Exploring the factors influencing the shared e-moped train combination

MSc thesis

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Exploring the factors influencing the shared e-moped train combination

by Gert de Wit

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Preface

This thesis marks the end of my Master Transport and Planning at the TU Delft. Almost everything you have ever wanted to know about the shared e-moped train combination can be found in this thesis. As a young child I was already very interested in mobility. Instead of playing with the cars, I built traffic jams with them (already a sign you should take the train and not the car ;)). Also, when we were in Blijdorp, the zoo of Rotterdam, the highlight of the zoo was not the animals, but the trains you could see riding, especially the section under the train bridge with the train description was very nice. No wonder my thesis ended up being train related. The thesis went like a high speed train on rails and it is the end of my 6 year study career in Delft. I want to thank NS Stations for providing me the opportunity to do my thesis there as an Intern and Check for willing to share shared e-moped trip data. Without the contributions of some people this thesis would not have been possible.

First of all I have to thank Cathelijn and Danique for their awesome supervision at NS Stations. Cathelijn, you complemented my weaker points very well. You always reminded me of telling my story so simple that even Tante Truus could understand. Our weekly meetings were very useful and I think you had a major contribution in making my story useful for practice. I was very honored to be your first intern to guide and I am convinced that the Gert's 2.0 will also have awesome guidance. Danique, you always managed to ask the questions to knock down my story, which made me rethink my story. This challenged me in a very good way and further improved my thesis. Besides, our beer tastes seemed to match quite well. Thanks to the both of you and my other colleagues for making my time at NS Stations so nice. Even so nice, that you convinced me to stay.

Secondly, I need to thank my supervisors from the TU Delft, Niels, Alexandra and Serge for providing their supervision. Niels, thanks for getting me in contact with NS Stations in the first place. Our meetings were very useful and after every meeting I always had to add or change a Figure to visualize the story. Alexandra, thanks for the very detailed feedback you always managed to give and for the fun meetings we had. Serge, thanks for being willing to chair the committee and thanks for reminding me to always validate and visualize the results.

My student time, didn't only consists out of my thesis. First of all, I have to thank my parents for helping me where needed during my time as a student. Secondly, I want to thank my fellow VGSD members for the nice and useful conversations at the Boot, the awesome activities, the nice friendships and providing opportunities such as being the secretary of the board. This made my time as a student way more fun and let me grow as a person in areas which were not part of my study. Lastly, there is one person who deserves a very big thank you. First of all, Emily, thanks for being my girlfriend and giving (un)wanted advice about my thesis and hearing me out. Second of all, a very big thanks for the awesome cover of this thesis and the two infographics.

I hope you enjoy reading this thesis. It has been a pleasure doing this study and I look forward to further contributing to a better sustainable accessible Netherlands for everyone.

Gert de Wit
Delfgauw, August 2023

Summary

Train stations are mobility hubs. They function as a place where different modes come together. Previously the stations provided a transfer opportunity between the train, walking, cycling, car and public transport. The last few years, however, shared micromobility modes are being introduced, providing new alternatives to reach the station. One of these shared micromobility modes is the shared e-moped. The Netherlands is one of the biggest shared e-moped markets in the world. In 2022 the shared e-moped market in The Netherlands grew with 794%. In The Netherlands shared e-mopeds are also used to go from and to the station. NS is interested in what the impact of the shared e-moped on the door-to door journey is to see whether it can contribute in making The Netherlands sustainable accessible for everyone. Furthermore, due to urbanisation in The Netherlands the space around the train stations has become a sparse good. This means NS and other parties involved have to decide how and if they want to facilitate the shared e-moped as a first- and last mile mode.

In literature little is known about the shared e-moped usage patterns. The literature shows that shared e-mopeds and train do have a complementary relationship but, to the best of the authors knowledge, no knowledge about the shared e-moped usage patterns in first- and last transportation is available in literature. Therefore, the research goal of this research is to explore the usage patterns of shared e-mopeds in first- and last mile transportation in the Netherlands and identify which factors influence the usage of shared e-mopeds in first- and last . The main research question of this report is therefore:

To what extent do various factors influence the usage of shared e-mopeds in first- and last mile transportation to train stations?

First, a literature study is performed to see which factors influence the shared e-bike or shared e-scooter combination with the train. This is done, because not enough literature about shared e-mopeds is available to identify possible factors influencing the shared e-moped usage in first- and last mile transportation. Then, a case study with data from shared e-mopeds of Check and train passenger data of NS is performed to see what the usage patterns of shared e-mopeds in first- and last mile transportation in The Netherlands are. Next, a conceptual framework is made to give an overview of all suggested influencing factors by the literature study and the empirical insights from the case study. Based on this framework four multiple linear regression models are set-up to identify the factors influencing the usage in first- and last mile transportation.

From the literature study it appears that the vehicle availability is the most mentioned factor positively influencing the shared micromobility train combination. Walking distance from the shared micromobility vehicle to the station and rain are mentioned the most frequent as negative influencing factors. Table 1 shows the factors and the effect of the factors on the shared micromobility train usage that are mentioned by more than four articles.

Table 1: Overview of factors in the literature study. / means the influence is unclear.

Author	Service area size	Parking capacity stations	Vehicle availability	Walking distance	Quality of train service	Presence of other modes	Points of interest	Recreational land use	Commercial land use	City center	Population density	Quality bike infrastrucure	Rain	Temperature	Weekend
Type of influence	+	+	**+**	**-**	+	-	+	+	+	+	+	+	**-**	+	/
Number of times mentioned	5	4	**11**	**6**	8	4	7	8	6	4	7	7	**6**	6	5

Usage patterns

The case study to usage patterns focuses on the shared e-moped usage in The Netherlands. Data from September and October 2022 is used. In the case study there are 40 stations, where both NS and Check are operating trains or shared e-mopeds. This study develops a classifying algorithm to classify a trip as a fist- or last mile trip. A shared e-moped trip is a first- or last mile trips, when the trip ends to starts within a radius of a train station. This radius differs per station (150-400 metres) and depends on the size of the station and the shared e-moped service area around the station. 18% of all shared e-moped trips are a first- or last mile trip. This shows that almost one in five shared e-moped trips start or end near a train station. The average distance of first- and last mile trips are 3039 metres and 3029 metres. Non-train related trips do have an average trip distance of 3362, which is significantly larger than first- and last mile trips. The type of station and the city a station is in seems to influence the average trip distance towards and from different train stations.

The average number of trips is significantly higher during the week than during the weekend. Friday is the day with the most shared e-moped trips.Figure 1 shows that over the day the first mile trips show a clear morning and afternoon peak, where the morning peak is larger but less wide than the afternoon peak. In last mile transport, the afternoon peak is larger, which is caused by a combined usage of commuting and leisure trips. During the weekend no morning peak is present in both first- and last mile. The usage is the highest at the beginning of the evening. Between the stations differences in patterns can be observed, which suggests that the built environment and urbanity of the city influence the usage over the day.

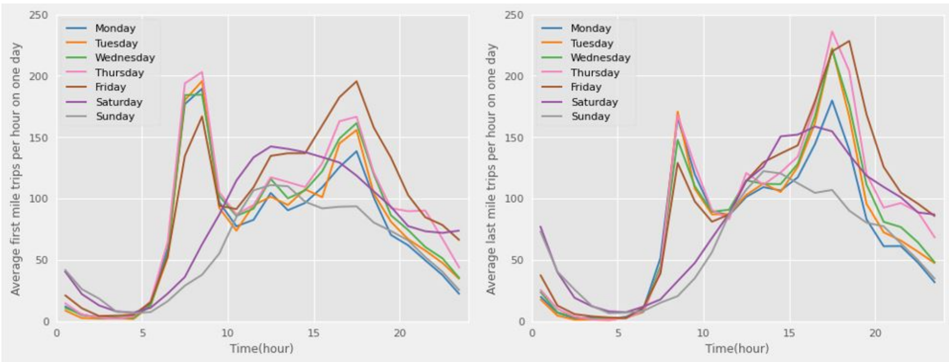


Figure 1: Temporal patterns on weekdays of shared e-mopeds in first- and last mile transport.

The purpose of a trip is determined based on the most frequent appearing building function in the grid cell of 100 by 100 metres, where the trip starts or ends. This grid has been developed by using data from BAG (Basisregistratie Adressen en Gebouwen). Figure 2 shows the shares of the shared e-moped trip purposes in first- and last mile transportation.

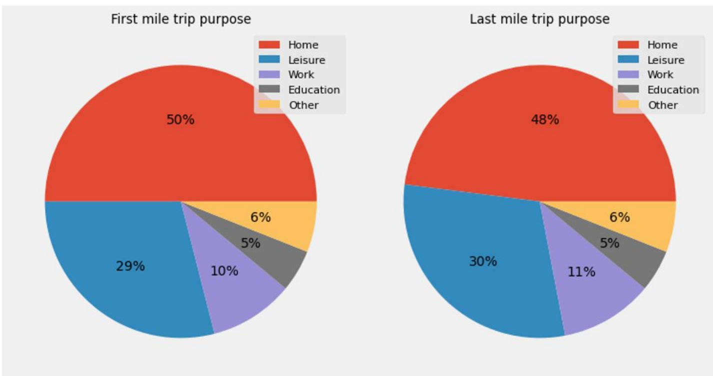


Figure 2: Share of trip purposes of shared e-moped trips in first- and last mile transportation in The Netherlands.

49% of the first- and last mile trips have a 'Home' trip purpose. This trip purpose entails both the home work traffic as well as social trips to friends or family. 29% of the first- and last mile trips have a leisure trip purpose. This shows that shared e-mopeds are used for both commuting as well as social recreational trips. Between stations there are large differences in trip purpose, which are caused by the differences in built environment around the station. The trip purpose influences both the trip distance and the trip start time, as home trips have a longer trip distance than activity related trips.

The modal share of shared e-mopeds is defined as the percentage of train passengers that goes to (first mile) or comes from (last mile) the train station by shared e-moped. A survey at the station Rotterdam CS, Breda and Amsterdam Sloterdijk is performed to check whether all shared e-moped trips that are starting or ending within a defined radius of the station are indeed train related. The percentage of people actually using the train, when parking or departing from the train station ranges from 67% to 93% depending on the station. Two percentages, 75% and 90%, based on three criteria on the structure of the shared e-moped service area are used to generalize these percentages to other stations. The modal share is calculated using this percentage. To calculate the modal share for all providers, this is multiplied by the ratio between the number of total shared e-mopeds and the number of Check shared e-mopeds, as well as a factor accounting for more usage of one provider than the other.

The modal share of shared e-mopeds per day during the week ranges from 0.06% to 2.5%. The majority of the stations has a modal share lower than 0.7%. The first and last mile modal shares are approximately the same. The stations with a modal share higher than 1.5% come for the majority from cities with a high shared e-moped usage per inhabitant. Also they are mostly Intercity stations. During the weekend the modal shares are higher as they range from 0.06%- 5.3%. The modal share is higher in the weekend, because there are relatively fewer train passengers and the quality of other modes such as public transport is lower in the weekend. Over the day, the modal share in last mile grows over the day, with its peak in the late afternoon. In first mile a morning peak in the modal share is present on weekdays. Also clear peaks can be seen at stations with a night train at the end of the evening in first mile and the beginning of the night in last mile. This indicates that shared e-mopeds are used to go to nightlife activities.

Model structure

From the literature study and empirical insights a conceptual framework is made, which shows the expected influence of factors on the shared e-moped usage. This framework is shown in Figure 3.

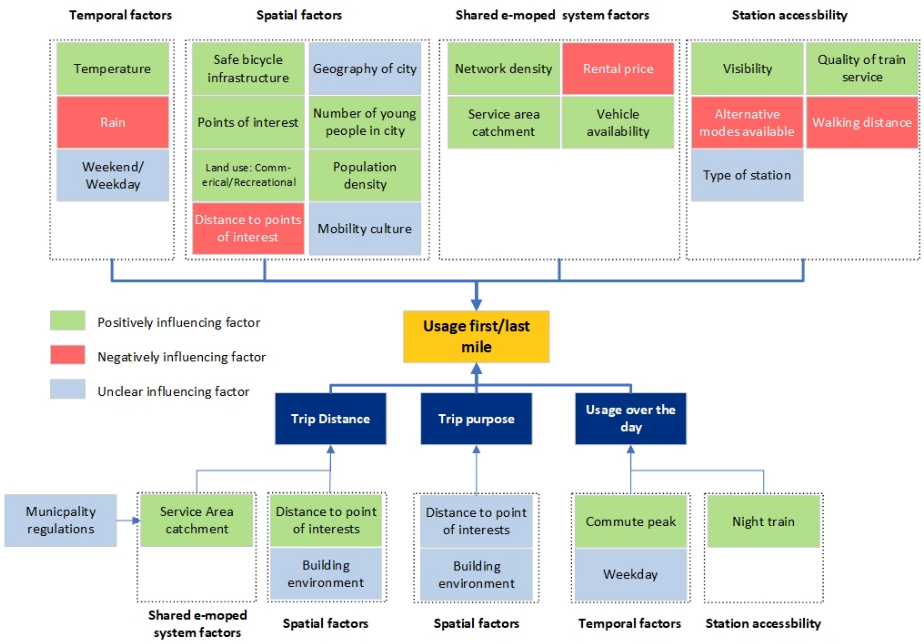


Figure 3: Conceptual model of factors influencing found in practice, from empirical insights and shared micromobility literature

From this framework only the usage first/last mile is modelled, as this study only focuses on the first/last mile usage. The dependent variables of the multiple linear regression model are the modal share and the number of shared e-moped trips. Also, separate models for first- and last mile are made. This means in total 4 multiple linear regression models are made. The best performing model structure of each model is based on the adjusted R^2 score. Based on the results of the model and the usage patterns an answer on the main research question is given.

Model results

The biggest influencing factor on the shared e-moped usage is the vehicle availability at the station side. Increasing this by one vehicle per day leads to approximately 4.8 more trips per day. In first mile transport the vehicle availability has a smaller influence with only 1.3 more trips per added moped/km^2. Another important factor is the share of young people at a station. In first- and last mile this leads to 2.33 and 2.30 more trips per day when increasing the share with 1%. When a station is or becomes an intercity station, the number of first mile trips increases with 22.5 and the number of last mile trips increases with 18.8, which shows this factor has a big influence. The walking distance has a negative influence on the shared e-moped usage (0.22 trips/ extra metre), while the visibility has a positive influence on the number of last mile trips with 6 added trips per day, when shared e-mopeds are visible. The modal share model shows that shared e-mopeds and busses are slightly competing with each other, as an increase of 10 busses/h leads to a decrease of 0.045%. of the modal share in first mile transport and 0.030%. in last mile transport. The shared e-moped and the shared bike, OV-fiets, also slightly compete with each other, although they only compete in last mile transport, as the OV-fiets is only rentable at train stations. Adding 100 shared bikes to the capacity, leads to a reduction in modal share of 0.02%.. The weekend day factor has the biggest influence on the modal share with an increase on weekend days of 0.25%. and 0.24%. in first- and last mile transportation.

The population density has a negative influence in all the models. This means that in highly density cities the number of shared e-moped trips becomes lower as the density increases. The negative influence is really small (-0.01 trips per person added), but can be explained by the fact that in highly density areas people live closer to their destination, which means people do not need a shared e-moped. Furthermore, more alternative transport options might be available. This finding does not mean that in rural areas the number of trips is high, because the models are trained on only cities. The temperature has a positive influence in all models, a one degree increase generates 0.6 more last mile trips, indicating that it does have an influence. It should be noted that the models are not trained on extremely high temperatures. The models cannot draw a reliable conclusion about the influence of the tram and metro frequency. The results from the modal share model show a positive influence, while the correlation with the modal share is negative for both the tram and metro frequency. In the trip model they are also positive, which is primarily caused by the fact that at bigger stations with more passengers there are also more trams and metros.

Discussion

The findings in the study are largely in line with the literature. The most noticeable difference is that rain has no significant influence according to the model, while the literature of shared micromobility mentions it as one of the two most negative influencing factors. The limitations of this study are that the survey to determine the percentage of train passengers among parking shared e-mopeds is only determined on 3 stations. Furthermore, to calculate the modal share per day the ratio between provider usage is used and based on observations from the survey and assumptions. The models are trained with only the modal share of Check, which means this does not impact the results directly. The data for used for the case study is only from 2 months, meaning that the influence of season effects cannot be determined. Also, for the models a more advanced regression model might be needed to prevent the influence of suppressor variables and reduce the still present influence of multicollinearity. Besides, the relationship of factors might be more complex than the linear assumption of the multiple linear regression model. Lastly, the data used for the analysis is before the helmet requirement in The Netherlands is introduced. This affects the demand and therefore the number of trips, which is used as training data for the model. Further research is needed to quantify the effect of the helmet requirement.

The results of the effect of factors can be generalized to other countries. In other countries, the safety of bicycle infrastructure and hilliness should also be taken into account, as this study did not, because there are no hills in the case study cities. The conceptual framework is based on a internationally literature study which means it can be used everywhere. The methodology of classifying a first- and last mile shared e-moped trips and the methodology of determining the trip purpose based on building function can be used in other countries as well.

Conclusion & Recommendations

The usage of shared e-mopeds in first- and last mile transport can be described by the usage patterns. 18.3% of all shared e-moped trips are train station related. The average trip distance in first- and last mile transportation is 3039 and 3028, which is significantly shorter than the non-train related usage with a distance of 3362 metres. The number of shared e-moped trips in first- and last mile transportation ranges from 1 to 499 per day, indicating that at the high usage stations it has a big impact on first- and last mile transport.In first mile transport a clear morning peak can be observed in the usage on weekdays, while in last mile transport the afternoon peak is bigger. The usage over the day and the trip purpose are influenced by the built environment of the station. 49% of the first- and last mile trips have a home trip purpose, which consists of home work traffic and social trips to friends and family. 30% of the first- and last mile trips have a leisure trip purpose. The modal share during the week ranges from 0.06% to 2.5% and during the weekend from 0.06% to 5.5%, indicating the modal share is higher during the weekend. The modal share in last mile transport increases over the day.

The vehicle availability at the station side has the highest influence on the number of last mile shared e-moped trips with 4.8 more trips per day per added shared e-moped at the station. In first mile, the vehicle availability has a lower impact with 1.3 more trips per day per added shared e-moped/km^2. An increase of 1 %. in the share of young people at a station leads to 2.3 more trips per day in both first and last mile transport. The station having an Intercity stop, leads to 22.5 and 18.8 more trips per day in first- and last mile transport. An extra metre of walking distance from shared e-moped towards the train station leads to 0.22 trips less per day. The visibility of shared e-mopeds also positively influences the number of trips, as them being visible from the station leads to 6 more trips, according to the model. Shared e-mopeds slightly compete with the bus and the shared bike 'OV-fiets', but these competing relations are really small.

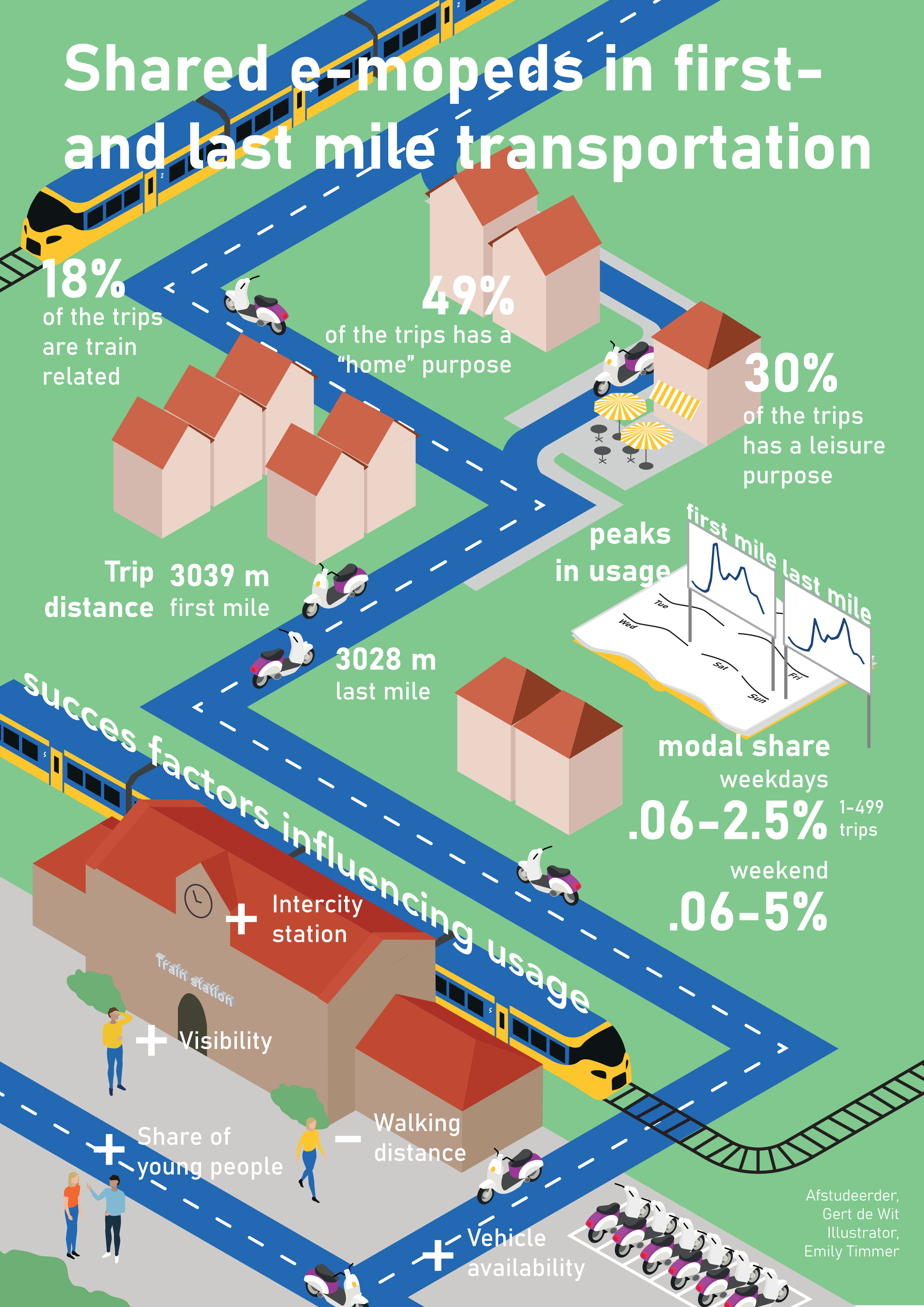
The population density has a negative influence. Since, the models are trained on data from cities, this means high density leads to less shared e-moped trips, as people live closer to the destination and have more options available for transport. This does not mean that in rural areas the number of trips is high, as the model is not trained on rural areas. The models were not able to draw a reliable conclusion about the influence of the tram and metro frequency. The models have a high internal validity, but are less suitable to predict the exact modal share and trip number, as the RMSE of the all models is high. This is caused by the high diversity of station characteristics in the training data. This model is primarily suitable for explaining the influence of factors and less suitable for predicting.

For further research, it is recommended to find out which modes shared e-mopeds replace to identify their impact on the first- and last mile transport to train stations. It is also recommended to perform the survey at more stations. Besides, a more advanced regression model might be used to determine the effect of tram and metro frequency. During this study, a helmet requirement for shared e-moped was introduced. The data for this study is from before the requirement, which makes it interesting to do the same study to identify the influence of the helmet requirement. Also, a study using data from a whole year can help in identifying seasonal effects. The methodology of determining the trip purpose on basis of the building function can also be applied on other shared micromobility modes. This might be an interesting research direction, as it can show the differences in purposes between shared micromobility modes.

The success factors for shared e-moped usage at a station are a high vehicle availability, the station being an Intercity station, a high share of young people at a station, visibility of shared e-mopeds from the station and a low walking distance from the shared e-moped to the station. When NS wants to encourage shared e-moped usage, they should focus on these factors. Shared e-moped providers

can improve the attractiveness of the shared e-moped train combination by offering a high number of vehicles at the station side. The survey showed that not all shared e-moped users parking at a station go to the train station. To limit the spatial impact of shared e-mopeds at the station it is recommended to position the service areas of shared e-mopeds in such a way, that there is no other reason to start or end a shared e-moped trip here then the station. This study also shows that combining data provides new insights into the first- and last mile usage of shared e-mopeds.

From a user perspective the shared e-moped improves the accessibility of the station both in first- and last mile, as it provides a new option to reach the station. It is a faster option than the bike and compared to public transport it has no waiting time, if a vehicle is available. Especially, in areas with low public transport frequencies the shared e-moped can contribute a lot to the optimal mix of modes, as it increases the accessibility of a station a lot. At the moment shared e-moped are only used in cities, as they are only profitable there. Governments could consider to subsidise the shared e-mopeds to provide a better accessibility of the station. The spatial impact of shared e-mopeds on the total access- and egress facilities footprint depends on which mode it replaces. Replacing the pedestrian, the public transport or cyclists, a shared e-moped might increase the spatial footprint, while replacing a car ride reduces the footprint. With regards to the sustainable footprint this is the same, as replacing the pedestrian and cyclist is less sustainable, while replacing a car trip is more sustainable. Therefore, it is recommended to find out which modes shared e-mopeds replace in first- and last mile transport to help in understanding how we can make the Netherlands better sustainable accessible for everyone.


Shared e-mopeds in first- and last mile transportation
18%
of the trips are train related
49%
of the trips has a "home" purpose
30%
of the trips has a leisure purpose
peaks in usage
first mile
last mile
Tue
Wed
Sat
Fri
Sun
Trip distance
3039 m
first mile
3028 m
last mile
modal share
weekdays
.06-2.5%
1-499 trips
weekend
.06-5%
succes factors influencing usage
+ Intercity station
Train station
+ Visibility
+ Share of young people
- Walking distance
+ Vehicle availability
Afstudeerder,
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Illustrator,
Emily Timmer

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1. Introduction

Train stations are mobility hubs. They function as a place to transfer from trains and to transfer from your first mile trip to the train or from the train to your last mile trip. This causes the station to have a unique position in the transport network. All kind of modes, such as trams, metros, bicycles and pedestrians come together to get people from and to the train. For years, this has been mainly public transport modes, bicycles and pedestrians. The last few years, however, shared (micromobility) modes are becoming more present in cities all around the world. Shared modes can be defined as a transport mean which can be used by people to make transport possible on a short term as needed basis (Shaheen and Chan, 2016). This provides the user access to a transport mode, which he previously did not have access to. This increases the number of options to get to and from the train station. This raises the question how these new shared modes act as first- and last mile modes and what their usage patterns look like.

One of these shared modes is the shared e-moped. Shared e-mopeds have been entering the world of shared micromobility since 2012 (Howe, 2021). Currently, there are approximately 130.000 shared e-mopeds around the world, which are available in 220 cities in 36 countries. In 2022 the number of shared e-mopeds around the world has grown with 8% with respect to the number of shared e-mopeds in 2021. Taiwan (20,000 vehicles), Spain (18,000 vehicles), and The Netherlands (17,000 vehicles) are the countries with the largest shared e-moped fleets (Howe et al., 2022) A shared e-moped is a sitting e-scooter. The maximum speed of a shared e-moped ranges from 25-100 km/h, although most shared e-moped maximum speeds are around 45 km/h (Howe et al., 2022). A shared e-moped can be ridden by either 1 or 2 persons. An example of a shared e-moped is given in Figure 1.1.

Figure 1.1: Example shared e-moped (NS, 2022)

The Netherlands is an interesting case for shared e-mopeds. In The Netherlands shared standing e-scooters, a similar micromobility mode, are not allowed due to regulations, while in other countries they are allowed. Furthermore, Maxwell et al. (2023) show that Rotterdam is the city with the most shared e-mopeds/inhabitant and Rotterdam is the second city with the most trips per capita. Besides, Amsterdam is the city with the most shared e-moped trips per vehicle. Lastly, the Netherlands saw the largest fleet size increases in 2022 from all Europe countries. In 2020 the number of shared e-mopeds rose with 794% (Howe and Jakobsen, 2020). This shows the shared e-mopeds in the Netherlands are interesting to look into.

NS is interested in what the impact of the shared e-moped is on the door-to-door journey. This can help in understanding what the mode can contribute in a seamless transition between a train trip and the first- or last mile trip. Furthermore, they want to know the impact to identify whether the shared e-moped can contribute to a sustainable accessible Netherlands for everyone. Over the last twenty years urbanisation has taken place in the Netherlands. In 1990 68.68% of the people lived in an urban area, while in 2019 92.24 % of the Dutch population lives in an urban area. This has caused space to become a scarce good in urban areas in The Netherlands (Ritchie and Rosier, 2019). Next to the urbanisation more and more people have started using the train. This means there are more access and egress facilities such as bike parkings, park and rides and bus stops needed around stations. Next to this, several building projects to create more apartments are located at or near stations. This leads to scarcity of space around the station. Therefore, NS and other parties involved in the surrounding of the station area, have to decide how they want to facilitate the shared e-mopeds in the station area, since there is not room for all modes to be close to the station. Therefore, it is needed to know what role shared e-mopeds play in first- and last mile transportation to and from train stations and what factors influence the usage of shared e-mopeds in first- and last mile transportation.

1.1 Research goal

The literature suggests that shared e-mopeds and train have a completing relationship (Garritsen, 2022; Knoope and Kansen, 2020). In these studies, little is explained about how the complementary relationship works and which factors influence it. Stam et al. (2021) have done a literature study on factors influencing the choice of first and last mile mode choice. They developed a framework which describes which aspects influence the first- and last mile mode choice. This framework is shown in Figure 1.2. From this framework it can be concluded that, the characteristics of the traveller, the characteristics of the access/egress trip, the access/ egress mode and the built environment influence the first/last mile mode choice along with main stage factors.

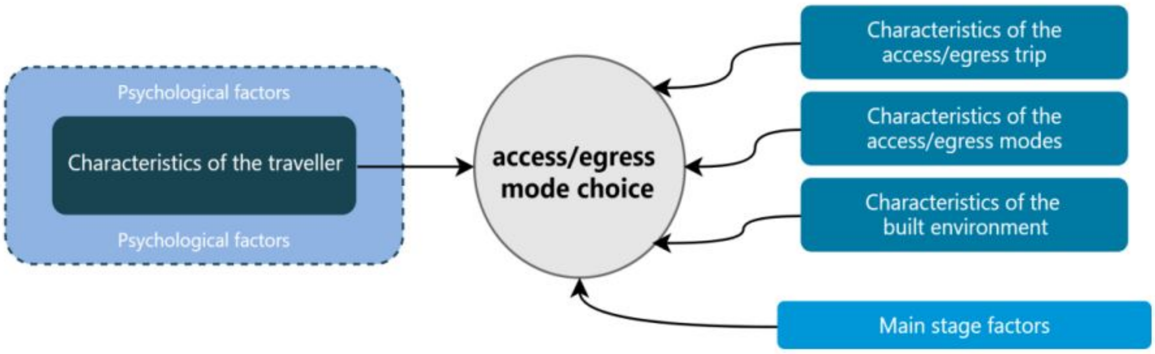

Figure 1.2: First- and last mile mode choice framework (Stam et al., 2021)

Research gap

The users of shared e-mopeds are in general young and highly educated (Knoope and Kansen, 2020; Aguilera-García et al., 2021). Users experience two main barriers for using a shared e-moped. The first barrier is that one needs a driving license to drive a shared e-moped (Aguilera-García et al., 2021). The second barrier is that people who have not driven a moped before, experience a barrier to start using a shared e-moped due to a lack of driving experience (Aguilera-García et al., 2021; Garritsen, 2022). Regarding trip characteristics a trip distance of 2.3- 5 kilometres for regular trips are found in literature (Wortmann et al., 2021; Faber et al., 2020; Arias-Molinares et al., 2021). No separation between regular usage and usage towards or from train stations has been made in these studies. Only Faber et al. (2020) mentions that 14% of the shared e-moped trips in the Netherlands starts or ends within 200 metres of a train station. No studies have investigated which factors influence the usage of shared e-mopeds in first- and last mile transportation to train station. Studying the factors that influence the combined shared e-moped train mode can help in understanding what the role is of a shared e-moped in the door-to-door journey.

Looking at the Figure 1.2 and the available knowledge in literature, it can be concluded that there is currently no to little knowledge about the trip characteristics of shared e-mopeds in first- and last mile transportation and no knowledge about which factors influence the usage of shared e-mopeds in first- and last mile transportation. Therefore, this research has as research goal to explore the usage patterns of shared e-mopeds in first- and last mile transportation to train stations and to determine which factors influence these usage patterns. Usage patterns are defined in this study as the trip characteristics (trip distance, duration, and purpose), the usage over the day, the number of trips and the modal share of shared e-mopeds in first- and last mile transportation to train stations.

1.2 Research questions

This research has as goal to explore the usage patterns of shared e-mopeds in first- and last mile transportation to train stations and to determine which factors influence these usage patterns. Therefore, the main research question will be:

To what extent do various factors influence the usage of shared e-mopeds in first- and last mile transportation to train stations?

To answer this research question, three sub-questions have been formulated:

- Which factors influence the usage of shared (e-)bikes or shared e-scooters in combination with train?
- What are the usage patterns of the usage of shared e-mopeds in first- and last mile transportation to train stations?
- What is the best performing model structure to quantify the influence of factors on the usage patterns of shared e-mopeds in first- and last mile transportation?

1.3 Research approach

Subquestion 1 is answered by performing a literature review. A literature review has the advantage of being a relatively quick way to get an overview of what is already known. Next to that a literature review provides the possibility to gain international insights from other studies. Since there is a low amount of literature available on shared e-mopeds, this literature review focuses on shared bikes and shared e-scooters. Both these modes are more often studied than shared e-mopeds (Aguilera-García et al., 2021). This literature review gives an overview of current knowledge about factors influencing the shared micromobility train combination. The findings can be used to determine a first selection of factors that should be taken into account to answer the main research question.

Subquestion 2 is answered with a case study on shared e-moped usage in first- and last mile transportation in the Netherlands. A case study provides the opportunity to study real life complex phenomena (Krusenvik, 2016). This provides the advantage of having revealed preference data. The disadvantage of the case study methods, is that findings are sometimes hard to generalize. To reduce this disadvantage, the case study is performed on all Dutch cities and not one specific city. For this case study shared e-moped trip data is used, because this provides accurate information about trip characteristics, such as trip distance and duration. A survey towards shared e-moped users would introduce inaccuracy, as people would have to estimate their trip distance. This case study has as goal to study the usage patterns of first- and last mile trips towards train stations.

Subquestion 3 aims to find the best performing model structure to quantify the effect of factors on the usage patterns of shared e-mopeds in first- and last mile transportation to train stations. This is done by looking at which methodologies are used in the literature study of subquestion one and by searching in the literature for a small overview of advantages and disadvantage of different methods. A conceptual framework is made to identify all factors originating from subquestion 1 and 2. These factors are translated into variables for the model. To determine the best model structure multiple models are ran with different set-ups to determine the best performing model.

1.4 Relevance & scope

1.4.1 Relevance for Science

This study provides a methodology which can be used to determine whether a shared e-moped trip is a first- or last mile trip. Furthermore, this study comes up with a methodology to determine the trip purpose of a shared e-moped trip, based on the building function of a cell where the trips starts or ends. This methodology is also suitable for other types of micromobility modes with GPS data, such as shared e-bikes. Besides, this study dives into the research gap which is existing about the usage patterns of shared e-mopeds in first- and last mile transportation and helps filling this gap.

1.4.2 Relevance for practice

Recently, the shared e-moped market in the Netherlands has had some major changes. In Utrecht,the shared e-mopeds are removed after a trial, because shared e-mopeds where mainly replacing bike trips (Bright, 2022), while in Nijmegen the shared e-mopeds have been introduced for the first time (Trommelen, 2022). This shows municipalities are still finding out the effects of the shared e-moped usage on the mobility system. This study provides an insight into how shared e-mopeds are used as a first- and last mile mode. It shows the average distance, trip purpose, usage over the day and the modal share of shared e-mopeds in first- and last mile transportation. Based on the influencing factors NS Stations, shared e-moped operators and municipalities can get an idea how the shared e-moped works as a first- and last mile mode and whether they, if not already, should implement the shared e-moped as a first- and last mile mode.

1.4.3 Out of scope

The environmental impact of the shared e-moped usage on the door-to-door journey is out of the scope of this research, since the scope would be too large, for the amount of time available. The spatial impact of a shared e-moped is also out of the scope of this research. Furthermore, the mode a shared e-moped replaces is not in the scope of this research. Besides, this research will not dive into the user characteristics as there is more known about those than is known about the usage patterns of shared e-mopeds. Therefore, this research only focuses on the usage in first- and last mile transportation, as information about regular usage is already available.

1.5 Thesis Outline

Chapter 2 describes the results of a preliminary literature review towards shared e-mopeds. These findings are used to formulate the research gap. Chapter 3 contains the methodology for each different part of this study. Chapter 4 shows the results of the literature study, after which Chapter 5 dives into the usage patterns. Chapter 6 shows the best performing set-up of the models and the results of these models. Chapter 7 continues with the the discussion. Finally, Chapter 8 presents the conclusion and the recommendations based on the findings.

2. Background e-moped users and usage

This chapter describes the results of a preliminary literature review on shared e-mopeds. This preliminary literature review is used to determine the research gap in shared e-moped users and usage knowledge. Section 2.1 dives into the user characteristics, while Section 2.2 talks about the trip characteristics. Lastly, Section 2.3 shows the literature knowledge about the relation of shared e-mopeds with public transport.

A limited amount of research to shared e-mopeds exists. In 2021, Aguilera-García et al. (2021) could only find three studies related to moped sharing in the research database SCOPUS. Also, research to other types of shared mobility has been done more often in comparison with shared e-mopeds. In the literature, shared e-mopeds are sometimes also called shared e-scooters. This causes confusion as shared e-scooters refer to standing (kick) scooters. An important difference between e-scooters and e-mopeds is that e-scooters are often allowed on sidewalks, and e-mopeds are not. Also, e-scooters take less place than e-mopeds, but e-mopeds are generally faster. Other synonyms found for e-mopeds are moped-style scooters and sitting scooters. This research focuses on the e-mopeds, and not on the standing e-scooters.

2.1 Users

Characteristics

In the literature, several studies have delved into the user characteristics of shared e-moped users. Garritsen (2022) has done a research to the usage patterns of shared e-mopeds at mobility hubs by using e-moped trip data for spatial analysis and a survey to find out the underlying reasons of choices for shared e-mopeds. From this survey, it becomes clear that shared e-moped users are primarily young and highly educated. This is supported by the research of Knoope and Kansen (2020) who show, in a research to the current and future role of light electric vehicles in the mobility system of the Netherlands, that the users are mainly millennial's, students, tourists and commuters.

In Spain, this trend is also observed, as people between the ages of 26 and 34 are the most frequent shared e-moped users (Aguilera-García et al., 2020). Aguilera-García et al. (2021) adds to this definition that shared e-moped users are highly educated, young and live in dense urban areas. This addition can be explained by the fact that shared e-moped service areas are concentrated around densely urban areas (Méndez-Manjón et al., 2021). According to van Kuijk et al. (2022), who have done a research into user preferences for first- and last mile shared mobility in Utrecht, shared e-moped users have a high value of travel time, which indicates that these users are willing to pay more to reduce their travel time.

Barriers

Two barriers can be found in starting to use a shared e-moped. As Aguilera-García et al. (2021) points out people need to have a driving license in order to be allowed to drive on a shared e-moped. Since not all people have a driver's licence, this makes shared e-mopeds for less people an option. This barrier is not present in other types of micromobility, which makes the shared e-moped available for fewer people than a shared bike or shared e-scooter (Rojas, 2021).

The second barrier to the use of shared e-mopeds is the fact that people who have not driven a moped before experience this as the most present barrier to start using the shared e-moped (Aguilera-García et al., 2021, Garritsen, 2022). In general this yields for all types of shared mobility modes, as is shown by Arendsen (2019) who performed a survey to identify the impact of shared modes on the access and egress trips to train stations. This shows that people who have used e-mopeds before are more likely to use shared e-mopeds. Therefore, the two biggest barriers for users to use a shared e-mopeds are having a driving license and having no e-moped driving experience.

2.2 Usage patterns

Trip distance

In a case study in Berlin on the potential of shared e-mopeds to replace car trips, it was found that average length of a shared e-moped trip is between 3.6-4.1 kilometres (Wortmann et al., 2021). In the Netherlands an average trip length of 2.3 kilometers has been found (Faber et al., 2020). This is lower than the Berlin case, because research in the Netherlands has been done in the early stages of the introduction of shared e-mopeds in the Netherlands. The service areas in The Netherlands of shared e-moped have been concentrated around the dense city, resulting in a small service area (Faber et al., 2020). This shows that the size of the service area has a direct influence on the average length of the trip.

In 2018 a market research has been done by Howe and Bock (2018). In this study the average trip distance by shared e-moped is four to five kilometres. In Spain, a research to the data of one shared e-moped provider Muving has been done. The average distance travelled on the Muving shared e-moped is 3.2 kilometres (Arias-Molinares et al., 2021). From this study, it also becomes clear that the spatial surroundings of a city affect the average length of trip. This is shown by demonstrating that Cadiz, which is surrounded by the sea from three sides and is a elongated city with only a north south pattern, has a significant higher average trip length than other Spanish cities (Arias-Molinares et al., 2021). The average trip distance of shared e-mopeds ranges from 2.3-5 kilometres.

Purpose

According to the research of Knoope and Kansen (2020) shared e-mopeds in the Netherlands are used often for leisure purposes. In Rotterdam specifically, this is also visible, as the main travel purpose is for recreational activities. In Rotterdam however, it is also noticed that in 2020, the trip purpose was 20% of the times related to commuting and education, This indicates that shared e-mopeds are also used for commuting (Gemeente Rotterdam, 2020). It must be mentioned that in 2020 Covid-19 has had an influence on these results, making them less reliable. In Spain, it can also be seen that shared e-mopeds are being used for commuting, as 72% of the total trips are made on working days and 28% of the trips is made on weekend days (Arias-Molinares et al., 2021). Therefore, shared e-mopeds are used for leisure and commute trips.

Travel patterns

When looking at daily patterns, the main travel purposes can also be recognised. In Rotterdam two peaks are noticed: one between 8:00-9:00 and one between 16:00-18:00. The first peak is caused by the use of shared e-mopeds for commuting to work or education. The second peak is caused by the commute in the afternoon and leisure traffic to activities after work and is larger than the peak in the morning (Garritsen, 2022). In Spain, the afternoon peak is between 18:00 and 20:00. This peak is also higher than the morning peak (Arias-Molinares et al., 2021). In the market research of Howe and Bock (2018) it also becomes clear that the early evening is the peak usage period. According to Faber et al. (2020) the shared e-moped use in the afternoon peak in the Netherlands can sometime be twice as large as the shared e-moped use in the morning peak. In Spain and the Netherlands, e-mopeds are also used in the night to go home or to train stations from night life activities (Arias-Molinares et al., 2021, Garritsen, 2022). These daily patterns confirm that shared e-mopeds are used for both leisure purposes as well as commuting purposes.

In the months March, May, and October the usage of shared e-mopeds in Spain is the highest. The first two months have peaks because of rising temperatures, while October has the highest peak, because inhabitants are back from their vacation. In popular cities for tourists these peaks are the other way around and the main peaks are in August and January (Arias-Molinares et al., 2021). This again shows that shared e-mopeds are used for both leisure trips and commute trips. Next to that, the seasonal effects indicate that weather conditions have an influence on the attractiveness of shared e-mopeds. This is also shown by Knoope and Kansen (2020). A respondent group of shared e-moped users indicate that they will be more likely to use shared e-mopeds in spring and summer than in autumn and winter. This indicates that weather has an influence on the shared e-moped demand.

2.3 Relation with other modes

Public Transport

Garritsen (2022) has looked into the integration of shared e-mopeds at mobility hubs. He has looked at the trips and defined whether they start or end at a mobility hub. From the results, it becomes clear that 60% of the trips by shared e-moped in Rotterdam started and ended within a 200 meter radius of a bus, tram, metro or train station. This suggests according to Yang et al., 2019 that these trips could have been made by public transport. This high percentage is partly due to the high density of bus and tram stops in Rotterdam. When only looking at metro and train, only 6% of the number of trips substitute public transport trips and 36% of the trips is a first/last mile trip. Over 13% of all the trips in Rotterdam are starting or ending at train stations. This shows that shared e-mopeds are complementary to the train network and serve as a first and last mile solution for the train network. This is also shown in the research of Faber et al. (2020), who show that 14% of the trips by shared e-moped in the Netherlands start or end within a 200m radius of train stations. It is, however, not clear whether all these users also go to or come from the station. They also mention that shared e-mopeds will compete with bus, tram and metro trips.

Montes et al. (2023) conclude from their research that for a complete trip in Rotterdam, the shared e-moped is an interesting alternative, and 9% of the respondents from his survey say that they would prefer the option of a direct travel by shared e-moped rather than going with different public transport options or driving by car. A report of the shared e-moped usage in Rotterdam also shows that shared e-mopeds primarily complement train and metro (Gemeente Rotterdam, 2020). According to Montes et al. (2023) shared e-mopeds are simultaneously competing as well as completing public transport. The relation of shared e-mopeds with public transport seems to be a competing relationship with bus and tram, a both competing and completing relationship with metro and a complementary relationship with train.

