Filling Buses with Train Passengers

How train connections influence bus ridership

Kristian Terlien

Delft University of Technology

TIL Thesis

Filling buses with train passengers: how train connections influence bus ridership

Kristian Terlien

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Student number:	5169941
TU Delft supervisors:	Dr. Ir. Maarten Kroesen
	Dr. Ir. Niels van Oort
TU Delft co-reader:	Dr. Jie Gao
Company supervisor:	Drs. Marnix van Witzenburg

Summary

Introduction

As cities strive for more sustainable and accessible mobility by promoting public transport, buses play a key role in connecting residents of all neighbourhoods to and from the wider rail network. Yet, despite growing attention to multimodal transport, ridership on urban bus routes has been slow to recover since the COVID-19 pandemic.

One opportunity lies in making it more attractive for the train passenger to travel to or from the train station by bus. For these travellers, transfer time can be a crucial factor in choosing the bus as first- or last-mile transport. Still, it remains unclear to transport operators whether better alignment between buses and trains truly leads to more passengers. This thesis investigates that question by exploring the effect of train-bus transfer times on urban bus ridership and identifying how attractive transfers can support network planning

One promising strategy lies in improving the quality of connections between buses and trains. Since train travellers are already public transport users, they may be more inclined to use the bus, as long as the transfer is convenient. Among the various aspects that define transfer quality, transfer time stands out as a potentially decisive factor. However, it remains uncertain to what extent better-aligned transfers actually lead to more passengers. This thesis investigates the relationship between train-bus transfer times and bus ridership, with the goal of providing guidance in network planning aimed at increasing passenger number.

Methodology

The analysis focuses on two mid-sized Dutch cities: Maastricht and Breda. These cities differ in the trains by which they are served, but both operate urban bus networks centred around their central train stations. To estimate how different factors influence bus ridership to and from the train station, a direct ridership model is developed. This type of model links passenger numbers at bus stops to externally observable characteristics such as demographics, land use, and service-level attributes.

A key deviation in this study from previous work is the use of a multi-level regression approach, which estimates ridership at the separately for each line per stop. This disaggregated method enables the observation of variation in transfer opportunities across bus lines that serve the same stop. This way, the endogenous variable representing the aggregated frequency of a stop becomes less dominant in explaining ridership.

To assess transfer quality, three approaches are tested. The first uses the average transfer time between bus and train, weighted by train usage. The second includes individual transfer times to selected train services. The third and most promising method introduces binary indicators representing whether the transfer time of a connection to a specific train falls within a feasible window of 5 to 12 minutes. This interval is selected after comparing previous literature finding and current planning principles of transit operators.

The model is applied to several time periods; weekday daytime, evenings, Saturdays, and Sundays, primarily because the transfer opportunities change across these periods due to different schedules being operated. By comparing these time windows, the variation in the effect of transfer timing can be studid. Finally, to check generalisability, the analysis is repeated for Breda using weekday daytime data, to make a comparison across two different regional contexts.

Key findings

In Maastricht, a clear link is found between better transfer coordination and higher bus ridership. Each additional minute of average transfer time is associated with a 2.3% drop in the number of boarding passengers. Meanwhile, bus lines offering a favourable connection to the intercity train—, with a layover time between 5–12 minutes, see ridership increase by 36%. These findings confirm that transfer timing significantly affects a traveller's decision to use the bus as a first- or last-mile mode to the train.

Among the tested methods, the binary transfer indicator was found to be the most accurate and practically applicable. It reflects the non-linear relationship in which both too short and too long transfers are deemed unfavourable.

The importance of transfer quality varies depending on the time of travel. During weekday evenings, no effect was observed, possibly because evening trips are more focused on travellers transferring from the train to the bus to return home. In contrast, on weekends, the transfer effect is stronger. On Saturdays, attractive connections are associated with a 43% increase in ridership; on Sundays, the effect grows to 65%, likely due to the lower frequencies operated on these days.

Breda, which has more frequent and varied intercity services, shows a smaller influence. While the transfer effect is still present, it is less pronounced, with the most favourable time interval linked to a 23% increase in ridership. This difference is likely caused by a wider variation in train departures and passenger flows, which reduce the dominance of one single transfer opportunity.

Overall, the analysis shows that the impact of transfer coordination is most noticeable when passenger flows are concentrated around a limited number of train services and when bus arrival or departure times can be meaningfully aligned.

Discussion

While the study clearly detects ridership changes related to transfer times, it assumes a constant effect limited to the 5–12 minute window. The exact shape of the relationship both within and outside this interval remains unknown and offers a direction for future research.

Still, the findings strongly indicate that poor transfer conditions discourage ridership, while well-timed connections support it. Despite local differences, the link between good transfers and higher passenger numbers holds across both cities. Especially at train stations where there are limited train services and passengers are unevenly distributed over the different trains, a strong transfer effect can be observed.

Analysing ridership at the stop-line level proves both feasible and insightful. For transit operators such as Arriva, these models offer a practical tool for evaluating the benefits of rescheduling or redesigning routes, helping balance service efficiency with passenger needs.

Practical recommendations

The findings suggest several practical considerations for transport authorities and operators aiming to enhance urban bus ridership through improved integration with rail services.

Improving transfer coordination at major train hubs may be especially beneficial in regions where train services are infrequent or concentrated around a few high-demand trains. Aligning bus services with these key departures or arrivals could help increase passenger numbers.

The 5–12 minute window appears to offer a favourable balance between reliability and convenience for passengers. Using this interval as a reference point when planning bus arrivals before train departures, or bus departures after train arrivals, may help in attracting multimodal travellers.

