*		
Transit	Income					-0.14519	***	-0.048046	*		
Transit	Travel party	-1.7131435	***	-1.1140557	***			-1.146553	***		
Auto	Total travel time	-2.8660224	***	-2.0970262	***	-2.32665	***	-3.107661	***	-4.902949	***
Transit	Total travel time	-2.4085491	***	-4.2807070	***	-4.38558	***	-4.944257	***	-1.756742	***
Log-likelihood		-776.07		-2235.8		-871.45		-845.34		-1118.5	
McFadden's $R^2$		0.46822		0.41175		0.54686		0.62903		0.20418	

Note. Significance code: \*\*\* 99.9% significance level, \*\* 99% significance level, \* 95% significance level

McFadden's  $R^2$  values demonstrate the overall goodness of fit of the model, as well as the log-likelihood test results. McFadden's  $R^2$  measures the variability proportion that can be explained, and the values close to 1 indicate a higher predictive value of the model. Table 10 illustrates that this value is the highest for visitors that have personal trips (LV model).

The likelihood function evaluates how fit is the model to input data with given unknown parameters' values, and the log-likelihood values are always negative. The likelihood ratio test (LRT) compares the log-likelihood values of two models to assess their goodness of fit. This test is carried out to determine whether the variables introduced in each of the estimated models improve their accuracy and fit the input data.



Table 11 demonstrates the log-likelihood values of complete models and models estimated only with constants. The values of the complete model improve in contrast to the constants-only model on average by 51%, with the most considerable change for the LV model (~63%).

Table 11. Log-likelihood Values and the LRT Results

Model	Log-likelihood values		LRT results	
	Constants-only model	Complete model	p-value	Significance
APM-BR	-1459.4	-776.07	< 2.2e-16	***
APM-LR	-3800.7	-2235.8	< 2.2e-16	***
APM-BV	-1923.1	-871.45	< 2.2e-16	***
APM-LV	-2278.7	-845.34	< 2.2e-16	***
AEM	-1405.4	-1118.5	< 2.2e-16	***

Note. Significance code: \*\*\* 99.9% significance level, \*\* 99% significance level, \* 95% significance level

The LRT is conducted for complete and constants-only models with generic function `lrtest` of `lmtest` package for R. The resulting p-values shown in Table 11 are very close to zero. Thus, we can confirm at 99.9% significance level that individual- and trip-specific variables increase the explanatory power of the models and improve their fit to the actual data. The improvement of log-likelihood values of the AEM is moderate compared to APMs, since the utility function is based on one variable (total travel time) only. Nevertheless, the LRT results verify the APMs with the total travel time parameter fit to the data considerably better at the same significance level.

Another method to assess the goodness of fit of the model is to define how closely the average probabilities from the input data match the probabilities of choosing auto or transit mode, estimated by the model. The actual probabilities of APMs and the AEM are compared to predicted probabilities in Table 12, and it can be noted that the probabilities estimated by each model have the same values as the ones in the input data. This indicates a very good model fit, but it is essential to recall that all modes were merged into two groups, which simplifies the created models.

Table 12. Actual and Predicted Probabilities of APMs and the AEM

Model	Actual probabilities		Predicted probabilities	
	Auto	Transit	Auto	Transit
APM-BR	0.6125	0.3875	0.6125	0.3875
APM-LR	0.5558	0.4442	0.5558	0.4442
APM-BV	0.5918	0.4082	0.5918	0.4082
APM-LV	0.5281	0.4719	0.5281	0.4719
AEM	0.7902	0.2098	0.7902	0.2098

The estimated parameters are used in utility equation as coefficient values and vary from model to model. As there are no individual-specific variables for airport workers, the total travel time is the only parameter of the AEM. The number of accompanying people influences the mode choice of all passengers except for business visitors. The monthly household income is an explanatory variable in both models for visitors. The age of airport passengers is a significant parameter only for residents of the study area, while gender is considered in APMs for business residents and leisure visitors.

The coefficients of each model presented in Table 10 are consistent with the theory. As the auto is chosen as the base mode for APMs and the AEM, the further discussion of estimated parameter values is made with respect to it.

### Total travel time

The total travel time parameter, comprised of the journey time and the transfer penalties, is present in a model for each airport user group. It has a negative sign that implies that if this value increases, the attractiveness of the transport mode is reduced. The total travel time estimate is the most negative for the transit trips of leisure visitors, followed by car trips of airport employees. This means that the visitors that have a non-business journey are more sensitive to changes in the duration of their trip by public transport to Munich Airport. There is a certain tendency among LR, BV and LV passengers that with the increase of total travel time the transit trips become less attractive compared to traveling by auto. An exception to this are residents that have a business trip – their time sensitivity is almost the same for trips by private and public transport.

### **Travel party**

The number of accompanying people is considered in all APMs except the model for business visitors, and all coefficients estimated for this parameter are negative. The growth of the travel party size makes traveling by transit modes less attractive compared to the auto. The coefficient values are very alike, with the most negative of them for the BR sub-model – it indicates that this passenger group has a higher sensitivity to a number of accompanying people compared to others.

### **Monthly household income**

As expected, the value of the income parameter used in both APMs for visitors has a negative sign. This means that in comparison to auto, people with a higher monthly household income are less likely to commute to Munich Airport by public transport. The probability of choosing transit modes is lower for business travelers compared to leisure trips of passengers within the same income group.

### **Gender**

In BR and LV sub-models, this dummy variable takes on the value of 1 for male travelers. Male residents on a business trip are more likely to choose transit modes to reach the airport than women, while female travelers have a higher probability to make this choice in the LV group.

### **Age**

Older residents in the study area are less likely to choose public transport – this can be concluded from the negative value of age parameter in BR and LR models. Traveling by transit can imply certain service unreliability and the need to make transfers. This creates some decrease in the comfort of a trip that is easier to accept for young passengers.