Active modes

According to Knoope and Kansen (2020) shared e-mopeds can replace bike trips, as the average distance of shared e-mopes in 2020 was 2.3 kilometre, while the average distance of shared bike trips was 2.1 kilometre (Faber et al., 2020). This shows that these modes compete for the same kinds of trip and shows the competing relationship of shared e-mopeds and shared e-bikes. This relationship is also shown by Aguilera-García et al. (2021) who argue that shared e-bike users are more likely to use shared e-mopeds than non shared e-bike usage. Short shared e-moped trips might also replace walking or cycling trips.

Car

Regarding the car Wortmann et al. (2021) show with a simulation, using the multi-agent transport simulation MATsim, that introducing a shared e-moped fleet of 10.000 shared e-mopeds could replace 23.3% of the total car trips. This shows that shared e-mopeds can replace car trips. A survey in the provinces of North-Brabant and Limburg in The Netherlands along car commuters shows, however, that only 10% of the car drivers might be willing to substitute their car trip with a shared e-moped trip (van Settem et al., 2022). This is a low estimate however, as this research took place in two relatively rural provinces. Since shared e-mopeds mainly occur in urban areas the results of this research might underestimate the willingness to use a shared e-moped.

2.4 Parking

99% of the shared e-mopeds system are free floating systems (Howe and Bock, 2018). This has as an advantage that it is easy to park the shared e-moped. This makes shared e-moped an interesting alternative in cities where there is a lack of car parking spaces (Aguilera-García et al., 2020, Knoope and Kansen, 2020). This however has the disadvantage that sometimes shared e-mopeds block the sidewalks, as is shown by Pérez-Fernández and García-Palomares (2021)). They have developed a methodology to determine possible parking locations, using a GIS allocation model to overcome this parking problem. Municipalities in the Netherlands recognize this parking problem. More municipalities are impleting designated parking areas to overcome this problem (Baggerman, 2022).

2.5 Synthesis

This chapter has as goal to identify the research gap in shared e-moped users and usage. From the literature it appears that the largest group shared e-moped users is young and highly educated. People experience two major barriers, which are having a driving license and having no driving experience on an e-moped. The average trip length of shared e-moped trips ranges from 2.3-5 kilometre. Shared e-mopeds are primarily used for commuting and leisure trips. The leisure purpose causes the late afternoon traffic peak to be substantially larger than the morning peak. Bad weather seems to negatively influence the number of trips, as users indicate that they would be more likely to take a shared e-moped in spring and summer than in autumn and winter. The studies that have been done to the relation of shared e-mopeds with other modes indicate that shared e-mopeds are complementary with train, both complementary and competing with metro and competing with (shared) bike, tram and bus. It should be noted that the number of studies used for these conclusions is limited, which means more research into how these relations work is needed. These conclusions are summarized in an infographic which is shown in Figure 2.1

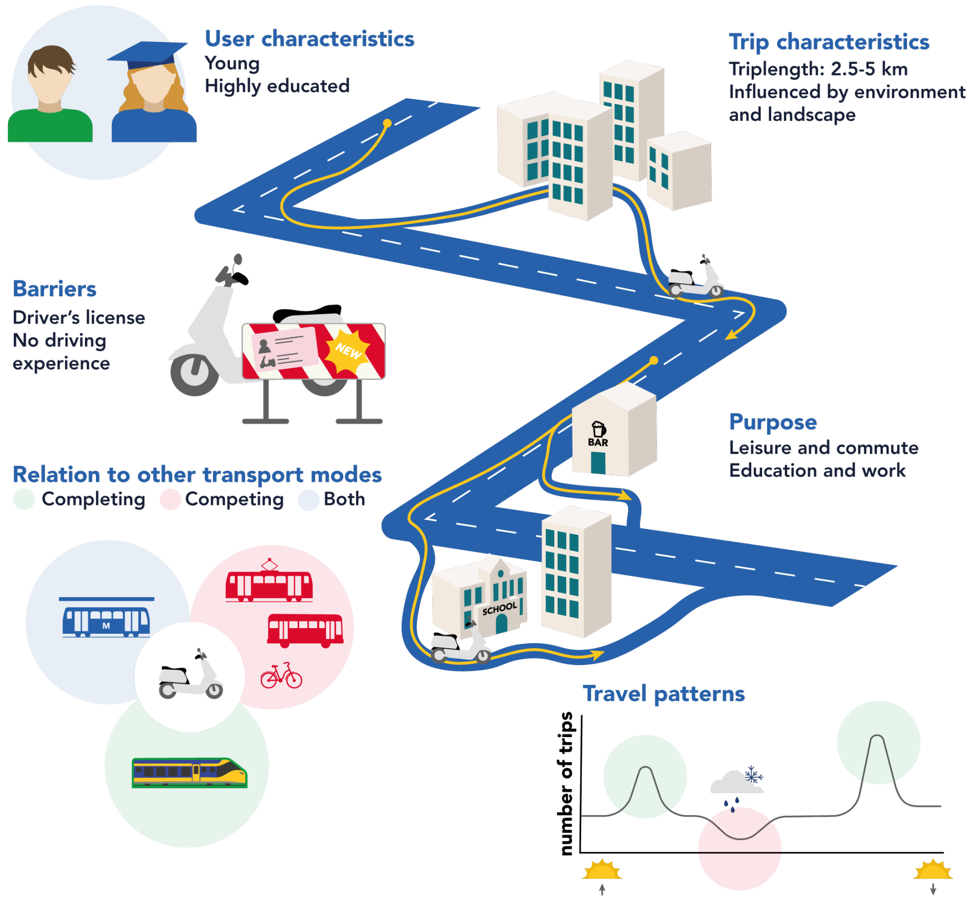

Figure 2.1: Summary literature findings shared e-mopeds

3. Methodology

This chapter describes the methodology used for different parts of this study. Section 3.1 shows how the literature review is performed to get an answer to the first question. Section 3.2 dives into the case study and shows how different parts of it, including a survey at three train stations, are performed. Section 3.3 describes the methods available and the method used for quantifying the influence of factors on the shared e-moped usage in first- and last mile transport to train stations.

3.1 Literature review

The literature review is used to answer the subquestion: 'Which factors influence the usage of shared (e-)bikes or shared e-scooters in combination with train?'. This literature review focuses on the other shared micromobility modes instead of the shared e-moped, as little articles about shared e-mopeds are available in literature. This literature review has as goal to identify possible factors that also might influence the shared e-moped train combination. The search engines SCOPUS and Google Scholar are chosen to find relevant articles to answer the research question. To capture as many relevant papers as possible, three concept groups are defined: micromobility mode, train station, and influencing factors. To find these papers several keywords are used, which are listed in Table 3.1. For train and train station no synonyms such as 'transit' are used, as this literature review aims at getting factors influencing the relationship between shared micromobility and train and not with other modes of transit. The search terms of different concept groups in Table 3.1 are combined together to find the most relevant papers. First, the shared micromobility mode concept groups and the train station concept group are combined, when that results in too many results, the influencing factors concept group is added, to make the results more likely to be relevant.

Table 3.1: Literature review keywords

Concept group	Keywords
Shared micromobility mode	'Shared bike', 'Bike sharing', 'Shared micromobility' , 'Micromobiltiy sharing', 'shared e-scooter'
Train station	'Train', 'Train station'
Influencing factors	'Usage Patterns' 'Factors affecting', 'Factors influencing'

The results of the search queries are analysed on relevance. Firstly, the title of each result is checked for relevance for this literature review. If so, the abstract is read and when the abstract says something about either factors influencing shared micromobility usage or factors or aspects influencing the shared micromobility train combination they are added to the list. Next, the relevant papers are read completely, when nothing about the influence of trains or train stations on shared micromobility usage is mentioned, the paper is emitted. Also, articles about private vehicles are emitted, next to papers that are not accessible due to a paywall. For the literature review, only articles in English and Dutch are used. The search is carried out in the months of January and February 2023. Next to the SCOPUS and Google Scholar search a search with the same queries both in English and in Dutch in Google is done, to find grey literature. This results in two documents from the KiM (Kennisinstituut voor Mobiliteitsbeleid), which is a Dutch research institution with a focus on mobility governance.

3.2 Case study

The case study has as goal to find out the usage patterns of shared e-mopeds in first- and last mile transportation to train stations. This case study tries to answer the second subresearch question: 'What are the usage patterns of the usage of shared e-mopeds in first- and last mile transportation to train stations?'. Usage patterns are defined in this study as the number of trips, the trip distance, the temporal patterns, the trip purpose and the modal share of shared e-mopeds in first- and last mile transportation. These usage patterns can be investigated with the data, while usage patterns such as the frequency of use or the demographics of a user cannot be determined as no user data is available.

The Netherlands has the third largest shared e-moped fleet of the world (Howe et al., 2022) and the largest growing shared e-moped market (Howe and Jakobsen, 2020). Therefore, the case study focuses on shared e-moped usage in first/last mile transportation to train station in the Netherlands. To gather knowledge about the usage patterns, shared e-moped trip data is needed. This data needs to be able to tell something about the trip characteristics. The case study is focused on the whole of the Netherlands, because the results will be better generalisable than when looking at only one city. Figure 3.1 provides an overview where in this section each method for the analysis of the case study is described.

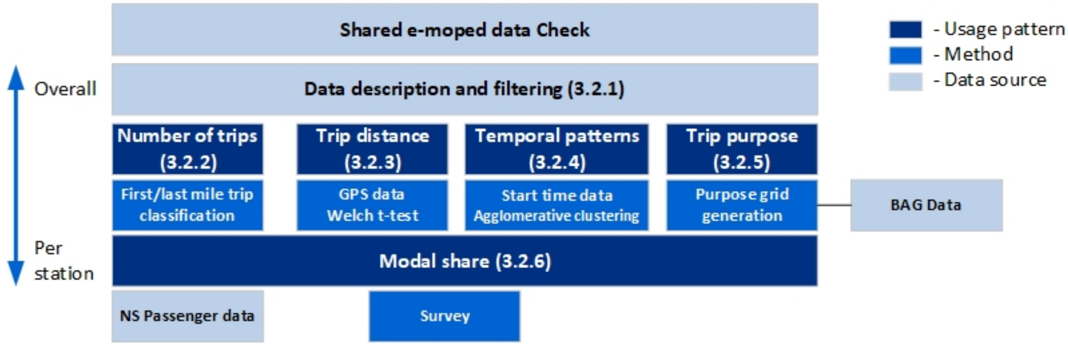

Figure 3.1: Structure of the methods used in the case study described in section 3.2.

3.2.1 Data

CROW, a Dutch research institute for infrastructure, public space and traffic and transport, has a dashboard which shows the live location of shared e-mopeds (CROW, 2022). However, the public version of this dashboard only tells the location of a vehicle and has no information of trips that are made. Data of trips is available on this platform, but access to this data was not acquired. Therefore, all three Dutch shared e-moped providers are contacted for trip data and the dashboard is not used. This case study uses data of shared e-moped trips, which is provided by shared e-moped provider Check. Check is the only provider that is willing to participate. The data is delivered in a csv format. Table 3.2 shows a data sample. The data contains information about the starting and ending place and time and the distance driven. This distance is the distance driven, which is measured by GPS trajectory data by Check.

Table 3.2: Sample shared e-moped data

id	start_time_utc	start_ latitude	start_ longitude	end_time_utc	end_ latitude	end_ longitude	meters_ driven
	2022-09-01 00:00:18.388+00	52.000	4.000	2022-09-01 00:10:45.291+00	52.000	4.000	6019
	2022-09-01 00:00:42.418+00	52.000	4.000	2022-09-01 00:06:51.139+00	52.000	4.000	2402
	2022-09-01 00:00:47.979+00	52.000	4.000	2022-09-01 00:11:40.146+00	52.000	4.000	4290

Data collection period

As is shown in the literature review on shared e-mopeds, a large part of the research on shared e-mopeds has been done during the Covid-19 pandemic. Therefore, to minimise the influence of the Covid pandemic on the data, data from September 2022 and October 2022 are asked at the shared e-moped providers. This also ensures that the influence of the summer holidays is filtered out. This makes the data more reliable to make conclusions about regular usage. However, September is the start of the new academic year, which means more students than usual travel.

Data preparation

The original dataset contains the start and end location and time and the distance driven. To prepare the data for filtering the coordinates need to be transformed and some trip characteristics are calculated. Furthermore, it was noted that with some measurements the longitude and latitude coordinates where switched around. These are switched around in the right order by applying a Python script, which can be found in Appendix A

The coordinates are given in the ESPG:4326 Geodetic system, which is the system that is also used by GPS. This gives the longitude and latitude in degrees. Since the case study is carried out in the Netherlands, these coordinates are translated to EPSG:28992 Amersfoort- RD New coordinate system. This system is calibrated on the Netherlands and the coordinates are in metres instead of degrees. This makes calculation easier. Furthermore, the Dutch government provides geospatial datasets of the Netherlands, which also use the EPSG:28992 coordinate system. The coordinate transformation from ESPG:4326 to ESPG:28992 is done in Python. This code can be found in Appendix A

Before filtering and analysing the data, several trip characteristics are calculated. To get insight into the usage patterns of shared e-moped in different cities, the start and end municipality of each trip is determined. To do this, it is checked whether the start or end location is within the boundary of a municipality. The boundaries of the municipality are collected from the National Geodata Register (PDOK, 2017). The duration of a trip can tell something about the average speed of a trip. Therefore, the duration of a trip is calculated by subtracting the start time from the end time. Lastly, the speed is calculated to help with the data filtering. This makes it possible to remove too slow and too fast observations. The trip speed is calculated by dividing the distance over time. This is all done in Python. The code can be found in Appendix A.

Data filtering

Before the data can be used for analysis, the data must be filtered to remove not possible or relevant values. For the filtering and analysis of the data the Python packages Pandas (McKinney, 2010) and NumPy (Harris et al., 2020) are primarily used. The objective for the data filtering is to remove unreliable observations that do not make sense, are impossible, or that do not serve the purpose of analysing first- and last mile transport trips. Trip distance and trip speed are used as filtering aspects, because trip distance can filter out too short or too long trips and speed can filter out too fast and too slow trips. Firstly trips with no distance, need to be removed, because the trip speed of these trips cannot be calculated.

Filter 1 is designed to remove trips that do not have a trip distance (0 metre). These are trips that are not real trips, as no distance is covered. These observations are likely due to customers noticing shortcomings on the hired shared e-moped such as a broken mirror or a dirty or missing helmet.

Shared e-mopeds in the Netherlands have a top speed of 45 km/h. This means that any observation with a speed larger than 45 km/h is probably a measurement error due to measurement errors by the GPS or other causes. Filter 2, therefore, removes all trips that have an average speed higher than 45 km/h. Furthermore, trips with an average speed which is lower than the walking speed also do not seem logical. This can be caused by people taking a break during the ride or measurement errors. Since no information is available about the trajectory, this data is considered unreliable, and therefore the data needs to be removed. This is done by filter 3 which removes all trips with a speed lower than 5km/h. This directly also filters out negative speeds due to measurement errors.

According to shared e-moped provider Check, all shared e-moped users are willing to walk up to 225 metres to get to a shared e-moped. An assumption is made that the distance travelled on a shared e-moped should be longer than the distance people are willing to walk to a shared e-moped. This distance is also found as the most optimal walking distance from station to share micromobility vehicle

(Böcker et al., 2020; Yang et al., 2019). Therefore, all trips with a distance of less than 225 meter are removed from the dataset.

Next to this, long trips do not make much sense as a first- and last-mile transport trip, as a shared e-moped user is likely to go to a closer train station when travelling long distances, then travel the whole distance on a shared e-moped. Therefore, all trips longer than 20 kilometers are also removed from the dataset, since these are unique measurement and often contain tours or alternative trajectories, which do not serve the purpose of analysing first- and last mile transport trips.

3.2.2 Number of trips

To determine the number of first- and last mile trips, a classification method to determine whether a trip is a first- or a last mile trip to a train station is needed. For classifying a trip as a first- and last-mile trip, two possible methods are considered. The first method is using a radius around a station and classifying a trip that starts or ends within the radius as a first/last mile trip (Yan et al., 2021). The second method is identifying an area with a x-min walking time from the station. The problem with this method, is that this only considers the walkable area. Some shared e-moped trips from the data seem to start within a building. This is due to the fact that around stations there are sometimes skycrapers which influence the accuracy of the GPS (Modsching et al., 2006). Since GPS measurements are often less accurate in areas with high buildings, this method would lead to not classifying all first- or last-mile trips as such, because they do not start or end within the walkable area. Therefore, the radius around the station method is chosen to classify a trip as first- or last mile trip.

Station Classification

According to Böcker et al. (2020) and Yang et al. (2019) shared bikes should be placed within a radius of 200-220 metres of a train station in order to be an attractive option as access or egress mode. It is assumed that this distance is equal for shared e-mopeds, as this is a shared micromobility mode as well. However, the shape and size of the station influence this radius. Each station is represented as a point. Larger stations often have a front area, have more tracks, and are set up larger with shops and access and egress facilities, which leads to longer walking distances, while smaller stations have a way smaller station area, reducing the walking distance to a shared e-moped. To classify the size and function of stations, the station classification KIS station typology is used (van Hagen and de Bruyn, 2002). This station typology aims to reflect the station accessibility in both the network as well as in its local environment. The station typology consists of 6 station types which are shown in Table 3.3.

Table 3.3: NS station classification: KIS typology

Location station / Connections	City center	Urban fringe	Rural
International, Intercity, Sprinter	Type 1		
Intercity, Sprinter	Type 2	Type 3	
Sprinter	Type 4	Type 5	Type 6

Radius determination

The KIS station typology is used to determine the radius. This radius is determined by looking at the size of the stations and surrounding environment. For type 1 stations, a standard radius of 350 metres is used, as these stations are urban stations with a large station front area. Besides, there is often limited space for shared e-moped close to the stations, because they are not allowed to be there by regulation. For type 2 stations, a standard radius of 250 metres is assumed, since these stations are set up a bit larger than other types of stations, since they often have a lot of public transport around them.

Type 3 stations are given a standard radius of 200 metres, as these stations are smaller than type 2 stations, and have in general less of front area. Type 4 stations are also given a standard radius of 200 metres, as these stations in the centre of smaller towns are sometimes also set up larger. For type 5 stations a radius of 150 meters is used. These are often small stations, and making the radius smaller than the suggested 200 meter by the literature reduces the chance that a trip is wrongly identified as a first- or last mile trips. This is shown in Figure 3.2. In the top of the figure shared e-moped users using the train station are unlikely to park their shared e-moped directly at the border of the 200 metres, because it is possible to park much closer. These trips are therefore probably not first- or last mile trips, but residential or commercial trips.

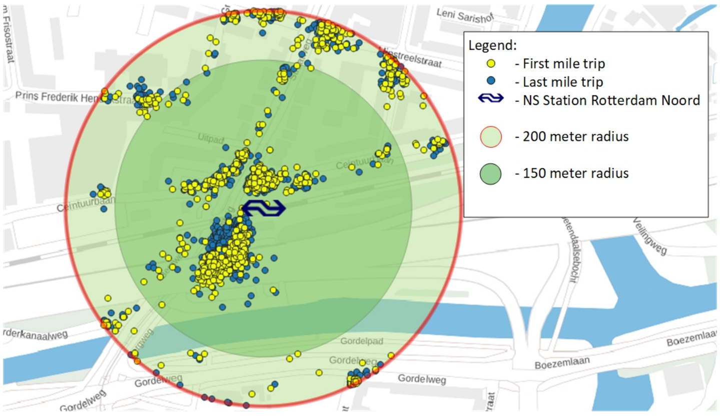

Figure 3.2: Example first- and last mile trips Rotterdam-Noord

Individual station radius determination

The radius size to classify all first- and last mile trips depends on both the station size and the service areas of the shared e-moped network. Therefore, each station in the dataset is checked manually for the presence of a shared e-moped network in the original radius. Second, is it checked whether all the closest parking spots for microvehicles that are in the service area from all directions are within the radius of the station. When that is not the case, the radius is enlarged to the furthest closest microvehicle parking point. A microvehicle parking point includes special parking points or a sidewalk where it is possible to park a microvehicle without blocking the side walk. This has resulted in several changes to the radius. Example of changes are Amsterdam Central station from 350 to 400 meters and Zwolle from 250 metres to 350 meters. These changes are not the only changes. An overview of the radius for each station can be found in Appendix B. If the radius does not match with the standard radius of each type of station, this means the radius has been changed.

Classification

A Python algorithm checks for each trip whether it starts or ends within a radius of a starts. It does so by running through each city and then through the stations belonging to that city. This results in 4 additional columns in the dataset which are: 'First Mile', 'Last Mile', 'Station_FM' and 'Station_LM', which represent for each trip whether a trip is a first- or last mile trip and to which or from which station it goes. The station item gets no value assigned when the trip is not a first or last mile trip. Separate station fields for first and last mile are used, because there are trips which go from one train station to another train station. If this is the case, a trip is determined as a first mile trip if it goes from a station of a higher type to a station of a lower type. A trip is classified as a last mile trip if a trip goes from a lower type of station to a higher type of station.

3.2.3 Trip distance

The trip distance of each trip is measured by the shared e-moped provider Check with GPS data. The total distance of a trip is given in the delivered data. For comparing the average distance in first mile, last mile and non train related transport a statistical test is used to conclude whether the differences in average are significant differences. The sample size of each dataset is larger than 100,000. The assumption is made that the samples are independent, since no user information is available from the data. This suggests that the independent t-test is an appropriate method to determine whether the averages of both samples differ significantly. The sample size of the non train related database is eight times larger than the first or last mile dataset. This makes the Student's t-test less appropriate as it assumes equal variances and equal sample sizes. Therefore, Welch's t-test is used. This test is able to perform a t-test with unequal variances or sample sizes and performs approximately similar as Student's test when sample size and variance are in fact equal (Welch, 1947) The formula for Welch's t-test is given in equations 3.1 and 3.2.

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{s_{\bar{X}_1}^2 + s_{\bar{X}_2}^2}} \tag{3.1}$$

$$s_{\bar{X}_i} = \frac{s_i}{\sqrt{N_i}} \tag{3.2}$$

where:

$\bar{X}_i$ = Mean of sample i
s_i = Standard deviation of sample i
N_i = The sample size of sample i

For comparing the distance on station based level, a scatterplot with the average distance in first- and last mile transport is made, to see whether there is a relation in the data and to see at which stations these two distances may differ.

3.2.4 Temporal patterns

The start time of a trip is given in the data. This start time is used for determining the time of a trip. A Python algorithm is made to calculate the average number of trips on each weekday. To check whether the number of trips differ per week and weekend day a Welch's t-test (see Equations 3.1 and 3.2 is performed, since the sample sizes again are not the same. To observe the overall patterns per day all first- and last mile trips are combined and plotted for each weekday per hour. This gives insights into the overall usage per day. In the dataset 40 stations are present. For readability purposes, these stations are not looked at one by one in this study. Therefore, clustering is used as a method to see whether there are similar stations which show the same temporal patterns per hour. This can tell whether certain station based or spatial factors have an influence on the temporal usage patterns.

For this analysis agglomerative clustering is used, because this enables the making of a dendrogram, which shows how much distance there is between each cluster (Nielsen, 2016). This provides insights into how the clusters are linked. Another clustering algorithm such as k-means is more of a black-box and only shows the results. Agglomerative clustering starts with the each datapoint as it's own cluster. This is called a bottom-up approach (Nielsen, 2016). It then matches the closest two clusters into one cluster and continues until there is one cluster left. This matching is based on a linkage criteria. For this study the linkage criteria proposed by Ward (1963) is used. This linkage criterion tries to minimize the deviation of points from their corresponding clusters. Ward (1963) is shown in Equations 3.3 and 3.4. The algorithm tries to find the minimum distance, shown in equation 3.4 between two clusters and matches that two clusters into one (Ward, 1963).

$$ESS(X) = \sum_{i=1}^{N_x} \left| x_i - \frac{1}{N_x} \sum_{j=1}^{N_x} x_j \right|^2 \tag{3.3}$$

where:

$ESS(X)$ = Error Sum of squares
$|.|s_i$ = Norm of the vector
N_x = The sample size of sample x

$$D(X,Y) = ESS(XY) - [ESS(X) + ESS(Y)] \tag{3.4}$$

where:

$D(X,Y)$ = Distance between cluster X and Y
$ESS(XY)$ = Error sum of squares combined cluster XY
$ESS()$ = Error sum of squares cluster

3.2.5 Trip purpose

The trip purpose of a trip has to be determined without having to ask the shared e-moped user, since no user data of a trip is available. Pluister (2022) has used a 100x100 metre grid with building characteristics to determine the purpose of each grid cell. He then assigns a trip ending in that cell with the corresponding trip purpose. This has been done for three stations: Arnhem Central, Eindhoven Central station and Amsterdam Sloterdijk. The same methodology can be used to determine the purpose of a shared e-moped trip. This is done for all cities that are part of the case study.

Grid generation methods

Pluister (2022) has generated his grid by using SPOTinfo data. This is a commercial database, upon which no access is acquired. Therefore, an alternative method for the grid generation has to be used. The first possible method is using the CBS vierkantstatistieken. This is a 100x100 metre grid, which describes the social-economical statistics of each cell and the distance to services (CBS, 2022). This, however, does not contain any information about offices, which means it is not suitable to use for this purpose.

The second possible method is using the BAG database of the national government. In this database, all Dutch buildings are registered. An important feature of this database is the usagefunction attribute. This usage function says what the current function of the building is. This can consist out of the following functions: residential, meeting , prison, healthcare, industrial, office, accommodation, education, sport, shop, other function (Kadaster, 2019). A limitation of this dataset is that not every building has a known usage. Nonetheless, this database is used, because when making a grid of this database, the missing building function of one building will not influence the building function of a grid cell.

The generation of the grid is done in a radius of 15 km around all cities that are part of the case study. This ensures that all trips from the data are within the grid, which means they can be assigned a trip purpose. This results in a 100x100 grid for every city which is shown for the city of Leeuwarden in Figure 3.3. A 100 x 100 grid has the advantage of not over aggregating results, as well as not being too overfit, as one cannot predict to which building someone goes.

Assigning usage function to grid cell

The usage function assigning to a grid cell consists of multiple steps. These steps are shown in Figure 3.4. First, for each building, it is determined whether a building is a home or an activity building. All buildings that have multiple functions or one function, which is not a home function, are determined to be an activity building. Only buildings that function just as residential building are considered as 'home' buildings. From the 'Activity' buildings the residential function is removed from the data to ensure that these buildings do not contribute to residential function being the most frequent value in a cell. This function appears more often and it would lead to competition between different activity functions, versus no competition for residential functions, leading to an over representation of the residential usage function

The goal of determining the trip purpose is to observe the trends and shares of trip purpose of shared e-mopeds in first- and last mile transportation to train stations. Therefore, five different trip purposes are determined to make the findings more usable for the main research question: Education, Home, Leisure, Work and Other. Since multiple building types have the same trip purpose, the building functions are mapped to a trip purpose. Figure 3.4 shows this mapping. Gathering function and shop

Figure 3.3: Example 100x100 grid with 15 km radius of Leeuwarden

function for example are different building types, but have the same trip purpose: Leisure. The mapping of the building functions results in the purpose per building.

Then, the occurring purposes of each building in one cell are determined. The most frequent occurring value is considered to be the trip purpose of that cell. This means information about other purposes in the cell is lost and not considered. In case of ties the value with the first letter in the alphabet gets assigned as value. This prevents the cells from having no value at all.

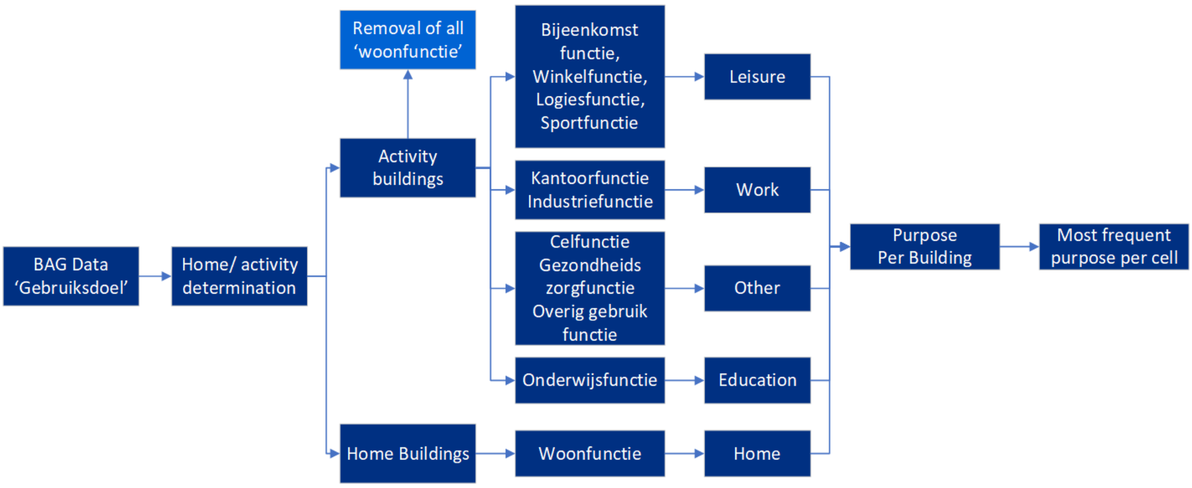

Figure 3.4: Assigning usage function to grid cell

Not all grids with shared e-moped trips in it have a cell purpose after running the algorithm in QGIS. This is solved by selecting the most frequent occurring purpose in the eight neighbouring cells. This is only done if there are 2 or more neighbour cells with a purpose. This algorithm results in a grid which is shown in Figure 3.5

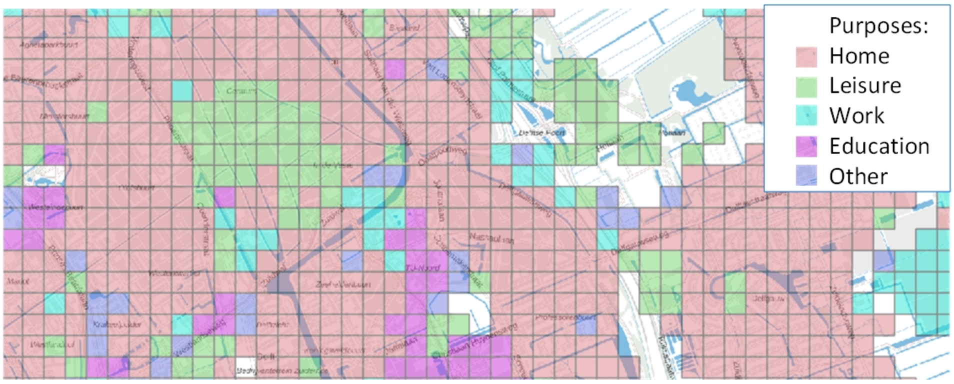

Figure 3.5: Example purpose grid of part of Delft.

Assigning trip purpose to trip

The trip purpose is only calculated for first- and last mile trips. This means the starting coordinates of a trip are used to determine the purpose of trip based on the origin of a first mile trip. The end coordinates of a last mile trip are used to determine its trip purpose. The trip purpose is determined based on the grid cell the coordinates are in. The trip gets the trip purpose assigned of the grid cell it starts in (first mile) or ends in (last mile).

If the cell where a trip starts or end has no purpose, the trip is assigned a leisure purpose. This is caused by the fact that the grid is generated by the usage function of buildings, meaning that when a cell has no purpose after the algorithm there are no buildings in the cell or the neighbouring cells. This is the case for example at the beach or at parks, meaning that these trips get assigned the trip purpose Leisure. In first mile transportation 0.31% of the trips got initially no value assigned, in last mile transportation 0.27% of the trips got no value assigned.

3.2.6 Modal share & Survey

The modal share of shared e-mopeds is calculated using NS passenger data. This data describes per hour the number of passengers entering and leaving the station. The number of passengers is set to 0, when there are less than 25 passengers per hour. This is due to privacy reasons. To calculate the modal share per day, a dataset with NS train passengers per day is used. Both these datasets consist of NS trains only, which means that passengers taking trains from other companies that offer a train service are not captured. These number are therefore multiplied by the ration between the NS train passengers and train passengers according to the Integrale Mobiliteitsanalyse 2021, which uses data of 2018 (Ministerie van Infrastructuur en Waterstaat, 2021). This gives a good indication of the total number of passengers.

Survey

In the previous method the assumption is made that all trips starting or ending near a train station within a certain radius are first- and last mile trips. In reality, people might park near the station to go to another location. To see whether this is indeed the case a survey is performed on three stations.The survey aims at determining the percentage of users which arrive at or depart from the train station by shared e-moped that actually use the train and do not have another destination. Therefore, the shared e-moped users are asked one question: 'Do you come from or do you go to the station?'. Only one question is asked because shared e-moped users departing from the station can only be identified as soon as they start renting a shared e-moped. Since shared e-moped users pay by minute, only one question is asked to increase the participation rate. No personal data is gathered. This experiment has been approved by the HREC committee of the TU Delft, of which the approval can be found in the appendix. Each answer is noted down and the time of the answer is also captured. The survey is performed in time slots from 7:00-9:00, 12:00-14:00 and 16:00-18:00 to capture the morning, afternoon and non peak periods.

Station typology

The survey is carried out, because there are often other points of interest near larger train stations, which means people could park at the station but not go to the station. Since there are no major points of interest near type 5 and type 6 stations of the KIS station typology (van Hagen and de Bruyn, 2002), it is assumed that every shared e-moped user that parks near a station of type 4, 5 or 6 also goes to the train. For type 4 stations, there is only one station in the dataset. Type 1, 2 and 3 stations often do have points of interest nearby, which means the survey is performed at at least one station of type 1, 2 and 3.

Station selection

The stations where the survey is carried out are selected based on the highest number of shared e-moped trips that arrive at and depart from the station. In this way, the chance of getting not enough respondent is reduced. This means that for type 1 stations the survey is done at Rotterdam Central Station. For type 2 stations, the survey is performed at Breda. For type 3 stations, the station with the highest number of shared e-moped trips is Rotterdam Blaak. However, this station is in the middle of the city centre, near a big tourist attraction: De Markthal and several other toursist or commuting attractions. This means Rotterdam Blaak will attract and generate more trips due to the points of interest in the near surroundings, which makes the station less representative for other type 3 stations. Therefore, the next highest number of shared e-moped trips is chosen: Amsterdam Sloterdijk. This station is not located in the city center, and has more similar station surroundings compared to other type 3 stations than Rotterdam Blaak.

Survey spot selection

The survey is carried out at one or two spots of the station. To identify the spot that is used for the survey, the number of shared e-moped trips in first and last mile transportation around the station is plotted in a 50 by 50 metre grid, which can be seen in Figure 3.6

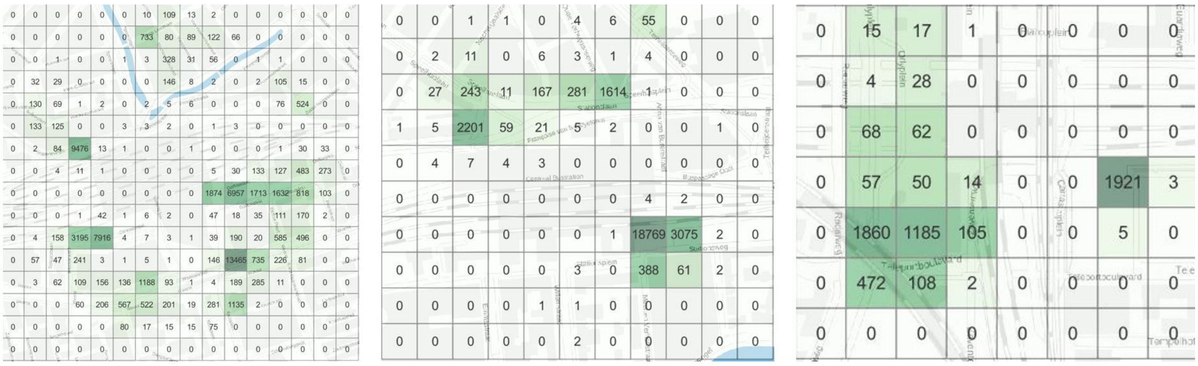

Figure 3.6: 50 by 50 metre grid with number of trips starting and ending around each station. Left:Rotterdam CS, center: Breda, right: Amsterdam Sloterdijk

For Rotterdam Central Station, the number of points of interests at each side of the station is different. At the south side of the station many points of interest are present, while at the north side of the station there are mainly residential buildings. Therefore, two sides of the station are picked. For Breda, the choice is made to observe the parking area in the southeast side. For Amsterdam Sloterdijk, the observation area is the area in between the two station, because in total the most number of shared e-moped trips depart from and arrive at this area. For each station, the greatest summation of two neighbouring cells is determined as the best place to perform the survey. This maximizes the chances of getting enough respondents. At the side, it is determined whether, there is a safe observing location, when that is not the case another location is chosen.

Calculation

The number of shared e-moped trips from the data only considers the data of one provider. The modal share of the Check shared e-mopeds can be multiplied by the number of shared e-moped providers in the city. Observations from practice show however that the usage per provider might differ and is not equal. This is covered by accounting for the vehicle fleet size and usage ratios, which is shown in section 5.6.

The number of shared e-moped trips per hours is then divided by the number of train passengers per hour to calculate the modal share of shared e-mopeds per hour. When calculating the modal share per day, the total shared e-moped trips per day is divided by the total number of train passengers. This leads to a modal share of shared e-mopeds both per hour and per day for all train stations in the case study.

3.3 Statistical model

The statistical model method has as goal to answer the subquestion: 'What is the best performing model structure to quantify the influence of factors on the usage patterns of shared e-mopeds in first- and last mile transportation?' The answer on this question also helps to answer the main research question. To find the best performing model structure, first the most appropriate method has to be chosen. The statistical method has to provide a way to estimate and explain relationships between the different factors and the shared e-moped usage in first- and last mile transportation. Three methods might be suited for this. The first possible method is regression. Regression is used to estimate relationships between two or multiple variables. It does so by fitting the data to a certain line minimizing the squared error between the model result and the data. This results in beta coefficients, which say something about the relationship between the two variables. Another possible method is using a neural network. This is a machine learning algorithm that can be used for non-linear statistical modeling. The last candidate method to quantify the influence of factors is discrete choice modelling. Discrete choice modelling is about describing, predicting and explaining the choice between two or multiple alternatives (Bierlaire, 1998). For discrete choice modelling a choice set with alternatives is needed.

According to Shin (2021) one of the benefits of regression compared to a neural network is that the model is less of a black box and easier to explain. Also a regression model can tell which variables are significant and which are not. Furthermore, the variability captured by the model can be explained with statistical measurements (Shin, 2021). On the other hand, a neural network often makes more accurate predictions. It is also able to capture complex non-linear relationships (Tu, 1996). Next to that, Tu (1996) also mentions that a neural network needs less formal statistical training. The disadvantage of a neural network, however, is that is prone to overfitting (Tu, 1996). If a model is overfitted, it means it only predicts accurate for the trained dataset and not for new data. Discrete choice modelling needs a choice set for the user. Since, no user data is available, the choice set of each user is not known. Therefore, discrete choice modelling would need many assumptions, which makes it less suitable for this study.

Since the goal of the model is to estimate and explain relationships between different variables, a regression model is considered as the best option. A regression model can more easily be explained and is less of a black box compared to a neural network. Furthermore, the coefficients of a regression model can be tested on statistical significance which can help to identify the influencing variables on shared e-moped usage in first- and last mile transportation to train stations. Therefore, multiple linear regression is chosen as method.

The conceptual framework in Figure 6.2 shows that there are multiple factors that influence the usage of shared e-mopeds in first- and last mile transportation. Single linear regression only considers one variable and an intercept. Therefore, multiple linear regression is used. This method provides the ability to identify the influence of multiple variables at the same time.

3.3.1 Multiple linear regression

A multiple linear regression model describes the relationship between the response y and predictors x. The formula for a multiple linear regression model is shown in Equation 3.5 (Montgomery et al., 1982).

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \epsilon \tag{3.5}$$

where:

y = response variable
β_i = regression coefficient of predictor x$_i$
x_i = predictor variable

The parameters β_i represent the expected change in the response variable y per unit change in x_j. To estimate the model parameters multiple linear regression uses the method of least squares. This method tries to minimize the error between the original data y and the fitted data $\hat{y}$. The error can be written as in Equation 3.6. The least squares methods tries thus to minimize the sum of the errors. The formula for the least squares calculation is shown in Equation 3.7.

$$e_i = y_i - \hat{y}_i \tag{3.6}$$

$$SSE = \sum_{i=1}^{n} \hat{e}_i^2 = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{3.7}$$

where:

y_i = orginal data point of observation i
$\hat{y}_i$ = fitted data point of observation i
e_i = error of observation i

The multiple regression model is based on five assumptions. First of all, the relation between the response variable and the predictor variable should be a linear relationship. Next, the predictors should not bee too highly correlated with each other. The phenomenon of too highly correlated predictors is called multilcollinearity. The observations are independent and randomly selected. The distribution of the residuals are normally distributed with mean 0 and variance σ. Lastly, the variance is constant throughout the model.

3.3.2 Finding the best model

First, the variables that are added as independent variables in the multiple linear regression model have to be determined. Therefore, conceptual frameworks of the expected relationships in from the literature study and the case study are made. These two conceptual frameworks are merged together to identify possible relevant independent variables. These variables are quantified and prepared, such that they can be used in the multiple linear regression model. This includes the translation of binary (yes/no) variables into dummy variables (1/0). To prevent the influence of multicollinearity between the different independent variables, the data, both the dependent and independent variables, are standardized by using the unit normal scaling. The equation for unit normal scaling is shown in Equation 3.8 (Montgomery et al., 1982).

$$z_{ij} = \frac{x_{ij} - \bar{x_j}}{s_j} \tag{3.8}$$

where:

z_{ij} = The standardized value of observation i of variable j
x_{ij} = The orignal value of observation i of variable j
x_j = The mean of variable j
s_j = The standard deviation of variable j

To find the best model, the methodology proposed by Montgomery et al. (1982) functions as inspiration for the approach. Montgomery et al. (1982) proposes to first fit the full model with all variables. Then a residual analysis is performed, which checks whether the residuals fulfil the assumptions for multiple linear regression. In addition, outliers with an studentized residual higher than 3 (Borse, 2020).

Next, forward selection is chosen as method to see which variables have to be added. Forward selection begins with an empty model with only the intercept β_0 in the model. The first variable that is added is the variable, which has the highest correlation with the dependent variable. The second variable that is added, is the variable with the highest partial correlation after adding the first variable. This procedure is continued until the model performance does not improve anymore (Montgomery et al., 1982). In each step, it is checked whether all variables are still significant at a 95% confidence level. Furthermore, to prevent a high impact of multicollinearity among the predictors no Variance inflation factor can be higher >10 (Montgomery et al., 1982). A variance inflation factor(ViF) shows by what extent the variance in this variable is explained by the variance of the other independent variables in the model. The equation for a variance inflation factor is shown in equation.

$$VIF_i = \frac{1}{1 - R_i^2} \tag{3.9}$$

where:

VIF_i = Variance inflation factor of variable i
R_i^2 = coefficient of determination of predictor variable i by other variables

After each run, the model runs are compared on performance by the adjusted R^2 score. The adjusted R^2 score tells how much of the variance in values is captured by the model (Miles, 2005). Adding a new variable always improves the regular R^2 score. The adjusted R^2 indicator also takes into account the number of variables added to the model, which means the model performance only improves when a variable has a significant effect. The equation for the adjusted R^2 is given in equation 3.10. The best model is eventually the model with the highest adjusted R^2 score, which fulfills all the multiple linear regression assumptions.

$$Adjusted\ R^2 = 1 - \frac{\frac{SS_{residuals}}{n-k}}{\frac{SS_{total}}{n-1}} \tag{3.10}$$

where:

$SS_{residuals}$ = Sum of squares of difference between predicted value and real value
SS_{total} = Sum of squares of differences between overall Y mean and each Y value
n = number of data points
k = number of parameters fit

3.3.3 Validating the model

To see whether the model gives reliable conclusions, the model needs to be validated. To do this k-fold cross validation has been applied. This means the data is split in k-parts and the model coefficients are estimated on k-1 parts of the data (Kargın, 2021). For this study 5-fold cross validation is applied. This means the data is splitted into five equal parts, where these parts consists out of randomly selected measurements. Five different models are built with the same variables as the full model, all based on different combination of 4 parts with 20% of the data.

To see whether the model has a high internal explanation power, the signs and coefficients of all models are checked whether they still have the same sign and are signficant. When this is the case it can be concluded that the model can draw reliable conclusions about the influence of certain factors. The adjusted R^2 score is also checked to see whether this does not variate too much between the different models. This is to see whether it is still able to explain approximately the same amount of variance. If this is not the case, the explanation power of the full model will be lower.

To assess the predictive power of the model, the Root mean squared deviation is calculated for each model for both the training data and the test data. The equation for calculation the root mean squared error (RMSE) is given in Equation 3.11

$$RMSE = \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{N} \tag{3.11}$$

N = number of observations
y_i = y value of i-th observation
$\hat{y}_i$ = value of i-th prediction

4. Literature shared micromobility train combination

This chapter describes the results of the literature study to factors influencing the use of the combined shared micromobility train mode. The chapter aims to answer the first subquestion: ‘Which factors influence the usage of shared (e-)bikes or shared e-scooters in combination with train?’. The methodology of the literature study is described in section 3.1. This methodology results in 34 studies that are used for the study, of which 2 sources are grey literature.

Several studies specifically mention that a train station generates and attracts more shared bike trips (Tran et al., 2015;Croci and Rossi, 2014;Guidon et al., 2020). This shows a completing relationship between shared bike and the train. Other studies specifically mention that a train station generates and attracts more shared e-scooter trips (Kjaerp et al., 2020, Tuli et al., 2021, Oehme et al., 2022). This shows that shared e-scooters also have a completing relationship with the train. This indicates that both shared (e-) bikes and shared e-scooters are used for first- and last mile transport to train stations.