Conclusion

This study finds that bus-train transfer times in the 5–12 minute range are associated with significantly higher ridership to and from the train station. Although the effect varies across time periods and networks, there is one consistent takeaway: **well-timed and convenient transfers between bus and train are key to attracting more passengers in urban networks**.

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Contents

1 Introduction

As an integral part of the Dutch public transport system, buses contribute to accessibility, sustainability, and the overall efficiency of urban mobility. On an average day, around 1.2 million bus trips are made daily in the Netherlands [CROW, 2024]. Within cities, it is an equitable, environmentally friendly and space-efficient means of travel as opposed to the private car, and the additional gained accessibility contributes to economic development [van Oort et al., 2017]. Hence, policymakers commit to ensuring adequate bus connections in Dutch urban regions.

Despite these efforts, bus passenger numbers drastically decreased during the COVID-19 pandemic and have not fully recovered [de Haas, 2023]. The public transport operator Arriva additionally reported a lagging recovery specifically for urban bus services [Arriva, 2023]. An explanation for these underperforming urban bus lines can be found in the strong competition of the bicycle as an alternative transport mode, especially in cities where distances are shorter [Ton and van den Heuvel, 2023].

One clear cycling advantage arises when comparing access modes to the train. While buses operate on a fixed schedule, and the duration of transferring to the train from the bus is directly determined by the timetables, the bicycle is completely flexible in arrival and departure times. Hence, to improve the relative competitiveness of the bus, the transfer time from bus to train needs to be optimised, to re-attract passengers.

Several arguments exist for providing favourable bus connections for access and egress transport to the train network, besides cycling facilities. The first argument is the indispensability of the bus to groups who are not physically able to cycle [Bakker and Zwaneveld, 2009]. Another reason is the lack of space around train stations to expand bicycle parking [Rijkswaterstaat, 2020], meaning that the number of train travellers cycling to the station cannot increase indefinitely. A third justification is to attract the subset of travellers who have a strong preference for accessing the train by bus [Stam et al., 2021]. Not providing adequate bus services for this sizeable group can lead to commuters relinquishing public transport altogether. Lastly, bus services expand last-mile accessibility by removing the need for a private vehicle, which is generally less accessible at the egress station [Martens, 2004].

These practical and societal considerations motivate improving the competitiveness of the bus. Given this objective, offering optimised intermodal connections emerge as a promising strategy. However, a clearer understanding of the relationship between transfer times and bus ridership is essential to support the necessary network redesigns and schedule changes for such an optimisation.

1.1 Problem statement

A challenge in improving public transport networks lies in understanding what drives bus ridership. While optimising transfer times appears to be promising to improve bus popularity, the relationship between transfer quality and bus passengers numbers has not been clearly established. However, existing research on both bus ridership and intermodal transfers offers a scientific foundation to explore this relationship further.

Numerous factors influencing bus ridership have been previously discovered, including population, frequency and land use [Chu, 2004; Dill et al., 2013; Kerkman et al., 2015]. These factors are mostly determined at the stop-level by studying the stop's catchment area. Other attributes, like average headway and number of directions, are derived from the network and timetable of the bus specifically, but predictors qualifying the intermodal connectivity between bus and train lack in these studies. This lack of integration limits the ability to assess whether improving transfer quality leads to ridership growth.

Meanwhile, the intermodal connectivity quantified as transfer time has been studied in the context of travel utility and route choice modelling. Specifically for the case of bus-train transfers in the Netherlands, both Bovy and Hoogendoorn-Lanser [2005] and Schakenbos et al. [2016] concluded that longer transfer times have a disproportionally negative effect on travel utility, greater than walking time or in-vehicle travel time. As a result, passengers are more likely to prefer other access/egress modes when the waiting time between modes is undesirably long.

These findings point to a negative influence of long transfer times on bus ridership, but it remains unknown whether and to what extent bus-train connections influence the number of passengers per stop or per bus line. This knowledge gap makes it difficult to assess whether improving transfer coordination could aid in re-attracting passenger numbers in urban areas. Addressing this lack of insight would provide a valuable perspective for public transport operators to improve integration and increase the attractiveness of bus services, particularly for networks which have an important feeder function for the train.

1.2 Transfer time complexities

Three explanations for the lack of transfer attributes in ridership estimation models can be found. The first is the difficulty of representing transfer quality in a consistent, quantifiable form. Another reason is the inherent dependency of transfer times on the timetables of bus and train services. Specifically, transfer time can only be reliably estimated for a time window in which the timetable remains constant, which is difficult due to the varying schedules throughout the week. A final complexity is introduced by each transfer station differing in bus and train services. The following paragraphs elaborate on these challenges and present how this study will address them.

The first analytical challenge is identifying how to incorporate a quantified measure of transfer attractiveness as a predictor for bus ridership. Multimodal hubs provide multiple bus-train transfer options, meaning that not all bus passengers connect to the same train service, if they transfer at all. Additionally, factors such as walking time between platforms and service reliability influence the perceived transfer quality [Schakenbos et al., 2016]. Accordingly, the first objective of this study is to establish an effective and practical method to represent transfer attractiveness in a ridership model.

The second consideration is temporal variability, since most operators use different timetables for peak, off-peak, evening, Saturday and Sunday. These non-identical schedules mean that the waiting time for a train is not the same at every hour of the week. The schedules are changed because of varying travel patterns, for example more work-related trips presumably occur during peak hours, while leisure travel is more prevalent on week-ends. Studying the effect of transfer times at each of these time periods is not only necessary to account for the different arrival and departure times, but also offers valuable insights in timetable design objectives for each of these time periods.