## 7. Scenario Analysis

This thesis aims to assess the impact of the new railway connections to Munich Airport on the mode choices of airport passengers and employees. In the study area, there are several railway projects – some of them are currently under construction, some are on the planning stage, or were postponed for a variety of reasons. They imply certain reductions in travel time and the number of transfers by providing express connections on the existing routes, or by the creation of new railway lines and links. These projects are divided into several scenarios, their influence on the airport users' travel behavior is evaluated with the APMs and AEM discussed in Chapter 6. The descriptions of each scenario, together with a spatial analysis of the results, are presented in Sections 7.2-7.7. Geospatial data used in QGIS to visualize the location of railways in each scenario was downloaded from Geofabrik (2018), a geodata download server of Openstreetmap. The predictions are made with generic function predict of car package for R.

### 7.1. Catchment Area

Before testing each scenario, certain assumptions about the catchment area should be made. First, each scenario is tested by changing the travel time and number of transfers across the whole city and county affected. Despite the simplicity of this method, it is discarded after consideration of predicted modal shares. They are slightly different compared to the results described further; however, in many cases, the postal code zones that are considered with this approach were located between two railway lines or were closer to the railway connection in another county, which made the changes in trip-specific variables for these areas questionable. To avoid these issues, the distance-related approach is adopted for every scenario.

In the regional public transport plan of MVV, a radius of 1,000 m is used for the catchment area of the suburban rail (MVV GmbH, 2018, p. 68). Based on this document, the trip-specific variables are modified in the postal code areas that are located within 1,000 m radius from the involved railway lines. It is worth mentioning that in some scenarios the corresponding adjustments are made in the areas around the urban and suburban rails in Munich: they might not be located in the vicinity of new railway projects, but are connected to them and produce changes in the travel time for the travelers that are using these networks to reach Munich Airport.

To justify this choice of the catchment area, the radii of 500 m and 2,000 m were also tested. The produced results are very similar to the initial output with 1,000 m catchment area. Table 13 compares the predicted transit shares with 500 m and 2,000 m radii with the results obtained with

1,000 m radius. In the case of 2,000 m, as expected, there is a slight increase in the share of transit, since the catchment area expanded. The changes are out of pattern with Scenario 2 and 2,000 m radius of the catchment area, as some postal code zones were included in the areas with a higher decrease in travel time.

Table 13. The Difference in Transit Shares Compared to Results with 1,000 m Catchment Area

Model	Scenario 1		Scenario 2		Scenario 3		Scenario 4	
	500 m	2,000 m	500 m	2,000 m	500 m	2,000 m	500 m	2,000 m
APM-BR	-0.05%	0.12%	-1.07%	0.19%	-0.18%	0.44%	-0.79%	0.60%
APM-BV	0.00%	0.05%	-0.44%	-0.05%	-0.07%	0.11%	-0.37%	0.19%
APM-LR	-0.03%	0.25%	-1.19%	0.35%	-0.10%	0.31%	-0.75%	0.84%
APM-LV	0.00%	0.03%	-0.44%	-0.07%	-0.03%	0.12%	-0.28%	0.21%
AEM	-0.12%	0.35%	-0.37%	-0.61%	-0.07%	0.43%	-0.73%	0.58%

The opposite effect is observed with a 500 m radius – the transit shares are lower in contrast to 1,000 m catchment area. When the catchment area is narrowed, there is a risk of not including certain postal code zones around the railways. This can be noted in Scenario 2, where business residents have a 1.07% decrease in transit trips with a 500 m radius and 0.19% increase with 2,000 m radius. For some scenarios (e.g. Scenario 1 and Scenario 3), there is a slight difference in modal shares between the 1,000 m and 500 m radii of the catchment area.

Given the mentioned drawbacks of 500 m and 2,000 m radii, it is decided to analyze the scenarios with 1,000 m radius of the catchment area, as defined in the regional public transport plan of MVV (2018). The resulting modal shares for each model with 500 m and 2,000 m radii can be found in Appendix D.

## 7.2. Scenario 1: Erding Ring Closure

Content removed due to data usage restrictions

### **7.3. Scenario 2: Munich Ring Railway**

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### **7.4. Scenario 3: Transrapid Munich**

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### **7.5. Scenario 4: Airport Express**

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### **7.6. Direct Bus Connections Scenario**

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## 7.7. Spatial Analysis

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## 8. Conclusions

The growing demand for air traveling increases the number of trips to the airport, which makes the ground access an essential factor in the airport attractiveness. Another motivating factor to study the transport accessibility of Munich Airport is the desire to investigate the effect of new rail connections on mode choices of airport workers and passengers.

This thesis describes the process of discrete mode choice models estimation to assess the variations of travel behavior in the response to changes in existing railway services. The models were based on revealed preference surveys of air passengers and employees of Munich Airport, together with the aggregated travel times and the number of transfers provided by the MSM research group. The model for air passengers was segmented into four sub-models by residence and travel purposes to account for distinctions of different market segments. The initial set of transport alternatives was merged into auto and transit clusters.

The models were iteratively estimated with various combinations and forms of explanatory variables using R software. The negative coefficients obtained for total travel time confirm that the increase in travel time and the number of transfers reduces the utility of transit. Other variables such as gender, age, number of accompanying people and monthly household income also influence the travel behavior of air passengers. The growth of the travel party size makes traveling by transit modes less attractive compared to auto. Senior citizens and people with higher income tend to commute to Munich Airport by auto. Male residents on a business trip are more likely to choose transit modes to reach the airport than women, while female visitors have a higher probability to make this choice during a leisure trip. All estimated parameters have at least a 95% level of significance and theoretically consistent signs. The statistical validity of every model was confirmed by log-likelihood and McFadden  $R^2$  values.