Table 4.1 shows a summarized overview of the literature review. It shows the effect of factors on usage of the shared micromobility train mode, that are mentioned by at least four different sources. This table provides a quick overview of the findings. A factor is considered as having an influence on the shared micromobility train mode, when it increases or decreases the usage of the micromobility mode or when a factor influences the integration between the two. In appendix H an overview of all mentioned articles and all factors can be found. Vehicle availability is mentioned by the most number of articles as positive influence. Walking distance from station to micromobility mode and rain are the two factors with a negative influence mentioned most. The factors are divided into four categories: micromobility system factors, station accessibility, environmental factors, and temporal factors. The factors are discussed in more detail in this chapter, including factors that are not mentioned more than four times.

Table 4.1 also shows that there are no major differences detected between different modes. This can be seen by the fact that no column has no signs for each mode. The only difference is the weekend factor. For shared bikes, this factor is not mentioned, while for shared e-bikes this factor has a negative influence. For shared e-scooters on the other hand a weekend day has a positive influence. This shows that the weekend factors works different for different modes.

Section 4.1 describes the micromobility system characteristics that have an influence on the usage of shared micromobility modes and train. Section 4.2 shows which station characteristics influence this combination, after which section 4.3 gives the spatial characteristics, both infrastructural and land use, that influence the shared micromobility train combination. Section 4.4 describes which temporal characteristics influence the combination. Lastly, section 4.5 answers the subquestion and gives a conclusion .

Table 4.1: Overview of factors found per article. MM stands for micromobility. The bold columns are factors, which are mentioned the most either positive or negative.

Author	Mode	Service area size	Parking capacity stations	**Vehicle availability**	**Walking distance**	Quality of train service	Presence of other modes	Points of interest	Recreational land use	Commercial land use	City center	Population density	Quality bike infrastrucure	**Rain**	Temperature	Weekend
Adnan et al. (2019)	bike						-							-		
Böcker et al. (2020)	bike		+	+				+			+	+				
Croci and Rossi (2014)	bike							+		+						
Faghih-Imani and Eluru (2016)	bike								+					-	+	
Faghih-Imani et al. (2017)	bike			+				+								
Guidon et al. (2019)	bike					+			+	+			+			
Guidon et al. (2020)	bike	+								+		+				
Jimenez and M.Nogal (2021)	bike	+		/												
Jonkeren et al. (2018)	bike			+	-	+										
Jorritsma et al. (2021)	bike			+								+	+			
Ma et al. (2020)	bike				-											
Tran et al. (2015)	bike			+												
van Mil et al. (2021)	bike					+	-						+	-	+	
Arias-Molinares et al. (2021)	e-moped	+		+											+	
Caspi et al. (2020)	e-scooter									+	+					
Dibaj et al. (2021)	e-scooter								+		+					
Heumann et al. (2021)	e-scooter							+								+
Hosseinzadeh et al. (2021)	e-scooter				-				+							
Jiao and Bai (2020)	e-scooter										+	+				
Kjærup et al. (2021)	e-scooter			+				+	+				+			
Mohammadian et al. (2022)	e-scooter					+				+			+		+	
Noland (2019)	e-scooter													-		+
Oehme et al. (2022)	e-scooter					+										
Kjaerp et al. (2020)	e-scooter							+	+							
Sherrif et al. (2022)	e-scooter	+														
Tuli et al. (2021)	e-scooter								+			+		-	+	+
Wang et al. (2022)	e-scooter		+		-											
Liao and Correia (2022)	e-MM					+		+				+	+	-	+	-
Moinse (2022)	MM				-	+	-						+			
Oeschger et al. (2020)	MM		+	+	-							+				
Reck et al. (2020)	MM		+	+												
Schwinger et al. (2022)	MM								+							/
Torabi et al. (2022)	MM			/			-			+						
Vale (2021)	MM	+				+										
Type of influence		+		**+**	**-**	+	-	+	+	+	+	+	+	**-**	+	/
Number of times mentioned		5	4	**11**	**6**	8	4	7	8	6	4	7	7	**6**	6	5

4.1 Micromobility system factors

Size of service area (+)

The size of the service area is positively influencing the number of trips. Examples from Lisbon and Spain suggest that more trip are made when the service area is bigger (Vale, 2021 ; Arias-Molinares et al., 2021). In addition, the number of shared e-scooter trips is reduced in Manchester due to geofencing, which indicates that a smaller service area reduces the number of trips (Sherrif et al., 2022). In Ireland the deployment area of the shared e-scooter is crucial to increase the number of shared bike trips (Jimenez and M.Nogal, 2021). Lastly, the larger service area size in Zürich compared to Bern, leads to more shared bike trips in Zürich (Guidon et al., 2020), indicating that the service area indeed positively influences the number of trips.

Station density & capacity (+)

With station based shared micromobility systems, people need to place their vehicle in a station when they have reached their destination. The density of these stations positively influences the attractiveness of the shared micromobility mode. In Lyon, and Spain the station density and parking capacity at these stations increase the number of shared bike trips (Tran et al., 2015 ; Faghih-Imani et al., 2017). For station based shared e-scooters the station density and parking capacity in Chicago also have a positive influence on the number of shared e-scooter trips (Tuli et al., 2021). In Vienna the parking capacity at shared micromobility stations also positively influences the nuber of shared bike and e-scooter truips (Reck et al., 2020).

Price (-)

In Belgium and The Netherlands the rental cost of a shared bike negatively influences the usage of shared bike in last mile transportation (Adnan et al., 2019; van Mil et al., 2021). Kjærup et al. (2021) claims that in Denmark a high priced shared e-scooter rental drops down the shared e-scooter demand. Next to price, Wang et al. (2022) claims that fare integration, so paying for the shared micromobility mode and the train via one platform or card, can improve the attractiveness of the combined shared micromobility train mode.

Vehicle availability(+)

Tran et al. (2015) and Faghih-Imani et al. (2017) show in Lyon and Spain that having a vehicle available at a bike station increases the number of shared bike trips. This is supported by Böcker et al. (2020) who claim that in Oslo the availability of shared bikes is crucial for the usage of the shared bike train combination. In the Netherlands the shared bike availability has a positive influence on both the number of trips (Jorritsma et al., 2021) as well as the shared bike train combination (Jonkeren et al., 2018). In contrast with this Jimenez and M.Nogal (2021) claim that the availability of a shared bike does not influence the bike sharing demand. For shared e-scooters the availability of vehicles also has a positive influence on the number of trips in Denmark and Zürich (Kjærup et al., 2021 ; Reck et al., 2020). Oeschger et al. (2020) conclude from a literature review that vehicle availability has a positive influence on the integration of shared micromobility and public transport. Next to availability, non availability has a significant negative impact on the shared bike demand, since users may sometimes not be sure that there is a bike available (Jorritsma et al., 2021). The greater part of the literature concludes that vehicle availability positively influences the number of shared micromobility trips positively. This also means that non-availability negatively influences the demand, as is shown by Jorritsma et al. (2021).

Summary

- The size of the service area positively influences the number of trips of a shared micromobility mode.
- Station density and parking capacity of station based systems positively influence the usage of a stationbased shared micromobility mode.
- The rental price of a shared micromobility vehicle negatively influences the usage of a shared micromobility system
- The availability of a shared microvehicle positively influences the usage of shared micromobility system.
- The non-availability of a shared microvehicle negatively influences the usage of a shared micromobility system.

4.2 Station accessibility

Walking distance (-)

The walking distance from a shared micromobility vehicle to a station or the other way around negatively influences the number of shared micromoiblity train users. In a comparison between three different shared bikes in Delft (OV-Fiets, Swapfiets and Mobike), Ma et al. (2020) show that the walking distance from the train station to a shared bike influences the attractiveness of the combination. The shorter the walking distance is, the better the integration is. This is supported by Oeschger et al. (2020) who show in a literature review to shared micromobility and public transport that a shorter walking distance increases the attractiveness of the shared micromobility train combination. The ideal walking distance in Oslo is 200-225 metres (Böcker et al., 2020). Besides, the walking distance, the safety of the walking infrastructure also positively influences the attractiveness (Oeschger et al., 2020). The walking distance also negatively influences the relation between shared e-scooter and train in Louisville (Hosseinzadeh et al., 2021). This is supported by the literature reviews to shared e-scooters of Wang et al. (2022). Lastly, Moinse (2022) conclude from his literature review that a shorter walking distance increases the number of shared micromobility trips. All in all, the walking distance from station to a shared micromobility mode negatively influences the integration between shared micromobility and the train.

Quality of train service (+)

Quality of train service is defined as the frequency of trains at the stations and the destinations that can be reached. The quality of the train service in the Netherlands increases the attractiveness of the bike-train combination. Furthermore, people are willing to cycle further to a station with a higher quality of train service (Jonkeren et al., 2018 ; van Mil et al., 2021). The same trend is observed in Karlsruhe for shared e-scooters (Oehme et al., 2022). In Chicago, train stations with a higher quality of train service also attract more shared e-scooter trips (Mohammadian et al., 2022). For shared e-bikes yields that train stations with a high quality of service also attract more trips in Zürich (Guidon et al., 2019), which is supported by Liao and Correia (2022) who conclude from their literature review towards shared e-modes that there are more shared e-bike trips towards train stations with a high quality of train service. Vale (2021) and Moinse (2022) also claim that for shared micromobility modes the quality of train service positively influences the number of trips and the integration of shared micromobility with the train.

Parking availability(+)

Near the European stations shared micromobility parking availability increases the attractiveness of the shared micromobility train combination (Moinse, 2022). The parking availability correlates with the walking distance, as stations having a close micromobility vehicle parking available, automatically also have a short walking distance. Parking availability also increases the number of bike trips in the Netherlands as well as the attractiveness of the combined mode (van Mil et al., 2021;Jonkeren et al., 2018).

Alternative modes (-)

Having multiple other transport modes, such as metro, tram and bus available at a station reduces the chance that a shared micromobility vehicle is chosen as first- or last mile mode, since there are more alternatives available (Moinse, 2022). In the Netherlands having more alternatives available also reduces the number of shared bike train users (van Mil et al., 2021 ; Jonkeren et al., 2018) Having alternative modes available at a train station, thus reduces the number of shared bike trips towards and from a train station. Torabi et al. (2022) show that this also yields for both shared e-scooters and shared e-bikes.

Summary

- The walking distance from station to shared micromobility negatively influences the usage of the combined mode.
- The quality of train service at a station positively influences the usage of the combined mode.
- The parking availability at a station positively influences the usage of the combined mode
- The number of alternative modes available at a station negatively influences the usage of the combined mode

4.3 Spatial factors

Points of Interest (+)

The number of points of interest in the built environment is one of the most significant influencers of generating shared bike demand in Spain (Faghih-Imani et al., 2017. Examples from Milan and Oslo also show that points of interest, such as cinema’s, universities and museums increase the usage of shared bikes (Croci and Rossi, 2014 ; Böcker et al., 2020). In Denmark and Vienna shared e-scooters are primarily used around tourist attractions and train stations (Kjaerp et al., 2020 ; Kjærup et al., 2021). Points of interest in Berlin also attract more shared e-scooter trips (Heumann et al., 2021). Lastly, Liao and Correia (2022) claim, based on their literature review, that working, dining and recreational points of interest all generate and attract more trips. This shows that the presence of points of interest positively influences the number of shared (e-)bike and e-scooter trips.

Land use (+)

In the literature type of land use is mentioned often as factor influencing the number of shared micromobility studies. Caspi et al. (2020) is the only article found that says that residential land use generate more trips. Industrial land use is also only determined once to cause more shared e-scooter trips (Caspi et al., 2020). Commercial land use, i.e. shops, hotels and offices, is also generating more trips (Guidon et al., 2019;Guidon et al., 2020; Faghih-Imani et al., 2017;Croci and Rossi, 2014). Furthermore, recreational land use, i.e. parks, bowling alleys, landmarks, etc. are causing more shared (e-)bike trips (Schwinger et al., 2022 ; Guidon et al., 2019) and especially more shared e-scooter trips (Dibaj et al., 2021; Tuli et al., 2021; Hosseinzadeh et al., 2021; Kjaerp et al., 2020; Kjærup et al., 2021). Lastly, educational land use also causes more trips, as students travelling to and from the university take either a shared bike or a shared e-scooter(Croci and Rossi, 2014;Caspi et al., 2020;Dibaj et al., 2021). The literature shows that mainly commercial, recreational and educational land use cause more shared micromobility trips.

Population and job density (+)

A higher population density around the station positively influences the usage of the shared micromobility train combination (Oeschger et al., 2020). In Oslo, Böcker et al. (2020) conclude that a higher population density positively influences the number of shared bike trips. This is also in the case in the Netherlands (Jorritsma et al., 2021) and Zürich and Berne (Guidon et al., 2020). Population density also increases the number of shared e-scooter trips in Chicago (Tuli et al., 2021) and Texas (Jiao and Bai, 2020). Furthermore, Liao and Correia (2022) conclude as well that population density increases the number of shared e-microvehicle trips. Böcker et al. (2020) claim that besides population density, the job density also increases the number of shared bike trips in Oslo. In Lyon and Zürich and Berne, the job density also increases the number of shared bike trips (Tran et al., 2015 ; Guidon et al., 2020). All in all, both population density and job density seem to positively influence the number of shared micromobility trips.

Topography (?)

Hilliness in the surrounding environment negatively influences the bike sharing demand in Lyon and Lisbon (Tran et al., 2015; Vale, 2021). van Mil et al. (2021) also conclude that hilliness negatively influences the number of bike train users. Hilliness also can cause longer trip lengths as people tend to cycle around hills if that is possible(Böcker et al., 2020). Besides hilliness, the shape of the city also influences the shared micromobility demand. Major barriers such as rivers increase the trip length of trips (Arias-Molinares et al., 2021). Arias-Molinares et al. (2021) and Böcker et al. (2020) also argue that the topography and the shape of the city also influence the usage patterns, but they do not conclude what the exact influence that has on the usage patterns.

The last topography aspect that has influence is the distance to the city center. In Oslo, the bike-share usage is the highest in the centre of the city (Böcker et al., 2020). Dibaj et al. (2021) observes the same trend in his literature review. The number of shared e-scooter trips in Texas also reduces with an increasing distance to the city center (Caspi et al., 2020. This shows that the distance to the city center has a negative influence on the number of shared micromobility trips.

Quality of infrastructure (+)

The last environmental characteristic that has an influence on the number of shared micromobility trips and the usage of the combined shared micromobility train mode, is the quality of the bike infrastructure. In the Netherlands the quality and safety of the bike infrastructure stimulates the shared bike usage (Jorritsma et al., 2021; van Mil et al., 2021). Guidon et al. (2019) show that this is also the case in Switzerland for e-bikes. The safety of the bike infrastructure is also crucial for improving the attractiveness of the shared micromobility train mode (Moinse, 2022). This trend also yields for shared e-scooters. In Denmark and Chicago the safety of the bike infrastructure positively influences the shared e-scooter usage (Kjærup et al., 2021 ; Mohammadian et al., 2022). The safety of the bike infrastructure thus positively influences the shared micromobility train usage.

Summary

- Points of interest generate and attract more shared micromobility trips.
- Commercial, recreational and educational land use generate and attract more shared micromobility trips
- The hilliness of a city negatively influences the number of shared bike trips.
- The shape of a city has an influence on the usage patterns of shared micromobility modes, but unclear is what that influence is.
- Hilliness reduces the number of shared bike trips
- Closer to the city center more shared micromobility trips are taking place.
- The quality of bicycle infrastructure positively influences the usage of a shared micromobility system.

4.4 Temporal factors

Rain & Wind (-)

In the Netherlands, rain reduces the number of shared bike train users (Jonkeren et al., 2018; van Mil et al., 2021). In New York, people are also less likely to use shared bikes when it rains (Faghih-Imani and Eluru, 2016). Shared e-scooters are used less frequent when it rains, as is shown by (Tuli et al. (2021)) in Chicago. Noland (2019) comes to the same conclusion for Louisville, but also notes that rain reduces the average distance travelled by shared e-scooter. Liao and Correia (2022) note that rain and wind negatively influence the number of shared e-bike and shared e-scooter users. The wind also negatively affects the number of shared bike trips in Belgium (Adnan et al., 2019). Noland (2019) does not observe a significant drop of number of shared e-scooter trips due to wind, but does see that the wind negatively influences the average trip distance.

Temperature (+)

van Mil et al. (2021) argue that the summer increases the bike demand and low temperatures decreases the bike demand. People are more likely to use shared bike under good weather conditions (Faghih-Imani and Eluru, 2016). Arias-Molinares et al. (2021) shows that for shared e-mopeds the temperature also positively influences the number of trips in Spain. In Chicago, the weather including the temperature is one of the largest considerations that affect e-scooter integration with transit (Mohammadian et al., 2022). Tuli et al. (2021) observes also that higher average temperatures generate more shared e-scooter trips in Chicago. Lastly, Liao and Correia (2022) also observe that higher average temperatures generate more shared e-bike and shared e-scooter trips. The average temperature thus positively influence the number of shared micromobility trips.

Day of the week (?)

During the weekend more shared e-scooter trips are taking place. Examples from Louisville and Berlin shows that the e-scooter usage is higher during the weekend (Noland, 2019, Heumann et al., 2021). In contradiction with this, shared e-bikes are primarily used during the week (Liao and Correia, 2022, Schwinger et al., 2022). This contradiction is also observed in Vienna, where shared e-bike are primarily used for commuting and shared e-scooters are primarily used for leisure trips (Reck et al., 2020). The day of the week definitely has an influence on the usage of shared micromobility, but the influence differs per day and per mode.

Summary

- Rain negatively influences the number of trips and the average distance
- Wind negatively influences the number of shared (e-)bike trips
- Temperature positively influences the number of shared micromobility trips
- The day of the weekend has an influence on the number of shared micromobility trips, but the impact differs per day and per mode.

4.5 Conclusion

The availability of the vehicle is the most mentioned factor influencing the share micromobility train combination. Having the vehicle available positively influences the combination, while non-availability also negatively influences the combination. The service area size of a shared micromobility also positively influences the usage of the shared micromobility mode. Regarding, station characteristics the walking distance from a train station to a shared micromobility vehicle negatively influences the number of shared micromobility users in first or last mile transportation. The quality of the train service at a train station also positively influences the usage of the combined mode. People are also willing to ride further to a train station with a better quality of train service. The availability of other modes, such as busses, trams or metros, reduces the number of people that use shared micromobility for first or last mile transportation.

The literature mentions several types of land use that attract and generate more trips, but especially commercial land use and recreational land use attract more shared micromobility trips, meaning that these types of land use can positively influence the usage of shared micromobility in combination with train. Points of interest also positively influence the usage, especially for tourists. Rain reduces the usage of the combination and also reduces the average distance travelled to a train station. The temperature has a positive influence of the number of shared micromobility trips. The day of the week influences the usage, but the influence differs both per day and per shared micromobility mode.

The usage of shared e-bikes or shared e-scooters in combination with the train is thus primarily influenced positively by vehicle availability, commercial and recreational land use, quality of train service, quality of bike infrastructure, population density, points of interest in the surrounding, temperature, the size of the service area, the day of the week, the parking capacity of a shared micromobility station and the distance to the city center. The combination is influenced negatively by the walking distance from the train station to a shared micromobility vehicle, rain and the presence of other modes at a train station. An overview of the influencing factors is shown in a conceptual framework in Figure 4.1. This framework functions as a basis for the framework for shared e-mopeds, discussed in chapter 6.

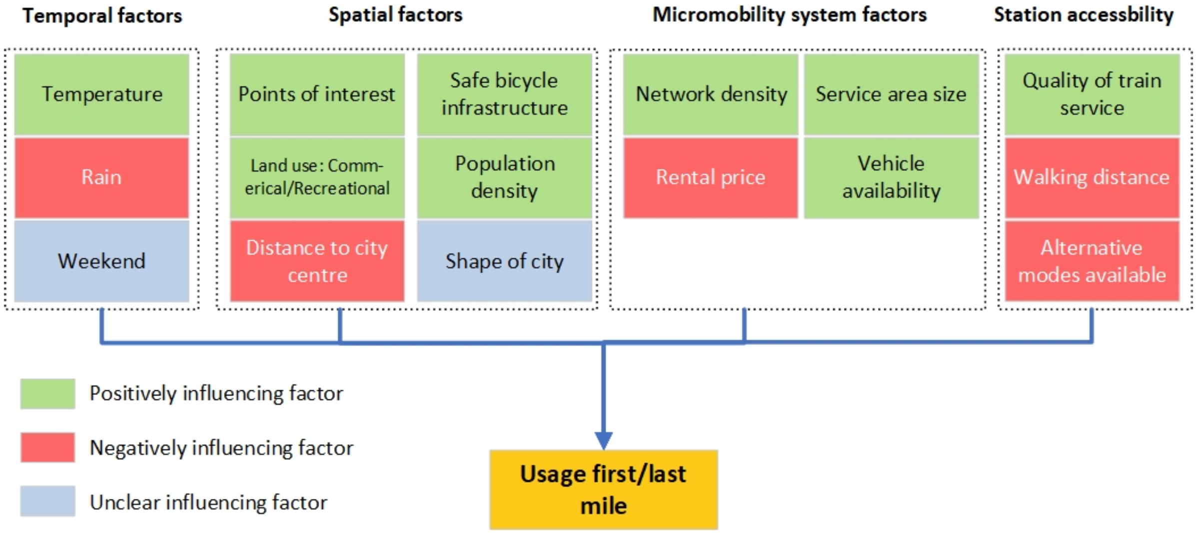

Figure 4.1: Conceptual framework findings literature shared micromobility train combination. MM stands for micromobility

5. Usage patterns

This chapter describes the usage patterns of shared e-mopeds in first- and last mile transportation towards all train stations that are within or near the service area of Check in The Netherlands. Usage patterns are defined as trip distance, number of trips, trip purpose, usage over the day and modal share. The chapter aims to get an answer on subquestion 2: 'What are the usage patterns of the usage of shared e-mopeds in first- and last mile transportation to train stations?' The usage patterns have been studied by applying the methodology of the case study towards shared e-moped usage in first- and last mile transportation in the Netherlands which can be found in chapter 3. First mile trips are defined as trips from a origin to a train station and last mile trips are trips from a train station towards a destination.

Figure 5.1 shows an overview of the structure of this chapter. This figure shows where which usage pattern can be found and provides a reading guide. Section 5.2-5.5 describe the overall pictures of the usage patterns as well as per station, while section 5.6 only describes the modal share per station.

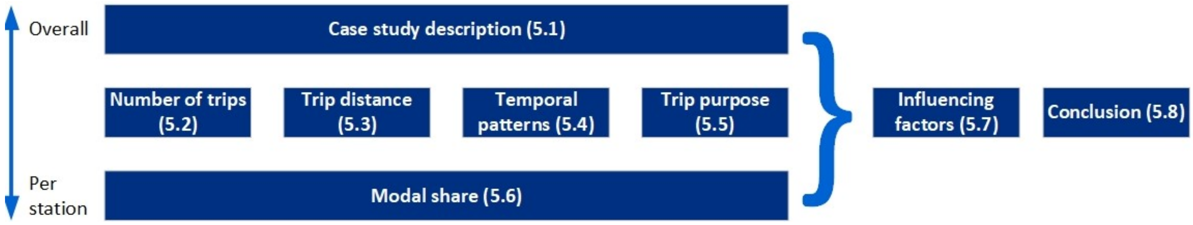

Figure 5.1: Overview of structure of chapter 5.

5.1 Case description

The case study is performed in The Netherlands. All cities where the shared e-moped provider Check is active are part of the case study. This provider has been selected, because it was the only shared e-moped provider wanting to share data. Check is one of the three major shared e-moped providers in the Netherlands. It started its operations in Rotterdam in 2020 with 160 shared e-mopeds and have expanded to 17 other cities in the Netherlands and one in Germany, offering more than 4000 shared e-mopeds to over half a million users. Users can rent a shared e-moped via the app of Check. Within the app of the NS, the shared e-mopeds of Check are also displayed, so people can book a shared e-moped when they are in the train.

The case study consists of all cities with a train station where NS has trains running and Check provides shared e-mopeds. This means the case study consists of: Rotterdam, Den Haag, Amsterdam, Breda, Delft, Zwolle, Leeuwarden, Groningen, Amersfoort, Hilversum, Enschede, Rijswijk and Capelle aan den IJssel. In these cities, 40 train stations are present where NS has a train service running and Check has a service area close to the station. The timespan of the case study is from 1 September 2022 till 31 October 2022, because data of this timespan has been delivered by Check.

Two types of shared e-mopeds are present in The Netherlands and offered by Check: a 25 km/h top speed version and a 45 km/h top speed version. With the 25 km/h top speed shared e-moped wearing a helmet was not required during the data collection period. For a 45 km/h top speed e-moped wearing a helmet was required. In the Netherlands 45 km/h e-mopeds have to drive on a bike/moped path, if that is not available they have to drive on the road (Rijkswaterstaat, 2023a). 25 km/h e-mopeds are allowed on regular bike paths. There are situations where they have to drive on the regular road (Rijkswaterstaat, 2023b).

Shared e-moped users of each shared e-moped provider in The Netherlands pay a starting fee and pay per usage minute. The shared e-mopeds in the Netherlands work with a free floating system. This means people can go from A to B and let the shared e-moped behind them at their destination. Users can only end rides in the service area of their provider. The service area determines where shared e-mopeds can be parked and is often regulated by municipalities. An example of a shared e-moped service area for Check is shown in Figure 5.2. The purple area represents the area where shared e-moped users can park their shared e-moped at the end of the ride. The purple dots represent the shared e-moped vehicles. Shared e-moped providers have to get a permit from the municipality to operate in a city with a fixed amount of shared e-mopeds. The municipalities can give restrictions on the service area. It is often not possible to travel from one city to another city. Exceptions of this are the service areas of The Hague, Amsterdam and Enschede, where users can travel freely between the municipalities surrounding the city and the city itself.

Figure 5.2: Service area (purple area) Check around Rotterdam Central station. The dots represent shared e-mopeds.

Data filtering

Figure 5.3 shows an overview of the data filtering process, which is described in subsection 3.2.1, including the removed number of trips per filter step.

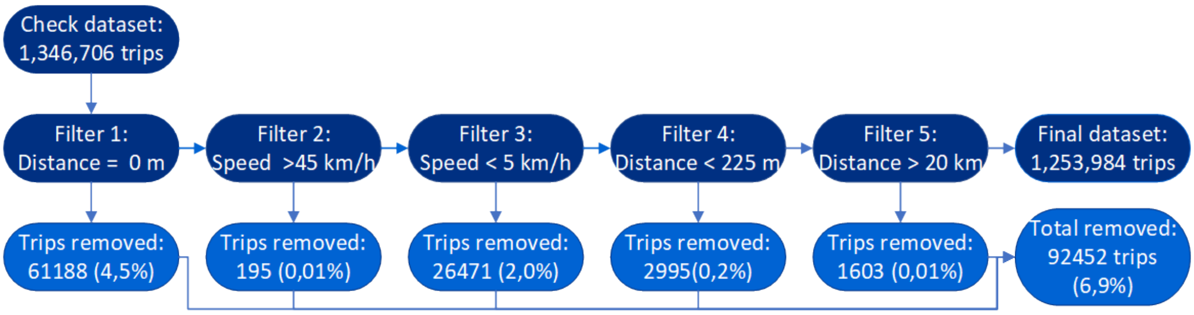

Figure 5.3: Data filtering process

In total, 92452 trips have been removed from the dataset. This equals 6.9% of the trips in the original data set. 66.2% of the removed trips (61188 trips) are removed because the trips have a trip distance of zero metres. This is probably partly caused by people notifying flaws on their rented shared e-moped, after which they decide not to rent it. 28.6% of the removed trips (26471 trips) are removed due to having an average speeds lower than 5 km/h. The applied filters result in a dataset of 1,253,984 trips, which are analysed for the case study.

5.2 Number of trips

In the months September and October 2022 1,253,984 trips have been made by shared e-mopeds of Check. This means on average 20,577 trips are made on a day. These are distributed between first mile trips, last mile trips and non-train related trips. Overall, 1,868 first mile trips per day are made and 1,901 last mile trips per day are made. On average 16,831 trips are non-train related. This means the combined overall share of first- and last mile trips of the shared e-moped trips is 18.33%, which means approximately 1 in 5 shared e-moped trips is a first- or a last mile trip.

5.2.1 Usage in cities

The number of trips in a city gives a first indication of the usage of shared e-mopeds in a city. Figure 5.4 shows the daily average number of trips in each municipality per 10000 inhabitants with at least 600 observations over 2 months. Note that the number of vehicles differs per city, which is partly shown in Figure 5.5. This figure shows in which municipality shared e-moped usage per inhabitant is relatively high.

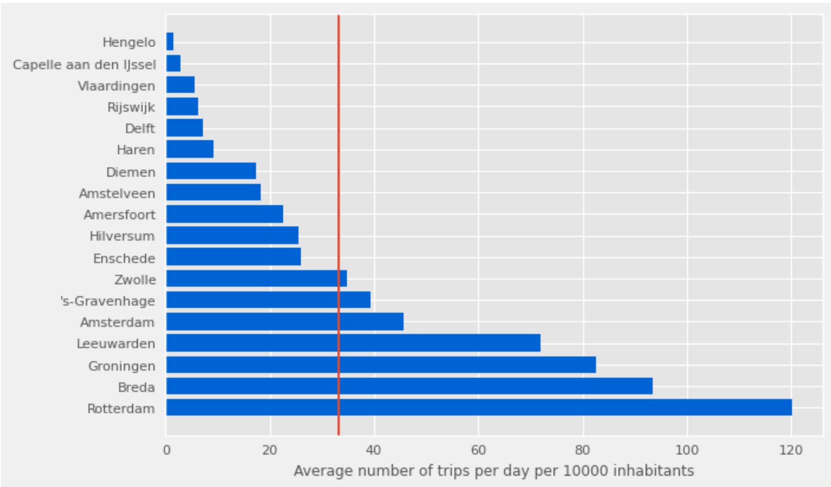

Figure 5.4: Average number of shared e-moped trips per 10000 inhabitants

Figure 5.4 shows that Rotterdam has the highest number of shared e-mopeds trip per day per 10000 inhabitants. This means that the shared e-moped usage in Rotterdam is relatively the highest. The second city is Breda, which has a relatively high usage per inhabitants compared to the average number. Also, two cities in the north of The Netherlands: Groningen and Leeuwarden are listed at place 3 and 4. The lowest usage is seen in Hengelo. In Hengelo there are also only three hubs present, which explains the low usage.

Figure 5.5 shows the average number of rentals per moped in each municipality. Note that some municipalities from Figure 5.4 are not shown in this Figure, because they only have a small amount of service area in them and they are not listed as official cities where Check is active. Figure 5.5 shows where the shared e-moped vehicles are used relatively the most.

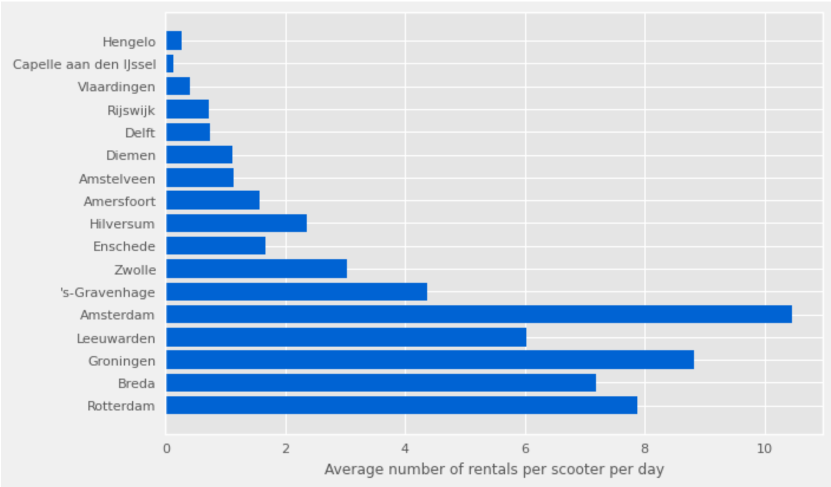

Figure 5.5: Average number of shared e-moped trips in municipalities

Figure 5.5 shows that in Amsterdam the number of trips per shared e-moped is the highest. This means that in Amsterdam the vehicles are used most often and that shared e-mopeds in Amsterdam are standing less time at one place than e-mopeds in other cities. Groningen is the second highest city with trips per shared e-moped, after which Rotterdam is the third highest. The lowest usage per shared e-moped can be seen in Capelle aan den IJssel

Figure 5.6 shows the percentage of trips in a municipality which are either a first- or last mile trip. This figure only shows municipalities that are in the case study and have a percentage higher than zero. Vlaardingen and Amstelveen, are therefore, not shown as no train station is present there. Figure 5.6 shows that the percentages differ between the cities. The three large cities in the case study: Rotterdam, 's Gravenhage and Amsterdam all have a percentage around the 18%. Hengelo, Hilversum, Delft, Zwolle and Haren have a percentage larger than 30%. This might indicate that smaller cities have a bigger share of first- and last mile transport, but cities as Groningen and Diemen have a relative low percentage. Smaller cities often have less points of interest, which might mean less non-train related usage that can explain the high first/last mile shares in those cities.

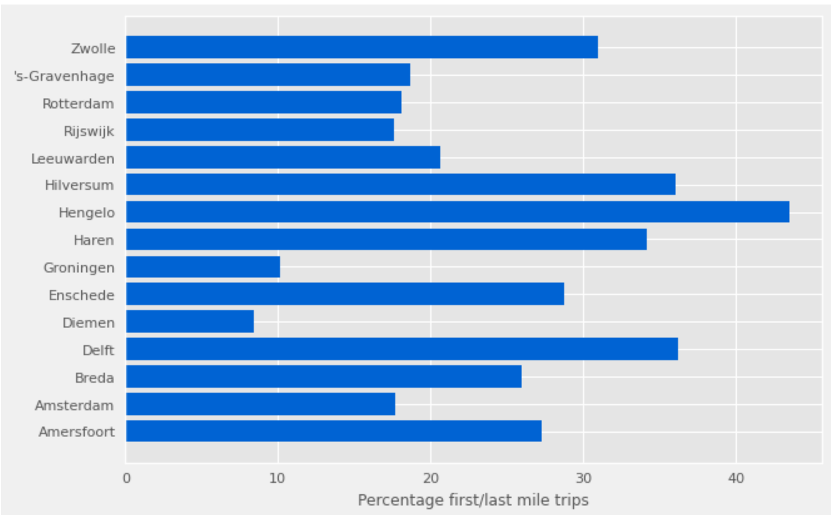

Figure 5.6: Percentage of shared e-moped trips within a municipality which are a first- or last mile trip.

5.2.2 Usage at stations

Table 5.1 shows the average number of first and last mile shared e-moped trips per day at highlighted stations. The distances at all the other stations are shown in Appendix C , where they are grouped per type of station. The share of trips per day in municipality column represents the share of Check shared e-moped trips in a municipality that goes to this station. This means that for example 12.47% of the shared e-moped trips by Check in Rotterdam goes or comes from Rotterdam central station.

Table 5.1: Average number of shared e-moped trips at mentioned stations. All stations are in Appendix C

Station name	Municpality	First mile trips per day	Last mile trips per day	Share of station related trips per day in municipality	Type station
Rotterdam CS	Rotterdam	474	500	12.5%	1
Den Haag CS	's-Gravenhage	116	119	10.9%	1
Amsterdam CS	Amsterdam	73	75	3.7%	1
Breda	Breda	218	219	25.6%	2
Groningen	Groningen	93	93	9.7%	2
Den Haag HS	's-Gravenhage	58	58	5.4%	2
Hengelo	Hengelo	3	3	43.4%	2
Rotterdam Blaak	Rotterdam	165	166	4.3%	3
Rijswijk	Rijswijk	3	3	17.6%	4
Rotterdam Noord	Rotterdam	11	11	0.3%	5
Rotterdam Lombardijen	Rotterdam	11	11	0.3%	5
Haren	Haren	3	3	34.11%	5

Table 5.1 shows that Rotterdam Central Station has the highest number of first/last mile trips with on average 973 trips/day. It stands out that Rotterdam central Station has approximately four times as many trips as Den Haag Central Station and more than 6 times more first/last mile trips by shared e-moped than Amsterdam Central station. The share of trips within the municipality at Amsterdam central station is also lower than the other two type 1 stations with 3.7%.

Breda has the highest number of first/last mile trips per day of the type 2 stations with 437 first- and last mile trips per day. This is more than two times more than any other type 2 station. This indicates that shared e-mopeds are used relatively often for first/last mile trips compared to other type 2 stations. The number of trips at Breda is also higher than two type 1 stations: Den Haag CS and Amsterdam CS. This indicates that the type of station does not explain the number of shared e-moped trips fully. The number of trips at Hengelo is relatively low with 3 trips per day compared to the other type 2 stations. The share of trips within the municipalities that go towards the stations are higher for type 2 stations than type 1 stations, as only Groningen and Den Haag HS have a share lower than 20%. This indicates that in medium sized cities of the Netherlands relatively more shared e-moped trips go to and depart from the station. Lastly, the number of first and last mile trips for all stations is approximately equal, which might suggest a station based usage pattern.

Rotterdam Blaak has the highest number of trips per day and has more than two times the number of trips compared to any other type 3 station. This is caused by the major points of interest around it, which means the numbers shown here might be an overestimation. Looking at the percentages of first- and last mile trips to the station within the municipality, the percentage are lower than the type 2 percentages. No type 3 station has a higher share than 5% Rijswijk, the single type 4 station has a share of more than 5%. Rijswijk, however has 6 trips per day, which is lower than all type 3 stations.

Type 5 stations have a maximum number of 22 trips per day. This means that the average number of first- and last mile trips per day is significantly lower for type 5 stations compared to the other types of stations. The highest number of trips are observed in Rotterdam at Rotterdam Noord and Rotterdam Lombardijen. This is line with the fact that the municipality of Rotterdam has the highest number of trips, which shows that the municipality a station is in, also matters. One share of first/last mile shared e-moped of all the trips in municipality that stands out is that of station Haren. 34.1% of the trips within Haren goes to or comes from the station. This is due to the fact that the service area in Haren consists of three small areas, one near the station, one near the centre of Haren and one near the highway.

Summary

- 18.33% of the shared e-moped trips is a first- or last mile trip.
- The number of first- and last mile trips per day ranges from 1 to 973 trips per day
- The number of trips at a station is influenced by the city and it's shared e-moped system

5.3 Trip distance

The trip distance is an important usage pattern of the shared e-moped trips. This tells something about the accessibility that can be provided by a shared e-moped as a first- or last mile mode.

5.3.1 Overall distances

The distribution of the distance of first mile, last mile and non train related trips is shown in Figure 5.7 by a density function of each type of trips. This figure shows that the distribution of first- and last mile trips is more skewed. This suggests that the average distance of non-train related trips is higher, It also shows that the distribution of first- and last mile trips in distance is very similar.

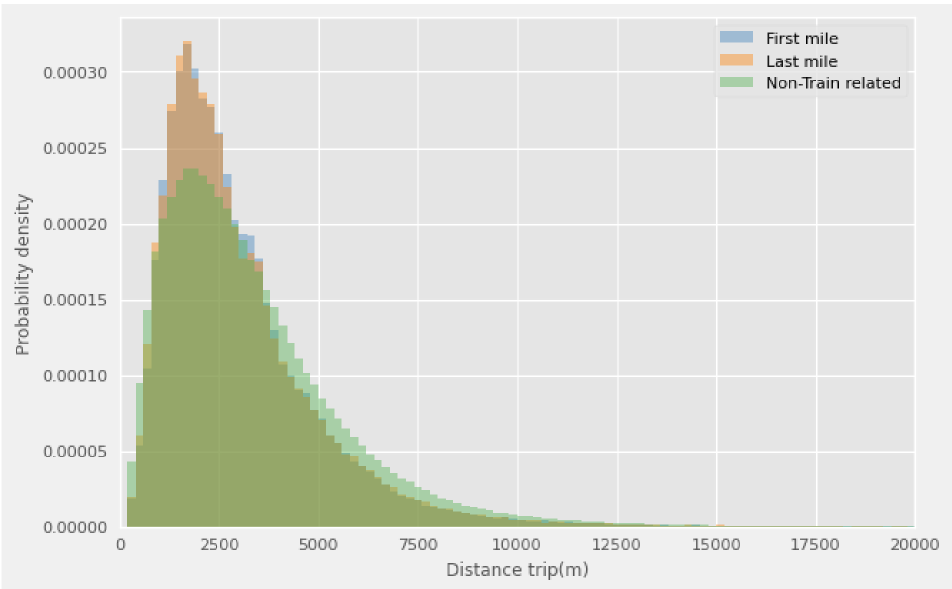

Figure 5.7: Density functions of first mile, last mile and non train related trips.

To get more insights into the distances of different kind of trips, the averages and medians are calculated. Table 5.2 provides an overview of the average and median distance in first mile, last mile, non train related and all trips by shared e-mopeds.
Table 5.2 shows that the average distance in first and last mile transportation are 3039 and 3028 metres. Non train related trips have an average distance of 3362 metres and all trips combined have an average distance of 3300 metres. This shows that the average distance of first- or last mile trips is shorter than the average distance of non train related usage. The same pattern is observed for the median distances.

To check whether this difference is significant, a t-test is performed. It is assumed that both samples are independent of each other as the user cannot be identified. A one tail Welch t-test, which is

Table 5.2: Average and median trip distances of shared e-moped trips

	Average distance (m)	Median Distance (m)
First Mile	3039	2520
Last Mile	3028	2492
Non train related	3362	2827
All	3300	2761

described in section 3.2, is performed to see whether the mean of the distance of non train related first mile is greater than the mean of the distance of first mile transport. A Welch t-test has the benefit of being able to capture different variances and sample sizes between the samples. Three hypothesises based on Table 5.2 are being tested. The results of these tests are shown in Table 5.3

Table 5.3: Results Welch t-test for comparing trip distances

Comparison	T-value	p-value
Non train related >First mile	49.55	0.0
Non train related >Last mile	51.41	0.0
First Mile >Last mile	1.234	0.1085

Table 5.3 shows that non-train related trips have a significantly higher average trip distance than first mile trips. Last mile trips are also significantly shorter on average than non-train related trips. Table 5.3 also shows that first mile trips are not significantly longer than last mile trips as the p-value is larger than 0.05. This means there is no significant difference in average distance between first- and last mile trips.

5.3.2 Station distances

To observe whether the distances differ per station, the average distance for first mile trips and last mile trips is calculated. Figure 5.8 shows the average distance in first- and last mile transportation to all of the stations in the case study. This figure shows that for most stations the distance is approximately equal, which is line with the findings for the overall usage. A detailed overview of average distance of each station can be found in Appendix D

Figure 5.8 shows that the station with the highest average distance is Amsterdam Holendrecht with an average trip distance of 8170 metres. The number of first mile trips near Amsterdam Holendrecht is low (3.5 trips per day). From Figure 5.8 stands out that the stations having an average first mile trip distance of 5 kilometres are all type 5 stations. At the same time however, the two stations with the smallest distance are also type 5 stations. This indicates that the type of station is not the only influencing factor. The long trip distances of some stations can partly be explained by the fact that all of these stations have an island in the service area where people can park their shared e-moped. The closest service area from this parking area is located further away, which means people have to travel further.

Another thing that appears from Figure 5.8, is that all stations from Amsterdam also seem to have a higher average first mile trip distance, as no station in Amsterdam has a shorter average distance than 3 km. Also, both stations in Delft have an average trip distance of less than 2.5 kilometres. This shows that the municipality a station is in, can have an influence. This can be caused by different regulations or different sizes of service areas per municipality.

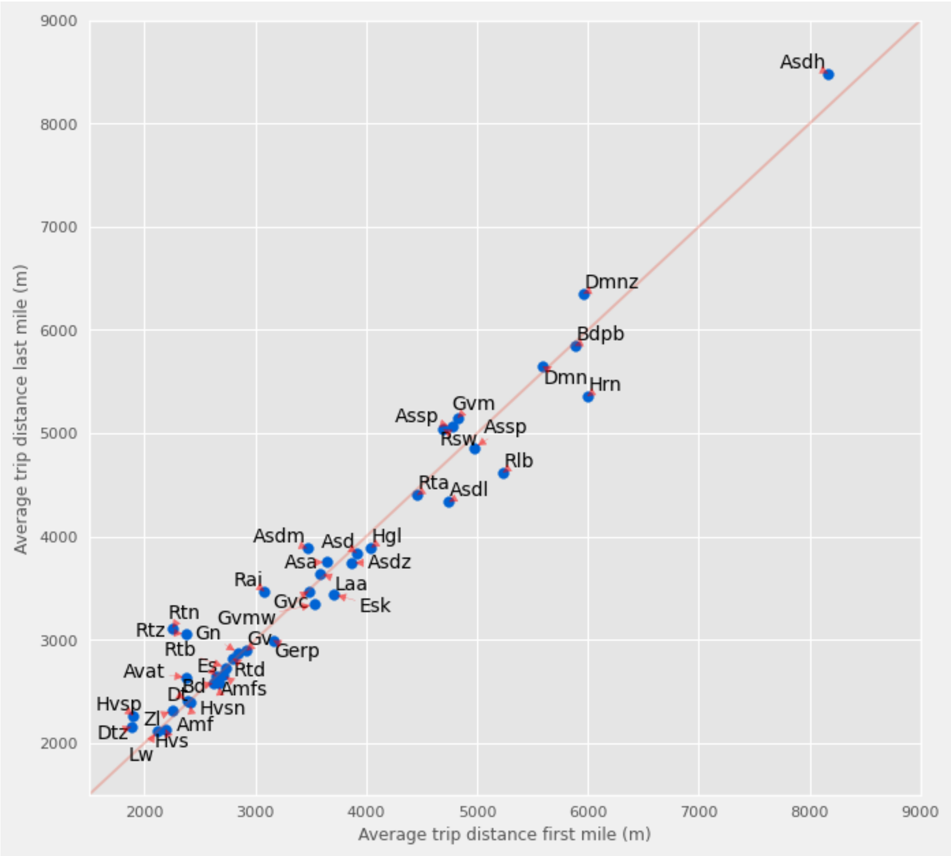

Figure 5.8: Average trip distances in first- and last mile transportation for each station.