In addition to temporal variation, geographic differences must be taken into account. Transfer-related attributes are shaped by the specific transfer opportunities available at each location. Consequently, the quality and range of transfer options can differ significantly between networks. To assess whether the effect of transfer time on bus ridership is consistent across locations, a comparative analysis involving investigating at least two study areas is required.

1.3 Research question

The objective of this study is to fill the knowledge gap on how bus–train transfer times affect bus ridership in an urban, multimodal context. However, three modelling complexities need to be overcome to obtain complete insight. First the optimal formulation to measure transfer times must be established, which should then be used to analyse ridership across different time periods and networks. This method allows temporal and geographic differences to be accounted for in pursuit of the research goal.

Based on this main objective, the research question is defined: *"What is the influence of train-bus transfer times on bus ridership?"*. Accordingly three sub-questions are formulated, to address the previously explained modelling complexities, which break down the central research question into specific aspects. These sub-questions are:

1. *How can transfer times accurately be defined, calculated and implemented as a predictor in direct ridership models?*
2. *To what extent is there variation between the different times of the day and week in the effect of transfer time on bus ridership?*
3. *Are there regional differences between bus networks in the effect of transfer time on bus ridership?*

The method to answer the research question is presented in the following section. First the basic concepts of the used model are explained, after which the approach to address the individual sub-questions is described.

1.4 Method

The main strategy involves modelling bus ridership using transfer-related and other explanatory variables within a so-called direct ridership model. These models estimate ridership *directly* using externally measurable factors related to the built environment and level-of-service of bus stops as predictors in a regression model. Previous studies model passenger numbers per stop [Chu, 2004; Dill et al., 2013; Kerkman et al., 2015], but since transfer times vary between bus lines serving the same stop, this study models bus ridership at the line-per-stop level. As an example, for one observation it is estimate how many passengers take bus line X at stop Y.

The modelling results provide insight into the importance and effect of the transfer-related attributes on ridership. The statistical significance of the associated coefficients give evidence for the reliability of the results, while the magnitude of the parameter quantifies the effect in terms of a percentage increase or decrease in ridership, associated with the transfer-related variable.

Using ridership data from two urban bus networks, pertaining to the cities of Maastricht and Breda, the relationship between transfer possibilities and bus ridership is analysed. The first sub-question is answered by testing and comparing three methods to implement transfer-related variables in a ridership model. The second sub-question is then addressed by applying the optimal method on data pertaining to the different time periods *weekdays*, *evenings*, *Saturdays* and *Sundays*, and subsequently comparing the results. A response to the final sub-question is sought by comparing the two study areas Breda and Maastricht, to understand whether the effects are context-dependent.

Together, these three analyses enable the formulation of a conclusion to the main research question. The expected findings can be applied to practical situations and additionally contribute to scientific problems, which are explained in the following section.

1.5 Practical relevance and scientific contribution

Uncovering the precise relationship between bus-train transfer times and bus ridership holds practical relevance for the public transport operator, Arriva, which operates the bus networks in the studied areas and provided the necessary data. In addition, the proposed modelling approach, estimating ridership at the stop-line level using line-specific level-of-service attributes (like transfer time) offers a methodological contribution to previous research.

The operational value of this study lies in its ability to estimate changes in passenger volumes resulting from adjustments to bus departure and arrival times. In this way, the costs of redesigning bus networks to optimise transfer times can be weighed against the predicted changes in ridership, enabling an assessment of cost-effectiveness. Similarly, the impact of efficiency improvements that may lead to longer transfer times can also be evaluated within this framework. In short, the model outcomes provide a basis for assessing the potential of prioritising transfer time considerations into timetable design to attract more passengers.

This study additionally aims to address the scientific challenge associated with the issue of endogeneity in variables typically employed in direct ridership models. Previous studies found that ridership is largely explained by level-of-service variables such as frequency and stop amenities (like shelters and dynamic travel information) [Cervero et al., 2010; Kerkman et al., 2015]. However, this relationship is bidirectional; locations with high travel demand are often allocated better service, for example in the form of higher frequency. As a result, high ridership may not be the outcome of high service levels, but rather the reason such service levels were implemented in the first place. Transfer time, by contrast, is presumed to be less endogenous with respect to ridership as opposed to frequency, as it is more constrained by external timetables and less responsive to demand patterns. To reduce endogeneity, this study models each line individually assuming a base frequency, rather than aggregating passengers and frequencies over all lines at one stop.

1.6 Report outline

To fulfil the research objectives stated in this chapter, first the existing literature is studied to understand which findings, methodological approaches and knowledge gaps have previously been the topic of research. The next chapter will therefore discuss and review the key findings from previous literature and provide a theoretical outline for this study. After the literature study, the employed method will be described in detail, together with an extensive description of the first study area, Maastricht. Subsequently, the first two sub-questions are answered by providing modelling results. The last sub-question first requires a description of the second study area, Breda, after which a conclusion to this final question is formulated. To finish this report, the results are reflected upon, and recommendations are made for further research, to come to a final conclusion.

2 Literature and theory on bus ridership and transfers

This chapter reviews the key findings, challenges and methods from previous research to provide the theoretical foundation for achieving the research objective, which entails uncovering how bus-train transfer times influence bus ridership. This objective mentions two extensively studied domains, bus ridership and intermodal transfers.

Accordingly, the chapter starts by reviewing the studies that successfully predicted bus ridership using various methods and explanatory variables. Afterwards, an overview is provided of literature on intermodal transfers and their influence on travel behaviour.

These two research areas together provide the basis for a theoretical framework that introduces the main concepts, outlines the necessary assumptions, and describes how the key variables are expected to relate to each other. This theory provides the basis for the modelling approach presented in the following chapter.