The models estimated for each group of airport users were applied to test four scenarios that suggest various improvements of the railway network in the study area. The comparison of initial and estimated mode shares confirms the assumption that the reduction in total travel time due to the provision of new rail links or the improvement of existing railway connections increases the attractiveness of public transport. In certain scenarios, the share of transit trips even became dominant among some groups of air passengers. The spatial analysis identified areas and airport users who demonstrated the most significant increase in the share of trips by public transport in each of the scenarios. Plotting the predicted changes in transit shares for air passengers and



airport employees revealed railway projects that have the most favorable impact on the attractiveness of public transport for each of the airport user groups.

The findings of this research create a foundation for ground transportation planning in the area of Munich Airport that takes into account factors influencing the travel behavior of air passengers and airport employees. The designed models can help to evaluate the concepts for improving transport accessibility of the airport and determine projects that will result in the highest growth of sustainable transport modes share. However, before the application of these models, they must be calibrated to improve the match to the observed travel behavior. Ideally, the datasets different from the ones used for the model estimation shall be engaged in the validation process.

## **8.1. Limitations and Suggestions for Further Research**

This study has certain limitations that should be tackled in future research:

### **1. Completeness and accuracy of the input data**

The results of this study confirm the importance of individual-specific variables. Comparing the estimation results of APMs and the AEM, it can be observed that the overall AEM's goodness of fit is lower. The travel costs of bus and train were aggregated on the county and city level and did not account for possible variations in the ticket prices. Other assumptions were made for the car rental and shared taxi costs due to the lack of information about these services. Higher data accuracy would create a possibility to test scenarios that involve changes in costs, which is an important transportation characteristic. More reliable travel cost information can also have a positive impact on the implied value of time estimation that would more accurately reflect the willingness to pay of each airport user group.

### **2. Model structure**

The alternatives in the APMs and the AEM were merged into auto and transit clusters, as the survey results indicated a few observations for certain modes. This improved the models' goodness of fit, but at the same time oversimplified them. The collection of more input data would allow an estimation of models with a more precise distinction among available transport modes with no loss in models' performance.

### 3. Scenarios tested

The new travel times and the number of transfers suggested by different railway projects were missing for certain areas. These values had to be approximated based on the data available and their validity cannot be checked.

Several suggestions for further research based on this study can be offered. The aggregated travel times used for the models indicate only the duration of the trip from origin to destination. Estimation of separate coefficients for access, egress, waiting and in-vehicle time would create a more complex time component, but increase the accuracy of predictions. Additionally, splitting the travel time into these components can provide insights into their role in the mode choice decisions of air passengers and airport employees.

The models chosen in this research are often criticized for their IIA properties. NL models help to overcome this problem and are worth being enlightened in more detail in future studies of mode choice models for Munich Airport. However, they shall be estimated with other software for statistical analysis.

To define the catchment area of the considered railway concepts, the 1,000 m radius was adopted from the regional public transport plan and used for scenarios testing. Another study can be conducted with a focus on catchment area estimation with respect to land use and population distribution.

The evaluation of bus services is another promising topic in the research of Munich Airport ground accessibility. The direct bus connections can result in an increase in the share of trips by public transport comparable to changes associated with new railway links. For such research, prior inspection and evaluation of the existing bus city-terminal services is advised.

One final comment should be done concerning the transferability of the estimated mode choice models for Munich Airport. The peculiarities of the airport's location, level of service provided by the surrounding transportation system, personal characteristics of the air passengers and employees challenge the implementation of the estimated models in other regions. It is recommended to address the other study cases individually to increase the forecasting accuracy.

## List of References

Ahlswede, A. (2020, January 8). Durchschnittlicher Kraftstoffverbrauch der in Deutschland zugelassenen Pkw in den Jahren von 2007 bis 2018 [Average fuel consumption of cars registered in Germany from 2007 to 2018]. Retrieved January 29, 2020, from <https://de.statista.com/statistik/daten/studie/484054/umfrage/durchschnittsverbrauch-pkw-in-privaten-haushalten-in-deutschland/>

Axhausen, K. W., Ehreke, I., Glemser, A., Hess, S., Jödden, C., Nagel, K., ... Weis, C. (2015). *Ermittlung von Bewertungsansätzen für Reisezeiten und Zuverlässigkeit auf Basis der Schätzung eines Modells für modale Verlagerungen im nicht-gewerblichen und gewerblichen Personenverkehr für die Bundesverkehrswegeplanung [Determination of valuation approaches for travel times and reliability based on the estimation of a model for modal relocations in non-commercial and commercial passenger transport for federal transport route planning]*. Zürich: ETH Zürich, Institut für Verkehrsplanung und Transportsysteme.

Baumgartner, S., Kantke, T., & Schwartz, D.-U. (2011, May 12). *Bahnknoten München. Ein Konzept aus einem Guss: Fernbahn, Regionalbahn, Güterbahn, S-Bahn, U-Bahn, Seilbahn und Tram [Munich railway junction. A unified concept: long-distance, regional, freight, urban and suburban rail, cable car and tram]* [PDF File]. Retrieved January 11, 2020, from [http://s-bahn-plus.de/documents/110512-BKS-BahnknotenMUC-20110512\\_000.pdf](http://s-bahn-plus.de/documents/110512-BKS-BahnknotenMUC-20110512_000.pdf)

Bavarian State Ministry for Economic Affairs, State Development and Energy. (2008). *Erdinger Ringschluss, Verbesserung der Schienenanbindung des Flughafens München [Erdinger ring closure, improvement of the rail connection of Munich Airport]* [PDF File]. Retrieved December 7, 2019, from [https://www.munich-airport.de/\\_b/00000000000000005463459bb5c08ddf0/pras\\_erdingerring.pdf](https://www.munich-airport.de/_b/00000000000000005463459bb5c08ddf0/pras_erdingerring.pdf)

Birolini, S., Malighetti, P., Redondi, R., & Deforza, P. (2019). Access mode choice to low-cost airports: Evaluation of new direct rail services at Milan-Bergamo airport. *Transport Policy*, 73, 113–124.