For some stations the distances between first- and last mile transportation differ however. For stations Haren, Rotterdam Lombarijden and Amsterdam Lelylaan the average trip distance of last mile trips is between 400 and 600 metres smaller than the average trip distance of first mile trips. For various type 5 stations the distance of last mile trips is 250-800 metres larger than the average trip distance of first mile trips.

In addition to this observation similar patterns regarding the municipalities can again be seen for the average distance of last mile trips. It is noticeable, that there are no trips any more in the 1500-2000 meter category. Amsterdam Holendrecht is again the station with the highest average distance. Furthermore, all type 2 stations except Hengelo have a average last mile trip distance lower than 3 kilometres.

Summary

- The average trip distances of first mile, last mile and non train related trips are 3039 m, 3028 m, 3362 metres. The non-train related trips are significantly longer than first- and last mile trips.
- The differences in regulations and service area size between municipalities can influence the average trip distance of first- or last mile trips.
- The trip distance in first- and last mile transportation differs for some stations.

5.4 Temporal patterns

This section describes the temporal usage patterns of shared e-mopeds in first- and last mile transportation. Section 5.4.1 describes the overall weekly and daily patterns, while Section 5.4.2 shows any observed differences between clusters of stations.

5.4.1 Overall temporal patterns

Over the week

Figures 5.9 and 5.10 show the average number of trips for both first- and last mile trips per weekday of all shared e-moped trips in the case study.

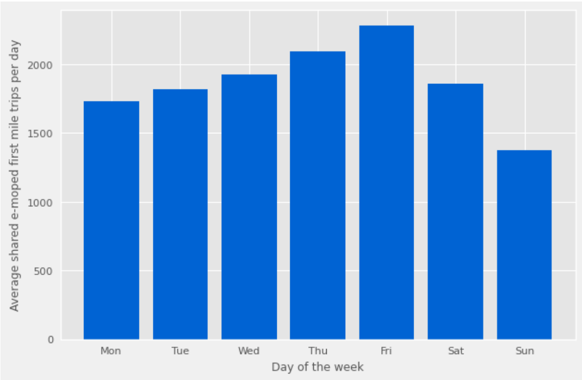

Figure 5.9: Average number of first mile trips per workday in all cities

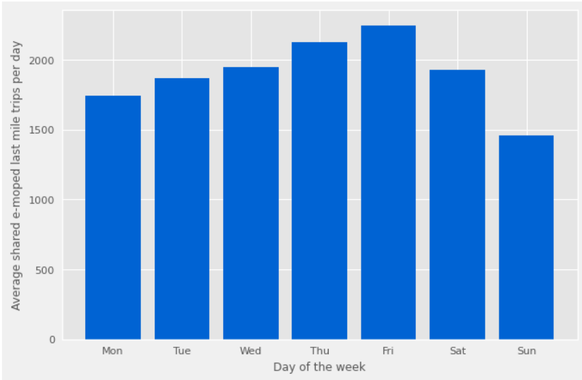

Figure 5.10: Average number of last mile trips per workday in all cities

Figure 5.9 shows that Sunday has the lowest first mile usage. The peak is present at Friday with 2280 shared e-moped trips per day. The usage on weekend days seems to be lower than on weekdays, especially on Sundays. This implies that shared e-mopeds are partly used for commuting in first mile transportation. It also implies that shared e-mopeds are not only used for commuting, as there are still many trips on Saturday (1856 trips per day) and also some trips on Sunday. This means shared e-mopeds are also used for trips with a leisure purpose. A Welch T-test shows that there are significantly more first mile trips on weekdays than on weekend days (T= 4.11, p= 0.0001)

Figure 5.10 demonstrates that the peak of last mile usage is also on Friday (2243 trips per day). The lowest usage is on Sunday with 1377 trips per day. The number of trips in last mile transportation is on the weekend a bit higher than the number of first mile trips. Besides, the usage on weekdays seems to be higher again than on weekend days, which shows that the last mile usage is also partly caused by commuting users. A Welch t-test assessing the hypothesis that the number of last mile trips is greater on weekdays than on weekend days confirms this observation with T= 3.56 and p=0.0005, which means the difference is significant. The usage patterns over the week for first- and last mile usage are thus comparable to each other.

Over the day

Figure 5.11 shows the average number of first mile trips per hour in all cities. Each line represents one different weekday. The values are gathered from a histogram and plotted in the middle of one bin, which means the value at 5.5 hour represents the number of trips between 5:00 and 6:00. This yields for all the graphs in this section.

Figure 5.11 shows that there is a clear morning peak in first mile usage of shared e-mopeds towards train station. This morning peak is not present on Saturday and Sunday, which shows that this morning peak is caused by commuting users. This morning peak occurs between 7:00 and 9:00, which overlaps with the commuting peak. Therefore, shared e-mopeds are used for commuting in the morning peak. In the afternoon, a smaller peak is also visible. This peak is less sharp than the morning peak and does not occur on Saturdays and Sundays. This is in line with usage peaks in other modes. This again implies that shared e-mopeds are used for commuting. On Friday the peak is the highest, which can probably be explained by a mix of commuting passengers and more people using a shared e-moped trip for leisure purposes.

On weekend days, there is no clear peak, although the usage is the highest in the afternoon, which is in contrast with the pattern of weekdays. On Friday and Saturday evening the usage is higher than on

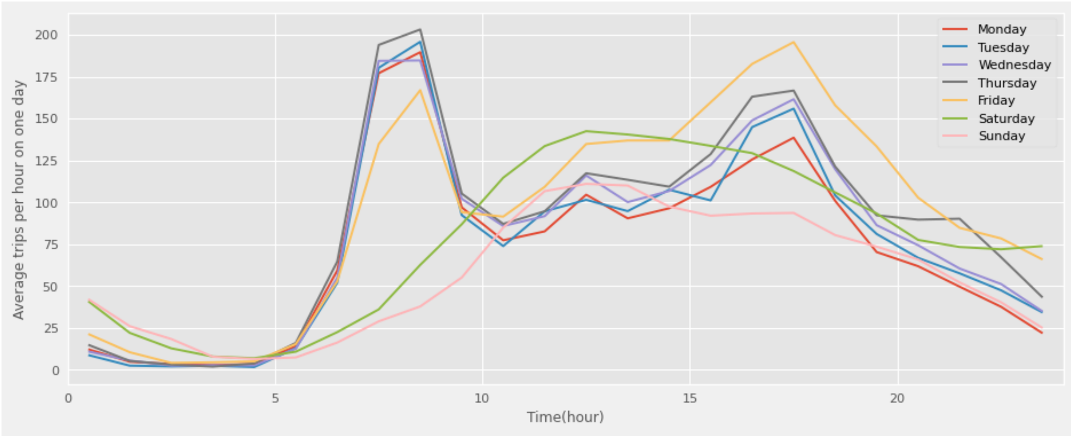

Figure 5.11: Average number of first mile shared e-moped trips per hour on each weekday.

weekday evenings. Especially, Saturday and Sunday night show higher usage of shared e-mopeds in first mile transportation compared to weekdays.

Figure 5.12 shows the average number of shared e-moped trips per hour on each weekday. This figure shows that there is again a morning peak. In last mile transportation, however, the duration of this peak is only one hour (from 8:00 to 9:00), as there is only one value at 8.5 hours that causes the peak. Also, the peak is noticeably smaller than in first mile transportation. The morning peak in last mile transportation is thus smaller in number, shorter in duration and begins an hour later than the first mile morning peak. This morning peak is again not appearing on Saturday and Sunday.

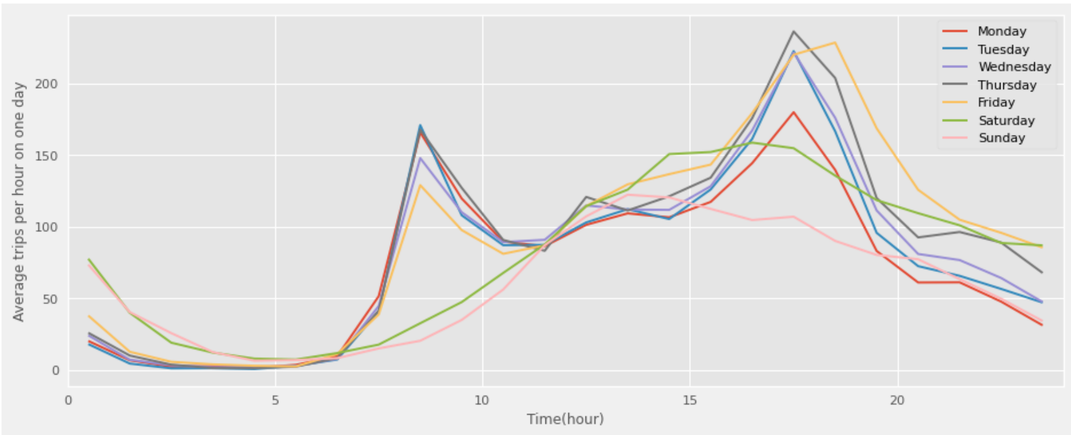

Figure 5.12: Average number of last mile shared e-moped trips per hour on each weekday.

The afternoon peak in last mile transportation is higher than the morning peak. This yields for all workdays. The largest hourly peak happens on Thursday. In general the peak on workdays, ranges from 17:00-18:00. On Friday, however, the peak continues and is even higher between 18:00 and 19:00. This peak can be caused by leisure traffic at the start of the evening from the station. The afternoon peak in last mile transportation is generally larger than for first mile transportation.

Besides, the afternoon peak, Figure 5.12 clearly shows that shared e-mopeds are also used to get from the train station towards a destination later in the evening. This happens more often on Thursday, Friday and Saturday. Especially on Saturday and Sunday night from 0:00-1:00 larger usage can be seen compared to weekdays. This is probably caused by people getting from the nightlife in another city or people going to the late nightlife.

5.4.2 Station patterns

To find out if there are factors influencing the trip start time, the number of trips started and ended at each station is calculated per hour. To see similarities between different stations, clustering is applied according to the methodology described in Subsection 3.2.4. This is done for all stations with more than 10 shared e-moped trips per day, because a lower number of trips will cause outliers due to people arriving at random. These outliers can influence the classification of the patterns, which makes the result of the clusters harder to interpret.

Figure 5.13 shows three clusters in first mile transportation during a weekday. This Figure shows three kind of patterns. Cluster 0 is shows two peaks which are approximately just as high (DP). Cluster 1 shows a pattern with a high morning peak(HM), which indicates that people go from their home to the station to get to work. Cluster 2 shows a high afternoon peak compared to the morning peak(HA), which can be explained by people. The sillhoute score is 0.23, which is relatively low on a scale from -1 to 1. This suggests there are no strongly different patterns present. These clusters show this three different patterns.

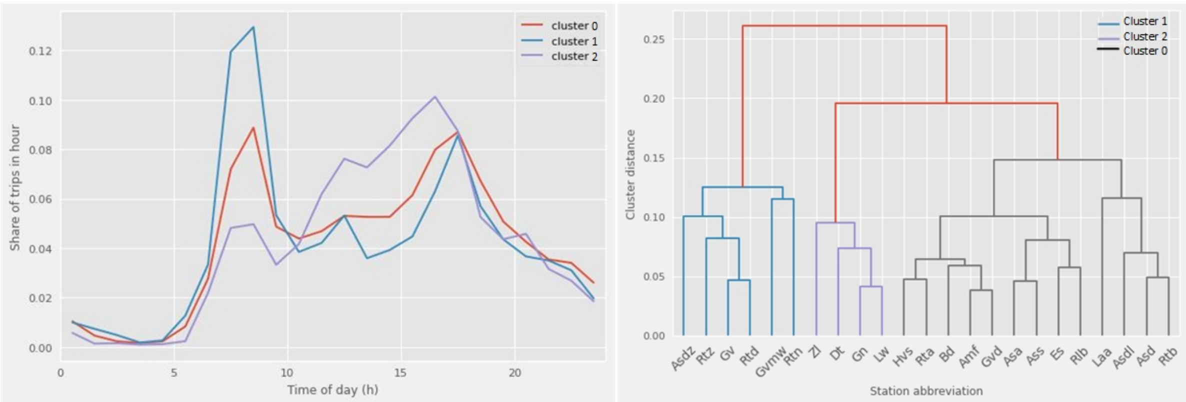

Figure 5.13: Clustering of usage patterns over the day in first mile on an average weekday. Left figure: usage per hour. Right figure: Dendrogram of clusters

Figure 5.14 shows three clusters in last mile transportation during a weekday. The difference in pattern between first- and last mile is in line with the overall difference, as the afternoon peak is higher than the morning peak. This figure shows that cluster 0 has the highest afternoon peak (HA). Cluster 1 has the highest morning peak (DP), which indicates commute usage to get from the station to the work/study place. Cluster 2 has wider and less higher peaks(WP), which could indicate that the commute purpose plays less of a role at these stations.

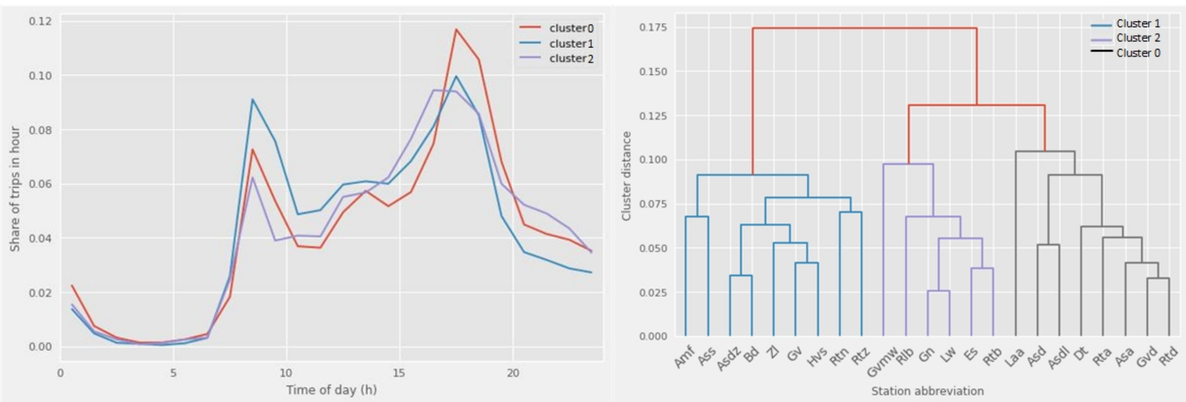

Figure 5.14: Clustering of usage patterns over the day in last mile on an average weekday. Left figure: usage per hour. Right figure: Dendrogram of clusters

Figure 5.15 shows three clusters in first mile transportation during a weekend day. Cluster 1 has a variable pattern (VP), which is due to only three stations being in that cluster, which makes it sensitive for outliers. All the clusters follow the same pattern: low amount of usage in the morning and more usage in the afternoon. Cluster 2 peaks around 15h, and has a high amount of trips at the beginning of the night, which suggests people take the shared e-moped to get home or to go out in the night (NP). Cluster 0 peaks around lunch time and has the lowest trips towards its stations in the night (LN).

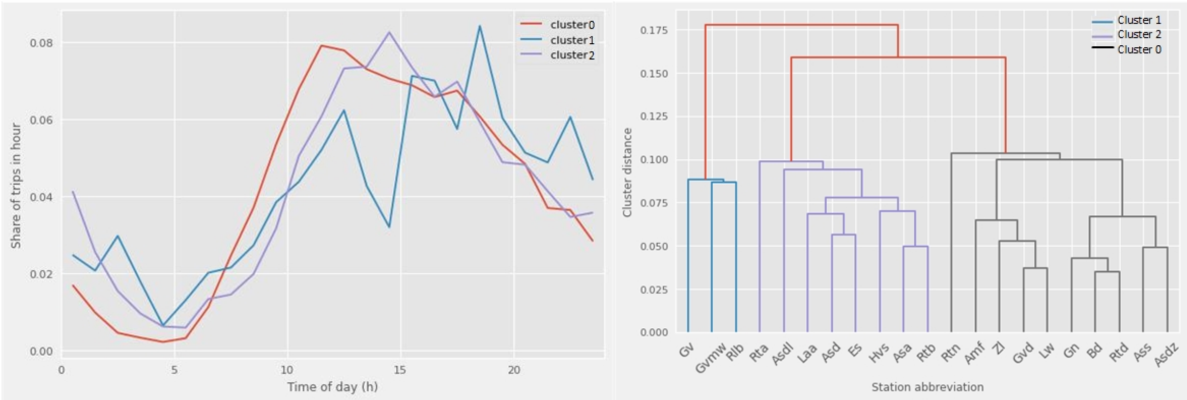

Figure 5.15: Clustering of usage patterns over the day in first mile on an average weekend day. Left figure: usage per hour. Right figure: Dendrogram of clusters

Figure 5.16 shows three clusters in last mile transportation during a weekend day. All clusters have a high usage at the beginning of the night, indicating that shared e-mopeds are used to go home after an evening away or to go to the nightlife. Cluster 0 has a variable pattern, which is again caused by the low number of station in the cluster (VP). Cluster 2 peaks again in the afternoon and has the lowest of trips during the night (AP). Cluster 1 has a lower afternoon peak, but more usage in the evening and during the night compared to cluster 2 (EN)

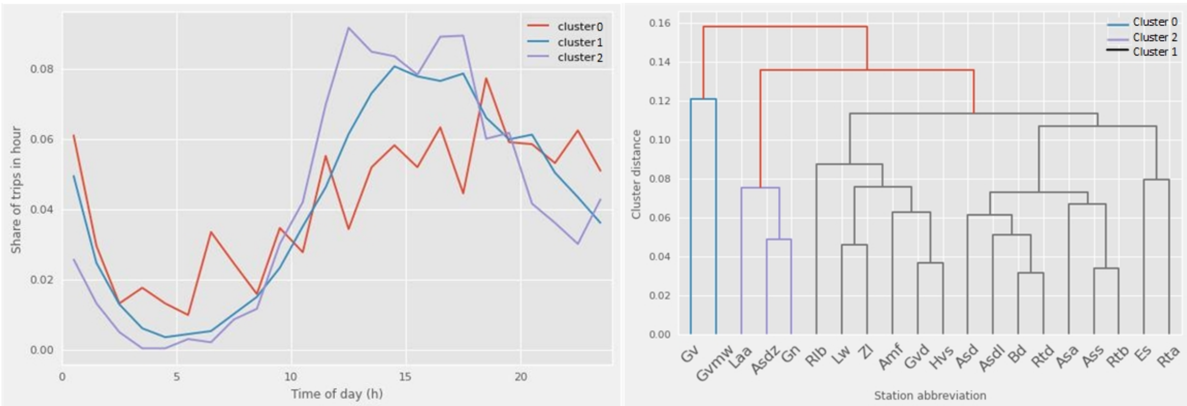

Figure 5.16: Clustering of usage patterns over the day in first mile on an average weekendday. Left figure: usage per hour. Right figure: Dendrogram of clusters

Table 5.4 shows the cluster each station is in in the 4 clustered scenarios. This makes it possible to see whether certain stations have similar patterns, because they are in the same clusters as other stations. Table 5.4 shows that the clusters differ per weekday and differ between first- and last mile transport. A station can be with one station in a cluster in first mile transportation, while it is with other stations in a cluster on a weekend day in last mile transportation.

Despite these differences there are also some groups which show similar clusters. The first group that can be observed is the group of stations: Amsterdam Amstel, Amsterdam Centraal, Amsterdam Lelylaan, Den Haag CS, Den Haag Laan van NOI and Rotterdam Alexander. They all have DP (double peak), HA (high afternoon peak) as score for weekday transport and WP, NP as weekend score, with exception from two stations. This shows that these stations have similar patterns in first- and last mile transportation, especially during the week. This cluster consists of four type 3 stations and two type 1 stations and only has stations from the big cities: Amsterdam, Den Haag and Rotterdam. This may show the influence of urbanised areas on usage patterns.

The second group that stands out from Table 5.4 is the group Amersfoort CS, Amsterdam Sloterdijk and Breda. These stations have the same score: 0 (double peak), 1 (double peak), 0 (lunch peak), 1 (no peak). This shows that these stations have a balanced first- and last mile patterns, as in both cases the peaks are approximately the same. Amersfoort and Breda stations are both balanced stations in terms of production and attraction according to data from NS. Amsterdam Sloterdijk is mainly an attraction station.

Table 5.4: Cluster number of each station for four first- and last mile on an average week and average weekend day. DP= Double peak, HA= High Afternoon peak, HM= High Morning peak LN= low night usage, NP= no peak, EN= Evening and Night Usage, AP= Afternoon peak, VP = Varibale pattern

Station	Weekdayfm	Weekdaylm	Weekendfm	Weekendlm
Amersfoort CS	*DP*	*DP*	*LN*	*EN*
Amsterdam Amstel	**DP**	**HA**	**NP**	**EN**
Amsterdam Centraal	**DP**	**HA**	**NP**	**EN**
Amsterdam Lelylaan	**DP**	**HA**	**NP**	**EN**
Amsterdam Sloterdijk	*DP*	*DP*	*LN*	*EN*
Amsterdam Zuid	HM	DP	LN	AP
Breda	*DP*	*DP*	*LN*	*EN*
Delft	HA	HA		
Den Haag CS	**DP**	**HA**	**LN**	**EN**
Den Haag HS	HM	DP	VP	VP
Den Haag Laan van NOI	**DP**	**HA**	**NP**	**AP**
Den Haag Moerwijk	HM	WP	VP	VP
Enschede	DP	WP	NP	EN
Groningen	HA	WP	LN	AP
Hilversum	DP	DP	NP	EN
Leeuwarden	HA	WP	LN	EN
Rotterdam Alexander	**DP**	**HA**	**NP**	**EN**
Rotterdam Blaak	DP	WP	NP	EN
Rotterdam CS	HM	HA	LN	EN
Rotterdam Lombardijen	DP	WP	VP	EN
Rotterdam Noord	HM	DP	LN	
Rotterdam Zuid	HM	DP		
Zwolle	HA	DP	LN	EN

All in all, the patterns per hour on different station show some similarities between the different stations, but the similarity is not very strong as the silhouette score is around the 0.20 for every station. During the week commute peaks can be recognized, which shows that commuting influence the usage over the day, as these peaks are not present in the weekend. Two major groups can be recognized of which the first group only consists of stations from Amsterdam, Den Haag and Rotterdam, indicating that the built environment and the urbanity of a city influences the usage over the day.

Summary

- On week days the average trip number is higher than on weekend days. Friday is the day with the most usage.
- The first mile usage over a day shows a larger morning peak than the afternoon peak. In last mile the afternoon peak is larger.
- The usage over the day differs per station and is influenced by the built environment and the urbanity around the station.

5.5 Trip purpose

To find out why people use shared e-mopeds in first- and last mile transportation, the purpose of each trip needs to be determined. This purpose is determined with the methodology which is described in section 3.2.5. The algorithm assigns a trip purpose to a cell based on the most frequently occurring building function in a cell. When a trip ends or starts in a cell, the trip gets the cell purpose of the starting cell or ending cell assigned as trip purpose.

The purposes are divided into five purposes. The home purpose consists of both home-work traffic, as well as people paying a visit to family or friends. The division between these two elements cannot be made based on the algorithm. The leisure purpose consists of all trips going to bars, shops, tourist attractions and other activity destinations. The work purpose consists of both home work traffic and business trips, while Education trips go to or come from any education institution.

5.5.1 Overall trip purpose

The overall trip purporse shares of all first- and last mile trips in The Netherlands are shown in Figure 5.17.

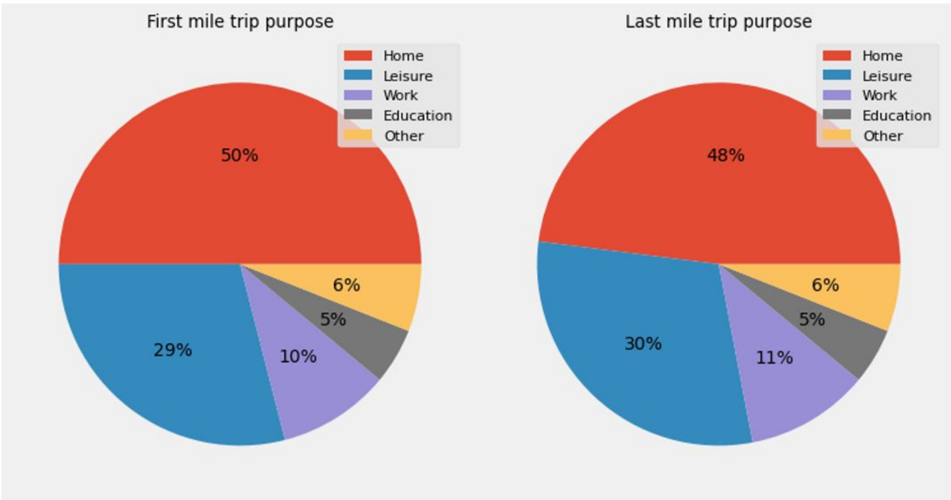

Figure 5.17: Trip purpose shares of first- and last mile shared e-moped trips in The Netherlands.

Figure 5.17 shows that the most frequent occurring trip purpose of shared e-moped trips in first- and last mile transportation is Home. This means shared e-mopeds are used most as an access- or egress mode in home work traffic or when visiting friends and family. Figure 5.17 also shows that almost 1 in 3 trips has a leisure trip purpose, indicating that this purpose plays in important role in explaining the usage patterns. 10-11% of the first and last mile trips by shared e-moped are used for work related reasons, while 5% of the trips are going or coming from an educational institution.

The purpose of a trip may influence the way a user uses a shared e-moped. One of the usage patterns that may be influenced is the trip distance. The first- and last mile trips can be distinguished into two categories: home-end trips and activity-end trips. Since the distance in first- and last mile transportation does not significantly differ (see Section 5.3), the first- and last mile trips are combined to calculate the average distance for home-end and activity-end trips. The average distance of home- end trips is 3093 metres. The average distance of an activity-end trip is 2954 metres. To check whether this difference is significant a one-tailed Welch test, as described in subsection 3.2.3. This results in T=16.59 and p= 4.58e-62. This means the difference between home-end and activity end trips in average trip distance is significant. This shows that the trip purpose influences the distance people travel on a shared e-moped

5.5.2 Station trip purpose

In Table 5.5 the percentages of trip purposes of last mile trips at all stations in the case study are shown. A complete overview of trip purpose share per station for both first- and last mile trips can be found in Appendix F. Between first- and last mile shares for each purpose there are mostly no major differences, except for Den Haag Mariahoeve where 24.6% of the first mile trips are leisure trips and 43.1% of the last mile trips are leisure trips. This difference is probably caused by a low amount of trips as Table C.4 shows that the average number of trips at Den Haag Mariahoeve is 1.13 trips per day.

Table 5.5: Trip purpose per station for last mile trips

Station name	Home	Leisure	Education	Work	Other
Amersfoort CS	55.8%	31.6%	0.7%	5.2%	6.7%
Amersfoort Schothorst	77.9%	13.6%	1.4%	1.8%	5.4%
Amersfoort Vathorst	82.8%	13.5%	1.2%	2.2%	0.2%
Amsterdam Amstel	51.4%	35.1%	2.7%	4.5%	6.3%
Amsterdam Centraal	45.9%	37.2%	0.9%	9.8%	6.3%
Amsterdam Holendrecht	26.2%	45.1%	0.4%	16.8%	11.5%
Amsterdam Lelylaan	44.7%	37.9%	1.6%	5.2%	10.7%
Amsterdam Muiderpoort	42.3%	33.1%	3.3%	10.7%	10.5%
Amsterdam RAI	48.2%	27.9%	2.0%	7.9%	14.1%
Amsterdam Science Park	40.9%	36.7%	4.2%	8.1%	10.0%
Amsterdam Sloterdijk	51.6%	35.4%	0.5%	7.5%	5.1%
Amsterdam Zuid	47.0%	31.7%	4.7%	6.6%	9.9%
Breda	46.0%	22.4%	10.0%	11.9%	9.7%
Breda Prinsenbeek	28.6%	24.3%	1.0%	30.6%	15.5%
Delft	41.8%	17.8%	27.6%	6.7%	6.1%
Delft Campus	34.8%	9.5%	37.9%	14.2%	3.6%
Den Haag CS	50.2%	27.1%	0.3%	16.6%	5.8%
Den Haag HS	42.8%	32.0%	0.1%	19.3%	5.8%
Den Haag Laan van NOI	52.7%	24.9%	1.0%	12.6%	8.8%
Den Haag Mariahoeve	38.9%	43.1%	1.4%	6.9%	9.7%
Den Haag Moerwijk	46.9%	29.6%	0.0%	16.2%	7.2%
Diemen	33.9%	37.3%	3.4%	6.8%	18.6%
Diemen-Zuid	37.9%	34.5%	0.0%	6.9%	20.7%
Enschede	64.0%	15.7%	5.9%	5.3%	9.0%
Enschede Kennispark	55.4%	18.6%	15.1%	3.9%	7.0%
Groningen	56.1%	22.2%	8.9%	6.2%	6.6%
Groningen Europapark	52.4%	31.3%	3.3%	6.5%	6.5%
Haren	65.6%	23.1%	0.0%	7.2%	4.1%
Hengelo	60.6%	16.1%	5.6%	7.8%	10.0%
Hilversum	75.3%	9.0%	1.4%	7.1%	7.2%
Hilversum Mediapark	65.2%	25.5%	0.6%	3.1%	5.6%
Hilversum Sportpark	70.2%	14.6%	3.3%	4.6%	7.3%
Leeuwarden	53.3%	32.8%	0.6%	3.8%	9.6%
Rijswijk	46.3%	36.6%	0.0%	7.3%	9.8%
Rotterdam Alexander	51.1%	23.0%	3.9%	16.8%	5.3%
Rotterdam Blaak	37.7%	39.0%	4.7%	16.0%	2.6%
Rotterdam CS	45.1%	35.2%	3.4%	13.4%	2.9%
Rotterdam Lombardijen	37.1%	34.9%	5.2%	15.2%	7.6%
Rotterdam Noord	57.9%	29.9%	2.5%	5.8%	3.7%
Rotterdam Zuid	33.9%	41.2%	3.3%	18.1%	3.6%
Zwolle	47.2%	28.2%	13.6%	3.0%	8.1%

Table 5.5 shows that the most frequent occurring trip purpose differs per station. Hilversum and Amersfoort have a relatively high share of Home related trips. Rotterdam and Amsterdam have higher shares

of leisure trips compared to the overall average. Delft has a high education share with 27-38% depending on the station. This is caused by the fact that Check e-mopeds are introduced on 1 October. Students are often the first early adapters who discover and try new modes. This means the shared e-mopeds of Check are used relatively often by students in Delft. Regarding the education share, it is also noticeable that stations without a university in the city have a low education share, which is sometimes zero. Den Haag CS en Den Haag HS have a high work share compared to other stations with 17% and 19%. This is probably caused by the high amount of offices and governmental institutions in the centre of the Hague. This shows that the building environment of the station has an influence on the purpose of shared e-moped trips in first- and last mile transportation. Between different types of station there are no noticeable difference, except for the fact that type 3 stations generally have a higher leisure share, which is due to most of the type 3 stations being in Rotterdam or Amsterdam.

Grid validation

To ensure the grid produces reliable results, the trip purposes shown in Table 5.5 are compared with results from survey by municipalities. The municipality of Amsterdam has done a survey which results in a trip purpose split of 40% Home, 36% Leisure, 9.5% education, 8.5% work and 6% other (Amsterdam, 2022). When comparing this to the trip purpose split of Amsterdam CS, this is approximately a right indication. Only the education share observed in the survey is underestimated in the grid. This can be explained that near Amsterdam CS no major universities are located, which means students will choose another station to go to, which is closer to the university, such as Amsterdam Zuid and Amsterdam Science Park. A report of the municipality of Amersfoort shows in a survey that the trip purpose Leisure is mentioned by 49% of the respondents, Commute by 40%, Social by 40%, shopping by 36% and education by 8% (Amersfoort, 2023). This shows that the combined purpose Home of commute and social is indeed one of the highest. A study by Movares (2023) shows that in the Netherlands visiting family and friends and commuter traffic are mentioned as most occurring trip purpose. After that trips to shops, cafes and other leisure activities are mentioned the most frequent. This shows that the grid gives a good indication of the most frequent occurring trip purpose, as the 'Home' purpose consists both out of visiting family and friends as well as commuter traffic.

The methodology of determining the trip purpose is also applied with a 200x200 metre grid. This leads to a higher home share (59%), which indicates that the larger grid size tends to overestimate the home share, as houses often are smaller, which means they are more frequent, which leads to more percentage of the cells being classified as 'Home'. The findings of the 100x100 metre grid seem to better match the validation studies. It can be concluded that the grid methodology gives a good representation of the trip purposes, although the exact values can differ by a couple of percentages.

Summary

- 49% of the first- and last mile trips have a Home purpose, which consists out of home work traffic as well as social trips. 30% of the trips have a leisure purpose
- The trip purpose differs per station, indicating that the built environment has an influence on it
- Home end trips are longer than activity end trips indicating that the trip purpose has an influence on the trip distance.

5.6 Modal share

This section describes the modal share of shared e-mopeds in first- and- last mile transportation. All trips that start or end within a certain radius are until now assumed to be a first/last mile trip. To check this assumption and calculate the modal share, the percentage of train users among shared e-moped users parking or starting near the station needs to be known. Therefore, a survey has been performed of which the methodology is described in Subsection **??**. The results of the survey are described in Subsection 5.6.1. After which the modal shares per day and per hour are described per station in Subsection 5.6.2.

5.6.1 Percentage train users

This subsection describes the results and the interpretation of the results of the survey described in Subsection 3.2.6. The goal of this survey is to determine the percentage of shared e-moped users parking near the station that actually goes to or comes from the train station for all stations in the case study. The survey is performed on 5 April 2023 at Rotterdam Central Station, 12 April 2023 at Amsterdam Sloterdijk, 14 april 2023 at Breda and 19 April 2023 at Rotterdam Central Station. Only in the morning of 12 April, rain was present. The rest of the days were sunny or cloudy days. Table 5.6 shows the results of the survey, including the exact survey location and the number of respondents.

Table 5.6: Results survey shared e-moped users

Station	Location	Percentage train users	Total respondents
Rotterdam CS back of the staiton	51.92546 4.466562	78%	N= 67
Rotterdam CS frontside	51.92466 4.471179	93%	N=54
Breda	51.59499 4.781148	91%	N=89
Amsterdam Sloterdijk	52.38785 4.836418	69%	N=35

Table 5.6 shows first of all that there is no station where all trips that start or end near the train station are in fact a first- or a last mile trip. This shows that the assumption of classifying every trip near a station as a first- or last mile trip, is not entirely true. Table 5.6 also shows that the percentage differs per station and per location. The highest percentage is observed at the front side of Rotterdam Central Station with 93%. 78% of the shared e-moped trips arriving or departing from the back of Rotterdam Central station is train-related. This is in contrast with the expected observation as it was expected that the backside would have a higher percentage, because there are fewer points of interest there. This shows that the points of interest is not the only factor influencing the percentage of train-related shared e-moped trips near a station.

91% of the shared e-moped trips departing or arriving near Breda is a first or a last mile trip to the train station. This is almost as high as the front side of Rotterdam Central station. Figure 5.18 shows the service area of Breda. In a service area people can start or end their shared e-moped trip.

Figure 5.18: Service Area Breda

Most shared e-moped trips take place in the center of cities (Knoope and Kansen, 2020), meaning that most trips start or end there. In Breda, when someone wants to go to the city centre, the person is less likely to park near the station, because he can park closer to the city centre for example at the east side of the city centre in Figure 5.18. This means that the shared e-moped user which is not using the train is less likely to park near the station. This suggests that the set up of the service area has an influence on the percentage of shared e-moped trains that are train related near train stations.

At Amsterdam Sloterdijk the percentage of train related trips is observed to be 69%. This is the lowest result of the survey. Figure 5.19 shows the service area of shared e-mopeds in the surroundings of the station.

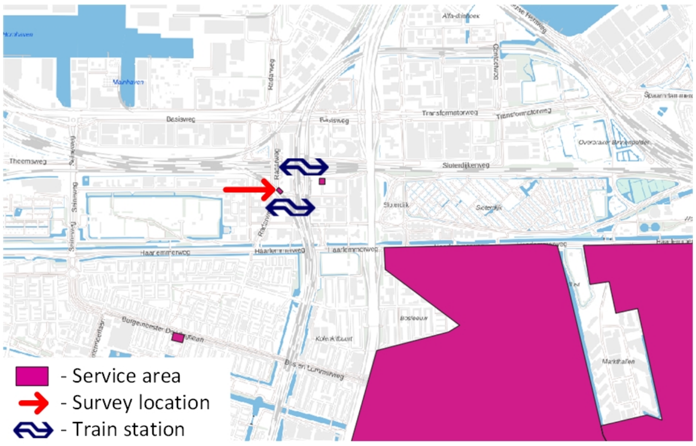

Figure 5.19: Service Area Sloterdijk

Figure 5.19 shows that there are two small hubs near the station where people can park their shared e-moped. At the west side and north side of the station there is no service area present, because the station is located at the edge of the shared e-moped network. This means the service area near the station is the first option to rent a shared e-moped for people who live or work in the north or west of the station. This means more non-train related shared e-moped trips start or end near the station, which explains the lower percentage at Amsterdam Sloterdijk. This again shows that the service area influences the percentage of train related shared e-moped trips near the station.

Figure 5.20 shows the service area around Rotterdam Central station. The backside of the station is the North side of the station. The difference in observed percentages between the front and back-side has several causes. For people arriving from the north the drop zone at the backside of the station is the most logical option to park to go to the metro. Also, this drop zone is for the houses near it the first possibility to rent a shared e-moped, which drops down the train related percentage. At the observed location at the front side of the station, the only reason why someone would park there is to go to the train station. This is because people going to the points of interest in Rotterdam or the city centre, will park closer to their destination.

Figure 5.20: Service Area Rotterdam

Observations during survey

During the survey, several observations about the usage and behaviours of shared e-moped users are made. People tend to follow the dedicated parking places, if they are available, although some users ignore them. This shows that regulation only does not solve the parking problem. Furthermore, the survey shows that Check e-mopeds are used more often than Felyx e-mopeds at the survey locations. Also, some shared e-mopeds are ridden by two persons, one driving and one at the back. The helmet regulation seems to have an effect, as most users were wearing the required helmet, although the influence of the observer cannot be ignored here. The user group seems to match the findings in literature, as most users appeared to be young. Besides, some shared e-moped users were met twice in one day, meaning that they used the shared e-moped to go from the station to their work and the other way around in the afternoon. This suggests station based usage.

Generalisation of survey results

To transform the percentage found in the survey, the results are transformed based on the set up of the survey area at each station. This is a better transformation, than using the type of station, because the survey showed that the type of station does not influence the percentage of shared e-moped users which are actually going to the train station. To make the transformation easily reproducible the stations are divided into two categories: Rotterdam CS front side and Breda with a percentage of 90% and Rotterdam CS backside and Amsterdam Sloterdijk (75%). To make the transformation into two categories, three indicators based on the findings in the previous section are set up. Since two sides of a station can differ in service area characteristics, this is done for both sides of a station. If two of below questions for one station side are answered with a yes, the assigned category of that side of the station is the 75% category. When a station has two different categories on both sides, the average percentage (82.5%) is assigned.

- Are there any other reasons such as point of interest or other transport modes that people go to from this drop zone? (Points of interest)
- Is the shared e-moped service system around the station set up as a station based system? (station based)
- Is the station located at the edge of a service area? (edge of service area)

This results in 26 stations ending up with a percentage of 75%, 12 stations with a percentage of 90% and 3 stations with a percentage of 82.5%. A detailed percentage per station can be found in Appendix B. These percentages are used in the next to calculate the modal share of Check e-mopeds.

5.6.2 Modal share per day

The modal share per day shows what percentage of the train passengers uses the shared e-moped as a first- or last mile mode. The number of train passengers shown are the estimated passengers of all train providers together. The estimated passengers only consider passengers boarding and alighting at that station. Hence, transferring passenger from one train line to the other are not considered. The modal share mentioned in this section is the estimated modal share of all shared e-mopeds.

The estimated modal share is based on the modal share of Check and multiplied by the ratio between the vehicles of Check in a city and the total number of vehicles available in the city. Table 5.7 shows the results the provider observed in the survey. These results show that the trips are not divided equally among the providers. This can be influenced by different factors, such as the type of vehicles (25 km/h vs. 45 km/h), the moment the provider is introduced in the city and the price of the provider.

Table 5.7 show that the ratio for these stations is between 1.1 and 1.7. Since, this survey is executed at a moment that Go Sharing mopeds were not available, this is taken as range that the actual modal share may differ from the expected modal share based on only the number of providers, when only Check and Felyx are present. During the survey, Go Sharing was not present due to to the bankruptcy of their parent company. Therefore, when only Go Sharing and Check mopeds were available in September and October 2022, the range is taken from 0.7-1.3, which has the same width as the Check Felyx ratio,

Table 5.7: Expected and observed ratio Check e-mopeds

	Percentage Check trips based on number vehicles	Observed percentage Check mopeds	Ratio
Rotterdam CS backside	45%	53%	1.17
Rotterdam CS frontside	45%	77%	1.71
Amsterdam Sloterdijk	50%	57%	1.14
Breda	61%	90%	1.48

but a mean of 1. When all 3 providers are present a range from 0.9-1.5 is taken as range. The ranged modal shares can be found in Appendix I. For the figures the mean is taken as ratio. The modal shares are calculated using equation 5.1

$$ms = \frac{N_{tripsCheck}}{N_{train}} p \frac{V_{Total}}{V_{Check}} \frac{1}{r} \tag{5.1}$$

where:

ms	= Modal share per day at a station in first- or last mile
$N_{tripsCheck}$	= Number of observed trips to station (fm) or from station (lm) in data Check
N_{Train}	= Number of train passengers boarding(fm) or alighting(lm) per day at a station
p	= percentage actual train passengers from survey
V_{Check}	= Number of shared e-mopeds Check in city of the station
V_{Total}	= Number of shared e-mopeds of all providers in city of the station
r	= ratio to compensate for more usage of one provider.

Figure 5.21 shows the average modal share of shared e-mopeds on a week day in both first- and last mile transportation. The horizontal axis represents the first mile modal share and the vertical axis represents the last mile modal share. The color represents the average number of last mile trips to give an indication where the absolute number of trips is the highest. The detailed number of trips per station can be found in section 5.2 and Appendix C.

Figure 5.21 shows that the modal shares of shared e-mopeds range from 0.02% to 2.5% in both first- and last mile transport on a weekday. The first mile modal share is also a little bit higher for every station than the last mile modal share. The figure clearly shows there is a linear relationship between the first mile modal share and last mile modal share. The correlation between the first- and last mile modal share is 0.9987, indicating a strong linear relationship. The first mile modal share is on average 1.06 higher than the last mile modal share. This suggests that shared e-mopeds might be used as an access- and egress mode by one person on a day, as the first and last mile modal share are almost equal. The slightly higher first mile modal share is mainly caused by the fact that there are more alighting than boarding train passengers at all the stations.

During the week three clusters can be identified in Figure 5.21. The first cluster being stations having a first and last mile modal share higher than 1.5%. This cluster consists of the stations Breda, Rotterdam Central Station, Den Haag Moerwijk, Rotterdam Noord, Rotterdam Blaak and Leeuwarden. Leeuwarden is the station with the highest modal share. In this highest cluster, there are three stations present from Rotterdam, which indicates that a high usage per inhabitant also leads to higher modal shares in first- and last mile transportation to train stations. Leeuwarden and Breda also have a relatively high usage per inhabitant, as is shown in Figure 5.4.

The second cluster consists of the stations Rotterdam Zuid, Groningen, Den Haag HS and Enschede. These are primarily type 2 stations and have a modal share around 1.0-1.5%. The majority of the stations has a modal share between 0.02% and 0.75%. This is the biggest cluster.