2.1 Ridership modelling

Before drawing conclusions on specific influences on bus ridership, it is important to understand the concept of ridership more broadly. Ridership can be defined in multiple ways, such as boarding passengers per stop, per line, per vehicle, or per passenger type, and is influenced by a variety of factors. The main methods are described in the following paragraph, after which the most suitable approach for this study is discussed in greater detail.

Bus ridership is a topic that has widely been studied in the last decades, using various methods. While estimating demand on a bus line by traditional 4-step transport modelling has been done in the past [Brands et al., 2014], this approach requires detailed survey data of entire trip chains composing a journey. Other studies focus on the elasticity of ridership due to changes in service or route, like van Oort et al. [2015] or De Lanoy [2019]. However, these methods require studying specific cases where the level of service changed, which is not possible in all cases, especially when focusing on bus-train transfer times.

Others employ a simpler approach, directly modelling the number of passengers boarding and alighting at every bus stop [Chu, 2004; Ryan and Frank, 2009; Dill et al., 2013; Cervero et al., 2010; Kerkman et al., 2015]. These so-called direct ridership models use a statistical regression method to estimate the number of passengers at a stop directly using externally observable variables, such as population, land use and frequency, without modelling route choice, network assignment or full trip chains. This straightforward method appears viable for this study, because of the ease of implementing additional variables, such as transfer time. Therefore, understanding how these models have been implemented in previous research is of great importance to outline the theory to also incorporate transfer-related variables.

2.2 Direct ridership models

Direct ridership models have been widely applied across different transport systems and geographical contexts. Previous studies differ in the selected independent variables, the choice of regression techniques and the type of transport mode examined. Since this research focuses on urban bus networks in the Netherlands, only studies related to bus systems are reviewed. The following sections discuss modelling approaches and commonly used predictor variables to support the methodological choices made in the analysis.

2.2.1 Regression methods

Before examining the various determinants of bus ridership, it is useful to first review the commonly applied statistical models in literature. The earliest studies used a Poisson distribution to account for the count-based nature of ridership data [Chu, 2004]. However, Ryan and Frank [2009] and Dill et al. [2013] preferred treating ridership as a continuous variable in an ordinary least squares (OLS)-regression, due to its simplicity and interpretability, which then became the more popular method [Kerkman et al., 2015].

OLS models were later improved by log-transformation of the dependent variable, the number of passengers. Taylor et al. [2009] established a substantially higher model fit with such a transformation, causing log-transformations to be widely applied in later research. While OLS-regression seems reasonably effective, there are two key shortcomings that researchers have tried to address in previous studies.

The first issue is the endogeneity present in service-level variables. Transit operators generally improve service on corridors where there is high demand in the first place. A high level of service is therefore often the result of high ridership, which violates the OLS assumption of a one-way causal relationship from the independent variable to the dependent variable.

Endogeneity can be resolved by employing a different modelling technique, such as two-stage least squares (2SLS) regression, which introduces instrumental variables to correct for endogenous effects. Estupiñán and Rodríguez [2008] and Taylor et al. [2009] successfully employed this method in their research. However, Aston et al. [2021] did a comparison of 2SLS and OLS when studying transit networks in Amsterdam, Melbourne and Boston, and did not observe significant improvements, citing the difficulty in finding a consistently strong instrumental variable as the main reason.

Using 2SLS-regression is not expected to be exceptionally important for this study, because of the focus on intermodal transfers to indicate level-of-service. Presumably, optimised transfer times are less likely caused by high transport demand as opposed to higher frequencies. Considering the difficulties encountered with 2SLS modelling and the fact that transfer variables are presumed to be less endogenous, the simpler OLS approach remains the preferred option.

That said, OLS models are limited by the inability to account for spatial autocorrelation in the data. Spatial autocorrelation is the phenomenon that stops close in proximity to each other are more likely to exhibit similar characteristics. For regression models, the data is ideally uncorrelated, meaning that not accounting for spatial autocorrelation might not yield optimal results [Pulugurtha and Agurla, 2012; Kerkman et al., 2017]. Methods such as geographically weighted regression and spatial lag models saw a slight improvement in results [Marques and Pitombo, 2022; de Boer, 2021], but not significantly enough to prefer them over the straightforward OLS method. Additionally, the effect of transfer opportunities on bus ridership is assumed to be minimally affected by spatial autocorrelation.

While spatial proximity may not significantly influence the relationship between transfer opportunities and bus ridership, the fact that transfer time is defined at the line level rather than at the stop level introduces a different source of multicolinearity in the data. All stops on the same line segment share the same departure or arrival time at the train station, and as a consequence the transfer time as well. This correlation violates the OLS assumption of independence among observations. To address this hierarchical structure in the data, multilevel regression modelling is a potential solution, dividing the attributes in a stop-level and a line-level. Wang and Park [2024] used this approach to distinguish variables at these two levels, allowing for a more appropriate estimation of the effects.

In conclusion, while OLS appears to be an appropriate method in most cases, the inclusion of transfer-related variables introduces a nested data structure, warranting the use of a multi-level regression model. The multi-level method distinguishes the stop-level from line-level attributes (such as transfer time) to account for any correlation present between stops on the same line, thus yielding more accurate parameter and error estimates. For these reasons, this study employs a multi-level regression model, grouping the observations according to the bus line that they pertain to.

2.2.2 Determinants of ridership

The determinants of ridership are the independent variables influencing the number of passengers. These predictors can be categorised in three groups; socio-demographic, built environment and level-of-service. To begin, the various definitions of the catchment area of a bus stop need to be reviewed, since the first two variable categories are based on this area. Afterwards, the separate functions of each category are explained, to finally conclude with an overview of the key variables used in literature.