Croissant, Y. (2019, December 9). *Package 'mlogit'* [PDF File]. Retrieved December 29, 2019, from <https://mirrors.e-ducation.cn/CRAN/web/packages/mlogit/mlogit.pdf>

Croissant, Y. (n.d.). Estimation of multinomial logit models in R: The mlogit Packages [PDF File]. Université de la Réunion: Author. Retrieved February 27, 2020, from <https://r-forge.r->

project.org/scm/viewvc.php/\*checkout\*/pkg/inst/doc/mlogit.pdf?revision=19&root=mlogit&pathrev=32

DB Netz AG. (2018a, January 26). Erdinger Ringschluss - 2. Bauabschnitt: Schwaigerloh–Altenerding [Erdinger ring closure - 2nd construction phase: Schwaigerloh – Altenerding]. Retrieved November 23, 2019, from <https://www.bahnausbau-muenchen.de/projekt.html?PID=37>

DB Netz AG. (2018b, December 8). Neufahrner Kurve [Neufahrn curve]. Retrieved November 17, 2019, from <https://www.bahnausbau-muenchen.de/projekt.html?PID=20>

DB Netz AG. (2018c, January 26). Walpertskirchener Spange [Walpertskirchener clasp]. Retrieved November 19, 2019, from <https://www.bahnausbau-muenchen.de/projekt.html?PID=47>

Flughafen München GmbH (2017). *Showing class: Integrated report* [PDF File]. Munich: Author. Retrieved November 26, 2019, from [https://www.munich-airport.com/\\_b/0000000000000005421826bb5c0009eb/Integrated-Report-2017.pdf](https://www.munich-airport.com/_b/0000000000000005421826bb5c0009eb/Integrated-Report-2017.pdf)

Flughafen München GmbH (2020). Parken am Flughafen München [Parking at Munich Airport] [PDF File]. Munich: Author. Retrieved January 12, 2020, from [https://www.munich-airport.de/\\_b/0000000000000008177314bb5e09bed7/flyer-parken-tarife-flughafen-muenchen-2020.pdf](https://www.munich-airport.de/_b/0000000000000008177314bb5e09bed7/flyer-parken-tarife-flughafen-muenchen-2020.pdf)

Garcia-Martinez, A., Cascajo, R., Jara-Diaz, S. R., Chowdhury, S., & Monzon, A. (2018). Transfer penalties in multimodal public transport networks. *Transportation Research Part A General*, 114, 52–66.

Geofabrik GmbH. (2018). Bayern [Data files]. Retrieved November 20, 2019, from <https://download.geofabrik.de/europe/germany/bayern.html>

Herzog, S., & Atabay, D. (2016). *Perspektiven für den Schienenverkehr im Großraum München* [Perspectives for rail transport in the Munich area] [PDF File]. Retrieved January 23, 2020, from [http://www.ringbahn.de/wp-content/uploads/2017/03/Herzog\\_Atabay\\_2016\\_Perspektiven\\_fuer\\_den\\_Schienenverkehr\\_im\\_Großraum\\_Muenchen.pdf](http://www.ringbahn.de/wp-content/uploads/2017/03/Herzog_Atabay_2016_Perspektiven_fuer_den_Schienenverkehr_im_Großraum_Muenchen.pdf)

Hohmann, M. (2020, February 14). Durchschnittlicher Benzinpreis in Deutschland in den Jahren 1972 bis 2020 [Average gasoline price in Germany from 1972 to 2020]. Retrieved February 27, 2020, from <https://de.statista.com/statistik/daten/studie/776/umfrage/durchschnittspreis-fuer-superbenzin-seit-dem-jahr-1972/>

- Koppelman, F., & Bhat, C. (2006, January 31). A self instructing course in mode choice modeling: multinomial and nested logit models. Washington, DC: FTA.
- Leigh Fisher Associates, Coogan, M. A. & MarketSense. (2000). Improving Public Transportation Access to Large Airports (Vol. 62, Transit Cooperative Research Program Report). Washington, DC: Transportation Research Board.
- Miyoshi, C., & Rietveld, P. (2015). Measuring the equity effects of a carbon charge on car commuters: A case study of Manchester Airport. *Transportation Research Part D: Transport and Environment*, 35, 23–39.
- Mode Choice Survey of Munich Airport Departing Passengers*. (2018). Unpublished raw data.
- Mode Choice Survey of Munich Airport Workers*. (2018). Unpublished raw data.
- Moreno, A., & Moeckel, R. (2018). Population Synthesis Handling Three Geographical Resolutions. *ISPRS International Journal of Geo-Information*, 7(5), 174.
- Murakami, J., Matsui, Y., & Kato, H. (2016). Airport rail links and economic productivity: Evidence from 82 cities with the world's 100 busiest airports. *Transport Policy*, 52, 89–99.
- MVV GmbH. (2018, November). Regionaler Nahverkehrsplan [Regional public transport plan] [PDF File]. Retrieved March 12, 2020, from [https://www.mvv-muenchen.de/fileadmin/mediapool/07-Ueber\\_den\\_MVV/02-Dokumente/RNP\\_final\\_November\\_2018.pdf](https://www.mvv-muenchen.de/fileadmin/mediapool/07-Ueber_den_MVV/02-Dokumente/RNP_final_November_2018.pdf)
- National Academies of Sciences, Engineering, and Medicine. (2008). Airport Ground Access Mode Choice Models. Washington, DC: The National Academies Press.
- Oslislo, D. (2018, October 23). Buchung [Booking]. Retrieved January 8, 2020, from <https://www.pfiffig-parken.de/index.php/buchung.html>
- Psaraki, V., & Abacoumkin, C. (2002). Access mode choice for relocated airports: The new Athens International Airport. *Journal of Air Transport Management*, 8(2), 89–98.
- Ravenhorst, N. (n.d.). Parken Flughafen München [Parking at Munich Airport]. Retrieved January 8, 2020, from <https://www.parkplatzvergleich.de/parken-flughafen-muenchen/>
- Rosenbaum, A. S., & Koenig, B. E. (1997). Evaluation of modeling tools for assessing land use policies and strategies. *Transportation and Market Incentives Group*.