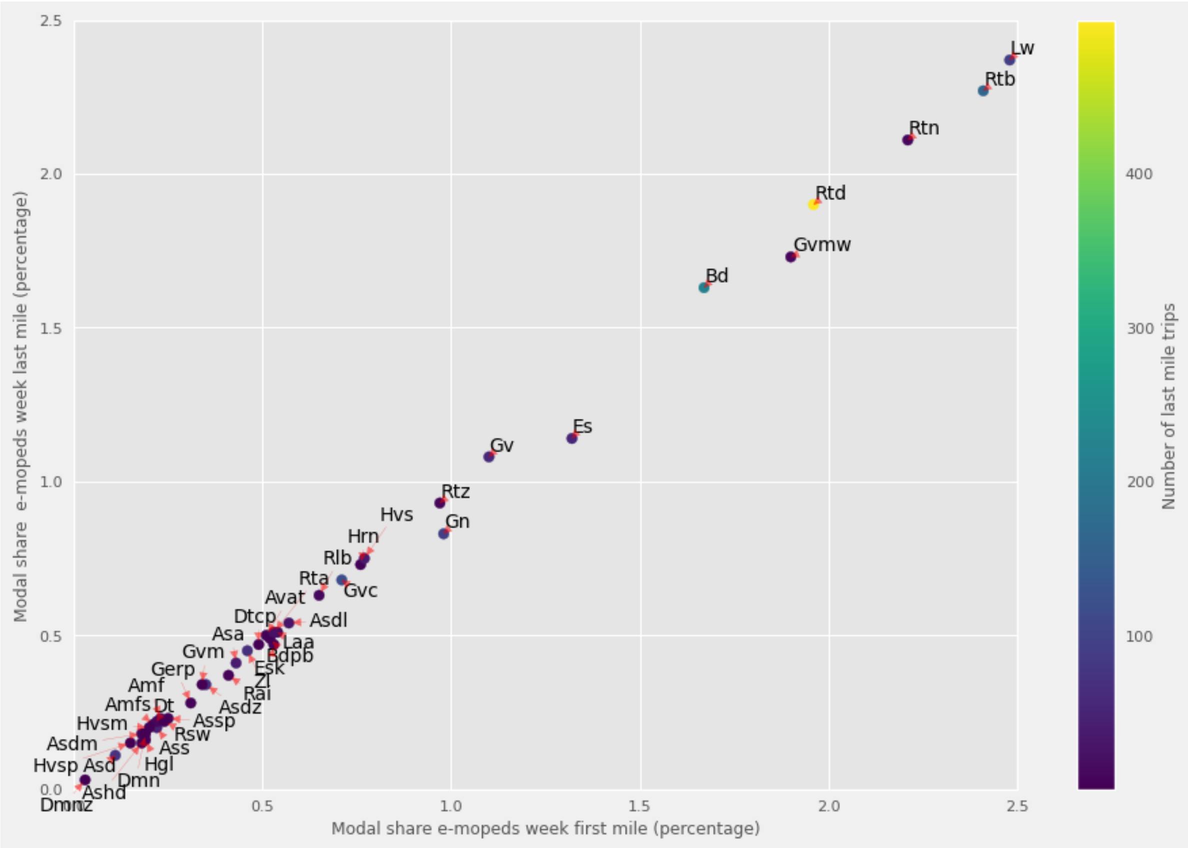

Figure 5.21: Average modal share per day during weekdays

Figure 5.22 shows the average modal share on weekenddays at all stations. This figure shows that on a weekendday these percentages range from 0.06% to 5.3%. As can be seen from Figure 5.21 and Figure 5.22, the modal shares are higher in the weekend than during the week. Especially the stations in Enschede have a significantly higher modal share in the weekend compared to a weekday. The correlation between first- and last mile modal share is 0.94, which is lower than the correlation during the week. On average the modal shares are 1.16 times higher in first mile than in last mile.
Figure 5.22 shows that during the weekend Rotterdam Blaak has the highest shared e-moped modal share. Again, three clusters can be identified. The first cluster consists of stations having a higher first mile modal share than 4% and consists out of the stations Enschede, Enschede Kennispark, Den Haag Moerwijk and Rotterdam Blaak. The low last mile modal share of Enschede Kennispark may be caused by the low number of trains of NS that stops there at Saturdays, which makes this share sensitive for outliers.

The second cluster in Figure 5.22 consists of the stations Breda, Rotterdam Central station, Noord and Zuid, Leeuwarden and Breda. These stations all have a modal share between 2 and 4%. These stations again are located in cities with high usage per inhabitant. On the other hand, Enschede has a lower usage per inhabitant and still has a higher modal share, which shows there are also other factors influencing the modal share.

The third cluster again describes the majority of the stations and has a modal share between 0 and 2%. This cluster does show, however, that the modal shares are higher in the weekend than during the week, which might be explained by other factors such as the lower quality of public transport services in the weekend and other trip purposes.

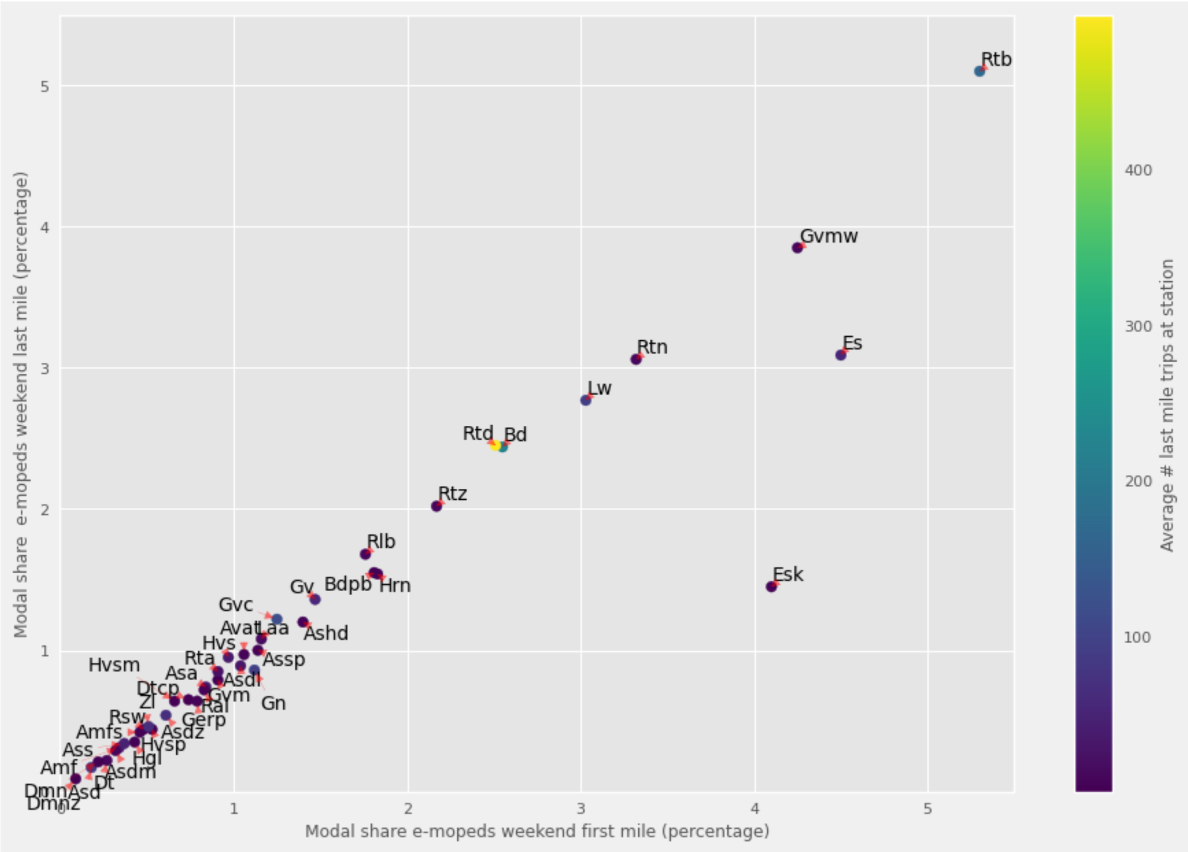

Figure 5.22: Average modal share per day during weekenddays

5.6.3 Modal share per hour

The modal share per hour is calculated according to the methodology described in section 3.2.6. The modal share per hour tells something about when shared e-mopeds are used relatively often in comparison with other modes. For this analysis only the shared e-moped number of Check is considered, as this analysis should indicate when shared e-mopeds are used relatively frequently in first/last mile transportation. Therefore, the correction for the fleetsize of each provider is not needed, as the absolute modal share is less important for this analysis. To show the hourly modal share patterns, patterns representative for the patterns of other stations are shown.

First mile transport

Figure 5.23 shows the average modal share on each weekday at Amersfoort Central station.
This figure shows that there is no usage of shared e-mopeds in the night at almost all days. This is due to the fact that there are no trains departing from Amersfoort Central station. This shows that stations having no night train connection do not have shared e-moped first- and last mile trips in the night. Another thing that stands out from figure 5.23 is that the modal share peaks on weekdays between 6:00 and 7:00. This could be caused by the fact that local public transport frequencies are lower at this time than in the peak of the morning peak (7:00-9:00). This peak is also present at other stations.

Figure 5.24 shows the modal share of shared e-mopeds in first mile of station Enschede. This figure again confirms the pattern found at Amersfoort Central that there is no modal share in the night, due to no trains departing in the night. The pattern in Enschede is quite different from that in Amersfoort. The modal share is the highest in the evening hours. The modal share is also higher on weekend days, than on weekdays, which is also observed in the modal share day analysis. The high modal share in the evening can be explained by a poorer public transport connection. Besides, the trip purpose might play a role in mode choice as well, as trips in the evening are most likely social or recreational trips.

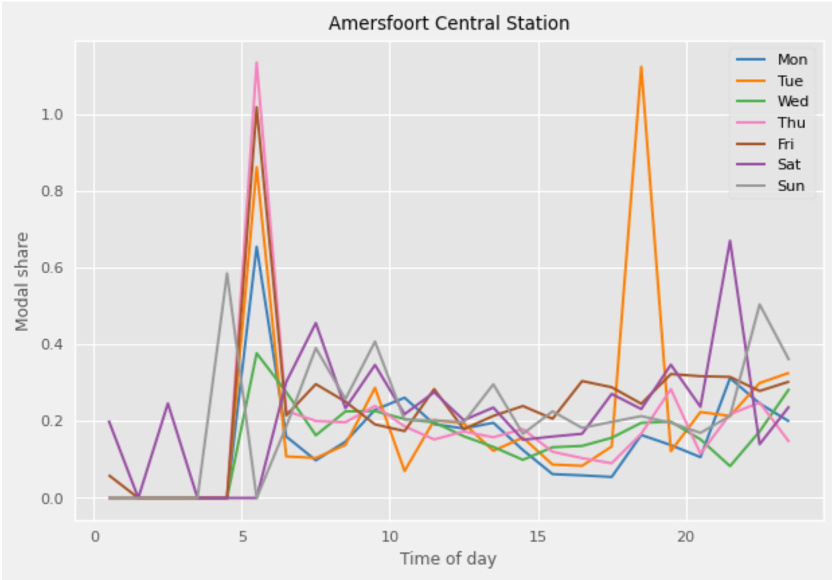

Figure 5.23: Average modal share Check e-mopeds first mile Amersfoort CS on each day

Other stations such as Leeuwarden, Groningen, Rotterdam Blaak and Den Haag CS tend to show the same patterns, albeit with a lower modal share.

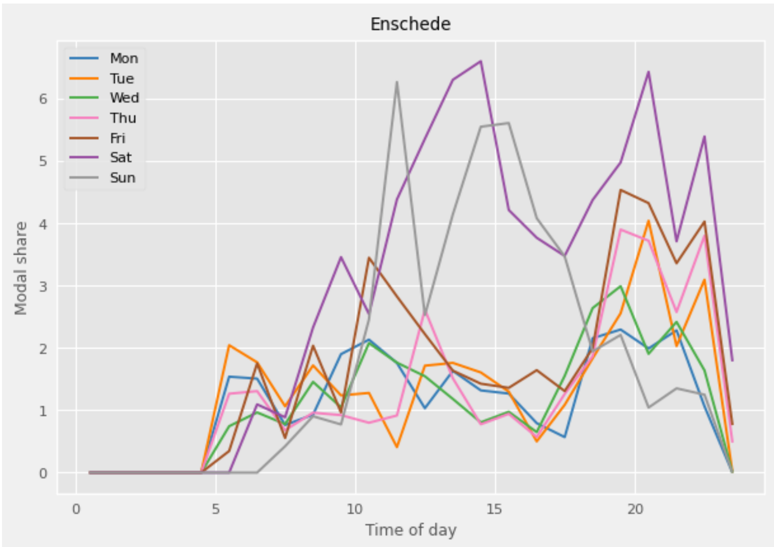

Figure 5.24: Average modal share Check e-mopeds first mile Enschede on each day

All in all the modal share of the hour patterns in first mile differ per station. At some stations such as Amersfoort CS and Breda a early morning peak can be observed, while at other stations such as Enschede and Leeuwarden a higher modal share in the evening can be observed. Also, it is clear that having a train departing in the night, significantly influences the modal share in the night, as there is no modal share, when there are no trains. For the rest, no clear differences can be distinguished in the modal share per hour.

Last mile transport

The modal share for last mile transport from trainstation shows slightly different patterns. Figure 5.25 shows the average modal share per hour on each weekday at Rotterdam Central station.
This figure shows that on weekendays, the usage in the night is higher compared to week days, indicating that shared e-mopeds are used for last mile transport to night life activities. On Sunday the peak

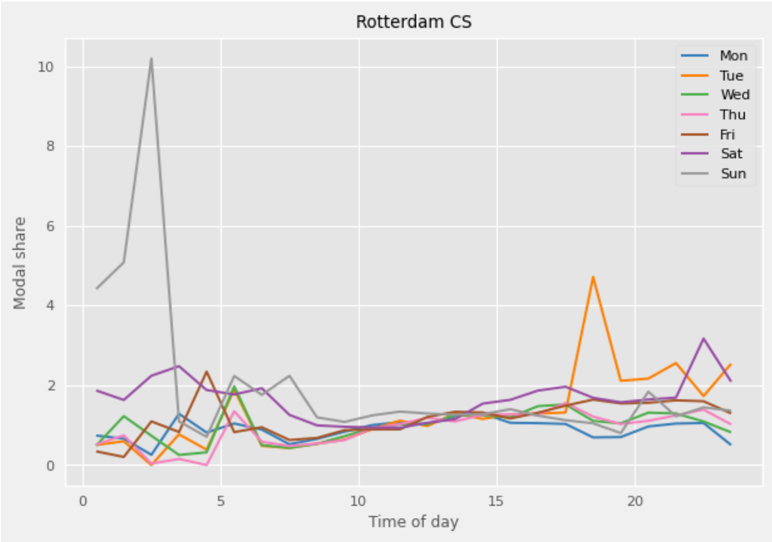

Figure 5.25: Average modal share Check e-mopeds last mile Rotterdam CS on each day

between 02:00 and 03:00 can be explained by a train arriving near the end of the previous timespan 01:00-02:00. This means the train passsengers are taken into account for the 01:00-02:00 hour slot, while they reach their shared e-mopeds a couple of minutes later in the 02:00-03:00 timespan. This is a limitation of the method and leads thus to over and underestimation of the modal share. The pattern of high night usage can also be found at stations Leeuwarden, Enschede, Amsterdam CS, Den Haag CS, Breda and Rotterdam Blaak indicating that the night usage is related to activities in city centres.

Besides, the night usage Figure 5.25 shows that on all days the usage over the day from the morning until the evening increases. This shows that shared e-mopeds are used relatively more often during the afternoon and evening in comparison with the morning. This matches the general shared e-moped pattern for trips over the day. Figure 5.26 shows the modal share of shared e-mopeds in last mile transportation from station Leeuwarden. This figure shows again a clearly higher usage on weekend evening, as the highest peak at Leeuwarden is Saturday night. Also, the same pattern of increasing usage from the morning until the evening is present. This confirms the observation from Rotterdam and can be seen at most stations. This is in line with the number of shared e-moped trips over the day, as that also increases over the day.

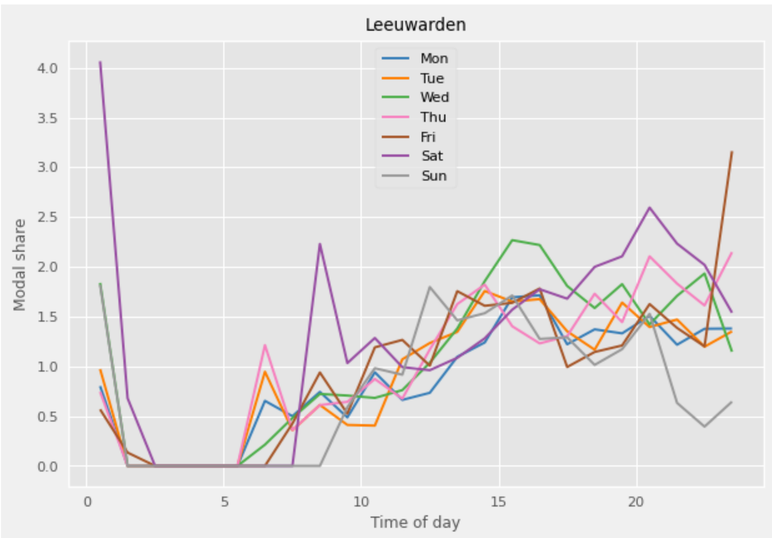

Figure 5.26: Average modal share Check e-mopeds last mile Leeuwarden on each day

The difference between first- and last mile hourly modal share patterns is thus primarily the increasing modal share over the day. In first mile transport morning peaks can be observed, while these are less or not present in last mile. Both in first- and last- mile transport the modal share is relatively higher during the evening/ nights in the weekend. For first mile, these are primarily the evenings, while for last mile these are primarily the nights. This indicates that people go from one station to another to go to nightlife activities.

Summary

- Most trips (65-93%) of the trips that arrive at or depart from a train station are train related.
- The modal share at stations ranges from 0.06%-2.5%. During the weekend the modal shares are higher.
- In first- and last mile transport the modal share is higher during the evening in weekends.
- Having a night train stopping at a station influences the modal share in the night.

5.7 Influencing factors

From the analysis to the usage patterns, several potential relations can be discovered. The findings that did during the analysis are summarized in the conceptual framework shown in Figure 5.27. This framework shows potential factors, which can be considered in the set-up of the model to answer the main research question. The factors describe the influence on four usage patterns: trip distance, trip purpose, trip start time and usage in first/last mile transport. The usage patterns also have interrelations as the trip distance is influenced by the trip purpose and the trip purpose also influences the trip start time. Lastly, the trip start time also influence the number of trips in first/last mile.

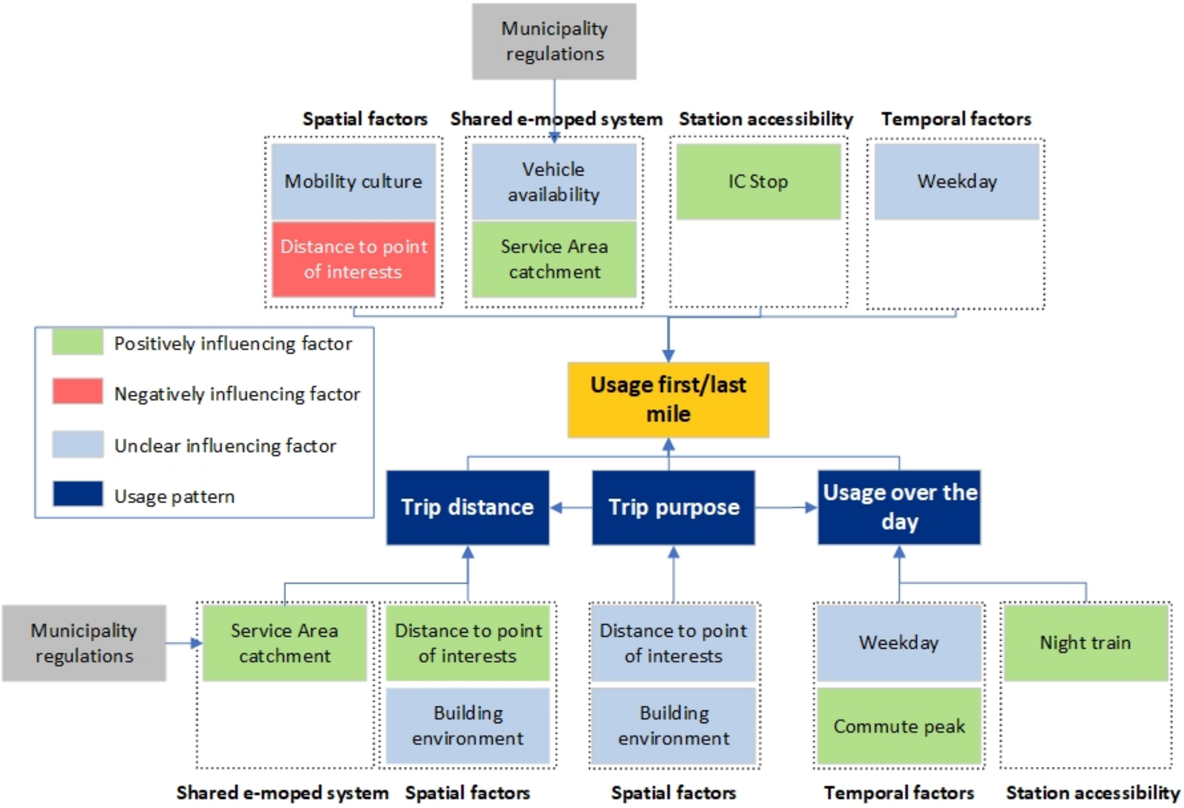

Figure 5.27: Conceptual framework observed relations usage patterns

5.8 Conclusion

This chapter describes the trip characteristics of shared e-mopeds in first- and last mile transportation to train stations and tries to answer the research question: 'What are the usage patterns of the usage of shared e-mopeds in first- and last mile transport to train stations?'. This chapter tries to answer that research question by doing a case study on shared e-moped data from shared e-moped provider Check from the months September and October 2022.

18% of the shared e-moped trips are a first- or a last mile trip. The most shared e-moped trips per 10000 inhabitants can be found in Rotterdam. The average number of first mile trips on train stations differs from 0.36-474 trips per day and the number of last mile trips ranges from 0.46 to 500 trips per day. Rotterdam Central Station has twice as much trips as the second station, station Breda.

The average distance of first- and last mile trips are 3039 metres and 3028 metres. Non-train related shared e-moped trips have an average distance of 3362 metres. First- and last mile trips are significantly shorter than non train related trips, but there is no significant difference between the distance of first- and last mile trips. The type of station seems to have an influence of the average trip distance to and from the station, as only type 5 stations (smaller sub-urban regional train station) have an average distance higher than 5 kilometres and most type 2 stations (intercity stations in medium sized cities) have an average distance lower than 3 kilometres. Also, the distances per municipality differ, which shows that the municipality has an influence on the average trip distance. This influence is shaped by regulations and mobility culture.

Over the week Friday is the day with the most first- and last mile shared e-moped trips. Sunday has the lowest number of trips, while on Saturday the number of trips is comparable to weekdays. This shows that shared e-mopeds are both used for commuting as well as for other purposes such as leisure. Over the day, there is a clear morning peak in first mile transportation, while in last mile transportation the afternoon peak is bigger than the morning peak. This is probably due to a combination of work and leisure traffic in the late afternoon. In weekends these peaks are not visible, a clearly higher usage in first- and last mile transportation in the end of the evening and beginning of the night compared to weekdays can be observed. Between stations small similarities in patterns are observed. This shows that the station does have a minor influence on the usage over the day. Especially, the built environment and urbanity of the city around the station seems to influence the usage over the day.

Between first- and last mile trips there are minor differences in trip purpose. Shared e-mopeds are primarily used for 'home' trips (50% of first mile trips and 48% of the last mile trips). This consists of people travelling the first or last part from or to their work, as well as social visits, such as visiting a family member. The second most frequent occurring trip purpose is leisure trips (29% in first mile and 30% in last mile). This again shows that shared e-mopeds are used both for commuting as well as social and leisure trips. Between the stations there are major differences in trip purposes. In the two big cities Rotterdam and Amsterdam there are higher leisure shares, while in smaller cities such as Amersfoort and Hilversum the home shares are larger. This shows the influence of the built environment around the station and in the city on the trip purposes. The trip purpose also has influence on the length of the trips as home end trips have significantly longer average trip distance than activity end trips. Also, the trip purpose influences the trip start time, as there are different peak patterns over the day between the different purposes.

The modal share of shared e-mopeds ranges from 0.02%-2.5% in first- and last mile transport during the week. The cluster with stations with a percentage between 1.5 and 2.5% mainly come from cities with a high shared e-moped usage per inhabitant. During the weekend the modal share of shared e-mopeds is higher. In the weekend the modal shares range from 0.06% to 5.3%. The majority of the stations has a modal share between 0.06% and 2% during the weekend.

The hourly modal share patterns in first mile differ per station. At some stations early morning peaks can be observed, while at other stations a higher modal share in the evening is present. . Also, it is clear that having a train departing in the night, significantly influences the modal share in the night, as there is no modal share, when there are no trains. The difference between first- and last mile hourly modal share patterns is primarily the increasing modal share over the day. In first mile transport morning peaks can be observed, while these are less or not present in last mile. Both in first- and last- mile transport the modal share is relatively higher during the evening/ nights in the weekend. The difference between this usage is that the peaks in first- mile are at the end of the evening, while the peaks in last mile are at the beginning of the night.

All in all the usage patterns of shared e-mopeds in first- and last mile transportation can be described as trips with an average distance of 3030 metres and a trip purpose distribution where 50% of the trips is home related and 29% Leisure. Also, the Friday is the most popular day and during the week clear commuting peaks are present in the usage over the day. The modal share of shared e-mopeds in first- and last mile range from 0.02% to 5%, which may be more when more providers are active in a city.

6. Model structure & results

This chapter describes the set up of the quantification of the influence of factors influencing shared e-moped usage in first- and last mile transport to train stations and the results of the model. The goal of the model and the set-up of it, is to quantify the influence of factors, which mains the primary goal is explaining the different factors. This chapter also shows how the conceptual framework is transformed into a multiple linear regression model to quantify and test the relationships within the conceptual framework. The chapter aims to answer the subquestion: 'What is the best performing model structure to quantify the influence of factors on the usage patterns of shared e-mopeds in first- and last mile transportation to train stations?'. Section 6.1 describes the set up of the conceptual framework following from the other conceptual frameworks in chapters 4 and 5. Section 6.2 dives into the structure of the model. Section 6.3 shows the model results, after which Section 6.4 dives into the validity of these results. Section 6.5 gives a conclusion and an answer on the sub research question.

6.1 Conceptual framework usage patterns shared e-mopeds

In chapter 4 and 5 the literature study and case study to usage patterns lead to possible factors influencing the usage patterns of shared e-mopeds. Figure 4.1 shows the finding from the literature study. Figure 5.27 shows all factors found from empirical insights influencing different usage patterns. The goal of this section is to make a conceptual framework, which can be used as a basis for the statistical model that can quantify the influence of factors on shared e-moped usage in first- and last mile transportation. Therefore, the two conceptual frameworks are combined together. Overlapping factors are merged and factors that come from practice are added. This results in a combined conceptual framework, which is shown in Figure 6.1.

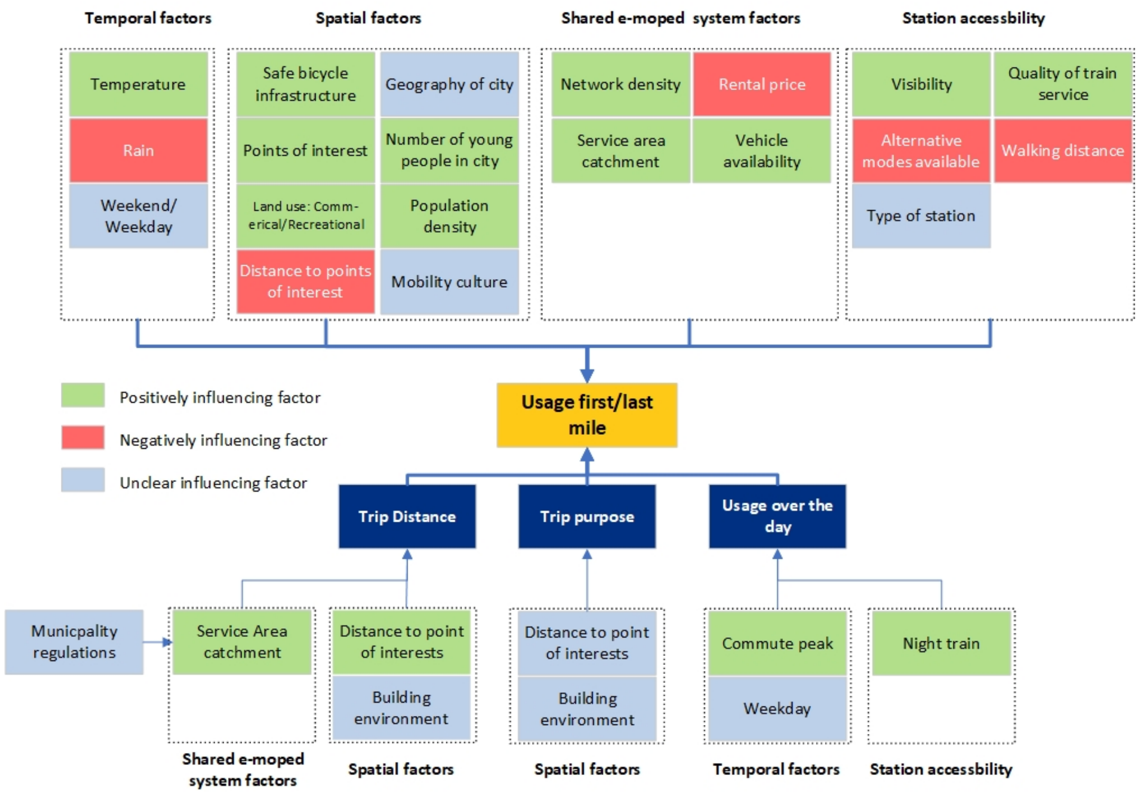

Figure 6.1: Overview of factors influencing found in practice, usage patterns and shared micromobility literature

The usage patterns can be described as the usage in first/last mile, which is the number of trips and the modal share. The usage is influenced by three usage patters: the trip distance, the trip purpose and the usage over the day. These three usage patterns can be seen as an internal part of the usage in the first/last mile. The trip purpose for example influences both the trip start time, as well as the distance, as well as the usage. Figure 6.1 also shows that these factors influence each other and the number of trips and the modal share. Therefore, the choice has been made to only model the usage in the first/last mile, since the other three usage pattern are primarily internal factors. Figure 6.2 shows the framework of factors influencing the usage in first/last mile of shared e-mopeds. This means this figure only shows the top half of Figure 6.1. This framework forms the basis for the model. The relations shown in this figure are expected relationships based on the literature study and usage patterns.

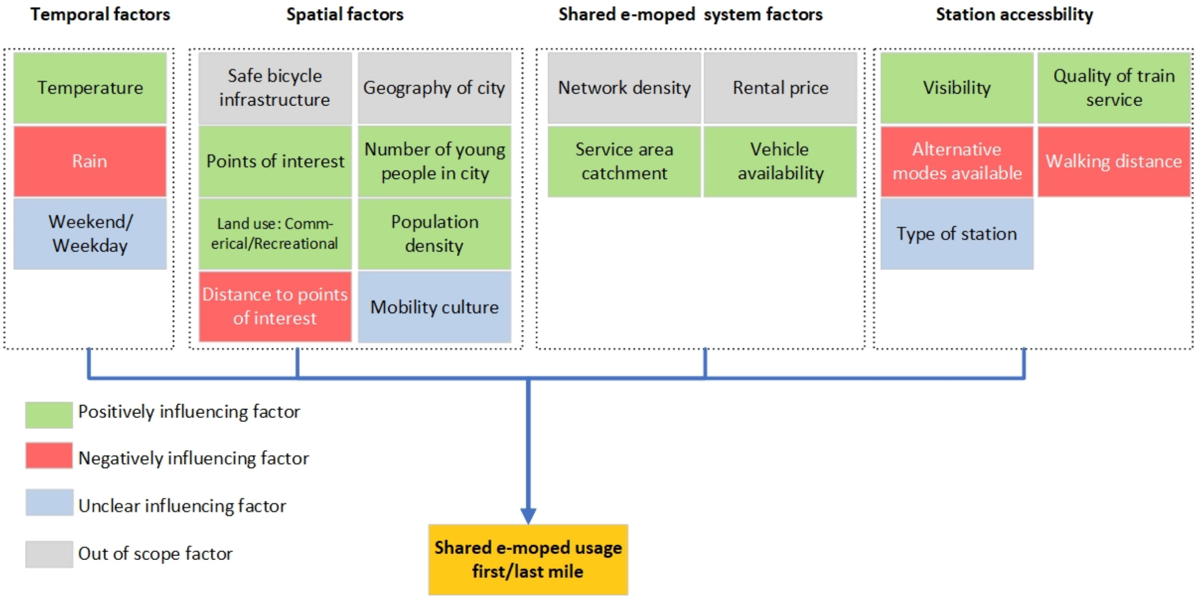

Figure 6.2: Conceptual frame work factors influencing shared e-moped usage in first- and last mile transportation

Figure 6.2 shows four group of factors influencing the shared e-moped usage in first/last mile transport to train station. Of these factors, some factors are identified as out of scope factors. These are factors that are relevant based on the literature study, but are not possible to detect the influence of in this study. The influence of safe bicycle infrastructure cannot be determined as the quantification is done based on data from The Netherlands. Since, the Netherlands has an excellent safe bicycle infrastructure and the design of it is constant through the whole country, the influence of safe bicycle infrastructure cannot be determined for this study. The influence of the geography of a city can also not be determined. The geography of a city consists of hills and other barriers as rivers in the city. Since, there are almost no hills in the Netherlands this influence of this variable cannot be appropriately determined. The network density is only relevant for station based systems and as the shared e-moped network is a free floating system, the influence of network density cannot be determined. The influence of rental price can also not be determined, as this study uses data from one provider only.

6.2 Model structure

This section describes the structure of the multiple linear regression model including the quantification of the factors into model variables and the results from the search process to the best model. The selection of this method and the characteristics of the multiple linear regression method are described in Section 3.4.

6.2.1 Model variables

Dependent variable

The regression model explains the influence of factors on shared e-moped usage in first- and last mile transportation. The usage in first- and last mile can be quantified in both the modal share of shared e-mopeds per day, as well as the number of shared e-moped trips per day. Therefore, both variables are selected as dependent variables. To run a multiple linear regression model, the factors need to be quantified for each observation. Since, some factors, such as vehicle availability differ for first and last mile, two different models are needed. Since there are two dependent variables, in total 4 models are built, two with the modal share as dependent variable and two with the number of trips as variable.

Independent variables

Table 6.1 gives an overview of all independent variables that are considered for the model. First their set up is described. This is done in order of the variables in Table 6.1. For temperature the average temperature between 6:00 and 23:00 is calculated. This is done, because this time interval covers the most usage, which means it is an more accurate representation than the average temperature over the whole day. For rain, it mainly matters whether it rains and not how much it rains on a day. If there is a high number of precipitation in one hour, this precipitation only influences this hour. This means the total number of precipitation does not give a good indication of the rain over a whole day. Therefore, the number of hours it actually rains on a day from 6:00 to 23:00 is calculated. During, the data collection period there are 27 days without rain (weather station Amersfoort). On other days the number of hours that it rains ranges from 1-15. The average temperature during the observation period is 14.8 °C. The min and max temperature range from 9.2-24.8 °C. Both the temperature and rain are calculated from KNMI data (KNMI, 2023). The train stations are matched to the closest weather station of the KNMI.

The influence of weekdays is captured in splitting the days into week and weekenddays, because the usage pattern analysis shows that there is a difference in modal share between week and weekenddays. This is modelled as a binary variable, where the variable is 1 if it is a weekend day and 0 if it is a weekday.

The points of interest and the distance to point of interests, as well as the land use (commercial/recreational) are captured in one variable: the number of points of interest within 5 kilometres of the station. This data comes from the 'CBS 100x100 vierkantstatistieken' (CBS, 2022). This dataset describes all kinds of statistics, including the distances to and the number of services. For this variable the dataset of 2020 is used, because this was the last completed dataset. The stations are matched to a 100x100 cell, of which the number of points of interests are copied to that station. The points of interests have been defined as: shops, cafes, restaurants, theaters, museums and cinemas. Hotels and grocery shops are not taken into account, because it is unlikely that someone will use the shared e-moped to get to these destinations. The distance is set at 5 kilometres. The data is available for most services on 3, 5, and 10 kilometre level. Since the average trip distance in first/last mile transportation is approximately 3.1 kilometres, 3 kilometres seems as the most logical choice. For 3 kilometres, however, not all data is available. Using a radius of 10 kilometres would make differences between different station in a city smaller, which is not the purpose of this variable. Therefore, 5 kilometres is the ideal radius to use, since all data is available and the distance is closer to the average distance travelled on shared e-moped in first- and last mile transportation. This variable also captures the influence of distance, since the distance will be larger if there are less points of interests.

The share of young people is quantified by taking the share of young people from the KIS10 dataset of NS. This dataset has the percentage of users in each age group at each station. The relevant age groups used in this dataset are 20-24 and 25-44. As discussed in chapter 2, shared e-mopeds users are generally young (Knoope and Kansen, 2020; Aguilera-García et al., 2021). Young people are defined as people between 20 and 35. Since, the NS data is only available in groups 20-24 and 25-44. The whole of group 20-24 is young and half of the group 25-44 is considered young. The share of young people at a station is calculated with equation 6.1

$$Share_{yp} = Share_{20-24} + 0.5 * Share_{25-44} \quad (6.1)$$

The population density is gathered from the CBS bodemgebruik (CBS, 2023). For Rotterdam the area of the Maashaven is removed from the total area, because no people live there, which gave a wrong indication of the population density. The observed densities range from 524 people $/km^2$ in Leeuwarden to 6712 people/km^2 in Den Haag. The service area catchment has as goal to measure the accessibility of the station by shared e-moped. Therefore, the service catchment area is defined as the average of the distance shared e-moped users can drive in each wind direction. This distance is maxed out at 3820 meter, which is the average 75th percentile of the trip distance. This means that 75% of the trips are shorter than this distance. This max value is introduced, because otherwise the average would be the same at every station, because when a service area is located at the west of the service area, the distance that can be travelled into the west direction is zero, but the distance in east area is in theory, the whole width of the service area, which means the average is the same as a train station in the center of a city. In practice, however, people would choose to not alight at this station due to the high driving distance. Therefore, the 75th percentile trip distance is used to show the differences in service catchment better. To measure the distances in each direction, the servicearea GeoJSON files are delivered by Check. The service catchment areas in this case study range from 1900 metres to 3800 metres.

The visibility shows whether shared e-mopeds are directly visible from the station. This has been checked at some real live locations as well as street view in Google maps, along with the service areas of Check. The vehicle availability in first mile should tell how far someone should walk to get to their shared e-moped. To give an indication for this value, the number of shared e-mopeds in a municipality is divided by the area of the municipality. The values of the vehicle availability in first mile range from 0.8-7.03 e-mopeds/km^2. The higher the number of shared e-mopeds per squared metre, the shorter someone has to walk to a shared e-moped.

The quality of train service is qualified in three variables. The first variable is the average number of departing trains per hour. This number is calculated using departing data provided by NS. For every day and every station the average frequency of departing trains is calculated. The second variable representing the quality of train service is the variable IC-stop. This variable is 1 when an Intercity train stops at this station and 0 when no Intercity train stops at this station. Lastly, the third variable is the type of station, according to the KIS typology by van Hagen and de Bruyn (2002). This is represented with dummy variables. For dummy variables one needs one variable less than the number of options. Since there are 4 types of station in the data this means three dummy variables are used.

Lastly, the alternative modes factor is represented by four different variables. The first variable is the bus frequency at the station. This is the frequency between 16:00 and 17:00 at a workday. This moment has been chosen, because all peak vehicles are also operating in this time window. This frequency has been gathered by counting the number of busses departing from each station from the NS site (NS, 2023). This option is chosen, because detailed information about all departure times was not available. The second variable is the tram frequency. This has been quantified in the same way as the busses. The third variable is the metro frequency, which is again gathered from the NS site and represents the number of metros departing between 16:00 and 17:00. The fourth variable is the number of OV-fiets at each station. This is gathered from internal data of NS. This independent variable ranges from 4 to 1250 bikes.

Table 6.1 shows an overview how all factors for first- and last mile transportation from the conceptual framework in Figure 6.2 are quantified. It shows the quantification, unit and the source of the data.

Table 6.1: Overview of factors used for first and last mile regression model

Variable	Quantification	Unit	Data source
Rain	Hours of rain between 6:00 and 23:00	h	KNMI
Temperature	Average temperature between 6:00 and 23:00	°C	KNMI
Weekend	1 if day is a weekend day, 0 if not	-	
Points of interest	Number of cafes, shops, restuanrants, museum, theaters and cinnemas within 5 kilometres of station	-	CBS
Young people	Share of young (20-35) people using the station	%	NS KIS10
Population Density	Population density of city	People/km^2	CBS
Service Area Catchment	Average distance one can come from to the station within the servicearea in each winddirection	m	Check
Visibility	1 if shared e-mopeds are visibile from station, 0 if not.	-	
Walking distance	Distance from shared e-moped to train station	metres	Check/NS
Vehicle availability	FM: Number of shared e-mopeds/ area municipality LM: Minimum average number of shared e-mopeds available at a station	moped/km^2	Check/ CBS
Quality of Train Service	Average frequency of trains on each day	trains/h	NS
Type of station	3 dummy variables for station	-	NS KIS10
Bus frequency	Number of busses at each station per hour	busses/h	NS.nl
Tram frequency	Number of trams at each station per hour	trams/h	NS.nl
Metro frequency	Number of metros at each station per hour	metros/h	NS.nl
OV-Fiets	Capacity of OV-fiets facilities	bikes	NS data
Train frequency	Average number of trains per hour on a day	trains/h	NS data

Table 6.1 shows for the last mile model, there is one factor which is different from the first mile. For the last mile, the number of vehicles present at a station represents the vehicle availability. The ideal quantification of this number would be to have the live number of shared e-mopeds at each station. This however cannot be calculated in the right way with the Check data, because there is a mismatch in the number of first- and last mile trips, which is caused by the data filtering and possible relocation movements by Check. Therefore, the minimum number of shared e-mopeds available at each hour at a station is calculated. This is done by calculating the number of arriving and departing shared e-moped trips at each station per hour. First mile trips are considered as +1, because they add a shared e-moped to the station. Last mile trips are considered as -1, because they remove the number of shared e-mopeds. The residual, i.e. the remaining number of shared e-mopeds at each hour is calculated and taken to the next hour. Per day the residual can never be lower than zero. This results in the minimum number of shared e-mopeds present per hour for each day. For each day the average is taken. The actual number can actually be higher, because the remaining shared e-mopeds at the end of each day are discarded.

6.2.2 Finding the best model

To find the most appropriate model structure the methodology described in subsection 3.3.2 is followed. The search process of the modal share models is shown in Table 6.2. This table shows the added variables per step and for each step the adjusted R^2 score and the number of VIF's >10 to make sure the multicollinearity present in the model is not too severe (Montgomery et al., 1982).

Table 6.2: Intermediate model results modal share models. (r) means the variable is removed directly after addin

First Mile			Last Mile		
Added variable	Adj. R^2	VIF>10	Added variable	Adj. R^2	VIF>10
Train frequency	0.194	0	Train frequency	0.187	0
POI* Vehicle availability	0.321	0	Vehicle availability	0.332	0
Metro frequency	0.435	0	Weekendday	0.367	0
Weekendday	0.475	0	Population Density	0.397	0
Weekend * train frequency	0.508	0	Visbility * Walking distance	0.477	0
IC stop (r)	0.527	0	Young People	0.505	0
Population Density	0.541	0	POI within 5km	0.526	0
Vehicle availability	0.562	0	Tram frequency	0.549	0
Young People	0.571	0	Bus frequency	0.572	0
Tram frequency	0.597	0	Weekend* Train frequency	0.591	0
Bus frequency	0.607	0	IC stop(r)	0.602	0
POI within 5 km	0.623	0	Temperature	0.595	0
Temperature	0.627	0	Visibility	0.597	0
			OV fiets	0.599	0

Table 6.2 shows the final models that are found. The first mile model has an adjusted R^2 score of 0.627 and the last mile model has an adjusted R^2 score of 0.599. In the first model, the IC stop variable becomes insignificant after adding POI_total, which means the IC stop variable is removed. The table shows that in the search process of the last mile model the IC stop variable is removed, because it causes coefficients to become larger than 1, which is a sign that the impact of multicollinearity is too severe. The first mile modal share model consists out of the variables train frequency, POI* vehicle availability, Metro frequency, Weekend day, weekend day * train frequency, population density, vehicle availability, young people, tram frequency, bus frequency, points of interest within 5 km and the temperature. The last mile modal share model consists out of the variables train frequency, vehicle availability, weekend day, population density, visibility * walking distance, young people, Points of interest within 5 km, Tram frequency, Bus frequency, Weekend*train frequency, Temperature, visibility and OV fiets. Table 6.3 shows the results of the search process for building the first- and last mile trip models.

Table 6.3 shows that the first mile model has an final adjusted R_2 score of 0.597. The last mile model score has an final adjusted R^2 score of 0.700. The first model consists out of the variables IC Stop, Vehicle availability* POI within 5 km, Service catchment, Bus frequency, Metro frequency, tram frequency, population density, young people, vehicle availability, train passengers, walking distance, train frequency and temperature. The last mile models consists out of the variables vehicle availability, IC stop, Population density, Service catchment, Young people, tram frequency, metro frequency, visibility and train passengers.