For both socio-demographic and built environment attributes, the catchment area is leading in collecting the necessary data, emphasising the importance to accurately establish first its size and then its shape. Some studies propose a 400 m (or 0.25 mile) circular buffer around the bus stop [Dill et al., 2013; Pulugurtha and Agurla, 2012; Kerkman et al., 2015], since 400 m is generally seen as the maximum distance most are willing to walk to access the bus. Pulugurtha and Agurla [2012] even concluded 400 m to be the most accurate size, after comparing multiple distances. Still, some studies have concluded that stops served by frequent and fast bus services tend to have larger catchment areas, as passengers are more willing to cycle to these stops [Ton et al., 2020; Brand et al., 2017]. However, Brand et al. [2017] also noted that this effect is primarily observed for bus rapid transit (BRT) services, a category that does not include the lines composing the urban networks examined in this study. Therefore, 400 m remains the most appropriate catchment radius for calculating the independent attributes in the context of this research.

An additional consideration is that street networks rarely allow for straight-line travel, meaning that the Euclidean distance often does not reflect the actual walking distance. This discrepancy arises because people must follow streets and pathways, which do not form perfect circles around bus stops. To more accurately model walking distances, catchment areas can instead be delineated by tracing realistic walking paths along the street network, as done by Ryan and Frank [2009] and Montero-Lamas et al. [2024]. While this approach provides a more realistic representation of walking accessibility, it is computationally more demanding and complex. Both methods did not produce substantially different results, but Montero-Lamas et al. [2024] suggest only using the more complex method when there are physical barriers present that significantly impact walking route lengths. In short, in most environments a circular buffer of 400 m around the bus stop adequately describes the catchment area to supply the necessary data for the socio-demographic and land use variables.

Socio-demographic statistics describe the residents living in the vicinity of a bus stop. Since some groups are more likely to travel by bus than others [KiM, 2023], knowing the characteristics of the population contributes to estimating the number of bus passengers.

The most important predictor is the population density or number of inhabitants [Cervero et al., 2010], which indicates a substantial share of the travel demand present at a bus stop. Some studies took into account different age groups [Dill et al., 2013], gender [Chu, 2004; Ryan and Frank, 2009] and ethnicity [Pulugurtha and Agurla, 2012; Ryan and Frank, 2009], but the effect was mostly small or insignificant. One variable that consistently showed a negative effect on ridership was income [Chu, 2004; Ryan and Frank, 2009; Pulugurtha and Agurla, 2012; Dill et al., 2013; Kerkman et al., 2015], since low-income households are less likely to own cars and are thus more often resorted to the bus. Nevertheless, car ownership in itself as a predictor produced varying results. While Chu [2004]; Ryan and Frank [2009]; Pulugurtha and Agurla [2012] found a negative effect, Dill et al. [2013] concluded a positive influence, whereas de Boer [2021] observed that car ownership was insignificant when using a spatial model.

Additional potential riders besides local inhabitants where defined by Kerkman et al. [2015], counting the local employers, students and train travellers as well. In their study, these groups were summed to calculate the predictor *potential travellers*. However, their individual impact on ridership was not studied, leaving a knowledge gap to be researched.

Understanding the *built environment* of a bus stop has also been proven to obtain insight in the number of boarding passengers, forming the second group of variables defined by the catchment area of the bus stop. Metrics include walkability [Chu, 2004; Ryan and Frank, 2009], spatial distance to the city centre [Dill et al., 2013; Kerkman et al., 2015] and accessible jobs [Chu, 2004; Dill et al., 2013]. Additionally, dividing the catchment area in land use percentages was also observed to be useful in explaining ridership [Pulugurtha and Agurla, 2012; Kerkman et al., 2015]. Residential and commercial land uses were found to attract more passengers than industrial zones [Pulugurtha and Agurla, 2012; Dill et al., 2013; Kerkman et al., 2015]. Understanding the physical features of the catchment area is thus an additional element in explaining patronage.

Factors describing the attractiveness of the *transit service* form the last category of variables explaining bus travel demand. Routes with a higher frequency attract more passengers [Cervero et al., 2010; Dill et al., 2013; Kerkman et al., 2015]. Likewise, transfer nodes in the system also seem to experience higher ridership [Kerkman et al., 2015]. Finally variables indicating stop amenities such as shelters, benches and dynamic travel information were associated with more popular bus stops [Kerkman et al., 2015; de Boer, 2021].

One predictor that has not yet been incorporated into direct ridership models is a variable that captures intermodal connectivity with the train, such as the transfer time between modes. This attribute is an important component of the level of service for multimodal travellers. Its absence in existing models contributes to the current knowledge gap regarding the influence of transfer quality on bus ridership.

All these findings are summarised in table 2.1.