SHARE NOW GmbH. (2019, November 12). About SHARE NOW. Retrieved December 20, 2019, from <https://www.share-now.com/de/en/faq/about-share-now#what-is-car-sharing>

SHARE NOW GmbH. (n.d.). Rates & Fees. Retrieved December 20, 2019, from <https://www.share-now.com/de/en/faq/rates-and-fees>

Sixt. (n.d.). AUTOVERMIETUNG MÜNCHEN FLUGHAFEN [Car rental Munich Airport]. Retrieved December 21, 2019, from <https://www.sixt.de/mietwagen/deutschland/muenchen/muenchen-flughafen>

Statistisches Bundesamt. (2019, September 11). Wöchentliche Arbeitszeit [Weekly work time]. Retrieved March 13, 2020, from <https://www.destatis.de/DE/Themen/Arbeit/Arbeitsmarkt/Qualitaet-Arbeit/Dimension-3/woechentliche-arbeitszeitl.html>

Statistisches Bundesamt. (2020, February 28). Data from the sample survey of income and expenditure to the income, receipts and expenditure of households in Germany. Retrieved March 17, 2020, from <https://www.destatis.de/EN/Themes/Society-Environment/Income-Consumption-Living-Conditions/Income-Receipts-Expenditure/Tables/income-expenditure-d-evs.html>

Taxi Munich. (2008, June 11). Tarif und Preise des Münchner Taxigewerbes [Tariff and prices of the Munich taxi industry]. Retrieved December 23, 2019, from <http://www.taxi-muenchen.com/privatkunden/tarif-und-preise.html>

Toronto Transit Commission. (2008, April). *Service Improvements for 2008* [PDF File]. Retrieved March 3, 2020, from [https://ttc.ca/PDF/Transit\\_Planning/service\\_improvements\\_2008.pdf](https://ttc.ca/PDF/Transit_Planning/service_improvements_2008.pdf)

Train, K. E. (2009). *Discrete choice methods with simulation* (2nd ed.). Cambridge: Cambridge University Press.

U.S. Department of Transportation. (2016). *Revised Departmental Guidance on Valuation of Travel Time in Economic Analysis*. Washington, DC: U.S. Department of Transportation.

Weiner, E. (1997). *Urban transportation planning in the United States: an historical overview* (5th ed.). Washington, DC: U.S. Department of Transportation.

Wissenschaftliche Dienste des Deutschen Bundestages. (2006). Transrapidprojekt München [Transrapid project Munich] (Report No. WD 7 - 254/06). Retrieved March 02, 2020, from <https://www.bundestag.de/resource/blob/408124/34ac631695a5ac2e1187da7da83f6864/WD-7-254-06-pdf-data.pdf>

## List of Abbreviations

AEM	Airport Employee Model
APM	Air Passenger Model
BR	Business residents
BV	Business visitors
DB	Deutsche Bahn
IIA	Independence of irrelevant alternatives
LR	Leisure residents
LRT	Likelihood ratio test
LV	Leisure visitors
MNL	Multinomial logit
MSM	Modeling Spatial Mobility
MVV	Münchner Verkehrs- und Tarifverbund
NASEM	National Academies of Sciences, Engineering, and Medicine
NL	Nested logit
TAZ	Traffic analysis zone
TC	Travel cost
TT	Travel time
USD	United States Dollar

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## Appendix A. Estimation results for APMs with three modes

Mode	Parameter	APM-BR		APM-LR		APM-BV		APM-LV	
		Estimate	Sig	Estimate	Sig	Estimate	Sig	Estimate	Sig
Bus	Intercept	1.091263	*	0.315783	*	-1.1154364	***	-0.772383	.
Train	Intercept	1.885858	***	0.896107	***	0.4921743	**	0.549812	**
Bus	Income							-0.068036	*
Train	Income	-0.090238	***					-0.072896	***
Bus	Travel party			-0.498462	***	0.1229133	*		
Train	Travel party	-1.496414	***	-1.621950	***	-0.4646060	***		
Bus	Age	-0.034747	**						
Train	Age	-0.013353	**			-0.0114680	**		
Car	Total travel time	-1.024627	***	-0.865103	***	-0.6186274	***	-1.809707	***
Bus	Total travel time	-2.300910	***	-2.653837	***	-0.9308695	***	-0.795722	***
Train	Total travel time	-1.901370	***	-1.608504	***	-1.2380693	***	-1.087022	***
Log-likelihood		-1560.4		-4087.9		-2316.1		-2652	
McFadden's R <sup>2</sup>		0.080006		0.10079		0.019538		0.027049	

Note. Significance code: \*\*\* 99.9% significance level, \*\* 99% significance level, \* 95% significance level. Please note that for bus intercept in LV model only 90% significance level was achieved.

## Appendix B. Comparison of models' goodness of fit with different transfer penalty values

Model	Progressive penalty	Uniform penalty
	<b>Log-likelihood</b>	
APM-BR	-776.07	-790.39
APM-LR	-2235.8	-2222.1
APM-BV	-871.45	-879.98
APM-LV	-845.34	-856
AEM	-1118.5	-1117
	<b>McFadden's <math>R^2</math></b>	
APM-BR	0.46822	0.45841
APM-LR	0.41175	0.41534
APM-BV	0.54686	0.54242
APM-LV	0.62903	0.62435
AEM	0.20418	0.20527

*Note.* The utility equations for each model correspond to the equations in Table 9.