Table 6.3: Intermediate model results trip models

First Mile			Last Mile		
Added variable	Adj. R^2	VIF>10	Added variable	Adj. R^2	VIF>10
IC stop	0.237	0	Vehicle availability	0.505	0
Vehicle availability * POI within 5 km	0.303	0	IC Stop	0.573	0
Service_catchment	0.354	0	Population density	0.596	0
Bus frequency	0.403	0	Service_catchment	0.637	0
Metro_Frequencie	0.457	0	Young People	0.649	0
Tram frequency	0.471	0	Tram frequency	0.664	0
Population density	0.525	0	Metro frequency	0.696	0
Young People	0.551	0	Visibility	0.697	0
Vehicle availability	0.563	0	Temperature	0.699	0
Train passengers	0.574	0	Train passengers	0.7	0
Walking distance	0.586	0			
Train frequency	0.592	0			
Temperature	0.597	0			

6.3 Model results

This section describes and discusses the results from the model, described in the previous section. The section begins with the results from the modal share modal's. First the first mile modal share model is discussed, after which the results of the last mile modal share model are shown. Section 6.3.3 and 6.3.4 give the results of the two trip models.

6.3.1 Modal share first mile

The model results of the best performing first mile model are shown in Table 6.4. This table shows that the model has an adjusted R^2 value of 0.627, which means 62.7% of the variance of the mean is explained by the model. For a travel behaviour phenomenon this is a descent score. This table shows the standardized coefficients, as the data is standardized. This means one unit change in standard deviation of a variable causes $beta$* standard deviation of the modal share change in the modal share. The order of the variables it the order in which they are added to the modal as can be seen in Table 6.2. The correlation matrix of the first mile modal share model can be found in Appendix E. This correlation matrix shows how much all the variables correlate with each other, including the variables that are not in the model.

Table 6.4: Model results first mile model share

Variable	β	std_v	unit	T-value	Unit change
Constant	-0.189			-11.229	
Train frequency	-0.077	7.65	Trains/h	-3.557	-0.0066
Vehicle availability* POI within 5 km	0.211	4059	e-mopeds/km2*POI	8.317	0.0000
Metro frequency	0.161	14.42	Metros/h	6.3345	0.0073
Weekendday	0.383			11.924	0.2524
Weekend*Train frequency	-0.328	5.67	Trains/h	-9.63	-0.0381
Population density	-0.657	1976	people/km^2	-17.923	-0.0002
Vehicle availibility	0.245	2.3	emopeds/km^2	12.2	0.0702
Young people	0.260	0.05	factor	12.683	0.0343
Tram frequency	0.242	28	trams/h	101.95	0.0057
Bus frequency	-0.189	27.57	busses/h	-8.762	-0.0045
POI within 5 km	0.216	961.95	Number POI	8.79	0.0001
Temperature	0.057	3.16	°C	4.13	0.0119
Modal share		0.659	%		
Model statistics	adj. $R2$	0.627	Condition number	6.69	

Table 6.4 shows that the regression coefficient are largely in line with the expected values in from the correlation and the conceptual framework. The variables are discussed in the four groups shown in the conceptual framework in Figure 5.27.

Temporal factors

The weekend day variable has a positive influence on the modal share, which matches the findings from the empirical findings, that the modal share is higher during the weekend. This is caused by less train passengers during the weekend and maybe less options to get to the station, because of less frequent public transport. The weekend variable has the biggest impact based on unit change (0.252), but this variable cannot be steered. A higher average day temperature leads to a higher modal share, as is shown by the positive coefficient (0.057) of the variable. This means that with higher temperatures more people choose for the shared e-moped as first mile mode, as the train frequency is not dependent on the weather. It is important to note that no extreme temperatures were present during the observation period, which means extreme high temperatures might have another effect.

Spatial factors

The number of points of interest within the station has a positive influence on the modal share. This shows that shared e-mopeds are used to get from the activity side back to the station, which again matches the empirical findings that 30% of the shared e-moped trips have a leisure purpose. The share of young people at station positively influences the modal share in first mile, which makes sense as the main user group are people between 18- and 35 years old. The population density has a negative influence on the modal share, while a positive influences is expected based on the conceptual framework in Figure 5.27. According to the model one needs a big change in population density (1976 people/km^2) to cause a modal change drop of 0.43%. . (-0.6565*0.659). This shows that the population density has a low impact on the modal share, as a large absolute effect is needed. The negative impact can be explained by the fact that in cities with a high population density people live closer to the station and more other public transport options are available. Therefore, there are more options for the user to go to the station, which means relatively less people choose the shared e-moped.

Shared e-moped system factors

The vehicle availability in first mile has a positive influence on the modal share. The influence of this variable is relatively big with a 0.07%. higher modal share, when one shared e-moped/ km^2 is added. The positive influence is in line with the interaction variable of vehicle availability and number of points of interest and makes sense as people have more shared e-mopeds available close by, which makes the shared e-moped more attractive as an first mile mode. The interaction variable: Vehicle availability * points of interest within 5 kilometres of the station has a positive influence on the modal share. This shows that it is important to have a high vehicle availability at places where there are a lot of points of interests. This matches the findings from the empirical insights that 30% of the shared e-moped first- and last mile shares have a leisure trip.

Station accessibility

The bus frequency has a negative influence on the modal share. This shows that the shared e-moped and bus have a competing relationship in first mile transport, meaning that an increase in attractiveness for one mode leads to a lower usage of the other. Adding 27 busses/h drops the modal share of shared e-mopeds by 0.06 %.. This shows that the shared e-moped and bus have a competing relationship, although the strength of that relationship is relatively small.

Table 6.4 shows that the train frequency has a negative influence on the modal share. This is counter intuitive as the conceptual framework shown in Figure 5.27 suggests that the quality of train service has a positive influence on the modal share. In areas with a high train frequency, there might be more train stations within a reasonable distance, reducing the need for shared e-mopeds. If passengers can easily access their destinations by foot or public transport from the train station, they may be less likely to use a shared e-moped as a first- or last mile mode. This is confirmed by the fact that at the four type 1 stations, which have a high train frequency, the share of people walking to the station is between 20 and 24% (NS, 2023). During the weekend, the train frequency also has a negative influence as the coefficient of the interaction variable: weekend*train frequency is negative. It is more negative than the regular train frequency variable. This shows that during the weekend a higher train frequency reduces the modal share more than during the week.

According to the model, the metro frequency has a positive influence on the modal share of shared e-mopeds in first mile transportation. This is a interesting finding, since the correlation of the metro frequency with the modal share alone is negative. This means that given the other variables in the model, the metro frequency has a positive influence, while on it's own it has a negative influence. This shows that there is some kind of a negative suppressor variable present in the model. This makes independent variables that have a relatively low correlation with the dependent variable change their sign (Pandey and Elliott, 2010). Therefore, no real conclusion about the impact of the metro frequency can be drawn from this model. The tram frequency has, just like the metro frequency, a positive influence according to the model, but a negative correlation sign with the modal share. This again implies the presence of a negative suppressor variable, which means no reliable conclusion from the model can be drawn from the model.

Not in the model

In the first mile model several variables are not significant. The number of OV rental bikes at a station is not significant, as this is a station based system. Therefore, the OV-fiets is not an option for the first mile trip, unless someone already hired one. This makes the variable have no effect on the modal share of shared e-mopeds in first mile transport. The visibility of shared e-mopeds from the station is also not significant in first mile transport, which makes sense as this is the visibility from the station, which has no impact on the first mile trips, as a first mile trip goes to the station.

The IC-stop variable is also not in the model, as during the model building process this variable caused multicollinearity issues in the model. This does not mean the IC-stop variable has no effect. The IC-stop still has an effect on the modal share, which from the correlation appears to be negative. The walking distance variable is also not in the model. This variable did not occur with the highest partial correlation in one of the model runs and has no significant effect given the variables that are already in the model. The walking distance appears to have, based on the correlation with the modal share to have a negative effect on the modal share, which means the greater the walking distance is, the lower the modal share will be.

6.3.2 Model share last mile

Table 6.5 shows the regression coefficients and model statistics of the best performing last mile model. Again, standardized regression coefficients are shown and the standard deviation of both the variable and the standard error of the beta's are shown. In Appendix E, the correlation matrix is shown.

Table 6.5: Modal results last mile model share model

Variable	β	std_v	unit	T-value	Unit change
Constant	-0.368			-9.592	
Train frequency	-0.054	7.65	Trains/h	-2.178	-0.0040
Vehicle availability	0.249	10.3	e-mopeds	11.09	0.0136
weekendday	0.433			11.999	0.2436
Population Density	-0.775	1976	people/km^2	-20.824	-0.0002
Visbility*Walking distance	-0.748	32.03	m	-11.848	-0.0132
Young people	0.233	0.05	factor	10.818	0.0262
POI within 5 km	0.236	961.95	number POI	9.701	0.0001
Tram frequency	0.359	28	Trams/h	10.788	0.0072
Bus frequencie	-0.175	27.57	Busses/h	-4.317	-0.0036
Weekend*Train frequency	-0.298	5.67	Trains/h	-7.844	-0.0296
Temperature	0.054	3.16	degree Celcius	3.505	0.0096
Visibility	-0.145			-2.915	-0.0817
OV fiets	-0.108	372.04	Number of OV-fiets	-2.68	-0.0002
Modal share		0.563	%		
Model statistics	adj. R^2:	0.599	Condition number	8.38	

Again, most regression coefficients shown in Table 6.5from the regression model mostly match the expected findings.

Temporal factors

During the weekend the modal share is higher according to the last mile modal share model, as the weekend day coefficient is 0.433. This is again in line with the observation from the empirical insights that the modal share is higher during the weekend. Again, this variable is the variable with the highest unit change. A higher temperature leads to a higher model share in last mile for shared e-mopeds, as the beta is 0.054, which matches both the conceptual framework as well as the first mile modal share findings

Spatial factors

The higher the share of young people is, the higher the modal share in last mile is. This is the same observation as in first-mile, which matches the target group found in the preliminary literature study. An increase of 0.05 (5%) in the share of young people at a station can lead, according to the model to an increased modal share of 0.13%.. The points of interest have a positive coefficient (0.236), which means the number of points of interest within 5 kilometres of the station increases the modal share. This is caused by 30% of the trips having a leisure purpose and shows that it is interesting to offer shared e-mopeds at stations where there are a lot of points of interest around. The population density has a coefficient of -0.775, which implies a negative relationship with the modal share in last mile. This means that in the densest cities, the modal share of shared e-mopeds is lower, this is again in contradiction with the expected value from the conceptual framework. It does not imply that shared e-mopeds have a higher modal share in rural villages, because the data is only trained on cities and not on rural areas.

Shared e-moped system factors

The vehicle availability at stations has a positive influence on the modal share. Increasing the average vehicle availability per day at a station reduces the chance for a user that no vehicle is available when he wants to use one. According to the model, increasing the shared e-moped availability at stations with 10 shared e-mopeds, increases the modal share in last mile with 0.14%.. This shows the vehicle availability can have a relatively big influence.

Station accessibility

The bus frequency has a coefficient of -0.175, which shows that the bus frequency has a negative influence on the modal share. This means shared e-mopeds have a competing relationship with busses in last mile transport, as a higher bus frequency, leads to a lower modal share of shared e-mopeds in last mile transportation. The visibility*walking distance coefficient is negative with -0.7484. This means that when shared e-mopeds are visible, the greater the walking distance is, the lower the modal share is. This makes sense, as it becomes less attractive for users to use a shared e-moped. The walking distance itself is not in the model, because it causes multicollinearity issues, but the correlation of walking distance alone with modal share is also negative, implying that the walking distance from the station to a shared e-moped negatively influences the modal share. The unit change of the interaction term implies that when shared e-mopeds are visible and the walking distance is increased with 1 metres, the modal share drops down with 0.01%., which is quite a significant impact. The OV-fiets coefficient is -0.1078. This means that the number of OV-fiets available at a station negatively influences the modal share. This shows that shared e-mopeds and the OV-fiets have a competing relationship. The strength of this relationship is relatively small though, as 1 extra OV-fiets lead to a reduction in modal share of 0.0002%. They are both shared micromobility modes which means they serve partly the same target group. This shows that shared e-mopeds and shared bikes compete slightly with each other in last mile transport.

Table 6.5 shows that the train frequency again has a negative influence on the modal share. This can be explained by the same logic as for the first mile model. Stations with a high frequency are often located in the middle of big cities, thus, people alighting here often have to be in the city center, which means they can walk to their destination. This is illustrated by the fact that at the four type 1 stations, the modal share of pedestrians in last-mile transport ranges from 42-59% (NS, 2023). This explains why a high train frequency leads to a lower modal share. This does not mean that a train frequency of 1 train per hour, leads to a higher modal share of shared e-mopeds than a train frequency of 2 trains per hour. The model is trained on stations with train frequencies not lower than 6 trains per hour, which means this model cannot tell something about the effect of lower train frequencies.

The tram frequency also positively influences the modal share in last mile transport. This is again, in contradiction with the individual correlation coefficient, which might be caused by a negative suppressor variable. This means no reliable conclusion about the individual influence of the tram frequency can be drawn. Visible shared e-mopeds from the station lead to a lower modal share of shared e-mopeds, although the impact is relatively small as it causes, according to the model a modal share decrease from 0.08%.. This negative regression coefficient conflicts with the positive correlation of the visibility variable with the modal share, indicating again the presence of a negative suppressor variable. This means no reliable conclusion can be drawn about the impact of the visibility.

Not in the model

Interesting to see is that the metro frequency is not in the last mile modal share model. This implies that the metro frequency has no significant effect on the modal share. Just like in all the other models, rain is also not present in the model, indicating that the hours of rain over the day has no influence on the modal share. The IC-stop variable is also not in the model, which is due to the fact that is causes multicollinearity issues with an interaction variable. This means its effect cannot solely be determined.

6.3.3 Trips first mile

In this section the first mile trip model is discussed. For the trip models, the data from Rotterdam Central Station is excluded from the data, because this station has twice as much trips then the next station (Breda). This would lead to results biased towards the high outliers of Rotterdam. Table 6.6 shows the best performing model results of the first mile model for the number of shared e-moped trips at a station. This table shows that the variance from the main is for 59.7% explained by the model, as the R^2 value is 0.597. The signs of the coefficient are all but one in line with the correlation of the individual variables with the number of trips. In Appendix E, the correlation matrix is shown.

Table 6.6: Model results first mile model

Variable	β	std_v	unit	T-value	Unit change
Constant	-0.376			-8.391	
IC stop	0.463			8.607	22.5522
Vehicle availbility* POI within 5 km	0.370	3756	mopeds/km2*poi	12.689	0.0048
Bus frequency	0.228	27.77	busses/h	6.502	0.4004
Metro frequency	0.421	14.48	metros/h	16.053	1.4151
Tram frequency	0.488	26.34	trams/h	14.011	0.9036
Population density	-0.578	2020	people/km^2	-12.974	-0.0139
Young People	0.240	0.05	factor	9.696	2.3341
Vehicle availability	0.112	4.14	mopeds/km^2	4.582	1.3183
Trainpassengers	0.417	15735	passenger/day	9.699	0.0013
Walking distance	-0.322	68.6	metres	-6.912	-0.2287
Train frequencie	-0.134	7.65	trains/h	-4.358	-0.8536
Temperature	0.065	15738	°C	4.277	0.0002
Trips		48.73	trips/day		
Modal statistics	adj. R_2	0.597	Condition number	9.62	

Temporal factors

Table 6.6 also shows that the higher the temperature is, the more shared e-moped trips are made, as the regression coefficient is 0.0647. This is in line with observations from Arias-Molinares et al. (2021) and Knoope and Kansen (2020) who also show that the shared e-moped usage is higher when the temperature is higher.

Spatial factors

The population density again has a negative influence on the number of trips. This is caused by the relatively low usage in the two densest cities: Den Haag and Amsterdam, while in less denser cities such as Breda and Leeuwarden, the usage is higher. The share of young people at a station positively influences the number of shared e-moped trips towards a station in first mile, which is caused by the fact that the main user group consists out of young people. When the share of young people increases with 1%, there are 2.3 trips more first mile shared e-moped trips per day, which shows that this variable has a large impact on the number of shared e-moped first mile trips.

Shared e-moped system factors

The vehicle availability in first mile also positively influences the number of trips. Increasing the vehicle availability with $1/km^2$ leads to 1.3 more shared e-moped trips. This shows the vehicle availability has a moderate impact, as one needs a lot of vehicles to increase the vehicle availability in the largest cities. As can be seen in Table 6.6 the regression coefficient is lower than that of the interaction term with POI (0.112 vs 0.3702), which indicates that vehicle availability in areas with a higher number of points of interest has more impact than in areas with less points of interest. The vehicle availability interaction term with the number of points of interest within 5 kilometres of the station, also has a positive influence, which is in line with the finding that shared e-mopeds are also used for leisure purposes. These first mile trips are likely to be returning trips from the points of interest to the station.

Station accessibility

When a station is an Intercity station, the station attracts more shared e-moped trips in first mile transport, as is shown by the positive beta in Table 6.6. An intercity stop provides faster and more direct connections to other stations in the network. An IC-stop attracts 22 more shared e-moped first mile trips per day, than a non-IC stop. This makes sense, as an Intercity station provides a opportunity to join the Intercity network, while a station with only a local service, such as a Sprinter, requires an additional change from the local service, to the intercity service. Also, Intercity stations often have more passengers than no Intercity stations, due to the better connections. The bus, metro and tram frequencies all have a positive influence on the number of shared e-moped trips towards a train station. This is in line with the individual correlation sign with the number of trips, in contradiction to the modal share model. This can be explained by the fact that at larger stations, the frequencies of most modes are higher, as there are more train passengers. This higher number of train passengers, automatically also leads to a higher number of shared e-moped trips. This does not mean the bus, tram and metro are not competing with shared e-mopeds as first mile mode, as the main reason for the positive relation is the higher frequencies of public transport at bigger stations.

The number of train passengers also has a positive influence. This variable confirms the observation from the bus,tram and metro frequencies. The train passengers variable has a relatively high coefficient (0.4165), but also a large standard deviation (15738) passengers, meaning that the impact per extra train passenger is small.The walking distance from the shared e-moped towards the station has a negative influence on the number of trips. This means the further away from the station the closest shared e-moped parking possibility is, the lower the number of shared e-moped trips will be. A longer walking distance will make the transfer from shared e-moped to the train less attractive, which therefore decreases the number of shared e-moped trips towards a train station. A shorter walking distance of 1 meter, leads to 0.23 more trips, meaning that a decrease of walking distance of 5 metres already leads to one more shared e-moped first mile trips. This shows the walking distance can have a big impact on the number of shared e-mopeds in first mile transportation.

The model implies that the train frequency has a negative impact on the number of shared e-moped trips. This is in contradiction with the individual regression sign. This can likely be explained by the effect of a negative suppressor variable, as the correlation of the train frequency with the number of trips is only 0.08. This means the impact of the train frequency is likely to be less relevant.

Not in the model

In the first mile model, the number of POI within 5 kilometres of the station is not significant as separate variable, also the service catchment seems to be not relevant for the first mile, as it does not appear in the model. This can be explained by the fact that people travel to the station, meaning that when they do travel, they start in the service area anyway.

6.3.4 Trips last mile

Table 6.7 shows the regression coefficients, the variables and the standard deviation of coefficients of the best performing model for the number of trips in last mile transport. The coefficients in Table 6.7 are again standardized coefficients. The variance from the mean is explained for 70.0%, which is the highest performing model. In appendix E , the correlation matrix is shown.

Table 6.7: Model results last mile trips

Variable	β	std_v	unit	T-value	Unit change
constant	-0.433			-9.256	
Vehicle availability	0.410	4.14	Shared e-mopeds	25.924	4.8386
IC stop	0.385			9.098	18.8065
Population density	-0.529	2020	people/km^2	-19.614	-0.0128
Service catchment	0.103	618	m	5.976	0.0082
Young people	0.236	0.05	factor	12.222	2.3038
Tram frequency	0.299	26.35	trams/h	11.54	0.5553
Metro frequency	0.188	14.48	metros/h	9.408	0.6351
Visibility	0.132			3.503	6.4185
Temperature	0.040	3.16	degree celsius	3.018	0.6132
Trainpassengers	0.063	15735	passengers/day	2.76	0.0002
Trips		48.81	trips/day		
Model statistics		0.700	Condition number	8.38	

Temporal factors

The temperature again also has a positive influence on the number of last mile shared e-moped trips. A 1 degree increase leads to 0.6 more trips per day, indicating that with higher temperatures the usage will be higher. This does not mean that with extreme temperatures the usage is also higher, as no extreme temperatures were present during the observation period.

Spatial factors

The young people share at a station again positively influences the number of shared e-moped trips. An increase of 1% in the share of young people leads to 2.3 more shared e-moped trips. This shows that the young people share at a station has a big influence on the number of last mile shared e-moped trips. The population density also has a negative influence on the number of shared e-moped trips in last mile, but it's impact is limited as the unit change is only -0.0128, meaning that one would need 100 people/km^2 more to reduce the number of shared e-moped trips by 1. Again, this observation does not mean that in rural areas with low density there are more shared e-moped trips, as the model is only trained on cities.

Shared e-moped system factors

The first variable, vehicle availability, explains when added as only variable already 50.5% of the variance. When not including it in the full model, the model performance is reduced by 23%. This shows that the vehicle availability at a station is a major determinant for the number of last mile trips by shared e-mopeds. This is primarily caused by the fact that people dislike it, when no vehicle is available. This in line with literature findings, as vehicle availability is the most mentioned factor in literature for other shared mopeds, which is shown in Table 4.1. The unit change shows that according to the model adding on average 1 vehicle at a station leads to 4.8 additional shared e-moped last mile trips. This shows that vehicle availability influences the number of trips significantly. The service catchment area has a positive influence on the number of shared e-moped trips in last mile, as the coefficient is 0.1034. This is caused by people being able to travel further by shared e-moped, which increases the attractiveness of shared e-mopeds as a last mile mode. The impact of this variable is low however, as the unit change is only 0.0083, meaning one would need an increase of service catchment by more than 100 metre to get one more trip.

Station accessibility

A intercity station has, just like in first mile a positive influence on the number of shared e-moped trips. These stations are better accessible in the train network, which makes it more logical to transfer from the train to a shared e-moped, as it saves an additional train change. An IC-stop generates 18.8 last mile trips per day. The visibility of shared e-moped from the station entrance positively influences the number of shared e-moped trips. This shows, that to increase the number of shared e-moped trips, increased visibility might be a solution. According to the model, the visibility increases the number of last mile trips per day by 6. Lastly, the number of train passengers, also has a positive influence on the number of shared e-mopeds trips, as more train passengers means more potential shared e-moped drivers. The tram and metro frequency again have a positive influence, which is caused by the higher number of train passengers present at the stations with a high tram and bus frequency.

Not in the model

In the last mile model, less variables are present. The number of OV-fiets has no significant influence on the number of trips at a station. This probably caused by a mix of the competing effect observed in the modal share model and the fact that at larger stations with more passengers more OV-fiets are available, which balances out to have no effect. Also, the points of interest is not in the model, implying that for the number of last mile trips, mostly station characteristics or shared e-moped network characteristics are relevant.

6.4 Model validation

In this section the explanation power and the prediction power of the proposed models is assessed. First, the explanation power is described by using 5-fold cross validation, after which the prediction power is discussed.

Model explanation power

To validate the model a 5-fold cross validation, which is described in Section 3.3.3 is performed. Table 6.8 shows the validation results of the modal share models. The minimum and maximum values represent what the lowest or highest coefficient found in the 5 separated models is. The percentage is the maximum absolute percentage deviation from the results of the full model. In Appendix J the results of the individual model runs can be found. The validation results show that the adjusted R^2 for both models differs at maximum 2.3%. This means that the modal share models are still able to explain approximately the same amount of variation for 80% of the data. Most coefficients of the first mile modal share model differ not more than 10%. Only the train frequency and the temperature differ more than 20%, which means the sign of the relation is still valid, but the exact effect has quite a large error margin. These two variables are also the least significant, as can be seen in Table 6.4. In the last mile model share the train frequency has a deviation of 53.7%. This is due to the fact that in two of the five model runs, this variable was not significant. This means no reliable conclusion about the effect of the train frequency on the modal share can be drawn. The visibility also has a big deviation of 49%. but this variable was significant in each model. This variable is mentioned in the result section as a suppressor variable, which means the variable might be effected by multicollinearity, causing an outlier. Therefore, no reliable conclusion about the effect of the visibility on the modal share can be drawn.

Table 6.8: Model validation results of modal share models. Min and max represent the minimum and maximum coefficient value found in different models. Values above 20% are highlighted

First mile modal share					Last mile modal share			
Variables	Min	Max	Full	Percentage	Min	Max	Full	Percentage
Adj. R2	0.621	0.63	0.627	1.0%	0.59	0.613	0.599	2.3%
constant	-0.205	-0.18	-0.189	8.5%	-0.387	-0.313	-0.368	14.9%
Train frequency	-0.0962	-0.06	-0.077	24.9%	-0.074	-0.025	-0.054	**53.7%**
Vehicle availability * POI within 5 km	0.205	0.224	0.211	6.2%	-	-	-	-
Metro frequency	0.134	0.184	0.161	16.8%	-	-	-	-
Weekendday	0.349	0.427	0.383	11.5%	0.423	0.467	0.433	7.9%
Weekkend * Train frequency	-0.333	-0.326	-0.328	1.5%	-0.322	-0.283	-0.298	8.1%
Population density	-0.671	-0.64	-0.656	2.4%	-0.805	-0.714	-0.775	7.9%
Vehicle availability	0.232	0.255	0.245	5.3%	0.257	0.281	0.249	12.9%
Young people	0.239	0.271	0.26	8.1%	0.216	0.259	0.233	11.2%
Tram frequency	0.222	0.261	0.242	8.3%	0.315	0.382	0.359	12.3%
Bus frequency	-0.195	-0.183	-0.189	3.2%	-0.189	-0.143	-0.175	18.3%
POI within 5 km	0.198	0.234	0.216	8.4%	0.207	0.257	0.236	12.33%
Temperature	0.045	0.067	0.057	**21.1%**	0.045	0.07	0.054	**29.63%**
Visibility* Walking distance	-	-	-	-	-0.793	-0.711	-0.748	6.0%
Visibility	-	-	-	-	-0.216	-0.137	-0.145	**49.0%**
OV-fiets	-	-	-	-	-0.134	-0.094	-0.108	**24.1%**

Table 6.9 shows the validation results of the trip models. Again, the detailed result per separate run can be found in Appendix J. The validation results of the trip models shows that the adjusted R^2 score differs at max 2.3%. This shows that the model is still able to explain approximately the same variance. This shows that the models perform constantly and are not overfitted. In the first mile trip mode, the

train frequency and the temperature have a higher deviation than 20%. These are the same variables as in the modal share models, which means there sign is still valid, but the exact effect has a high confidence interval. Most coefficients in the first mile modal share are below 10%, indicating that the internal validity of the model is good, as the most coefficient deviate a limited amount. In the last mile modal, these deviations are even lower, as most coefficient have a deviation of max 7.5%, while the highest deviation is 13.7%, which occurs at the train passengers. This shows that this model is valid and reliable. The last mile trip model seems to validate the best out of the four models, making this model suitable to form the basis for answering the main research question. The conclusion from the validation is that all models can be used for explaining the effects of factors, although some notion should be taken for the train frequency and the visibility in the modal share model as these variables have a high deviation.

Table 6.9: Model validation results of trip models. Min and max represent the minimum and maximum coefficient value found in different models. Values above 20% are highlighted

First mile trips					Last mile trips			
FMTRIPS	Min	Max	Full	Percentage	Min	Max	Full	Percentage
Adj. R2	0.589	0.611	0.597	2.3%	0.687	0.714	0.7	2.3%
Constant	-0.385	-0.357	-0.376	5.1%	-0.453	-0.405	-0.433	5.1%
IC stop	0.411	0.48	0.463	11.2%	0.369	0.4	0.385	2.8%
Vehicle availability * POI within 5 km	0.36	0.377	0.370	2.8%	-	-	-	-
Bus frequency	0.212	0.24	0.229	7.4%	-	-	-	-
Metro frequency	0.412	0.427	0.421	2.1%	0.183	0.195	0.188	7.1%
Tram frequency	0.473	0.509	0.488	4.3%	0.279	0.323	0.3	3.1%
Population density	-0.592	-0.56	-0.578	3.1%	-0.549	-0.508	-0.529	7.4%
Young people	0.223	0.255	0.24	7.1%	0.224	0.248	0.236	4.3%
Vehicle availability	0.106	0.119	0.112	6.3%	0.39	0.433	0.41	11.2%
Train passengers	0.39	0.437	0.417	6.5%	0.055	0.069	0.063	13.7%
Walking distance	-0.366	-0.295	-0.322	13.7%	-	-	-	-
Train frequency	-0.155	-0.104	-0.134	22.4%	-	-	-	-
Temperature	0.051	0.078	0.065	21.5%	0.035	0.045	0.04	6.5%
Service catchment	-	-	-	-	0.094	0.114	0.103	2.1%
Visibility	-	-	-	-	0.109	0.149	0.132	6.3%

Model prediction power

To see whether the model can be used for predictions outside the trained data, 5-fold cross validation again is used. Table 6.10 shows the average root mean square deviation of both the trainset and the testingset for all four models. Also, since this RMSE is calculated using standardized data, this is transformed in the fourth and fifth column into the original units. Table 6.10 shows that the models have

Table 6.10: Average prediction results of 5-fold cross validation on all four models.

	Average RMSE Train	Average RMSE Test	RMSE Train (% or trips)	RMSE test (% or trips)
First modal share	0.699	0.698	0.48%	0.48%
Last mile modal share	0.739	0.739	0.42%	0.42%
First mile trip	0.729	0.724	35.5	35.3
Last mile trip	0.673	0.671	32.8	32.8

quite a high average error with 0.48% for the modal share and 35 trips for the trip models. This shows that the model is not suited for prediction individual values, as there could be a large error. For the smaller stations this could lead to negative modal shares, as some stations in the case study have a modal share lower than 0.48%. For the number of the RMSE is also high with 35 trips for the first mile model and 32 for the last mile model. To reduce the impact on the predictions, multiple days should be used, to make sure the modal share and trips per day are based on multiple days. The model is thus not able to predict the modal share and number of trips on a single day reliably. When wanting to use the models for prediction one should use a large enough number of days to ensure the RMSE balances out. Still, this prediction would not be very reliable, as a station could also have a bias to a positive or negative error, due to the station characteristics. Furthermore, when wanting to use the models for prediction, it should be checked whether the station characteristics are in the range of the stations that are used for training the model, as the model is trained on standardized data. This would mean that for example Utrecht CS would not be a suitable prediction station, as the number of busses is higher than any station in the training data. Stations such as 's Hertogebosch, Eindhoven, Haarlem or Maastricht might be better suitable as these stations characteristics match better. The model seems to have a higher explanation power than a prediction power.

6.5 Conclusion

This chapter tries to answer the subquestion: 'What is the best performing model structure to quantify the influence of factors on the usage patterns of shared e-mopeds in first- and last mile transportation to train stations?.

For quantifying the influence of factors on the usage patterns four different models are built. Two models have as the dependent variable the modal share, where one model is for the first mile modal share and one model is for the last mile modal share. The two other models have the number of shared e-moped trips per day as dependent variable. Again, one of those models is for first mile and the other is for last mile.

The best performing first mile modal share model has an adjusted R^2 score of 0.627 and consists out of the variables train frequency, POI* vehicle availability, Metro frequency, Weekend day, weekend day * train frequency, population density, vehicle availability, young people, tram frequency, bus frequency, points of interest within 5 km and the temperature. The last mile models consists out of the variables vehicle availability, IC stop, Population density, Service catchment, Young people, tram frequency, metro frequency, visibility and train passengers. The best performing last mile modal share modal has an adjusted R_2 score of 0.599 and consists out of the variables train frequency, vehicle availability, weekend day, population density, visibility * walking distance, young people, Points of interest within 5 km, Tram frequency, Bus frequency, Weekend*train frequency, Temperature, visibility and OV fiets

The best performing first mile trip model has an adjusted R_2 score of 0.597 and consists out of the variables IC Stop, Vehicle availability* POI within 5 km, Service catchment, Bus frequency, Metro frequency, tram frequency, population density, young people, vehicle availability, train passengers, walking distance, train frequency and temperature. The best performing last mile trip model has an adjusted R_2 score of 0.700 and consists of the variables vehicle availability, IC stop, Population density, Service catchment, Young people, tram frequency, metro frequency, visibility and train passengers.

The last mile trip model clearly shows that the vehicle availability is the factor influencing the number of last mile trips the most, as adding 1 vehicle to the average number of vehicles present at a station leads to 4.8 more shared e-moped trips. The vehicle availability in first mile has less of an impact, because it takes much vehicles to increase the vehicle availability in first mile. The share of young people at a station is a big influencing factor in first- as well as in last mile transport, as an increase of 1% leads to 2.33 and 2.3 more shared e-moped trips per day. The walking distance has a large impact in first mile transportation as the number of trips increases with 0.22 trips per day per reduced metre walking distance. In last mile transport, the visibility is important, as changing the visibility of shared e-mopeds from not visible to visible leads to an increase of 6 trips/day. Whether a station is an IC stop also has a big impact with 22.55 and 18.80 more trips in first- and last mile transportation. Whether a station is an intercity station has no significant influence on the modal share according to the model.

The modal share model confirms that the vehicle availability and share of young people have a positive influence. These models show that the bus and shared e-moped are competing with each other, as an increase of bus frequency with 10 busses/h leads to a decrease of the shared e-moped modal share of 0.045% in first mile and 0.036% in last mile. This shows that the competing relation is present, but not very strong. The OV-fiets, a shared station based bike system, also competes with shared e-mopeds. Offering 100 more OV-fiets reduces the modal share of shared e-mopeds with 0.02%, This shows that they are competing, but also shows that the competing relation is weak. This factor only has influence on the last mile as the bike needs to be picked up at the station. Weekend is the most influencing factor on the modal share in both first- and last mile transportation, but this variable cannot really be adjusted. During the weekend the modal shares are higher.

The population density is negative in each model. This means that in the most dense cities in the Netherlands (Amsterdam and Den Haag) relatively lower modal shares are obtained. This does not mean that in rural areas the modal share will be high, as this model is only trained on cities and not on rural areas in The Netherlands. The temperature is positive in each model, which means the modal share and number of trips is higher with higher temperatures, although no extreme temperatures were present, which means it cannot be concluded that during extremely high temperature the usage will be higher.

In the trip models the bus, tram and metro frequency have a positive influence on the number of shared e-moped trips. This is primarily caused by the fact that there a high frequencies at stations with a high number of passengers. Also, in the last mile modal share model, the tram- and metro frequency have a positive influence on the modal share, while there individual correlation suggests a negative relation. This means no reliable conclusion can be drawn about the effect of the tram- and metro frequency on the shared e-moped usage in first- and last mile transportation. The validation of the model shows that the coefficients generally have a confidence interval around 10%. The model has good explanation power, as the adjusted R^2 score does not change much when a applying 5-fold cross validation. The prediction power of the model is limited as the RMSE is around 0.7 standard deviation, which is around 0.45% or 34 trips.

All in all the shared e-moped usage is positively influenced by the vehicle availability, the share of young people, the visibility of shared e-mopeds, the IC stop and the temperature, while the shared e-moped usage is negatively influenced by a longer walking distance in first mile transport and a really high population density. The modal share is positively influenced by the day being a weekend day. The vehicle availability at a station and the share of young people seem to have the largest impact on the shared e-moped usage in first- and last mile transportation. The bus competes slightly with the shared e-moped in first- and last mile transportation, while the shared bike only slightly competes with the shared e-moped in last mile transport. No clear conclusion can be drawn about the influence of the bus- and tram frequency

7. Discussion

This chapter discusses the results of the research. Section 7.1 interpreters the results and compares them with literature. Section 7.2 discusses the shortcomings of the methods and assumptions used in the research. Lastly, Section 7.3 dives into the generalisability of this research.

7.1 Interpretation and comparison with literature

The case study to the usage patterns of shared e-mopeds in first- and last mile transportation to train station in The Netherlands shows that 18 % of the shared e-moped trips is a train station related trip. This is a bit higher than the results found by Knoope and Kansen (2020) who showed that 14% of the shared e-moped trips started within 200 metre of a train station. The average trip distance in first- and last mile transportation is 3030 metres, which is line with the large range from 2.3-5 kilometres found in the preliminary literature review, but significantly higher than the average shared e-moped trip distance observed in 2020 in the Netherlands, which was 2.3 kilometres (Faber et al., 2020). This can be explained by the larger service areas in 2022 and the growth of the shared e-moped market in The Netherlands.

When looking at the usage over the day the patterns match the descriptions of Garritsen (2022) and Aguilera-García et al. (2021) meaning that there are commuting peaks visible and the afternoon peak is bigger. The difference is that this is especially the case for last mile, while the afternoon peak is not that much bigger in first mile transport. Also, the agglomerative clustering shows that the patterns differ per station and that having a night train departing from the station influences the night usage of shared e-mopeds as first- and last mile mode.

In first- and last mile transportation 50 and 48% of the trips is determined as trip with a home purpose. This is done by an algorithm which uses the building function of a building to determine the most frequent occurring building function in a 100 by 100 metre grid. These home trips consist out of the first or last mile of home work or work home trips and out of social trips to friend and family members. 30% of the trips has a leisure purpose, meaning it goes too or comes from a leisure activity. This is in line with the findings by Knoope and Kansen (2020) and Arias-Molinares et al. (2021) who argue that shared e-mopeds are used for both commuting as well as for leisure trips. The trip purpose is however, influenced by the built environment, as the trip purpose can differ massively between different cities and stations.

The majority of stations has a modal share of shared e-mopeds in first- and last mile transportation between 0 and 0.7%. Stations in cities with high usage per inhabitant such as Rotterdam Breda and Leeuwarden have a modal share between 1.5 and 2.5%. No research has been done too this before, indicating a new finding. A smaller cluster of stations, primarily stations in medium sized cities, such as Enschede and Groningnen have a modal share between 1 and 1.5%. The modal shares over the day are higher during the weekend. This is caused by different factors such as the trip purpose and the quality of other first- and last mile modes, especially the public transport quality.

The model results show that vehicle availability at the station side is the most influencing factor. This in line with the results of the literature study to shared micromobility modes, as for example Böcker et al. (2020) and Oeschger et al. (2020) show that vehicle availability, especially for the last mile, is positively influencing the number of trips to a station. In the literature review vehicle availability is mentioned the most, indicating it's importance both for shared e-mopeds as well as other shared micromobility modes. A station having an intercity stop also generates more shared e-moped trips. This matches the findings of Guidon et al. (2019) that a well connected train station in the national network leads to more shared e-bike usage. On the other hand, the results of this study show that the train frequency has a negative influence on the modal share. This is in contrast with the literature finding by Moinse (2022) who argue that the train frequency has a positive influence. This is primarily caused by the fact that with larger frequencies and thus more passengers, it becomes more challenging to have space for the number of needed shared e-mopeds. This factor does not mean that a station with a frequency of 1 train per hour gets a high shared e-moped modal share.

The results also show that the bus and OV-fiets have a slightly competing relationship with the shared e-moped in first- and last mile transportation. This is in line with the findings by Adnan et al. (2019) who argue that the presence of other modes reduces the number of shared e-moped trips and that bikesharing is competing with the bus. About the tram and metro frequency no reliable conclusion is drawn by the model. The walking distance from a shared e-moped to the train station negatively influences the number of first mile trips to a station. This is in line with the studies by Hosseinzadeh et al. (2021) for shared e-scooters and Ma et al. (2020) for shared bikes. This has thus the same effect for shared micromobility modes as for shared e-mopeds. The model also shows that the visibility of shared e-mopeds has a positive influence on the number of shared e-moped last mile trips. In literature this factor is not mentioned. A higher temperature also leads to more shared e-moped usage, which matches the the study of Arias-Molinares et al. (2021) who show that in Spain higher temperatures also have a positive influence on the shared e-moped usage.

The biggest difference with literature lies in the fact that the results show that rain does not have an effect on the shared e-moped usage, while from the literature review this is along with walking distance, the most mentioned negative factor. This might show that for other micromobility modes, rain might be more of problem. With this finding it should be noted that the results shows that on daily basis the number of hours rain does not significantly influences the shared e-moped usage in first- and last mile. This means it might have an effect on hourly basis. Another difference is the observed negative effect of population density by the model. This is due to the training data only consisting out of cities, which means that in highly densified cities the population density has a negative effect, because there are a lot of other options to go the station and the distances to and from their destination might be shorter. This does not mean that in rural areas there will be a lot of shared e-moped trips, as these models are only trained on cities which are urban areas.

7.2 Methods and assumptions discussions

To determine the percentage of shared e-moped trips at station, which is actually a train related trip, a survey is performed. The results of this survey are based on three stations and transformed with 3 criteria to the other stations. This transformation leads to less detailed results for the other station. When actually performing the survey at another station, the found percentage of train users may differ. This can lead to an underestimation or an overestimation, depending on the observation, of the modal share in the results. This for example, might be the case at Rotterdam Blaak, where the actual percentage may be lower than the used 75%, due to the high number of points of interest close to this station. This means the modal share of Rotterdam Blaak might be overestimated. This has as implication that the modal share and number of trips should be lower, which affects the training of the data. Since, Rotterdam Blaak has a high modal share and number of trips, this might lead to overestimation of the coefficients of the positive factors, or underestimation of the coefficients of the negative factors.

To calculate the modal share per day at each station for the total number of shared e-mopeds equation 5.1 is used. This equation uses the ratio between the number of Check mopeds and the total number of mopeds, as well as ration between the usage of each provider. The ratio of usage of the provider is partly based on the results from the survey, but since there are only 4 observation dates, this is not a reliable ratio. Also, Go Sharing was present during September and October, but during the survey period in April. Therefore, assumptions are made about the ratio between the usage of Check and Go Sharing, as well as the ratio Check, Go Sharing and Felyx. This ratio should be investigated further, since the survey showed that the usage of two providers with the same fleet size is not equal. This ratio does not influence the model results, as the models are trained on the modal share and trip numbers of Check e-mopeds only. It only affects the detailed e-moped modal shares in Section 5.6.

For determining the trip purpose of a trip, a grid of 100 by 100 metre is used with the most frequent occurring building type per grid cell. This grid assumes that all trips that end in one cell have the trip purpose of the most frequent occurring building type, while in reality some trips may have the purpose of the less frequent occurring building type. The 100 by 100 metre grid aggregates the results, which means the total impact of this wrong assumption is small, as the algorithm will approximately balance this out. The percentages of the trip purpose found in this study are thus reliable, but the real percentages may differ slightly. Since, the values of the share of trip purposes are not used for answering the main research question, the error in the exact values does not significantly influence the results.

In the multiple linear regression models, the independent variable population density is based on the population density of the whole municipality. This means the population density of all the stations in a city is equal according to this variable. In reality, this is not the case, as stations in less urban areas, often have a lower population density in the area surrounding the station. Changing this into the population density area around the station may result in a more detailed representation of the effect of population density. The current solution does give the right indication, but the effect can be observed in more detail.

Other variables in the multiple linear regression model are the bus, tram and metro frequency. No observed data of all departing and arriving times during the months September and October were acquired. Instead, the bus, tram and metro frequencies at stations are only observed during the afternoon peak. This is done, because the frequencies had to be counted by hand from the public transport tables. This means that the model assumes that the frequency is constant over the days, while in reality the frequency might be lower in the evening hours, but also on weekend days. This influences both the bus, tram and metro frequencies as well as the weekend variable, as the effect of lower bus, tram and metro frequencies, might now be partially in the weekend variable.

The signs of the regression coefficients match for the majority with the individual correlation signs. For four variables this is not the case, meaning that a negative correlation is followed by a positive regression coefficient or the other way around. This shows the presence of some kind of negative suppressor variable. No reliable conclusion therefore can be drawn about the influence of the variables with changing signs. The negative suppressor variable is unknown, but the presence of it indicates there is still some multicollinearity present in the model, although the amount is not too severe according to the linear regression requirements. This may indicate that a more advanced regression method, which is able to cope better with multicollinearity, is needed.

The effects of the variables in the model are currently given as linear effects. In reality factors such as vehicle availability will not have a linear effect, as the strength of the effect will become lower, when there way too much shared e-mopeds available for the demand. This is a limitation of the multiple linear regression method and has as impact on the results that the strength of the factors cannot be used indefinitely. The compared strength of the factors to each other remains the same however. When one wants to predict the number of shared e-moped trips or the modal share of shared e-mopeds one could use a neural network, as a neural network can take into account more complex relations.

The last important discussion note to mention is that the data is for this study is collected before the helmet requirement for 25 km/h e-mopeds was introduced in The Netherlands. The helmet requirement has an influence on the demand, as the shared e-moped becomes less attractive compared to other alternatives. For walking, cycling and public transport no helmet is needed, which means these modes become more attractive. This leads to less demand and thus less trips. This affects thus the number of trips and the modal share. It can also influence the influence of other factors, but since no data after the helmet requirement is acquired, this should be investigated further.

The validation of the model results show that the coefficients of the models in general have a small confidence interval (<10%). Especially, the coefficients of the last mile trip model are reliable with a low confidence interval. This shows the models have good explanation power. The prediction power of the models are not that high as the RMSE is around the 0.7. This means the models are less suitable for prediction, but do have a high explanation power.