Variable	Relationship	Reference
Socio-demographic		
No. of residents	+	[Chu, 2004; Dill et al., 2013]
% female	+	[Chu, 2004; Ryan and Frank, 2009]
% aged 65+	ns	[Dill et al., 2013; Kerkman et al., 2015]
% without car	+	[Chu, 2004; Ryan and Frank, 2009]
Income	-	[Chu, 2004; Kerkman et al., 2015; Ryan and Frank, 2009]
Built environment		
Population density	+	[Aston et al., 2021; Cervero et al., 2010]
Job density	+	[Chu, 2004; Dill et al., 2013; Guo and Huang, 2020]
Land use (LU) residential	+	[Kerkman et al., 2015]
LU commercial	+	[Dill et al., 2013; Pulugurtha and Agurla, 2012]
LU agricultural	-	[Kerkman et al., 2015]
LU sociocultural	+	[Kerkman et al., 2015]
LU institutional	+	[Pulugurtha and Agurla, 2012]
LU industrial	-	[Pulugurtha and Agurla, 2012]
Pedestrian amenities	+	[Estupiñán and Rodríguez, 2008]
LU mix	ns	[Dill et al., 2013]
Walkability	+	[Chu, 2004; Ryan and Frank, 2009]
Transit accessibility	+	[Chu, 2004]
Level of service		
Transfer stop	+	[Dill et al., 2013; Kerkman et al., 2015]
Transit centre	+	[Dill et al., 2013; Kerkman et al., 2015]
Terminal stop	ns	[Kerkman et al., 2015; Guo and Huang, 2020]
Frequency	+	[Kerkman et al., 2015]
Average headway	-	[Dill et al., 2013; Cervero et al., 2010]
No. of directions	+	[Kerkman et al., 2015]
No. of bus stops within buffer	-	[Dill et al., 2013]
No. of feeder trains	+	[Cervero et al., 2010]
Dynamic information	+	[Kerkman et al., 2015]
Benches	+	[Kerkman et al., 2015]

Table 2.1: An overview of the most important independent variables used in previous research

2.2.3 Conclusion on direct ridership models

While direct ridership models have shown to successfully explain bus ridership in multiple instances, some issues and knowledge gaps remain unaddressed. The first problem is the variation in variables and associated effects across study areas. Researches have concluded that these models are typically only locally applicable, requiring a different model to be estimated for each region [Kerkman et al., 2015]. de Boer [2021] stated that there are probably differences even between rural and urban areas for the same reason. These arguments support limiting the scope to urban areas and selecting variables based on an analysis conducted in a similar geographical region, for example the study by Kerkman et al. [2015].

The main research gap identified is the absence of variables that capture transfer quality in direct ridership models. While various stop-level and service-level attributes have been widely studied, the influence of intermodal transfer characteristics remains unexplored. The following section presents arguments supporting the expectation that these variables also affect bus ridership.

2.3 Intermodal transfers

The most important predictors and methods have been discussed, and the effectiveness of direct ridership models has been proven. One underlined knowledge gap was the potential of including bus-train transfer times as a ridership predictor. Its impact has been studied in several different research approaches and the consensus is that access and egress time (and the associated need to transfer) have a disproportional negative impact on the perceived travel utility of public transport trips [Krygsman et al., 2004].

Travel utility refers to the overall perceived value or burden of a trip, considering not only actual travel time but also how different components of the journey are experienced by passengers. A higher utility or lower disutility is associated with a higher probability that a specific travel mode is chosen.

In the case of accessing a train station by bus, the trip requires walking to the bus stop, waiting for the bus, travelling by bus, walking to the train station and finally waiting for the train. Bovy and Hoogendoorn-Lanser [2005] concluded that these different stages of a multimodal trips contribute differently to the travel resistance. Wait time was found to have an impact of a factor 2.2 higher than in-vehicle travel time. A similar transfer penalty has been established by numerous other studies as well [Wardman and Hine, 2000].

Transfer penalties can also be expressed as the additional perceived minutes of delay that passengers associate with a transfer, beyond the actual waiting time. Train-train transfers in the Netherlands have been studied by Arentze and Molin [2013] and De Keizer et al. [2012], who reported a penalty of 22 and 23 minutes respectively, meaning that trip containing one transfer needs to be at least 22 minutes quicker than a direct trip to be perceived as equally attractive.

Yap et al. [2024] investigated bus transfers to the metro in the greater London area, and estimated a penalty of over 10 minutes for bus-metro transfers, which is more than the 4 minutes reported for a metro-metro transfer. Bus-train transfers, which are the focus of this study, have only been researched by Schakenbos et al. [2016], who compared bus, tram and metro as access and egress modes for Dutch train travellers. In their study, the additional disutility was estimated between 5 and 9 minutes for transfer from train to bus, and between 6 and 7 minutes for bus to train, depending on the frequency of the connecting mode. Another finding of Schakenbos et al. [2016] was that the optimal transfer time is 8 minutes, and that both shorter and longer wait times in the 3-15 minutes range resulted in a lower probability that a passenger would choose the bus.

These negative effects of ridership on travel utility have been the motivation for multiple planning problems where bus schedules were optimised to minimise transfer times [Liu et al., 2021]. The studies mentioned in the review by Liu et al. [2021] are successful in finding ways to decrease transfer times within a bus network, but the consequent change in bus passengers remains unknown.

2.3.1 Conclusion on intermodal transfers

In summary, transfer time is an important contributor to travel impedance of a public transport trip. However, its effect is mainly studied in mode choice models to measure the attractiveness of the bus in comparison to other modes. As a result, the impact on the number of passengers *in the bus* remains unknown.

Other level-of-service variables similarly affect travel resistance, such as frequency and travel time [Brands et al., 2014]. Since higher utility increases the likeliness of the bus being chosen by travellers, increasing utility by providing more attractive services is expected to lead to a growth in bus ridership. This relationship has been established for the service level attribute *frequency*, which is clearly positively related with passenger numbers. Using the same reasoning, transfer time is expected to similarly affect ridership. Longer transfer times result in lower utility and therefore fewer passengers. Vice versa, shorter transfer times are hypothesised to be associated with more popular bus services.

2.4 Secondary factors outside the scope of this analysis

Some aspects may affect ridership or transfers, but are not suited to be included in the direct ridership model.

One such factor is punctuality, for which Lee et al. [2014] states that the distribution of arrival times of the vehicles is important in the attractiveness of the transfer. Specifically, high variance in arrival time decreases reliability and thus the transfer valuation. Reliability also directly impacts ridership, as has been observed in the study by Van Oort [2016], in which punctuality improvements such as splitting up lines were found to increase passenger numbers.