## Appendix C. Complete output of mlogit function

### Business residents (BR) model

Call:

```
mlogit(formula = BR, data = logit_data, reflevel = "auto", method = "nr")
```

Frequencies of alternatives:

```
auto      transit
0.61253    0.38747
```

nr method

6 iterations, 0h:0m:0s

$g'(-H)^{-1}g = 0.0016$

successive function values within tolerance limits

Coefficients :

	Estimate	Std. Error	z-value	Pr(> z )	
transit:(intercept)	3.2802258	0.3236468	10.1352	< 2.2e-16	***
transit:gender	0.4435049	0.1465992	3.0253	0.002484	**
transit:age	-0.0183097	0.0058204	-3.1458	0.001657	**
transit:accompnum	-1.7131435	0.3170499	-5.4034	6.539e-08	***
auto:ttime	-2.8660224	0.3222865	-8.8928	< 2.2e-16	***
transit:ttime	-2.4085491	0.0997908	-24.1360	< 2.2e-16	***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Log-Likelihood: -776.07

McFadden R<sup>2</sup>: 0.46822

Likelihood ratio test: chisq = 1366.6 (p.value = < 2.22e-16)

**Appendix C (continued). Complete output of mlogit function****Business visitors (BV) model**

Call:

```
mlogit(formula = BV, data = logit_data, reflevel = "auto", method = "nr")
```

Frequencies of alternatives:

```
auto      transit
0.59177    0.40823
```

nr method

6 iterations, 0h:0m:0s

$g'(-H)^{-1}g = 1.65E-05$

successive function values within tolerance limits

Coefficients :

	Estimate	Std. Error	z-value	Pr(> z )	
transit:(intercept)	5.06111	0.29604	17.096	< 2.2e-16	***
transit:hhmonth	-0.14519	0.02804	-5.178	2.243e-07	***
auto:log(ttime)	-2.32665	0.18491	-12.583	< 2.2e-16	***
transit:log(ttime)	-4.38558	0.13392	-32.748	< 2.2e-16	***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Log-Likelihood: -871.45

McFadden R<sup>2</sup>: 0.54686

Likelihood ratio test: chisq = 2103.4 (p.value = < 2.22e-16)

**Appendix C (continued). Complete output of mlogit function****Leisure residents (LR) model**

Call:

```
mlogit(formula = LR, data = logit_data, reflevel = "auto", method = "nr")
```

Frequencies of alternatives:

```
auto      transit
0.55576   0.44424
```

nr method

6 iterations, 0h:0m:0s

$g'(-H)^{-1}g = 8.53E-05$

successive function values within tolerance limits

Coefficients :

	Estimate	Std. Error	z-value	Pr(> z )	
transit:(intercept)	4.0262908	0.1490346	27.0158	< 2.2e-16	***
transit:age	-0.0076957	0.0023393	-3.2897	0.001003	**
transit:accompnum	-1.1140557	0.0965695	-11.5363	< 2.2e-16	***
auto:log(ttime)	-2.0970262	0.1163806	-18.0187	< 2.2e-16	***
transit:log(ttime)	-4.2807070	0.1101799	-38.8520	< 2.2e-16	***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Log-Likelihood: -2235.8

McFadden R<sup>2</sup>: 0.41175

Likelihood ratio test : chisq = 3129.9 (p.value = < 2.22e-16)

## Appendix C (continued). Complete output of mlogit function

### Leisure visitors (LV) model

Call:

```
mlogit(formula = LV, data = logit_data, reflevel = "auto", method = "nr")
```

Frequencies of alternatives:

```
auto      transit
0.52807    0.47193
```

nr method

6 iterations, 0h:0m:0s

$g'(-H)^{-1}g = 0.00133$

successive function values within tolerance limits

Coefficients :

	Estimate	Std. Error	z-value	Pr(> z )	
transit:(intercept)	5.476835	0.267091	20.5055	< 2.2e-16	***
transit:gender	-0.303748	0.133237	-2.2798	0.02262	*
transit:hhmonth	-0.048046	0.021896	-2.1943	0.02821	*
transit:accompnum	-1.146553	0.141385	-8.1095	4.441e-16	***
auto:log(ttime)	-3.107661	0.199602	-15.5693	< 2.2e-16	***
transit:log(ttime)	-4.944257	0.144026	-34.3289	< 2.2e-16	***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Log-Likelihood: -845.34

McFadden R<sup>2</sup>: 0.62903

Likelihood ratio test: chisq = 2866.8 (p.value = < 2.22e-16)

**Appendix C (continued). Complete output of mlogit function****Airport employees model (AEM)**

Call:

```
mlogit(formula = AEM, data = logit_data, reflevel = "auto", method = "nr")
```

Frequencies of alternatives:

```
auto      transit
```

```
0.7902    0.2098
```

nr method

6 iterations, 0h:0m:0s

$g'(-H)^{-1}g = 0.000596$

successive function values within tolerance limits

Coefficients :

	Estimate	Std. Error	z-value	Pr(> z )	
transit:(intercept)	-0.747848	0.147402	-5.0735	3.905e-07	***
auto:ttime	-4.902949	0.313037	-15.6625	< 2.2e-16	***
transit:ttime	-1.756742	0.096575	-18.1905	< 2.2e-16	***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Log-Likelihood: -1118.5

McFadden R<sup>2</sup>: 0.20418

Likelihood ratio test : chisq = 573.93 (p.value = < 2.22e-16)