7.3 Generalisability

The findings from the usage patterns may differ for other countries. In the Netherlands people travel a lot by bike and the bike infrastructure is of good quality. Also, the Netherlands is a relatively dense country. These two factors might influence the trip distance. Also different regulations in other countries might be present, which also influences the usage patterns. The differences between first- and last mile transport and regular transport, however, can be copied, as well as the trip purpose, since they are not expected to be different in other countries. The method of determining the number of first- and last mile shared e-moped trips can be used in other countries without limitation. The method of determining the trip purpose can also be used in other countries, although the dataset used for this method only describes the building function of building in The Netherlands. Therefore, an additional dataset is needed to apply this method in other countries.

The conceptual framework shown in Figure 5.27 is made based on an international literature study. This framework can thus also be used for other countries. The model set-up can also be copied, although some variables are quantified with data from Dutch institutions which is only available for the Netherlands. The findings of the influence of different factors on the shared e-moped usage patterns can largely be copied to other countries. The exact influence of the factors will differ, as for example the train frequency might be lower, but the general sign will remain valid.

When trying to explain the influence of factors, some factors that are not relevant in The Netherlands might be relevant in other countries. In countries where there also shared e-scooters, the shared e-scooter should be added as an alternative mode variable. This variable can replace the OV-fiets variable that is in the Dutch version of the model. Also, when applying the model for other countries, safety of bike infrastructure and the geometry, i.e., hills in a city should also be included in the model. In The Netherlands there are no hills and the quality of the bike infrastructure is constant throughout the country. This means the influence of these factors cannot be determined. Therefore, in countries where this is not the case these variables should be included.

8. Conclusion and recommendations

This report has aimed for answering the research question: 'To what extent do various factors influence the usage of shared e-mopeds in first- and last mile transportation to train stations?'. This chapter gives the answer to this question by providing the answers from the subquestion. Section 8.1 gives the answer on the research questions, Section 8.2 dives into the recommendations for practice and future research.

8.1 Conclusion

Which factors influence the usage of shared (e-)bikes or shared e-scooters in combination with train?

This research question is answered by performing a literature study. The factors found in this literature study can be distinguished in four categories: micromobility system factors, station accessibility, spatial factors and temporal factors. The most mentioned factor by the literature is the vehicle availability. A higher vehicle availability positively influences the usage of shared microvehicle train combination. The most mentioned negative factors are walking distance and rain. The longer one needs to walk to a shared microvehicle the lower the attractiveness of the combined mode becomes. Also people are less likely to use the shared microvehicle train combination when it rains. Table 8.1 shows the found factors in literature and the number of articles they appear in, which is the answer to the research question.

Table 8.1: Overview of factors in the literature study. means the influence is unclear.

Author	Service area size	Parking capacity stations	Vehicle availability	Walking distance	Quality of train service	Presence of other modes	Points of interest	Recreational land use	Commercial land use	City center	Population density	Quality bike infrastrucure	Rain	Temperature	Weekend
Type of influence	+		**+**	**-**	+	-	+	+	+	+	+	+	**-**	+	/
Number of times mentioned	5	4	**11**	**6**	8	4	7	8	6	4	7	7	**6**	6	5

What are the usage patterns of the usage of shared e-mopeds in first- and last mile transportation to train stations?

18% of the shared e-moped trips in the Netherlands are classified as a first- or last mile trip to or from a train station. The average distance of a first mile trip is 3039 metres, while the average last mile trip is 3028 metres long. Trips in first- and last mile transport are significantly shorter than non-train related trips, which are 3362 metres long on average. The type and city of a station seem to have an influence on the average trip distance in first- and last mile transportation. During the week more trips occur than during the weekend. Friday is the day with the highest usage. In first- and last mile transportation commuting peaks can be seen in the shared e-moped usage patterns. The afternoon peak is higher and wider than the morning peak, which shows a combination of commuting and leisure trips.

Between first- and last mile transportation by shared e-mopeds minor differences in trip purpose are observed. The trip purpose is based on the most frequent occurring building function in the cell a trip starts or ends in. 49% of the first- and last mile trips has a 'Home' trip purpose. This trip purpose consists out of the home-station or station- home trip of a commute trip and out of people social trips, such as people visiting their relatives or friends. 29% of the shared e-moped trips in first- and last mile transportation has a leisure purpose. This shows shared e-moped are used for commuting, social and leisure purposes.

The modal share of shared e-mopeds in first- or last mile transportation ranges from 0.02% to 2.5% during the week. The modal share is defined as the percentage of shared e-mopeds that comes from or goes to the station by shared e-moped. In first- and last mile these percentages are almost equal. The stations with a percentage between 1.5 and 2.5% come from cities with a high usage per inhabitant. During the weekend the modal share ranges from 0.06% to 5.3%. This shows the modal share of shared e-mopeds is higher during the weekend. Over the day, the modal share generally speaking rises. In first mile transport a morning peak can be observed, while this is not present in last mile transport. In last mile the usage is higher at the end of the afternoon and the evening.

What is the best performing model structure to quantify the influence of factors on the usage of shared e-mopeds in first- and last mile transportation?
A conceptual framework based on the literature study and empirical findings from the case study is made. This framework is transformed into variables for a multiple linear regression model that can be quantified. The influence of factors on the usage of shared e-mopeds in first- and last mile transportation is quantified by making four models. Two models have the modal share per day of shared e-mopeds as the dependent variable, where one model has the first mile modal share as dependent variable and the other the last mile modal share. The two other models have the number of shared e-moped trips per day as dependent variable, where the two models again describe the first- and last mile. Table 8.2 shows the best performing model along with the R^2 score of the best performing model for all four models.

Table 8.2: Best performing model set-up for the four models

Model	Adj. R^2	Variables
First mile modal share	0.627	train frequency, POI* vehicle availability, Metro frequency, weekend day, weekend day * train frequency, population density, vehicle availability, young people, tram frequency, bus frequency, points of interest within 5 km, temperature.
Last mile modal share	0.599	train frequency, vehicle availability, weekend day, population density, visibility * walking distance, young people, Points of interest within 5 km, Tram frequency, Bus frequency, Weekend*train frequency, Temperature, visibility and OV fiets.
First mile trips	0.597	IC Stop, vehicle availability* POI within 5 km, service catchment, bus frequency, metro frequency, tram frequency, population density, young people, vehicle availability, train passengers, walking distance, train frequency, temperature.
Last mile trips	0.700	vehicle availability, IC stop, population density, service catchment, young people, tram frequency, metro frequency, visibility, train passengers.

Given the answers on the previous research questions and the model results of the best performing model set-up's an answer can be formulated for the main research question:

To what extent do various factors influence the usage of shared e-mopeds in first- and last mile transportation to train stations?

The vehicle availability at the station side is the most influencing factor on the shared e-moped usage in last mile transportation. Adding one vehicle per day to the vehicle availability at a station generates, according to the multiple linear regression model, 4.8 more shared e-moped last mile trips. In first mile transportation the vehicle availability also has a positive influence, but the impact is less severe, as adding 1 shared e-mopeds/km^2 only leads to an increase of 1.3 trips per day, but adding one shared e-moped/km^2 takes more shared e-mopeds. The share of young people at a station is also a big influencing factor. An increase of 1% in the share of young people leads to 2.33 and 2.30 shared e-moped trips in first- and last mile. In first- and last mile transport 22.5 and 18.8 trips more are generated, according to the models, when a station is or becomes an intercity station. The walking distance from the shared e-moped to the station negatively influences the number of shared e-moped trips in first mile transportation. The number of trips decreases with 0.22 trips per day per added metre walking distance, which shows this factor can have quite a significant influence. In last mile transport visibility is an important factor as the number of shared e-moped trips increases with 6 trips/day when the visibility is changed at a station from not visible to visible.

With regard to the modal share, the vehicle availability and young people again have a big influence. The modal share model also shows that the bus and the shared e-moped are slightly competing with each other. Adding 10 busses/h results in a lower shared e-moped modal share of 0.045%. in first mile and 0.030%. in last mile transport. This shows the modes are competing, but also shows that the competing relation is minor, as the reduction in modal share is small. The shared e-moped and the shared bike, OV-fiets, also compete with each other. Again, this competing relationship is only slightly, as the modal share in last mile transport only drops with 0.02%. when adding 100 shared bikes to the capacity of the OV-fiets rental point. Shared e-mopeds are only competing with the OV-fiets in last mile transport, as in first mile the OV-fiets is not an option, because it needs to be rented at a train station. The weekend day factor is the most influencing factor on the modal share, as it increases the modal share in first mile with 0.25%. and 0.24%., but this factor cannot be influenced. The number of points of interest have an positive impact on the modal share, but it's impact is only 0.001% per additional point of interest, which shows that this factor has a low influence.

The population density has, according to the models, a negative influence on both the modal share, as well as the number of shared e-moped trips. This does not mean that at in rural areas, there will be a lot of shared e-moped trips, as the models are trained on data of cities only. The negative influence on the modal share is relatively small with a reduction in modal share of -0.0002%.. In number of trips this reduction is -0.01 per added person/km^2. This shows the impact of this factor is limited. The negative influence can be explained by the fact that in the densest cities(The Hague and Amsterdam) people live closer to their destination and more other options are available for transport.

The models cannot draw a reliable conclusion about the influence of the tram and metro frequency. On the number of trips they have a positive influence, but this is mainly caused by the fact that at stations with more passengers there also higher tram and metro frequencies, which means the real effect of the tram and metro frequency cannot be determined. In the modal share model they have a positive influence, which conflicts with the individual correlation sign of the variables with the modal share. Therefore, no reliable conclusion can be made about the influence of tram and metro frequency. The number of hours it rains on day is not significant in any model. This means that over the day, rain does not have an influence. It does not mean that it has no influence on a shorter time basis, such as an hourly basis.

All in all, before this study only the study by Arias-Molinares et al. (2021) looked into which factors affect shared e-moped usage. This study adds more knowledge to this, specifically about factors influencing the usage in first- and last mile. Arias-Molinares et al. (2021) shows that the service area size, vehicle availability the shape of city and the temperature affect the shared e-moped usage. This study confirms the service catchment, temperature and vehicle availability factors. It adds to this that also factors such as the share of young people, bus frequency, shared bike availability, walking distance, visibility and points of interest have an influence. This study also provides a quantification to show which factor has the biggest influence. According to the model results, the vehicle availability at a station is the most important factor. Next, to the factors, this study also shows what the usage patterns of shared e-mopeds in first- and last mile transportation are. This study therefore helps in understanding the usage of shared e-mopeds as a first- and last mile mode.

8.2 Recommendations

In this section recommendations for science, i.e. further research, as well as recommendations for practice are mentioned.

8.2.1 Recommendations for future research

The first recommendation for further research is to do this research in another country than the Netherlands. In this way it possible to also quantify the influence of the hilliness of a city, as well as the effect of safe bicycle infrastructure. Furthermore, interesting differences might occur between two countries. It is important to note that this study has used some Dutch databases for the data, which means another data source has to be found if the research is applied to another country. Secondly, this research has tried to prove that the assumption that all trips that start or end near train stations is wrong. This is indeed the case and a generalization to other stations has been made. This generalization relies on a lot of assumptions, which means further research to more stations should be done to see what the percentage of shared e-mopeds trips ending near and starting from the stations is a train related trip. This research could also be applied to other shared micromobility modes as the methodology does not change.

Another possible further research topic is to improve the models. In the current model, a few variables primarily the bus and tram frequency have a opposing sign than their correlation. Therefore, a more advanced regression method such as Ridge regression (Hoerl and Kennard, 1970), Lasso regression (Tibshirani, 1996) or Elastic net regression (Zou and Hastie, 2005) might be used. These methods are better able to cope with multicollinearity in the model. This reduces the chance that variables get the wrong sign and is better able to identify the effect of the variables. Furthermore, some variables might be better quantified such as a public transport frequency per hour over the day instead of only taking the public transport frequency on a weekday during 16:00-17:00. Also, no suitable data was found to quantify the influence of the mobility culture. This model is also only trained on data of September and October 2022. It might be interesting to train the model on a whole year of data. In this way it would be possible to also identify seasonal trends, such as lower usage during the winter.

The modal share model already reported that the bus and shared e-moped compete with each other, as well as the shared bike, OV-fiets, and the shared e-moped. It might therefore, be interesting to see which modes the shared e-moped in fact really replace by doing a study into this. This gives a better overview of the role of shared e-mopeds in first- and last mile transportation. During the research period a helmet requirement for all shared e-mopeds has been introduced. It would be interesting to do the same research with data of after the helmet requirement, to identify which effect the helmet requirement has on the usage patterns of shared e-mopeds in first- and last mile transportation.

The methodology of determining the trip purpose based on the building function of buildings might also be interesting to use for determining other the trip purpose of other shared micromobility trips. This would be possible for modes which work with a GPS system. This is therefore, for example possible for shared e-scooters and shared e-bike systems, as long as the data is available.

8.2.2 Recommendations for practice

The success factors for the implementation of shared e-mopeds at a station seem to be to have a high vehicle availability both at the station side as well as in the rest of the service areas. Especially, the vehicle availability at the station is important, since people want to be sure there is a shared e-moped available when they want to depart from the station to their destination. One vehicle more at a station can already lead, according to the model, to an increase of 5 shared e-moped trips per day in last mile transportation. Furthermore, the higher the share of young people at a station, the higher the modal share of shared e-mopeds will be. Also, an Intercity station has more potential as transfer point from the shared e-moped towards train than a station with only a local service, as it saves the train passenger from an additional train change. Furthermore, the walking distance from the train to the shared e-moped should be low, as the walking distance has a negatively influences on the number of shared e-moped trips in first- and last mile transportation. Besides, the visibility of the shared e-moped is an important factor in last mile transport. The usage of shared e-mopeds is higher during higher temperatures.

When NS wants to encourage shared e-moped usage as a first- and last mile mode, NS should therefore encourage the usage at stations with a high share of young people between 18- and 35 years old. Furthermore, the station should ideally be an IC-stop as no additional train transfer is needed, which improves the door-to-door journey. Since, the walking distance is also important, NS Stations might want to consider to offer space to shared e-moped providers to park their vehicles. If NS wants to fully encourage the e-moped usage, this is recommended, since shared e-mopeds can be located closer to the station in this way. It should be noted that the ground positions differ per station, meaning that this is not for every situation the case.

The shared e-moped providers can contribute to the shared e-moped usage in first- and last mile transportation by increasing the vehicle availability. This is not always the case as the shared e-moped providers often have a permit for a limited number of shared e-mopeds. On the other hand, the shared e-moped providers might consider relocating their shared e-mopeds to train stations, when the availability of shared e-mopeds at a station is low. This prevents people from not being able to choose the shared e-moped as their last mile mode, which increases the attractiveness and therefore the usage of a shared e-moped as a first- or last mile mode. Shared e-moped providers can also increase the number of trips by increasing the service area size, but this impact is limited, as a 100 metre average increase leads to only 0.8 trips per day more.

The number of shared e-mopeds in a city in The Netherlands is often regulated by permits from the municipality. These permits give a maximum number of vehicles that can be offered. The municipality also gives requirements about the service area. The results show that both the vehicle availability and the service catchment area size can positively influence the number of shared e-moped trips in first- and last mile transportation. This shows that the municipalities can have a lot of influence on the modal share and the number of shared e-moped trips in first- and last mile transportation. For municipalities, it is therefore recommended to take a proactive role. The municipalities can have a big impact on the shared e-moped usage, as well as the usage in first- and last mile. They can increase or decrease ,depending on their wishes, the vehicle availability and the service area set-up and size. Since, the vehicle availability is one of the most influencing factors and the service area determines the visibility, walking distance and the service catchment area, they can have a massive influence on the usage.

The survey also suggests that the set-up of the service area has influence on the percentage of shared e-moped users that parks there, which are actually a train user. Since space is scarce around the station, the service area of shared e-mopeds near the station should be designed such that shared e-moped users have no other reason to park there than the station. This can reduce the spatial impact of shared e-mopeds as less people will park there due to the lower number of non train parkings. Regulation can thus be used to reduce the spatial impact and impact on the street scene of shared e-mopeds. Parking regulation can reduce the messiness caused by wrongly parked shared e-mopeds. NS, the shared e-moped providers and the municipality therefore can work together to reduce the spatial impact of shared e-mopeds around the station.

This study has showed that combining data of both the train operator and the shared e-moped operator can generate interesting insights. For NS, the recommendation is therefore to keep combining data with shared e-moped providers, to get a better overview of the usage and impact on the door-to-door journey of different modes on the first- and last mile transportation. This may improve the first- and last mile transportation, which can help in achieving a seamless door-to-door journey. This can help in making the Netherlands sustainable accessible for everyone. Next to this, the modes shared e-moped replace in first- and last mile should be determined. This can give a clearer view of what the spatial impact of the shared e-moped is on the spatial footprint of the access- and egress facilities. Besides, it can give a better view on the impact of the shared e-moped on the door-to-door journey.

Optimal mix

The shared e-moped also has an impact on the optimal mix of modes both in first- and last mile transport as well as regular transport. The average distance people travel in first- and last mile transportation on a shared e-moped is 3 kilometres. The shared e-moped provides a new option in first- and last mile transport. This increases the number of options and therefore the accessibility of a station. From a user perspective, the shared e-moped provides a faster alternative to the bike, while it has most of it's advantages. The disadvantage of a shared e-moped is that the vehicle needs to be available, that one needs to wear a helmet and the price of a trip. Especially, in last mile transport the shared e-moped can be an attractive alternative compared to the bike, as people often do not have an own bike at the destination station available. Compared to public transport the shared e-moped has as benefit that one can take a shared e-moped when one needs it. This means no waiting time is needed, which reduces the travel time and increases the accessibility of a station. A shared e-moped also provides an alternative to the car, as it is easier to park. In city centres in The Netherlands it is also often a faster alternative as Dutch city centres are either not designed for the car or have a lot of traffic lights and less direct routes.

At the moment shared e-mopeds are primarily used in cities. This shows that shared e-mopeds are currently primarily used as a local solution in cities and not as a regional solution. This means the shared e-moped is a part of the puzzle of first- and last mile transport. The current role of the shared e-moped in the mix of the modes is thus primarily in urban cities, where it provides a fast and direct alternative to the bike, public transport and the car. However, especially in areas with a low public transport frequency, which are often rural areas, the shared e-moped can increase the station accessibility massively as it provides an option to reduce the long waiting times for the bus. This means that when looking at the optimal mix of modes from a user perspective the best place for a shared e-moped might be the rural and sub-urban stations with a low bus frequency, as it provides a massive waiting time saving. From an operator perspective however, sub-urban and rural areas are less interesting as the demand is lower, meaning that it is harder to gain profits. A solution for this might be to subsidize the shared e-mopeds in this area to improve the accessibility of the station.

Spatial and Sustainable impact

The spatial impact of shared e-mopeds at the station can be reduced by designing the service area in such away that shared e-moped users only park there to go to the station. This means shared e-moped user should have no other reason, such as a point of interest to park there. This can be achieved by providing a shared e-moped service area with a closer distance to the point of interest. In this way the spatial impact of shared e-mopeds can be minimized, which is needed due to the scarcity of space around the stations. The spatial impact on the total station area footprint depends on the mode the shared e-moped otherwise would use to go to the station. If a shared e-moped replaces walking and cycling the total spatial footprint will increase as these modes take less space. The spatial impact of public transport will also be lower than the spatial impact of shared e-mopeds, meaning that replacing public transport will lead to larger footprint areas. If a shared e-moped replaces a car trip to or from the station, the total spatial footprint will go down. Therefore, it is needed to know what mode a shared e-moped replaces in first- and last mile transport.

The sustainable impact of shared e-mopeds also differs per mode it replaces. If shared e-mopeds replace walking and cycling to the station, the first- and last mile transport will get less sustainable. If the shared e-moped replaces car trips to the station or causes people to move from a direct car trip to a shared e-moped train trip, the overall sustainable impact will be positive. More research to this however is needed as the sustainable impact of shared e-mopeds is still unclear and the mode it replaces is also unclear.

To conclude, from a user perspective the shared e-moped is a good addition to the mix of first- and last mile modes as it provides a faster alternative to the bike and less waiting time compared to public transport, especially in areas with a low public transport frequency. From a station owner perspective, the shared e-moped increases the footprint when it mainly replaces walking and cycling in public transportation, while it decreases the footprint when a shared e-moped trip replaces the car. More research is needed to which mode a shared e-moped replaces to conclude what the exact spatial and sustainable impact of the shared e-moped is in first- and last mile transportation. In this way it can be determined whether the shared e-moped contributes to making The Netherlands sustainable accessible for everyone.

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A. Python code data filtering

In [1]:
```
import pandas as pd
import geopandas as gpd
import matplotlib.pyplot as plt
import datetime
from osgeo.osr import SpatialReference, CoordinateTransformation
from shapely.geometry import Point, Polygon
```

In [2]:
```
data= 'https://geodata.nationaalgeoregister.nl/cbsgebiedsindelingen/wfs?request=GetFeature&service=WFS&version=2.0.0&typeName=cbs_gemeente_2017_gegeneraliseerd&outputFormat=json'
municipal_boundaries= gpd.read_file(data)
emopeddata= pd.read_csv('check_ritrapportage_tu_delft.csv')
```

In [3]:
```
### This coordination transformation algorithm is copeid from https://publicwiki.deltares.nl/display/OET/Python+convert+coordinates

# Define the Rijksdriehoek projection system (EPSG 28992)
epsg28992 = SpatialReference()
epsg28992.ImportFromEPSG(28992)

# correct the towgs84
epsg28992.SetTOWGS84(565.237,50.0087,465.658,-0.406857,0.350733,-1.87035,4.0812)

# Define the wgs84 system (EPSG 4326)
epsg4326 = SpatialReference()
epsg4326.ImportFromEPSG(4326)
latlon2rd = CoordinateTransformation(epsg4326, epsg28992)
```

In [22]:
```
#fixing coordinates swithced around
for i in range (len(emopeddata)):
    if emopeddata['start_latitude'][i]< emopeddata['start_longitude'][i]:
            Storage_value= emopeddata['start_longitude'][i]
            emopeddata['start_longitude'][i]= emopeddata['start_latitude'][i]
            emopeddata['start_latitude'][i] = Storage_value
            Storage_value2= emopeddata['end_longitude'][i]
            emopeddata['end_longitude'][i]= emopeddata['end_latitude'][i]
            emopeddata['end_latitude'][i] = Storage_value
```

```
C:\Users\Gert\AppData\Local\Temp\ipykernel_88\4238892661.py:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  emopeddata['start_longitude'][i]= emopeddata['start_latitude'][i]
C:\Users\Gert\AppData\Local\Temp\ipykernel_88\4238892661.py:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  emopeddata['start_latitude'][i] = Storage_value
C:\Users\Gert\AppData\Local\Temp\ipykernel_88\4238892661.py:8: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  emopeddata['end_longitude'][i]= emopeddata['end_latitude'][i]
C:\Users\Gert\AppData\Local\Temp\ipykernel_88\4238892661.py:9: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  emopeddata['end_latitude'][i] = Storage_value
```

In [23]:
```
def coordinate_transformation(latitude,longitude):
    coordinatesrd=latlon2rd.TransformPoint(latitude,longitude)
    return coordinatesrd

for i in range(len(emopeddata)):
    start_coordinates= coordinate_transformation(emopeddata.loc[i,'start_latitude'], emopeddata.loc[i, 'start_longitude'])
    emopeddata.loc[i,'start_coordinate_x_rd']= start_coordinates[0]
    emopeddata.loc[i,'start_coordinate_y_rd']= start_coordinates[1]
    end_coordinates= coordinate_transformation(emopeddata.loc[i, 'end_latitude'], emopeddata.loc[i, 'end_longitude'])
    emopeddata.loc[i, 'end_coordinate_x_rd']= end_coordinates[0]
    emopeddata.loc[i, 'end_coordinate_y_rd']= end_coordinates[1]
```

In [24]:
```
emopeddata.to_csv('tijdelijk.csv', index= False)
```

In [25]:
```
def municipality_determination(x, y):
    point = Point(x, y)
    for i in range(len(municipal_boundaries)):
        if point.within(municipal_boundaries['geometry'][i]):
            municipality= municipal_boundaries['statnaam'][i]
            return municipality
            break
```

In [41]:
```
print(emopeddata['end_coordinate_y_rd'])
for i in range(len(emopeddata)):
    emopeddata.loc[i, 'start_municipality']= municipality_determination(emopeddata.loc[i,'start_coordinate_x_rd'], emopeddata.loc[i, 'start_coordinate_y_rd'])
    emopeddata.loc[i, 'end_municipality']= municipality_determination(emopeddata.loc[i, 'end_coordinate_x_rd'], emopeddata.loc[i,"end_coordinate_y_rd"])
```

```
0          441790.678407
1          435692.668704
2          437158.720068
3          473842.617064
4          435959.419183
               ...
1346701    487030.655141
1346702    436806.492648
1346703    486353.395791
1346704    505947.424690
1346705    440648.161037
Name: end_coordinate_y_rd, Length: 1346706, dtype: float64
```

In [44]:
```
# function that calculates the duration of one trip.
def trip_duration(start_date, end_date):
    # converting the string dates to integers and seperate years, months, etc. for datetime function.
    # every date has the same length
    start_year= int(start_date[0:4])
    start_month= int(start_date[5:7])
    start_day= int(start_date[8:10])
    start_hour= int(start_date[11:13])
    start_minute= int(start_date[14:16])
    start_seconds= int(start_date[17:19])
    # converting the string end dates to integers
    end_year= int(end_date[0:4])
    end_month= int(end_date[5:7])
    end_day= int(end_date[8:10])
    end_hour= int(end_date[11:13])
    end_minute= int(end_date[14:16])
    end_seconds= int(end_date[17:19])
    start_time= datetime.datetime(start_year,start_month,start_day,start_hour,start_minute,start_seconds)
    end_time= datetime.datetime(end_year,end_month,end_day,end_hour,end_minute,end_seconds)
    duration= end_time-start_time
    duration= duration.total_seconds()
    return duration
```


In [48]:
```
for i in range(len(emopeddata)):
    emopeddata.loc[i, 'trip_duration'] = trip_duration(emopeddata.loc[i,'start_time_utc'], emopeddata.loc[i, 'end_time_utc'])
    emopeddata.loc[i, 'trip_speed']= emopeddata.loc[i, 'meters_driven']/ emopeddata.loc[i, 'trip_duration']*3.6
```

In [4]:
```
#emopeddata.to_csv('data_speed_rd.csv', index= False)
emopeddata=pd.read_csv('data_speed_rd.csv')
```

In [5]:
```
#Removing the zero meter trips
indexes_zero=[] #Creating an empty list to store the indexes of trips with zero distance
for i in range(len(emopeddata)):                  #Looping through each trip
    if emopeddata['meters_driven'][i]==0:         #checks wheter distance is 0
        indexes_zero.append(i)                    #Appends the index of the trip to the indexes zero list
datafilter1= emopeddata.drop(indexes_zero)        #Dataframe drops rows with indexes of zero distance trips
datafilter1= datafilter1.reset_index(drop=True) #Reset the index of the dataframe for next step and drop original index
print('Data step 1 has filtered out', len(indexes_zero),  'trips' )
```

```
Data step 1 has filtered out 61188 trips
```

In [6]:
```
indexes_45=[] #Creating an empty list again
for i in range(len(datafilter1)):               # Looping through the dataset after filter step 1
    if datafilter1['trip_speed'][i]>45:         # If speed is bigger than 45 km/h append the index
        indexes_45.append(i)
datafilter2= datafilter1.drop(indexes_45)       # Drops the rows with trip speed > 45 km/h
datafilter2= datafilter2.reset_index(drop=True)# Reset the index for the next step
print('Filter step 2 has filtered out', len(indexes_45), 'trips')
```

```
Filter step 2 has filtered out 195 trips
```

In [7]:
```
indexes_lowspeed=[]
for i in range(len(datafilter2)):              # Looping trough the dataset after filter 2
    if datafilter2['trip_speed'][i]<5:         # Checks whether speed is smaller than 5 km/h then appends index
        indexes_lowspeed.append(i)
datafilter3= datafilter2.drop(indexes_lowspeed)# Drop the rows with speed <5 km/h
datafilter3= datafilter3.reset_index(drop=True)# Reset the index for the next step
print('Filter step 3 has filtered out', len(indexes_lowspeed), 'trips')
```

```
Filter step 3 has filtered out 26741 trips
```

In [8]:
```
indexes_100m=[]
for i in range(len(datafilter3)):              # Looping through the dataset after filter 3
    if datafilter3['meters_driven'][i]<225:    # Check whether the distance is greater than 225 meters
        indexes_100m.append(i)
datafilter4= datafilter3.drop(indexes_100m)    # Drop rows with distance < 225 m
datafilter4= datafilter4.reset_index(drop=True) # Reset index for next filter step
print('Filter step 4 has filtered out', len(indexes_100m), 'trips')
```

```
Filter step 4 has filtered out 2995 trips
```

In [9]:
```
indexes_100km=[]
for i in range(len(datafilter4)):              # Looping trough the dataset after filter 4
    if datafilter4['meters_driven'][i]>20000:# Check whether the distance is bigger than 20000m= 200 km
        indexes_100km.append(i)
datafilter4= datafilter4.drop(indexes_100km)  # Drop the rows with distances larger than 20 km.
datafilter5= datafilter4.reset_index(drop=True) # Reset index for next filter step.
print('Filter step 5 has filtered out', len(indexes_100km), 'trips')
```

```
Filter step 5 has filtered out 1603 trips
```

In [9]:
```
#emopeddata= datafilter5
emopeddata= pd.read_csv('emopeddata_filtered.csv')
stationdata= pd.read_excel('Stationsdata.xlsx', index_col=None)
Municipalities= ['Amsterdam', 'Rotterdam', "'s-Gravenhage",
                 'Groningen', 'Leeuwarden', 'Zwolle', 'Enschede',
                 'Hengelo', 'Hilversum','Breda', 'Delft',
                 'Amersfoort', 'Haren', 'Capelle aan den IJssel',
                 'Amstelveen', 'Diemen', 'Rijswijk']
```

In [10]:
```
for city in Municipalities:
    citydata= emopeddata[(emopeddata['start_municipality']== city) | (emopeddata['end_municipality']== city)]                #Loading the data for each city
    indexes= citydata.index.values                                          #index in original dataframe for each trip in city
    stations= stationdata[stationdata['Municipality']== city]               #Getting the stations for each city
    stations=stations.reset_index(drop=True)                                #reset index, so its easier to use in the loop
    circle_stations= []                                                     #Creating an empty list for the circle objects
    #This loop calculates the radius around all the stations in the city
    for i in range(len(stations)):
        circle_stations.append(Point(latlon2rd.TransformPoint(stations.loc[i, 'Latitude'], stations.loc[i, 'Longitude'])).buffer(stations.loc[i, 'Radius']))
    for j in range(len(indexes)):
        #Transferring coordinates to RD coordinate system
        Coordinate_start= Point(emopeddata['start_coordinate_x_rd'][indexes[j]],emopeddata['start_coordinate_y_rd'][indexes[j]])
        Coordinate_end= Point(emopeddata['end_coordinate_x_rd'][indexes[j]],emopeddata['end_coordinate_y_rd'][indexes[j]])
        # Check for each station in city, whether trip starts or end within a radius around the station.
        for k in range(len(circle_stations)):
            #Check whether trip starts within station radius -> Last mile trips
            if Coordinate_start.within(circle_stations[k]):
                emopeddata.loc[indexes[j], 'Last Mile'] = 'Yes'
                emopeddata.loc[indexes[j],'Station_LM']= stations.loc[k,'Station name']
            #Check wheter trip ends within station radius -> First mile trips
            if Coordinate_end.within(circle_stations[k]):
                emopeddata.loc[indexes[j], 'First Mile'] = 'Yes'
                emopeddata.loc[indexes[j],'Station_FM']= stations.loc[k,'Station name']

    print(city)
```

```
Amsterdam
Rotterdam
's-Gravenhage
Groningen
Leeuwarden
Zwolle
Enschede
Hengelo
Hilversum
Breda
Delft
Amersfoort
Haren
Capelle aan den IJssel
Amstelveen
Diemen
```

B. Stationdata

Table B.1: Stationdata

Station name	Type	Latitude	Longitude	Radius	Municipality
Amersfoort CS	2	52.15394	5.37401	250	Amersfoort
Amersfoort Schothorst	5	52.17471	5.403652	200	Amersfoort
Amersfoort Vathorst	5	52.1923	5.433224	200	Amersfoort
Amsterdam Amstel	3	52.3465	4.917491	200	Amsterdam
Amsterdam Centraal	1	52.37914	4.900255	400	Amsterdam
Amsterdam Holendrecht	5	52.29808	4.959912	150	Amsterdam
Amsterdam Lelylaan	3	52.35793	4.834026	200	Amsterdam
Amsterdam Muiderpoort	5	52.36048	4.930504	150	Amsterdam
Amsterdam RAI	5	52.33675	4.890527	150	Amsterdam
Amsterdam Science Park	5	52.35274	4.948781	150	Amsterdam
Amsterdam Sloterdijk	3	52.38903	4.838452	220	Amsterdam
Amsterdam Zuid	3	52.33884	4.871946	280	Amsterdam
Breda	2	51.59568	4.779605	250	Breda
Breda Prinsenbeek	5	51.60559	4.721553	200	Breda
Capelle Schollevaar	5	51.95416	4.584233	150	Capelle aan den Ijssel
Delft	2	52.00713	4.356773	250	Delft
Delft Campus	5	51.99111	4.364706	150	Delft
Den Haag CS	1	52.08118	4.324112	350	's-Gravenhage
Den Haag HS	2	52.06963	4.322017	200	's-Gravenhage
Den Haag Laan van NOI	3	52.07897	4.343257	250	's-Gravenhage
Den Haag Mariahoeve	5	52.09054	4.36898	150	's-Gravenhage
Den Haag Moerwijk	5	52.05472	4.308546	150	's-Gravenhage
Diemen	5	52.34518	4.967462	150	Diemen
Diemen-Zuid	5	52.33063	4.956942	150	Diemen
Enschede	2	52.22237	6.890307	250	Enschede
Enschede Kennispark	5	52.2373	6.83901	150	Enschede
Groningen	2	53.2108	6.564107	350	Groningen
Groningen Europapark	5	53.20464	6.585773	200	Groningen
Haren	5	53.17502	6.6182	150	Haren
Hengelo	2	52.26188	6.793584	250	Hengelo
Hilversum	2	52.22611	5.182023	250	Hilversum
Hilversum Mediapark	5	52.23776	5.174076	150	Hilversum
Hilversum Sportpark	5	52.21656	5.18733	150	Hilversum
Leeuwarden	2	53.19629	5.793037	250	Leeuwarden
Rijswijk	4	52.03748	4.322192	200	Rijswijk
Rotterdam Alexander	3	51.95172	4.552353	200	Rotterdam
Rotterdam Blaak	3	51.91974	4.489452	200	Rotterdam
Rotterdam CS	1	51.92512	4.46916	350	Rotterdam
Rotterdam Lombardijen	5	51.88039	4.530882	150	Rotterdam
Rotterdam Noord	5	51.94226	4.481468	150	Rotterdam
Rotterdam Zuid	5	51.90495	4.509808	150	Rotterdam
Zwolle	2	52.50526	6.091158	350	Zwolle

C. Shared e-moped usage at stations

Table C.1 shows the average shared e-moped usage per day at all type 1 stations.

Table C.1: Average number of shared e-moped trips per day at type 1 stations

Station name	Municipality	First mile trips per day	Last mile trips per day	First/Last mile trips per day	Share of trips per day in municipality
Rotterdam CS	Rotterdam	473.87	499.64	973.51	12.47%
Den Haag CS	's-Gravenhage	116.38	118.85	235.23	10.89%
Amsterdam Centraal	Amsterdam	72.62	74.93	147.56	3.68%

Table C.2 shows the average shared e-moped usage per day at all type 2 stations.

Table C.2: Average number of shared e-moped trips per day at type 2 stations

Station name	Municipality	First mile trips per day	Last mile trips per day	First/Last mile trips per day	Share of trips per day in municipality
Breda	Breda	217.82	218.61	436.43	25.52%
Groningen	Groningen	92.54	93.49	186.03	9.71%
Leeuwarden	Leeuwarden	90.21	93.34	183.56	20.62%
Zwolle	Zwolle	69.00	69.62	138.62	30.98%
Den Haag HS	's-Gravenhage	57.92	57.57	115.49	5.36%
Enschede	Enschede	54.25	54.98	109.23	26.47%
Amersfoort CS	Amersfoort	37.66	38.52	76.18	21.41%
Hilversum	Hilversum	36.93	37.08	74.02	32.13%
Delft	Delft	11.31	11.46	22.77	30.87%
Hengelo	Hengelo	2.67	2.67	5.34	43.47%

Table C.3 shows the average shared e-moped usage per day at all type 34 stations.

Table C.3: Average number of shared e-moped trips per day at type 3 stations. Rijswijk is a type 4 station

Station name	Municipality	First mile trips per day	Last mile trips per day	First/Last mile trips per day	Share of trips per day in municipality
Rotterdam Blaak	Rotterdam	165.23	165.70	330.93	4.25%
Amsterdam Zuid	Amsterdam	72.92	68.85	141.77	3.57%
Amsterdam Sloterdijk	Amsterdam	45.62	45.56	91.18	2.33%
Amsterdam Amstel	Amsterdam	38.77	39.02	77.79	1.96%
Amsterdam Lelylaan	Amsterdam	28.72	28.95	57.67	1.48%
Rotterdam Alexander	Rotterdam	22.84	22.77	45.61	0.59%
Den Haag Laan van NOI	's-Gravenhage	13.92	14.11	28.03	1.29%
Rijswijk (Type 4)	Rijswijk	3.05	3.02	6.07	17.61%

Table C.4 shows the average shared e-moped usage per day at all type 5 stations.

Table C.4: Average number of shared e-moped trips per day at type 5 stations.

Station name	Municipality	First mile trips per day	Last mile trips per day	First/Last mile trips per day	Share of trips per day in municipality
Rotterdam Noord	Rotterdam	11.25	10.84	22.08	0.28%
Rotterdam Lombardijen	Rotterdam	10.66	10.54	21.20	0.28%
Den Haag Moerwijk	’s-Gravenhage	10.52	10.11	20.64	0.98%
Rotterdam Zuid	Rotterdam	8.90	8.85	17.75	0.23%
Amsterdam Muiderpoort	Amsterdam	8.23	8.30	16.52	0.41%
Amersfoort Vathorst	Amersfoort	6.13	6.20	12.33	3.52%
Amsterdam Science Park	Amsterdam	5.93	6.05	11.98	0.30%
Amsterdam RAI	Amsterdam	5.07	4.92	9.98	0.25%
Enschede Kennispark	Enschede	4.72	4.59	9.31	2.25%
Groningen Europapark	Groningen	4.52	4.46	8.98	0.47%
Amersfoort Schothorst	Amersfoort	4.05	4.07	8.11	2.35%
Amsterdam Holendrecht	Amsterdam	3.51	3.69	7.20	0.19%
Breda Prinsenbeek	Breda	3.64	3.15	6.79	0.41%
Haren	Haren	3.05	2.93	5.98	**34.11%**
Hilversum Mediapark	Hilversum	2.21	2.43	4.64	2.05%
Hilversum Sportpark	Hilversum	2.18	2.15	4.33	1.86%
Delft Campus	Delft	1.93	1.97	3.90	5.36%
Diemen	Diemen	1.87	1.89	3.75	6.87%
Den Haag Mariahoeve	’s-Gravenhage	1.13	1.18	2.31	0.11%
Diemen-Zuid	Diemen	0.36	0.46	0.82	1.51%

D. Station trip distances

Table D.1: Distances station

Station name	Distance First Mile (m)	Distance Last Mile(m)	Distance municipality(m)	Difference last and first mile(m)
Delft Campus	1881	2159	2777	278
Hilversum Sportpark	1899	2266	2292	368
Leeuwarden	2116	2118	2271	3
Hilversum	2189	2136	2292	-53
Rotterdam Noord	2251	3114	3114	863
Zwolle	2257	2318	2699	61
Rotterdam Zuid	2375	3053	3114	678
Amersfoort Vathorst	2382	2634	2841	252
Delft	2394	2408	2777	14
Amersfoort CS	2408	2396	2841	-12
Breda	2617	2577	2669	-39
Enschede	2644	2645	2971	2
Hilversum Mediapark	2673	2578	2292	-95
Amersfoort Schothorst	2709	2664	2841	-45
Rotterdam Blaak	2733	2732	3114	-1
Rotterdam CS	2798	2819	3114	21
Groningen	2845	2874	3141	29
Den Haag HS	2920	2892	3371	-28
Amsterdam RAI	3084	3471	4212	387
Groningen Europapark	3160	2995	3141	-165
Amsterdam Muiderpoort	3468	3885	4212	417
Den Haag CS	3481	3471	3371	-10
Den Haag Moerwijk	3529	3342	3371	-186
Den Haag Laan van NOI	3583	3642	3371	59
Amsterdam Amstel	3645	3753	4212	108
Enschede Kennispark	3709	3438	2971	-270
Amsterdam Zuid	3867	3745	4212	-123
Amsterdam Centraal	3915	3843	4212	-72
Hengelo	4045	3894	3967	-151
Rotterdam Alexander	4459	4401	3114	-59
Rijswijk	4695	5039	4498	344
Amsterdam Lelylaan	4746	4335	4212	-411
Amsterdam Science Park	4774	5063	4212	289
Den Haag Mariahoeve	4823	5149	3371	325
Amsterdam Sloterdijk	4977	4860	4212	-117
Rotterdam Lombardijen	5233	4619	3114	-614
Diemen	5590	5648	6006	57
Breda Prinsenbeek	5881	5845	2669	-36
Diemen-Zuid	5957	6354	6006	397
Haren	5992	5359	5696	-633
Amsterdam Holendrecht	8168	8486	4212	318

E. Correlation Matrix

Figure E.1 shows the correlation matrix of the first mile modal share variables

	Modal_Share	Rain	Temperature	Walking_distanc	IC_stop	Vehicle_availabili	Population_Densit	Visbilit	Train_frequenci	Young_people	POI_total	Busfrequency	Tramfrequency	Metrofrequency	weekday	weekend	Service_catchment	OV_fiets	type1	type2	type3
Modal_Share	1.00	-0.04	0.07	-0.23	-0.10	0.13	-0.29	0.07	-0.41	0.34	-0.14	-0.11	-0.16	-0.14	-0.29	0.29	0.04	-0.21	-0.10	0.11	-0.15
Rain	-0.04	1.00	-0.27	0.00	-0.01	0.00	0.02	0.01	0.02	-0.01	0.03	-0.01	0.01	0.03	0.00	0.00	0.02	0.00	0.01	-0.03	0.03
Temperature	0.07	-0.27	1.00	-0.03	-0.04	0.05	0.05	0.04	0.00	-0.01	0.05	-0.06	0.02	0.06	-0.09	0.09	0.03	-0.03	0.02	-0.08	0.04
Walking_distance	-0.23	0.00	-0.03	1.00	0.46	-0.47	-0.11	-0.70	0.57	-0.48	0.29	0.71	0.37	0.15	0.00	0.00	0.02	0.87	0.66	0.14	-0.28
IC_stop	-0.10	-0.01	-0.04	0.46	1.00	-0.40	-0.27	-0.42	0.44	-0.41	-0.15	0.43	0.09	0.25	0.00	0.00	0.06	0.47	0.21	0.42	0.13
Vehicle_availability	0.13	0.00	0.05	-0.47	-0.40	1.00	0.45	0.54	-0.27	0.04	-0.05	-0.57	0.29	-0.05	0.00	0.00	0.37	-0.35	0.13	-0.48	-0.04
Population_Density	-0.29	0.02	0.05	-0.11	-0.27	0.45	1.00	0.23	0.14	0.05	0.56	-0.54	0.62	0.41	0.00	0.00	0.50	-0.06	0.28	-0.74	0.39
Visbility	0.07	0.01	0.04	-0.70	-0.42	0.54	0.23	1.00	-0.29	0.02	-0.12	-0.68	0.01	-0.04	0.00	0.00	0.13	-0.54	-0.23	-0.24	0.13
Train_frequencie	-0.41	0.02	0.00	0.57	0.44	-0.27	0.14	-0.29	1.00	-0.47	0.29	0.22	0.26	0.44	0.20	-0.20	0.04	0.50	0.45	-0.08	0.11
Young_people	0.34	-0.01	-0.01	-0.48	-0.41	0.04	0.05	0.02	-0.47	1.00	-0.05	-0.20	-0.32	-0.16	0.00	0.00	0.02	-0.43	-0.52	-0.01	0.12
POI_total	-0.14	0.03	0.05	0.29	-0.15	-0.05	0.56	-0.12	0.29	-0.05	1.00	-0.14	0.36	0.75	0.01	-0.01	0.51	0.35	0.47	-0.72	0.38
Busfrequencie	-0.11	-0.01	-0.06	0.71	0.43	-0.57	-0.54	-0.68	0.22	-0.20	-0.14	1.00	-0.12	-0.18	0.00	0.00	-0.22	0.68	0.16	0.49	-0.36
Tramfrequencie	-0.16	0.01	0.02	0.37	0.09	0.29	0.62	0.01	0.26	-0.32	0.36	-0.12	1.00	0.20	0.00	0.00	0.53	0.41	0.76	-0.33	-0.09
Metrofrequencie	-0.14	0.03	0.06	0.15	0.25	-0.05	0.41	-0.04	0.44	-0.16	0.75	-0.18	0.20	1.00	0.01	-0.01	0.45	0.24	0.31	-0.62	0.73
weekday	-0.29	0.00	-0.09	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.01	0.00	0.00	0.01	1.00	-1.00	0.00	0.00	0.00	0.00	0.01
weekendday	0.29	0.00	0.09	0.00	0.00	0.00	0.00	0.00	-0.20	0.00	-0.01	0.00	0.00	-0.01	-1.00	1.00	0.00	0.00	0.00	0.00	-0.01
Service_catchment	0.04	0.02	0.03	0.02	0.06	0.37	0.50	0.13	0.04	0.02	0.51	-0.22	0.53	0.45	0.00	0.00	1.00	0.26	0.41	-0.42	0.18
OV_fiets	-0.21	0.00	-0.03	0.87	0.47	-0.35	-0.06	-0.54	0.50	-0.43	0.35	0.68	0.41	0.24	0.00	0.00	0.26	1.00	0.71	0.06	-0.25
type1	-0.10	0.01	0.02	0.66	0.21	0.13	0.28	-0.23	0.45	-0.52	0.47	0.16	0.76	0.31	0.00	0.00	0.41	0.71	1.00	-0.31	-0.26
type2	0.11	-0.03	-0.08	0.14	0.42	-0.48	-0.74	-0.24	-0.08	-0.01	-0.72	0.49	-0.33	-0.62	0.00	0.00	-0.42	0.06	-0.31	1.00	-0.52
type3	-0.15	0.03	0.04	-0.28	0.13	-0.04	0.39	0.13	0.11	0.12	0.38	-0.36	-0.09	0.73	0.01	-0.01	0.18	-0.25	-0.26	-0.52	1.00

Figure E.1: Correlation matrix first mile modal share

Figure E.2 shows the correlation matrix of the last mile modal share model.