Including punctuality as a predictor is, however, not deemed viable, since realised arrival times fluctuate wildly and are sensitive to disruptions. These fluctuations contrast with other predictors such as population or service frequency, which are relatively stable and quantifiable. As a result, it lacks the consistency needed for a reliable explanatory variable in a model based on the fixed schedule and stop-level characteristics.

Secondly, it has been established that lower fares also attract more passengers [Kholodov et al., 2021]. However, no conclusions can be drawn on the effect of price on ridership within the studied area, since the price per km is the same on all bus lines. Although costs differ per trip, calculating the price is equivalent to measuring the distance, due to the kilometre-based pricing in the Netherlands. Consequently, any observed cost-related effects are likely correlated with a change in ridership due to increasing distance, preventing any reliable conclusions to be drawn.

For the aforementioned reasons, these two factors are not considered in the selection of variables for the model in this study.

2.5 Theoretical framework

The previous sections reviewed literature on both bus ridership and bus-train transfers. Combining the conclusions to frame a theoretical basis, first requires defining the most important concepts. Afterwards, the expected influence of transfer time on ridership is discussed. From these relationships, a set of modelling assumptions is drawn, which inform the methodological choices for the analysis in the following chapters.

2.5.1 Definitions

Three concepts are central to this study, and require a precise definition. The research question refers explicitly to both *ridership* and *transfer time*, which are therefore defined first. The relationship between these two concepts is analysed using a *direct ridership model*, which is subsequently explained.

Ridership per stop in this study refers to the number of passengers travelling between a given bus stop and the central station. Since the focus is on evaluating the potential in attracting passengers using the bus as an access or egress mode to the train, only station-related trips are included, since transfers can only be made at the train station. For first-mile trips, the ridership is defined as the number of passengers boarding at a stop and travelling to the station. Conversely, for last-mile trips, ridership refers to the number of passengers alighting at that stop, coming from the station.

These passengers have the opportunity to transfer to a train at the central station, where they are subject to a transfer time, that depends on the specific train service they connect to. The transfer time is defined in two ways. For accessing transfers from the bus to the train, the transfer time is defined as the difference between the scheduled arrival time of the bus and departure time of the train. For egressing transfers from the train to the bus, the transfer time refers to the difference between arrival time of the train and departure time of the bus.

The relationship between these two concepts is uncovered using a direct ridership model. This model estimates the number of bus passengers travelling to or from the station from a given stop, using a specific line service. This estimation is based on a set of stop-level and line-level attributes (like transfer time), to uncover the specific effects pertaining to these variables.

2.5.2 Theory on bus ridership and bus-train transfers

From the reviewed literature, a number of theoretical principles have emerged, which form the basis of the approach taken in this study. First, it is established that bus ridership at the stop level can be meaningfully explained using level-of-service variables. Second, transfer time is recognised as an important aspect of service level, with a demonstrated influence on travel behaviour. Finally, this established influence provides a reasoning for exploring multiple ways to incorporate transfer time as a level-of-service variable in the model.

Bus ridership is influenced by a range of factors, many of which are related to either the catchment area of a bus stop or the level of service. The level of service can be quantified using, for example, the frequency of buses serving a stop, the average headway or the operational speed. From a multimodal perspective, transfer time is a metric to quantify service quality as well, where shorter waiting times are generally more attractive.

For this reason, shorter transfer times are generally associated with higher travel utility. Travel utility refers to the perceived benefit or attractiveness of a transport option. According to Schakenbos et al. [2016], acceptable bus–train transfer times typically fall within a 3 to 15-minute window, with 8 minutes being optimal. Travel utility decreases as the transfer time approaches either end of this range, indicating a non-linear relationship. This non-linearity is a challenge when incorporating transfer time into a direct ridership model, which typically assumes linear effects of predictors.

Another challenge is the dispersion of passengers over the different trains at the train station. These two difficulties show that transfer time is not a fixed attribute and that it can be represented in multiple ways, such as an average transfer time or as a binary indicator of whether an attractive connection is offered. These alternative formulations reflect different assumptions about how passengers experience and respond to transfer quality, and are explored further in the methodology chapter.

Combining these theories, it is hypothesised that longer transfer times lead to lower passenger numbers.

2.5.3 Conceptual model

The theory concludes that multiple factors influence ridership, among which transfer time is presumed to have a negative effect. The most important variables that were encountered in previous literature are visually represented in a conceptual model, which is shown in figure 2.1.

2.5.4 Assumptions

Developing a model to account for ridership at the stop-line level involves some initial assumptions. A key premise is that bus schedules are coordinated with the train timetable: both operate at a frequency of two trips per hour with fixed departure and arrival patterns relative to the half-hour. In addition, all vehicles are assumed to operate on time. The analysis is limited to trips to and from the central station, under the reasoning that transfer time only affects these passengers.

For the definition of transfer-related attributes, three additional assumptions are made. First, it is considered that bus passengers are distributed across train services in a manner similar to the general train passenger population, when calculating the average transfer time. Second, given the non-linear relationship between transfer time and perceived travel utility, it is expected that transfers are most *attractive* within a specific time window. The transport planners at Arriva, who designed the current network and timetable in Maastricht and Breda, state that they aim to plan transfers within the interval of 5 to 12 minutes, which is therefore defined to be the attractive transfer time window. Lastly, as the

Figure 2.1: Conceptual model, green showing a positive relationship, red negative. Grey indicates that the findings summarised in table 2.1 are inconsistent in literature findings

effect of transfer quality is expected to vary by time period and location, separate models need to be estimated for each study area to reflect these differences.