**Appendix D. The base modal shares compared to predicted modal shares with 500 m and 2,000 m radii of catchment area**

Model	Base modal shares		Predicted modal shares (r = 500 m)		Predicted modal shares (r = 2,000 m)	
	<b>Scenario 1</b>		<b>Scenario 1</b>		<b>Scenario 1</b>	
	Auto	Transit	Auto	Transit	Auto	Transit
APM-BR	61.25%	38.75%	59.99%	40.01%	59.82%	40.18%
APM-LR	55.58%	44.42%	53.87%	46.13%	53.59%	46.41%
APM-BV	59.18%	40.82%	58.35%	41.65%	58.29%	41.71%
APM-LV	52.81%	47.19%	52.05%	47.95%	52.02%	47.98%
AEM	79.02%	20.98%	74.50%	25.50%	74.03%	25.97%
	<b>Scenario 2</b>		<b>Scenario 2</b>		<b>Scenario 2</b>	
	Auto	Transit	Auto	Transit	Auto	Transit
APM-BR	61.25%	38.75%	56.04%	43.96%	54.78%	45.22%
APM-LR	55.58%	44.42%	48.31%	51.69%	46.77%	53.23%
APM-BV	59.18%	40.82%	55.14%	44.86%	54.75%	45.25%
APM-LV	52.81%	47.19%	49.14%	50.86%	48.78%	51.22%
AEM	79.02%	20.98%	72.87%	27.13%	73.11%	26.89%
	<b>Scenario 3</b>		<b>Scenario 3</b>		<b>Scenario 3</b>	
	Auto	Transit	Auto	Transit	Auto	Transit
APM-BR	61.25%	38.75%	55.96%	44.04%	55.33%	44.67%
APM-LR	55.58%	44.42%	49.19%	50.81%	48.78%	51.22%
APM-BV	59.18%	40.82%	55.22%	44.78%	55.04%	44.96%
APM-LV	52.81%	47.19%	49.48%	50.52%	49.33%	50.67%
AEM	79.02%	20.98%	74.44%	25.56%	73.93%	26.07%
	<b>Scenario 4</b>		<b>Scenario 4</b>		<b>Scenario 4</b>	
	Auto	Transit	Auto	Transit	Auto	Transit
APM-BR	61.25%	38.75%	56.81%	43.19%	55.42%	44.58%
APM-LR	55.58%	44.42%	49.40%	50.60%	47.81%	52.19%
APM-BV	59.18%	40.82%	55.75%	44.25%	55.19%	44.81%
APM-LV	52.81%	47.19%	49.70%	50.30%	49.22%	50.78%
AEM	79.02%	20.98%	73.37%	26.63%	72.06%	27.94%

## Appendix E. The spatial distribution of predicted transit shares

County	Initial transit shares						Predicted transit shares (Scenario 1)						Predicted transit shares (Scenario 2)					
	BR	BV	LR	LV	E		BR	BV	LR	LV	E		BR	BV	LR	LV	E	
Ingolstadt (city)	0.709	0.785	0.732	0.787	0.619		0.709	0.785	0.732	0.787	0.619		0.709	0.785	0.732	0.787	0.619	
Erding	0.544	0.585	0.482	0.467	0.131		<b>0.564</b>	<b>0.597</b>	<b>0.496</b>	<b>0.472</b>	<b>0.139</b>		<b>0.561</b>	<b>0.597</b>	<b>0.496</b>	<b>0.472</b>	<b>0.134</b>	
Freising	0.498	0.423	0.411	0.373	0.128		<b>0.624</b>	<b>0.634</b>	<b>0.609</b>	<b>0.595</b>	<b>0.205</b>		<b>0.704</b>	<b>0.843</b>	<b>0.674</b>	<b>0.806</b>	<b>0.246</b>	
Fürstenfeldbruck	0.424	0.437	0.453	0.436	0.317		0.424	0.437	0.453	0.436	0.317		<b>0.811</b>	<b>0.838</b>	<b>0.854</b>	<b>0.875</b>	<b>0.633</b>	
Landsberg	0.343	0.577	0.409	0.544	0.384		0.343	0.577	0.409	0.544	0.384		<b>0.396</b>	<b>0.615</b>	<b>0.466</b>	0.544	0.384	
Miesbach	0.310	0.417	0.361	0.431	0.283		0.310	0.417	0.361	0.431	0.283		<b>0.564</b>	<b>0.732</b>	<b>0.596</b>	<b>0.851</b>	<b>0.566</b>	
München	0.325	0.274	0.313	0.254	0.134		<b>0.327</b>	<b>0.277</b>	<b>0.321</b>	0.254	<b>0.140</b>		<b>0.420</b>	<b>0.341</b>	<b>0.439</b>	<b>0.312</b>	<b>0.255</b>	
München (city)	0.412	0.406	0.499	0.483	0.299		<b>0.416</b>	<b>0.407</b>	<b>0.504</b>	<b>0.483</b>	<b>0.329</b>		<b>0.466</b>	<b>0.436</b>	<b>0.571</b>	<b>0.507</b>	<b>0.430</b>	
Landshut (city)	0.831	0.971	0.937	0.948	0.495		<b>0.885</b>	<b>0.991</b>	<b>0.980</b>	<b>0.989</b>	<b>0.626</b>		0.831	0.971	0.937	0.948	0.495	
Landshut	0.430	0.429	0.389	0.489	0.243		<b>0.615</b>	<b>0.580</b>	<b>0.569</b>	<b>0.542</b>	<b>0.356</b>		0.430	0.429	0.389	0.489	0.243	
Dingolfing-Landau	0.156	0.253	0.175	0.344	0.138		<b>0.488</b>	<b>0.572</b>	<b>0.422</b>	<b>0.712</b>	<b>0.319</b>		0.156	0.253	0.175	0.344	0.138	
Bad Tölz-Wolfratshausen	0.143	0.167	0.281	0.345	0.138		0.143	0.167	0.281	0.345	0.138		<b>0.183</b>	0.167	<b>0.355</b>	<b>0.425</b>	<b>0.138</b>	
Dachau	0.101	0.152	0.164	0.149	0.044		0.101	0.152	0.164	0.149	0.044		<b>0.159</b>	<b>0.246</b>	<b>0.278</b>	<b>0.224</b>	<b>0.067</b>	
Ebersberg	0.141	0.109	0.191	0.220	0.062		<b>0.180</b>	<b>0.139</b>	<b>0.266</b>	<b>0.253</b>	<b>0.068</b>		<b>0.233</b>	<b>0.136</b>	<b>0.303</b>	<b>0.362</b>	<b>0.070</b>	
Augsburg (city)	0.253	0.396	0.342	0.487	0.342		0.253	0.396	0.342	0.487	0.342		<b>0.289</b>	<b>0.455</b>	<b>0.427</b>	<b>0.566</b>	<b>0.391</b>	
Aichach-Friedberg	0.199		0.288	0.387	0.261		0.199		0.288	0.387	0.261		<b>0.239</b>		<b>0.310</b>	0.387	0.261	
Augsburg	0.250	0.417	0.341	0.177	0.390		0.250	0.417	0.341	0.177	0.390		0.250	0.417	<b>0.416</b>	0.177	0.390	

Note. Predicted transit shares that differ from base values are marked in bold. Empty cells indicate no trips from a county for the specified groups of airport users.