	Modal_Share	Rain	Temperature	Walking_distance	IC_stop	Population_Density	Visbility	Train_frequency	Young_people	POI_total	Busfrequency	Tramfrequency	Metrofrequency	weekday	weekend	Service_catchment	Vehicle_availability	OV_fiets	type1	type2	type3
Modal_Share	1.00	-0.04	0.08	-0.26	-0.11	-0.28	0.11	-0.42	0.33	-0.13	-0.15	-0.15	-0.13	-0.28	0.28	0.06	0.22	-0.22	-0.09	0.09	-0.15
Rain	-0.04	1.00	-0.27	0.00	-0.01	0.02	0.01	0.02	-0.01	0.03	-0.01	0.01	0.03	0.00	0.00	0.02	-0.01	0.00	0.01	-0.03	0.03
Temperature	0.08	-0.27	1.00	-0.03	-0.04	0.05	0.04	0.00	-0.01	0.05	-0.06	0.02	0.06	-0.09	0.09	0.03	0.03	-0.03	0.02	-0.08	0.04
Walking_distance	-0.26	0.00	-0.03	1.00	0.46	-0.11	-0.70	0.57	-0.48	0.29	0.71	0.37	0.15	0.00	0.00	0.02	0.16	0.87	0.66	0.14	-0.28
IC_stop	-0.11	-0.01	-0.04	0.46	1.00	-0.27	-0.42	0.44	-0.41	-0.15	0.43	0.09	0.25	0.00	0.00	0.06	0.24	0.47	0.21	0.42	0.13
Population_Density	-0.28	0.02	0.05	-0.11	-0.27	1.00	0.23	0.14	0.05	0.56	-0.54	0.62	0.41	0.00	0.00	0.50	-0.03	-0.06	0.28	-0.74	0.39
Visbility	0.11	0.01	0.04	-0.70	-0.42	0.23	1.00	-0.29	0.02	-0.12	-0.68	0.01	-0.04	0.00	0.00	0.13	0.02	-0.54	-0.23	-0.24	0.13
Train_frequencie	-0.42	0.02	0.00	0.57	0.44	0.14	-0.29	1.00	-0.47	0.29	0.22	0.26	0.44	0.20	-0.20	0.04	0.28	0.50	0.45	-0.08	0.11
Young_people	0.33	-0.01	-0.01	-0.48	-0.41	0.05	0.02	-0.47	1.00	-0.05	-0.20	-0.32	-0.16	0.00	0.00	0.02	-0.16	-0.43	-0.52	-0.01	0.12
POI_shops	-0.05	0.03	0.05	0.19	-0.25	0.64	-0.01	0.22	0.01	0.97	-0.26	0.43	0.68	0.01	-0.01	0.56	0.15	0.27	0.51	-0.81	0.35
Busfrequency	-0.15	-0.01	-0.06	0.71	0.43	-0.54	-0.68	0.22	-0.20	-0.14	1.00	-0.12	-0.18	0.00	0.00	-0.22	-0.01	0.68	0.16	0.49	-0.36
Tramfrequency	-0.15	0.01	0.02	0.37	0.09	0.62	0.01	0.26	-0.32	0.36	-0.12	1.00	0.20	0.00	0.00	0.53	0.40	0.41	0.76	-0.33	-0.09
Metrofrequency	-0.13	0.03	0.06	0.15	0.25	0.41	-0.04	0.44	-0.16	0.75	-0.18	0.20	1.00	0.01	-0.01	0.45	0.16	0.24	0.31	-0.62	0.73
weekday	-0.28	0.00	-0.09	0.00	0.00	0.00	0.00	0.20	0.00	0.01	0.00	0.00	0.01	1.00	-1.00	0.00	0.07	0.00	0.00	0.00	0.01
weekendday	0.28	0.00	0.09	0.00	0.00	0.00	0.00	-0.20	0.00	-0.01	0.00	0.00	-0.01	-1.00	1.00	0.00	-0.07	0.00	0.00	0.00	-0.01
Service_catchment	0.06	0.02	0.03	0.02	0.06	0.50	0.13	0.04	0.02	0.51	-0.22	0.53	0.45	0.00	0.00	1.00	0.31	0.26	0.41	-0.42	0.18
Vehicle_availability	0.22	-0.01	0.03	0.16	0.24	-0.03	0.02	0.28	-0.16	0.08	-0.01	0.40	0.16	0.07	-0.07	0.31	1.00	0.32	0.55	-0.08	-0.15
OV_fiets	-0.22	0.00	-0.03	0.87	0.47	-0.06	-0.54	0.50	-0.43	0.35	0.68	0.41	0.24	0.00	0.00	0.26	0.32	1.00	0.71	0.06	-0.25
type1	-0.09	0.01	0.02	0.66	0.21	0.28	-0.23	0.45	-0.52	0.47	0.16	0.76	0.31	0.00	0.00	0.41	0.55	0.71	1.00	-0.31	-0.26
type2	0.09	-0.03	-0.08	0.14	0.42	-0.74	-0.24	-0.08	-0.01	-0.72	0.49	-0.33	-0.62	0.00	0.00	-0.42	-0.08	0.06	-0.31	1.00	-0.52
type3	-0.15	0.03	0.04	-0.28	0.13	0.39	0.13	0.11	0.12	0.38	-0.36	-0.09	0.73	0.01	-0.01	0.18	-0.15	-0.25	-0.26	-0.52	1.00

Figure E.2: Correlation matrix last mile linear regression model

Figure E.3 shows the correlation matrix of the first mile trip model

	Rain	Temperature	Walking_distanc	IC_stop	Vehicle_availability	Population_Density	Visbility	Train_frequencie	Young_people	POI_total	Busfrequencie	Tramfrequencie	Metrofrequencie	weekday	weekend	Service_catchment	OV_fiets	type1	type2	type3	Trips	Trainpass
Rain	1.00	-0.27	0.00	-0.01	0.00	0.02	0.02	0.02	-0.01	0.03	-0.01	0.02	0.03	0.01	-0.01	0.02	0.00	0.01	-0.04	0.03	-0.03	0.01
Temperat	-0.27	1.00	-0.03	-0.04	0.05	0.05	0.03	-0.01	-0.01	0.05	-0.06	0.01	0.05	-0.09	0.09	0.03	-0.03	0.00	-0.08	0.05	0.02	0.00
Walking_	0.00	-0.03	1.00	0.46	-0.51	-0.11	-0.72	0.58	-0.48	0.29	0.73	0.38	0.15	0.00	0.00	0.00	0.89	0.76	0.15	-0.28	0.30	0.79
IC_stop	-0.01	-0.04	0.46	1.00	-0.46	-0.28	-0.45	0.43	-0.40	-0.17	0.46	0.05	0.23	0.00	0.00	0.02	0.46	0.18	0.45	0.15	0.44	0.39
Vehicle_a	0.00	0.05	-0.51	-0.46	1.00	0.46	0.52	-0.38	0.09	-0.10	-0.56	0.20	-0.12	0.00	0.00	0.30	-0.45	-0.04	-0.46	0.01	0.27	-0.31
Populatic	0.02	0.05	-0.11	-0.28	0.46	1.00	0.23	0.13	0.06	0.56	-0.54	0.66	0.41	0.00	0.00	0.52	-0.07	0.31	-0.75	0.40	-0.34	0.21
Visbility	0.02	0.03	-0.72	-0.45	0.52	0.23	1.00	-0.35	0.05	-0.14	-0.67	-0.06	-0.08	0.00	0.00	0.08	-0.60	-0.40	-0.22	0.15	-0.37	-0.45
Train_fre	0.02	-0.01	0.58	0.43	-0.38	0.13	-0.35	1.00	-0.46	0.27	0.28	0.17	0.41	0.19	-0.19	-0.05	0.48	0.38	-0.03	0.15	0.07	0.78
Young_pe	-0.01	-0.01	-0.48	-0.40	0.09	0.06	0.05	-0.46	1.00	-0.03	-0.23	-0.29	-0.13	0.00	0.00	0.07	-0.41	-0.54	-0.04	0.10	-0.03	-0.54
POI_total	0.03	0.05	0.29	-0.17	-0.10	0.56	-0.14	0.27	-0.03	1.00	-0.12	0.34	0.74	0.01	-0.01	0.50	0.33	0.49	-0.72	0.41	-0.08	0.49
Busfrequ	-0.01	-0.06	0.73	0.46	-0.56	-0.54	-0.67	0.28	-0.23	-0.12	1.00	-0.06	-0.15	0.00	0.00	-0.17	0.75	0.31	0.48	-0.39	0.38	0.37
Tramfreq	0.02	0.01	0.38	0.05	0.20	0.66	-0.06	0.17	-0.29	0.34	-0.06	1.00	0.14	0.00	0.00	0.47	0.35	0.71	-0.29	-0.04	0.02	0.46
Metrofrec	0.03	0.05	0.15	0.23	-0.12	0.41	-0.08	0.41	-0.13	0.74	-0.15	0.14	1.00	0.01	-0.01	0.42	0.21	0.25	-0.60	0.78	0.05	0.46
weekday	0.01	-0.09	0.00	0.00	0.00	0.00	0.00	0.19	0.00	0.01	0.00	0.00	0.01	1.00	-1.00	0.00	0.00	0.00	-0.01	0.01	0.10	0.20
weekend	-0.01	0.09	0.00	0.00	0.00	0.00	0.00	-0.19	0.00	-0.01	0.00	0.00	-0.01	-1.00	1.00	0.00	0.00	0.00	0.01	-0.01	-0.10	-0.20
Service_c	0.02	0.03	0.00	0.02	0.30	0.52	0.08	-0.05	0.07	0.50	-0.17	0.47	0.42	0.00	0.00	1.00	0.21	0.31	-0.40	0.24	0.10	0.22
OV_fiets	0.00	-0.03	0.89	0.46	-0.45	-0.07	-0.60	0.48	-0.41	0.33	0.75	0.35	0.21	0.00	0.00	0.21	1.00	0.72	0.10	-0.22	0.35	0.75
type1	0.01	0.00	0.76	0.18	-0.04	0.31	-0.40	0.38	-0.54	0.49	0.31	0.71	0.25	0.00	0.00	0.31	0.72	1.00	-0.26	-0.22	0.14	0.77
type2	-0.04	-0.08	0.15	0.45	-0.46	-0.75	-0.22	-0.03	-0.04	-0.72	0.48	-0.29	-0.60	-0.01	0.01	-0.40	0.10	-0.26	1.00	-0.56	0.32	-0.13
type3	0.03	0.05	-0.28	0.15	0.01	0.40	0.15	0.15	0.10	0.41	-0.39	-0.04	0.78	0.01	-0.01	0.24	-0.22	-0.22	-0.56	1.00	-0.08	-0.04
Trips	-0.03	0.02	0.30	0.44	-0.27	-0.34	-0.37	0.07	-0.03	-0.08	0.38	0.02	0.05	0.10	-0.10	0.10	0.35	0.14	0.32	-0.08	1.00	0.22
Trainpass	0.01	0.00	0.79	0.39	-0.31	0.21	-0.45	0.78	-0.54	0.49	0.37	0.46	0.46	0.20	-0.20	0.22	0.75	0.77	-0.13	-0.04	0.22	1.00

Figure E.3: Correlation matrix first mile trip model

Figure E.4 shows the correlation matrix of the last mile trip model.

	Rain	Temperature	Walking_distance	IC_stop	Population_Density	Visbility	Train_frequencie	Young_people	POI_total	Busfrequencie	Tramfrequencie	Metrofrequencie	weekday	weekend	Service_catchment	Vehicle_availability	OV_fiets	type1	type2	type3	Trips	Trainpass
Rain	1.00	-0.27	0.00	-0.01	0.02	0.02	0.02	-0.01	0.03	-0.01	0.02	0.03	0.01	-0.01	0.02	-0.03	0.00	0.01	-0.04	0.03	-0.03	0.01
Temperat	-0.27	1.00	-0.03	-0.04	0.05	0.03	-0.01	-0.01	0.05	-0.06	0.01	0.05	-0.09	0.09	0.03	-0.01	-0.03	0.00	-0.08	0.05	0.02	-0.01
Walking_	0.00	-0.03	1.00	0.46	-0.11	-0.72	0.58	-0.48	0.29	0.73	0.38	0.15	0.00	0.00	0.00	0.29	0.89	0.76	0.15	-0.28	0.31	0.80
IC_stop	-0.01	-0.04	0.46	1.00	-0.28	-0.45	0.43	-0.40	-0.17	0.46	0.05	0.23	0.00	0.00	0.02	0.35	0.46	0.18	0.45	0.15	0.45	0.40
Populatic	0.02	0.05	-0.11	-0.28	1.00	0.23	0.13	0.06	0.56	-0.54	0.66	0.41	0.00	0.00	0.52	-0.17	-0.07	0.31	-0.75	0.40	-0.35	0.20
Visbility	0.02	0.03	-0.72	-0.45	0.23	1.00	-0.35	0.05	-0.14	-0.67	-0.06	-0.08	0.00	0.00	0.08	-0.32	-0.60	-0.40	-0.22	0.15	-0.37	-0.45
Train_fre	0.02	-0.01	0.58	0.43	0.13	-0.35	1.00	-0.46	0.27	0.28	0.17	0.41	0.19	-0.19	-0.05	0.09	0.48	0.38	-0.03	0.15	0.07	0.78
Young_pe	-0.01	-0.01	-0.48	-0.40	0.06	0.05	-0.46	1.00	-0.03	-0.23	-0.29	-0.13	0.00	0.00	0.07	-0.09	-0.41	-0.54	-0.04	0.10	-0.03	-0.53
POI_shop	0.03	0.05	0.19	-0.28	0.64	-0.05	0.18	0.04	0.97	-0.23	0.39	0.67	0.01	-0.01	0.53	-0.08	0.23	0.49	-0.81	0.39	-0.11	0.40
Busfrequ	-0.01	-0.06	0.73	0.46	-0.54	-0.67	0.28	-0.23	-0.12	1.00	-0.06	-0.15	0.00	0.00	-0.17	0.36	0.75	0.31	0.48	-0.39	0.39	0.39
Tramfreq	0.02	0.01	0.38	0.05	0.66	-0.06	0.17	-0.29	0.34	-0.06	1.00	0.14	0.00	0.00	0.47	0.18	0.35	0.71	-0.29	-0.04	0.03	0.46
Metrofrec	0.03	0.05	0.15	0.23	0.41	-0.08	0.41	-0.13	0.74	-0.15	0.14	1.00	0.01	-0.01	0.42	0.01	0.21	0.25	-0.60	0.78	0.05	0.46
weekday	0.01	-0.09	0.00	0.00	0.00	0.00	0.19	0.00	0.01	0.00	0.00	0.01	1.00	-1.00	0.00	0.08	0.00	0.00	-0.01	0.01	0.08	0.19
weekend	-0.01	0.09	0.00	0.00	0.00	0.00	-0.19	0.00	-0.01	0.00	0.00	-0.01	-1.00	1.00	0.00	-0.08	0.00	0.00	0.01	-0.01	-0.08	-0.19
Service_c	0.02	0.03	0.00	0.02	0.52	0.08	-0.05	0.07	0.50	-0.17	0.47	0.42	0.00	0.00	1.00	0.12	0.21	0.31	-0.40	0.24	0.10	0.23
Vehicle_a	-0.03	-0.01	0.29	0.35	-0.17	-0.32	0.09	-0.09	-0.08	0.36	0.18	0.01	0.08	-0.08	0.12	1.00	0.35	0.26	0.17	-0.07	0.69	0.24
OV_fiets	0.00	-0.03	0.89	0.46	-0.07	-0.60	0.48	-0.41	0.33	0.75	0.35	0.21	0.00	0.00	0.21	0.35	1.00	0.72	0.10	-0.22	0.35	0.76
type1	0.01	0.00	0.76	0.18	0.31	-0.40	0.38	-0.54	0.49	0.31	0.71	0.25	0.00	0.00	0.31	0.26	0.72	1.00	-0.26	-0.22	0.15	0.77
type2	-0.04	-0.08	0.15	0.45	-0.75	-0.22	-0.03	-0.04	-0.72	0.48	-0.29	-0.60	-0.01	0.01	-0.40	0.17	0.10	-0.26	1.00	-0.56	0.33	-0.13
type3	0.03	0.05	-0.28	0.15	0.40	0.15	0.15	0.10	0.41	-0.39	-0.04	0.78	0.01	-0.01	0.24	-0.07	-0.22	-0.22	-0.56	1.00	-0.08	-0.04
Trips	-0.03	0.02	0.31	0.45	-0.35	-0.37	0.07	-0.03	-0.08	0.39	0.03	0.05	0.08	-0.08	0.10	0.69	0.35	0.15	0.33	-0.08	1.00	0.22
Trainpass	0.01	-0.01	0.80	0.40	0.20	-0.45	0.78	-0.53	0.49	0.39	0.46	0.46	0.19	-0.19	0.23	0.24	0.76	0.77	-0.13	-0.04	0.22	1.00

Figure E.4: Correlation matrix last mile trip model

F. Detailed trip purposes

In Figure F.1 the detailed trip purpose per station is shown.

Station name	Afkorting	share_fm Home	share_lm Home	share_fm Leisure	share_lm Leisure	share_fm Education	share_lm Education	share_fm Work	share_lm Work	share_fm Other	share_lm Other
Amersfoort CS	Amf	53.3	55.8	28.5	31.6	0.6	0.7	4.3	5.2	7.2	6.7
Amersfoort Schothorst	Amfs	77.9	77.9	13.8	13.6	0	1.4	3.3	1.8	5.1	5.4
Amersfoort Vathorst	Avat	84.5	82.8	10.5	13.5	1.5	1.2	2	2.2	1.5	0.2
Amsterdam Amstel	Asa	50.9	51.4	35.6	35.1	2	2.7	5.7	4.5	5.7	6.3
Amsterdam Centraal	Asd	46.8	45.9	37.1	37.2	0.9	0.9	9.1	9.8	6.1	6.3
Amsterdam Holendrech	Ashd	19.3	26.2	50.6	45.1	1.3	0.4	15.9	16.8	12.9	11.5
Amsterdam Lelylaan	Asdl	45.8	44.7	37.5	37.9	1.4	1.6	4.8	5.2	10.4	10.7
Amsterdam Muiderpoo	Asdm	41.8	42.3	37.1	33.1	2.7	3.3	11	10.7	7.5	10.5
Amsterdam RAI	Rai	47.6	48.2	26.8	27.9	2.2	2	10.9	7.9	12.5	14.1
Amsterdam Science P	Assp	39.6	40.9	36.9	36.7	2.4	4.2	11.5	8.1	9.6	10
Amsterdam Sloterdijk	Ass	51.1	51.6	37.2	35.4	0.7	0.5	6.9	7.5	4.2	5.1
Amsterdam Zuid	Asdz	49	47	33.1	31.7	2.5	4.7	6.2	6.6	9.2	9.9
Breda	Bd	48.1	46	21.7	22.4	8.5	10	10.8	11.9	11	9.7
Breda Prinsenbeek	Bdpb	36	28.6	25.4	24.3	1.3	1	23.7	30.6	13.6	15.5
Delft	Dt	40.6	41.8	17.9	17.8	28.8	27.6	5.3	6.7	7.3	6.1
Delft Campus	Dtcp	39.2	34.8	11.2	9.5	32	37.9	12.8	14.2	4.8	3.6
Den Haag CS	Gvc	48.3	50.2	29.6	27.1	0.2	0.3	15.9	16.6	6.1	5.8
Den Haag HS	Gv	44.2	42.8	29.5	32	0.4	0.1	20.4	19.3	5.5	5.8
Den Haag Laan van NO	Laa	53.2	52.7	21.8	24.9	0.5	1	10.2	12.6	14.3	8.8
Den Haag Mariahoeve	Gvm	36.2	38.9	26	43.1	1.4	1.4	20.3	6.9	15.9	9.7
Den Haag Moerwijk	Gvmw	47.1	46.9	29.6	29.6	0.3	0	15.8	16.2	7.2	7.2
Diemen	Dmn	37.6	33.9	28.2	37.3	0.9	3.4	10.3	6.8	23.1	18.6
Diemen-Zuid	Dmnz	30.4	37.9	39.1	34.5	8.7	0	8.7	6.9	13	20.7
Enschede	Es	66.3	64	13.7	15.7	5.4	5.9	5.6	5.3	9	9
Enschede Kennispark	Esk	52.9	55.4	16.4	18.6	21.5	15.1	5.1	3.9	4.1	7
Groningen	Gn	56.2	56.1	22.4	22.2	9.1	8.9	5.7	6.2	6.7	6.6
Groningen Europapark	Gerp	53.6	52.4	29.7	31.3	2.5	3.3	8.2	6.5	6.1	6.5
Haren	Hrn	55.7	65.6	32.3	23.1	1	0	8.5	7.2	2.5	4.1
Hengelo	Hgl	58.2	60.6	15.9	16.1	4.4	5.6	10.4	7.8	11	10
Hilversum	Hvs	77.5	75.3	7.2	9	1.7	1.4	6.6	7.1	7.1	7.2
Hilversum Mediapark	Hvsn	58.4	65.2	28.2	25.5	0	0.6	8.7	3.1	4.7	5.6
Hilversum Sportpark	Hvsp	62.7	70.2	10.7	14.6	2.3	3.3	14.7	4.6	9.6	7.3
Leeuwarden	Lw	54.2	53.3	33.3	32.8	0.5	0.6	3.1	3.8	9	9.6
Rijswijk	Rsw	46.9	46.3	32.7	36.6	0	0	9.5	7.3	10.9	9.8
Rotterdam Alexander	Rta	48.9	51.1	22.9	23	6.4	3.9	16.8	16.8	4.9	5.3
Rotterdam Blaak	Rtb	39.6	37.7	37.2	39	5	4.7	15.5	16	2.8	2.6
Rotterdam CS	Rtd	49.9	45.1	32.3	35.2	3	3.4	12.1	13.4	2.6	2.9
Rotterdam Lombardijer	Rlb	36.2	37.1	36.3	34.9	8.8	5.2	12.6	15.2	6.2	7.6
Rotterdam Noord	Rtn	67.6	57.9	20.3	29.9	2	2.5	5	5.8	5	3.7
Rotterdam Zuid	Rtz	35.8	33.9	41	41.2	3.4	3.3	15.6	18.1	4.2	3.6
Zwolle	Zl	45.2	47.2	25.2	28.2	16.5	13.6	3.3	3	9.8	8.1

Figure F.1: Detailed trip purpose per station

G. HREC Apporval

Date 27-Feb-2023
Contact person Dr. Cath Cotton, Policy Advisor Academic Integrity
E-mail [redacted]

Human Research Ethics Committee
TU Delft
(http://hrec.tudelft.nl/)
Visiting address
Jaffalaan 5 (building 31)
2628 BX Delft
Postal address
P.O. Box 5015 2600 GA Delft
The Netherlands

Ethics Approval Application: Exploring the usage patterns of shared e-mopeds in first- and last mile transport to train stations
Applicant: Wit, Gert de

Dear Gert de Wit,

It is a pleasure to inform you that your application mentioned above has been approved.

In addition to any specific conditions or notes, the HREC provides the following standard advice to all applicants:
• In light of recent tax changes, we advise that you confirm any proposed remuneration of research subjects with your faculty contract manager before going ahead.
• Please make sure when you carry out your research that you confirm contemporary covid protocols with your faculty HSE advisor.
• Our default advice is not to publish transcripts or transcript summaries, but to retain these privately for specific purposes/checking; and if they are to be made public then only if fully anonymised and the transcript/summary itself approved by participants for specific purpose.
• Where there are collaborating (including funding) partners, appropriate formal agreements including clarity on responsibilities, including data ownership, responsibilities and access, should be in place and that relevant aspects of such agreements (such as access to raw or other data) are clear in the Informed Consent.

Good luck with your research!

Sincerely,

Dr. Ir. U. Pesch
Chair HREC
Faculty of Technology, Policy and Management

H. Literaturetable

		Shared micromobility train combination																												
		Micromobility system								Station accesibility				Environment characteristics											Temporal factors					
Author	shared mode	Service area size	Network density	Bike station density	Dockless system	Parking capacity stations	Fare integration with PT	Price	Vehicle availability	Walking distance	Quality of train service	Safe walking infrastructure	Present other modes	Points of interest	Industrial land use	Recreational land use	Commercial land use	Shape of city	City center	Population density	Number of Jobs/Job density	road safety	Unsafe built environment	Quality of bicycle infrastructure	Rain	Wind	Temperature	Weekday	Weekend	Commuting peaks
Ardman et al.	bike							-					-												-	-				
Arias Molinarez (2022)	e-moped	+							+									?									+			
Böcker	bike					+			+					+				?	+	+	+									+
Caspi 2020	e-scooter														+		+		+				+							
Croci en Rossi (2014)	shared bike													+	+		+													
Dibaj et al. (2021)	e-scooter															+			+											
Faghih-Imani (2016)	bike															+		-							-		+			
Faghih-Imani (2017)	shared bike			+					+					+									+							
Guidon	e-bike										+					+	+							+						
Guidon , Reck	bike	+															+			+	+									
Heumann et al. (2021)	e-scooter													+															+	+
Hosseizeidah et al. (2022)	e-scooter									-						+														
Jiao & Bai (2020)	e-scooters																		+	+										
Jimizez et al.	bike	+							/																					
Jonkeren	bikes								+	-	+																			
Jorritsma	bikes							-	+											+				+						
Kjaerup	e-scooter				+			-	+					+		+								+						
Liao and Correia (2022)	e-micromobility										+			+						+				+	-	-	+		-	
Ma et al. (2020)	shared bike									-																				
Mezahbin-Tulli et al. (2021)	e-scooter		+	+												+				+					-	-	+		+	
Mohammadein (2022)	e-scooter										+						+					-		+			+			
Moinse (	micromobility									-	+		-											+						
Noland (2019)	e-scooters																								-				+	
Oehme ()	e-scooter										+																			
Oeschger	Micromobility					+			+	-		+								+										
Radics	e-scooter													+		+														
Reck et al. (2020)	multiple					+			+																					
Schwinger	ebike/scooter															+												+	-	
Sherrrif	e-scooters	+																												
Torabi et al. (2022)	Non specific								/				-				+													
Tran et al. (2015)	shared bike			+					+												+									
Ushijima et al. (2021)	e-scooter																													
Vale(2021)	Non specific	+									+																			
Van Mille et al.	bike										+		-									+		+	-		+			
Wang (2022)	e-scooter					+				-																				
Total		**5**	**1**	**3**	**1**	**4**	**0**	**3**	**11**	**6**	**8**	**1**	**4**	**7**	**2**	**8**	**6**	**3**	**4**	**7**	**3**	**2**	**2**	**7**	**6**	**3**	**6**	**1**	**5**	**2**

I. Detailed modal share per station

		Observed Check modal share									High scenario				Low range				Mid Range			
Station	Abbriviation	Week FM	Week LM	Weekend FM	Weekend LM	Check mopeds	Total mopeds	Provider	Low ratio	High ratio	Week FM	Week LM	Weekend FM	Weekend LM	Week FM	Week LM	Weekend FM	Weekend LM	Week FM	Week LM	Weekend FM	Weekend LM
Amersfoort CS	Amf	0.17	0.17	0.25	0.23	230	271	CG	0.7	1.3	0.29	0.29	0.42	0.39	0.17	0.17	0.25	0.23	0.23	0.23	0.34	0.31
Amersfoort Schothorst	Amfs	0.16	0.16	0.34	0.31	230	271	CG	0.7	1.3	0.27	0.27	0.57	0.52	0.16	0.16	0.34	0.31	0.21	0.21	0.46	0.42
Amersfoort Vathorst	Avat	0.38	0.37	0.79	0.72	230	271	CG	0.7	1.3	0.64	0.62	1.33	1.21	0.38	0.37	0.79	0.72	0.51	0.5	1.06	0.97
Amsterdam Amstel	Asa	0.28	0.27	0.55	0.48	385	790	CF	1.1	1.7	0.52	0.50	1.03	0.90	0.34	0.33	0.66	0.58	0.43	0.41	0.84	0.74
Amsterdam Centraal	Asd	0.07	0.07	0.12	0.11	385	790	CF	1.1	1.7	0.13	0.13	0.22	0.21	0.08	0.08	0.14	0.13	0.11	0.11	0.18	0.17
Amsterdam Holendrecht	Ashd	0.12	0.1	0.91	0.78	385	790	CF	1.1	1.7	0.22	0.19	1.70	1.46	0.14	0.12	1.10	0.94	0.18	0.15	1.4	1.2
Amsterdam Lelylaan	Asdl	0.37	0.35	0.68	0.58	385	790	CF	1.1	1.7	0.69	0.65	1.27	1.08	0.45	0.42	0.82	0.70	0.57	0.54	1.04	0.89
Amsterdam Muiderpoort	Asdm	0.12	0.12	0.21	0.19	385	790	CF	1.1	1.7	0.22	0.22	0.39	0.35	0.14	0.14	0.25	0.23	0.18	0.18	0.32	0.29
Amsterdam RAI	Rai	0.27	0.24	0.54	0.47	385	790	CF	1.1	1.7	0.50	0.45	1.01	0.88	0.33	0.29	0.65	0.57	0.41	0.37	0.83	0.72
Amsterdam Science Park	Assp	0.16	0.15	0.74	0.65	385	790	CF	1.1	1.7	0.30	0.28	1.38	1.21	0.19	0.18	0.89	0.78	0.25	0.23	1.14	1
Amsterdam Sloterdijk	Ass	0.14	0.13	0.24	0.22	385	790	CF	1.1	1.7	0.26	0.24	0.45	0.41	0.17	0.16	0.29	0.27	0.22	0.2	0.37	0.34
Amsterdam Zuid	Asdz	0.23	0.22	0.4	0.35	385	790	CF	1.1	1.7	0.43	0.41	0.75	0.65	0.28	0.27	0.48	0.42	0.35	0.34	0.61	0.54
Breda	Bd	1.34	1.31	2.05	1.96	240	394	CF	1.1	1.7	2.00	1.96	3.06	2.93	1.34	1.31	2.05	1.96	1.67	1.63	2.55	2.44
Breda Prinsenbeek	Bdpb	0.42	0.39	1.45	1.24	240	394	CF	1.1	1.7	0.63	0.58	2.16	1.85	0.42	0.39	1.45	1.24	0.52	0.49	1.81	1.55
Delft	Dt	0.11	0.11	0.13	0.11	100	186	CG	0.7	1.3	0.29	0.29	0.35	0.29	0.16	0.16	0.19	0.16	0.22	0.22	0.27	0.22
Delft Campus	Dtcp	0.24	0.23	0.36	0.32	100	186	CG	0.7	1.3	0.64	0.61	0.96	0.85	0.34	0.33	0.52	0.46	0.49	0.47	0.74	0.65
Den Haag CS	Gvc	0.25	0.24	0.44	0.43	500	1593	CFG	0.9	1.5	0.89	0.85	1.56	1.52	0.53	0.51	0.93	0.91	0.71	0.68	1.25	1.22
Den Haag HS	Gv	0.39	0.38	0.52	0.48	500	1593	CFG	0.9	1.5	1.38	1.35	1.84	1.70	0.83	0.81	1.10	1.02	1.1	1.08	1.47	1.36
Den Haag Laan van NOI	Laa	0.19	0.18	0.41	0.38	500	1593	CFG	0.9	1.5	0.67	0.64	1.45	1.35	0.40	0.38	0.87	0.81	0.54	0.51	1.16	1.08
Den Haag Mariahoeve	Gvm	0.12	0.12	0.32	0.28	500	1593	CFG	0.9	1.5	0.42	0.42	1.13	0.99	0.25	0.25	0.68	0.59	0.34	0.34	0.91	0.79
Den Haag Moerwijk	Gvmw	0.67	0.61	1.5	1.36	500	1593	CFG	0.9	1.5	2.37	2.16	5.31	4.81	1.42	1.30	3.19	2.89	1.9	1.73	4.25	3.85
Diemen	Dmn	0.13	0.12	0.15	0.14	50	100	CF	1.1	1.7	0.24	0.22	0.27	0.25	0.15	0.14	0.18	0.16	0.19	0.18	0.22	0.21
Diemen-Zuid	Dmnz	0.02	0.02	0.06	0.06	50	100	CF	1.1	1.7	0.04	0.04	0.11	0.11	0.02	0.02	0.07	0.07	0.03	0.03	0.09	0.09
Enschede	Es	0.89	0.77	3.04	2.09	250	416	CFG	0.9	1.5	1.65	1.42	5.62	3.86	0.99	0.85	3.37	2.32	1.32	1.14	4.5	3.09
Enschede Kennispark	Esk	0.36	0.32	2.77	0.98	250	416	CFG	0.9	1.5	0.67	0.59	5.12	1.81	0.40	0.35	3.07	1.09	0.53	0.47	4.1	1.45
Groningen	Gn	0.64	0.54	0.73	0.56	220	449	CF	1.1	1.7	1.19	1.00	1.35	1.04	0.77	0.65	0.88	0.67	0.98	0.83	1.12	0.86
Groningen Europapark	Gerp	0.2	0.18	0.52	0.42	220	449	CF	1.1	1.7	0.37	0.33	0.96	0.78	0.24	0.22	0.62	0.50	0.31	0.28	0.79	0.64
Haren	Hrn	0.5	0.48	1.2	1.01	220	449	CF	1.1	1.7	0.93	0.89	2.23	1.87	0.60	0.58	1.44	1.21	0.76	0.73	1.83	1.54
Hengelo	Hgl	0.07	0.06	0.16	0.13	50	150	CFG	0.9	1.5	0.23	0.20	0.53	0.43	0.14	0.12	0.32	0.26	0.19	0.16	0.43	0.35
Hilversum	Hvs	0.35	0.34	0.44	0.43	100	200	CG	0.7	1.3	1.00	0.97	1.26	1.23	0.54	0.52	0.68	0.66	0.77	0.75	0.97	0.95
Hilversum Mediapark	Hvsm	0.09	0.09	0.3	0.29	100	200	CG	0.7	1.3	0.26	0.26	0.86	0.83	0.14	0.14	0.46	0.45	0.2	0.2	0.66	0.64
Hilversum Sportpark	Hvsp	0.07	0.07	0.24	0.2	100	200	CG	0.7	1.3	0.20	0.20	0.69	0.57	0.11	0.11	0.37	0.31	0.15	0.15	0.53	0.44
Leeuwarden	Lw	1.13	1.08	1.38	1.26	150	300	CG	0.7	1.3	3.23	3.09	3.94	3.60	1.74	1.66	2.12	1.94	2.48	2.37	3.03	2.77
Rijswijk	Rsw	0.11	0.1	0.22	0.2	50	100	CG	0.7	1.3	0.31	0.29	0.63	0.57	0.17	0.15	0.34	0.31	0.24	0.22	0.48	0.44
Rotterdam Alexander	Rta	0.27	0.26	0.46	0.43	1000	2223	CFG	0.9	1.5	0.67	0.64	1.14	1.06	0.40	0.39	0.68	0.64	0.53	0.51	0.91	0.85
Rotterdam Blaak	Rtb	1.22	1.15	2.68	2.58	1000	2223	CFG	0.9	1.5	3.01	2.84	6.62	6.37	1.81	1.70	3.97	3.82	2.41	2.27	5.3	5.1
Rotterdam CS	Rtd	0.99	0.96	1.27	1.24	1000	2223	CFG	0.9	1.5	2.45	2.37	3.14	3.06	1.47	1.42	1.88	1.84	1.96	1.9	2.51	2.45
Rotterdam Lombardijen	Rlb	0.33	0.32	0.89	0.85	1000	2223	CFG	0.9	1.5	0.82	0.79	2.20	2.10	0.49	0.47	1.32	1.26	0.65	0.63	1.76	1.68
Rotterdam Noord	Rtn	1.12	1.07	1.68	1.55	1000	2223	CFG	0.9	1.5	2.77	2.64	4.15	3.83	1.66	1.59	2.49	2.30	2.21	2.11	3.32	3.06
Rotterdam Zuid	Rtz	0.49	0.47	1.1	1.02	1000	2223	CFG	0.9	1.5	1.21	1.16	2.72	2.52	0.73	0.70	1.63	1.51	0.97	0.93	2.17	2.02
Zwolle	Zl	0.29	0.28	0.32	0.29	150	319	Cf	1.1	1.7	0.56	0.54	0.62	0.56	0.36	0.35	0.40	0.36	0.46	0.45	0.51	0.46

Figure I.1: Overview modal share values including high and low ratio scenarios

J. Validation results

This chapter shows the reuslts of all individual runs of the 5-fold cross validation of the multiple linear regression models. Table J.1 shows the results of the individual runs of estimating the coefficients.

Table J.1: Validation results first mile modal share model

First Mile Modal share	Model 1	2	3	4	5	Real model	Min	Max	Percentage max	Percentage min
Adj. R2	0.629	0.627	0.621	0.626	0.63	0.627	0.621	0.63	99.04%	100.48%
const.	-0.1925	-0.18	-0.18	-0.19	-0.205	-0.189	-0.205	-0.18	108.47%	95.24%
Train frequency	-0.087	-0.0962	-0.073	-0.06	-0.068	-0.077	-0.0962	-0.06	124.94%	77.92%
Interaction2	0.21	0.224	0.205	0.206	0.211	0.2109	0.205	0.224	97.20%	106.21%
Metro frequency	0.184	0.175	0.134	0.159	0.153	0.161	0.134	0.184	83.23%	114.29%
Weekendday	0.396	0.349	0.376	0.367	0.427	0.383	0.349	0.427	91.12%	111.49%
Interaction 1	-0.327	-0.327	-0.326	-0.328	-0.333	-0.328	-0.333	-0.326	101.52%	99.39%
Population density	-0.665	-0.649	-0.671	-0.659	-0.64	-0.656	-0.671	-0.64	102.29%	97.56%
Vehicle availability	0.232	0.243	0.242	0.252	0.255	0.245	0.232	0.255	94.69%	104.08%
Young people	0.239	0.251	0.271	0.271	0.25	0.26	0.239	0.271	91.92%	104.23%
Tram frequency	0.261	0.2362	0.248	0.243	0.222	0.242	0.222	0.261	91.74%	107.85%
Bus frequency	-0.188	-0.1885	-0.195	-0.188	-0.183	-0.189	-0.195	-0.183	103.17%	96.83%
POI	0.1978	0.216	0.2339	0.2095	0.221	0.216	0.1978	0.2339	91.57%	108.29%
Temperature	0.0584	0.045	0.067	0.064	0.05	0.057	0.045	0.067	78.95%	117.54%

Table J.2 shows the validation results of the last mile modal share model. The red numbers indicate that the variable train frequency is not significant on two of the model runs.

Table J.2: Validation results last mile modal share model

Last mile Model Share	Model 1	2	3	4	5	Real model	Min	Max	Percentage max	Percentage min
Adj. R2	0.596	0.613	0.59	0.609	0.598	0.599	0.59	0.613	98.50%	102.34%
constant	-0.347	-0.387	-0.376	-0.3602	-0.313	-0.368	-0.387	-0.313	105.16%	85.05%
Train frequency	-0.052	-0.025	-0.061	-0.068	-0.074	-0.054	-0.074	-0.025	137.04%	46.30%
Vehicle availability	0.257	0.257	0.281	0.265	0.281	0.249	0.257	0.281	103.21%	112.85%
weekend day	0.444	0.467	0.423	0.437	0.429	0.433	0.423	0.467	97.69%	107.85%
Population density	-0.793	-0.805	-0.714	-0.766	-0.722	-0.775	-0.805	-0.714	103.87%	92.13%
Interaction 4	-0.793	-0.789	-0.751	-0.737	-0.711	-0.748	-0.793	-0.711	106.02%	95.05%
Young people	0.219	0.259	0.22	0.225	0.216	0.233	0.216	0.259	92.70%	111.16%
POI total	0.236	0.257	0.216	0.2479	0.207	0.2361	0.207	0.257	87.67%	108.85%
Tram frequency	0.37	0.382	0.319	0.3429	0.315	0.359	0.315	0.382	87.74%	106.41%
Bus frequency	-0.168	-0.155	-0.143	-0.185	-0.189	-0.175	-0.189	-0.143	108.00%	81.71%
Interaction 1	-0.283	-0.322	-0.304	-0.312	-0.295	-0.298	-0.322	-0.283	108.05%	94.97%
Temperature	0.052	0.063	0.045	0.053	0.07	0.054	0.045	0.07	83.33%	129.63%
Visibity	-0.194	-0.148	-0.161	-0.137	-0.216	-0.145	-0.216	-0.137	148.97%	94.48%
OV-fiets	-0.13	-0.134	-0.11	-0.099	-0.094	-0.108	-0.134	-0.094	124.07%	87.04%

Table J.3 shows the validation results of the first mile trip model.

Table J.3: Validation results first mile trip model

First mile model trip	1	2	3	4	5	Real model	Min	Max	Percentage max	Percentage min
Adj. R2	0.606	0.589	0.591	0.611	0.591	0.597	0.589	0.611	98.66%	102.35%
Constant	-0.357	-0.379	-0.382	-0.385	-0.381	-0.376	-0.385	-0.357	102.39%	94.95%
IC stop	0.411	0.48	0.48	0.476	0.472	0.463	0.411	0.48	88.77%	103.67%
Interaction 2	0.362	0.374	0.374	0.36	0.377	0.3702	0.36	0.377	97.24%	101.84%
Bus frequency	0.24	0.212	0.225	0.224	0.24	0.229	0.212	0.24	92.58%	104.80%
Metro frequency	0.427	0.412	0.42	0.425	0.416	0.421	0.412	0.427	97.86%	101.43%
Tram frequency	0.509	0.481	0.483	0.495	0.473	0.488	0.473	0.509	96.93%	104.30%
Population density	-0.581	-0.586	-0.573	-0.592	-0.56	-0.578	-0.592	-0.56	102.42%	96.89%
Young people	0.223	0.248	0.238	0.255	0.239	0.24	0.223	0.255	92.92%	106.25%
Vehicle availability	0.106	0.108	0.119	0.118	0.11	0.112	0.106	0.119	94.64%	106.25%
Train passengers	0.416	0.437	0.417	0.39	0.421	0.417	0.39	0.437	93.53%	104.80%
Walking distance	-0.366	-0.31	-0.316	-0.295	-0.318	-0.322	-0.366	-0.295	113.66%	91.61%
Train frequency	-0.104	-0.155	-0.129	-0.134	-0.146	-0.134	-0.155	-0.104	115.67%	77.61%
Temperature	0.051	0.063	0.078	0.065	0.067	0.065	0.051	0.078	78.46%	120.00%

Table J.4 shows the validation results of the last mile trip model.

Table J.4: Validation results first mile trip model

Last mile model trip	1	2	3	4	5	Real model	Min	Max	Percentage max	Percentage min
Adj. R^2	0.687	0.692	0.714	0.708	0.704	0.7	0.687	0.714	98.14%	102.00%
Constant	-0.448	-0.405	-0.43	-0.453	-0.429	-0.433	-0.453	-0.405	104.62%	93.53%
Vehicle availability	0.409	0.406	0.39	0.433	0.42	0.41	0.39	0.433	95.12%	105.61%
IC stop	0.399	0.379	0.379	0.4	0.369	0.385	0.369	0.4	95.84%	103.90%
Population density	-0.532	-0.535	-0.549	-0.519	-0.508	-0.529	-0.549	-0.508	103.78%	96.03%
Service catchment	0.103	0.114	0.105	0.101	0.094	0.103	0.094	0.114	91.26%	110.68%
Young people	0.235	0.224	0.248	0.242	0.23	0.236	0.224	0.248	94.92%	105.08%
Tram frequency	0.311	0.291	0.323	0.291	0.279	0.3	0.279	0.323	93.00%	107.67%
Metro frequency	0.191	0.183	0.195	0.188	0.184	0.188	0.183	0.195	97.34%	103.72%
Visibility	0.145	0.109	0.127	0.149	0.127	0.132	0.109	0.149	82.58%	112.88%
Temperature	0.041	0.04	0.035	0.045	0.039	0.04	0.035	0.045	87.50%	112.50%
Trainpassengers	0.058	0.068	0.062	0.055	0.069	0.063	0.055	0.069	87.30%	109.52%