## Appendix E (continued). The spatial distribution of predicted transit shares

County	Initial transit shares						Predicted transit shares (Scenario 3)						Predicted transit shares (Scenario 4)					
	BR	BV	LR	LV	E		BR	BV	LR	LV	E		BR	BV	LR	LV	E	
Ingolstadt (city)	0.709	0.785	0.732	0.787	0.619		0.709	0.785	0.732	0.787	0.619		<b>0.713</b>	<b>0.799</b>	<b>0.754</b>	<b>0.794</b>	0.619	
Erding	0.544	0.585	0.482	0.467	0.131		<b>0.555</b>	<b>0.596</b>	<b>0.495</b>	<b>0.471</b>	<b>0.133</b>		<b>0.554</b>	<b>0.597</b>	<b>0.496</b>	<b>0.472</b>	<b>0.139</b>	
Freising	0.498	0.423	0.411	0.373	0.128		<b>0.615</b>	<b>0.638</b>	<b>0.558</b>	<b>0.572</b>	<b>0.196</b>		<b>0.653</b>	<b>0.632</b>	<b>0.640</b>	<b>0.602</b>	<b>0.229</b>	
Fürstenfeldbruck	0.424	0.437	0.453	0.436	0.317		<b>0.698</b>	<b>0.713</b>	<b>0.730</b>	<b>0.728</b>	<b>0.527</b>		<b>0.743</b>	<b>0.767</b>	<b>0.801</b>	<b>0.791</b>	<b>0.571</b>	
Landsberg	0.343	0.577	0.409	0.544	0.384		<b>0.381</b>	<b>0.604</b>	<b>0.448</b>	0.544	0.384		<b>0.366</b>	<b>0.593</b>	<b>0.433</b>	0.544	0.384	
Miesbach	0.310	0.417	0.361	0.431	0.283		<b>0.489</b>	<b>0.626</b>	<b>0.515</b>	<b>0.710</b>	<b>0.467</b>		<b>0.417</b>	<b>0.537</b>	<b>0.447</b>	<b>0.587</b>	<b>0.388</b>	
München	0.325	0.274	0.313	0.254	0.134		<b>0.397</b>	<b>0.330</b>	<b>0.411</b>	<b>0.304</b>	<b>0.212</b>		<b>0.373</b>	<b>0.314</b>	<b>0.377</b>	<b>0.289</b>	<b>0.176</b>	
München (city)	0.412	0.406	0.499	0.483	0.299		<b>0.472</b>	<b>0.441</b>	<b>0.571</b>	<b>0.510</b>	<b>0.419</b>		<b>0.460</b>	<b>0.438</b>	<b>0.558</b>	<b>0.508</b>	<b>0.382</b>	
Landshut (city)	0.831	0.971	0.937	0.948	0.495		0.831	0.971	0.937	0.948	0.495		<b>0.883</b>	<b>0.993</b>	<b>0.969</b>	<b>0.992</b>	<b>0.579</b>	
Landshut	0.430	0.429	0.389	0.489	0.243		0.430	0.429	0.389	0.489	0.243		<b>0.606</b>	<b>0.590</b>	<b>0.572</b>	<b>0.548</b>	<b>0.366</b>	
Dingolfing-Landau	0.156	0.253	0.175	0.344	0.138		0.156	0.253	0.175	0.344	0.138		0.156	0.253	0.175	0.344	0.138	
Bad Tölz-Wolfratshausen	0.143	0.167	0.281	0.345	0.138		<b>0.173</b>	0.167	<b>0.334</b>	<b>0.407</b>	0.138		<b>0.162</b>	0.167	<b>0.312</b>	<b>0.384</b>	0.138	
Dachau	0.101	0.152	0.164	0.149	0.044		<b>0.144</b>	<b>0.221</b>	<b>0.243</b>	<b>0.207</b>	<b>0.058</b>		<b>0.127</b>	<b>0.192</b>	<b>0.210</b>	<b>0.186</b>	<b>0.051</b>	
Ebersberg	0.141	0.109	0.191	0.220	0.062		<b>0.207</b>	<b>0.131</b>	<b>0.273</b>	<b>0.331</b>	<b>0.067</b>		<b>0.183</b>	<b>0.123</b>	<b>0.242</b>	<b>0.292</b>	<b>0.065</b>	
Augsburg (city)	0.253	0.396	0.342	0.487	0.342		0.253	0.396	0.342	0.487	0.342		<b>0.291</b>	<b>0.458</b>	<b>0.432</b>	<b>0.569</b>	<b>0.394</b>	
Aichach-Friedberg	0.199		0.288	0.387	0.261		0.199		0.288	0.387	0.261		<b>0.244</b>		<b>0.312</b>	0.387	0.261	
Augsburg	0.250	0.417	0.341	0.177	0.390		0.250	0.417	0.341	0.177	0.390		0.250	0.417	<b>0.421</b>	0.177	0.390	

Note. Predicted transit shares that differ from base values are marked in bold. Empty cells indicate no trips from a county for the specified groups of airport users.

## **Appendix F. The spatial distribution of predicted transit shares by airport user groups**

Content removed due to data usage restrictions

## **Declaration concerning the Master's Thesis**

I hereby confirm that the presented thesis work has been done independently and using only the sources and resources as are listed. This thesis has not previously been submitted elsewhere for purposes of assessment.

Munich, May 5th, 2020

A handwritten signature in black ink, appearing to read 'S. Vernydub', with a long horizontal stroke extending from the end of the signature.

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Sofia Vernydub