2.5.5 Methodological choices

Based on these assumptions and the conclusions from the literature review, three key methodological choices are made. The first choice involves defining the dependent variable as the (log-transformed) number of passengers travelling to or from the station at a given stop using a specific line. This formulation enables the comparison of bus lines serving the same stop, differing from the regular method aggregating boardings over all lines at one stop.

Collecting separate entries at the same stop but with a different line, introduces correlation over the stops served by the same level. For this reason, a multi-level regression model is employed, distinguishing between stop-level and line-level variables.

Third, the selection of variables for both levels is primarily based on the model proposed by Kerkman et al. [2015]. Given the geographic specificity of ridership modelling, their study is considered an appropriate reference due to its comparable study area. Moreover, their model demonstrated strong performance using a limited number of variables, of which most are readily obtainable.

2.6 Conclusion

The literature review informed how bus ridership can be modelled and how transfer times affect travel behaviour. Direct ridership models have proven to be an effective tool to estimate passenger volumes at the stop level using observable characteristics, and the reviewed studies helped identify the most relevant socio-demographic, built environment, and service-level variables. However, one notable gap in the existing literature is the absence of intermodal transfer quality as a variable in these models.

While transfer time is often studied in the context of travel behaviour and mode choice, its direct impact on bus ridership levels has not been thoroughly explored. Several studies cite the disproportionate penalty that passengers associate with transferring between modes, leading to the hypothesis that longer transfer times may negatively affect bus ridership. Yet, the non-linear nature of transfer time effects and the hierarchical structure of the data pose methodological challenges that require specific modelling choices.

To address the research gap, a modelling approach is outlined in the next chapter. It integrates transfer time as a level-of-service variable within a multi-level direct ridership model. This approach allows for obtaining a clearer understanding of how train transfers influence bus ridership and provides practical insights for schedule improvements.

3 Methodology

This chapter describes the specific steps that were taken to carry out this research. These steps include the selection of the study areas, data collection, variable calculation and the estimation of the regression model. Together these procedures are designed to enable the analysis aimed at uncovering the relationship between bus-train transfer times and bus ridership. The details of the research design are presented in the following section. Second the model is explained, after which the selected attributes are discussed. Finally, the data sources consulted to obtain the attribute values are listed.

3.1 Research design

Central to this study is the analysis of the number of passengers using a specific bus line at a particular bus stop. This study applies a quantitative approach using cross-sectional data, with the objective to identify statistical relationships between ridership at the line-per-stop level and transfer-related attributes, alongside other explanatory variables. As opposed to studying changes over time, the average ridership within a predefined time period is compared between stop-line combinations. By assessing the respective differences in transfer possibilities and correcting for other known factors in attracting passengers, relationships can be observed between transfer time and ridership.

To answer the sub-questions, multiple estimations are done using different attributes, and over varying time windows. In addition, a second study area is explored and compared with the original results. These three analyses provide insight in the generalisability of the model, and the context-dependence of the results.

Finally, the ridership change for two planned route alterations is estimated, to test the model and to provide as example for the practical applicability.

3.2 Model development

The analysis is done using a direct ridership model. Direct ridership models are efficient tools to explain bus ridership, since they require less data than traditional 4-step transport models, which are reliant on precise travel survey data to produce trip distributions and consequently predict passenger flows. In addition, direct ridership models show better interpretability as they are also able to capture the influence of transit level-of-service and the built environment, for which the 4-step model lacks the explanatory power. Lastly, direct ridership models can also give insight into travel demand in locations where there is no transit yet, since the production of new results is not dependent on past travel behaviour. These arguments support the potential of uncovering the effect of transfer times on ridership using a direct model.

First the observations that together make up the input for the model are clarified. Afterwards, the regression model is explained. Finally, the adaptations to answer the separate sub-questions are described.

3.2.1 Observations

Capturing the influence of bus-train transfers requires a slightly different approach to traditional direct ridership modelling, since transfer possibilities are a route attribute and not a stop characteristic. Usually, there is one observation per stop, counting the number of passengers using the stop (in a day, week, etc.). Instead, the approach in this report records a separate data point for every single bus line that serves the stop. For instance, when two bus lines serve the same stop but follow different routes to the train station, they result in distinct travel and transfer times. Therefore, they are represented as separate observations in the model to account for these differences. Nevertheless, transfer times do not only vary between bus lines, but optionally also across trips pertaining to the same line.

This phenomenon is observed for lines with a frequency different from two per hour. Since train services in the Netherlands follow a standard pattern that repeats itself every 30 minutes, bus services with a 30 minute headway have a constant transfer time to the same trains (not accounting for delays). When the bus frequency increases, the transfer time is not equally distributed over all buses. For example, when the frequency is 4 times per hour, one pair of buses shows different transfer possibilities from the other pair. To capture this phenomenon, bus services with a 15-minute headway are included as two separate lines with the same routes, but with different transfer times, resulting in each observation representing a bus serving a stop 2 times per hour. In this research, all bus lines had a frequency of either 2 or 4 times per hour. By accounting for all variations in arrival and departure times at the station for every bus trip and tying them to the half-hour pattern of the railways, the effect of transfer possibilities on ridership is optimally observed.

In addition to splitting up the trips of high-frequency bus lines, the dependent variable undergoes a mathematical logarithmic transformation. The same transformation is applied to the variables *inhabitants*, *students* and *frequency*, because of their skewed distribution. Log-transforming these variables enhances the numeral stability and results in a normal distribution of the residuals.

3.2.2 Multi-level regression

The previously described individual observations are collectively used to estimate the coefficients of the multi-level regression model. This approach accounts for the hierarchical structure in the data, since some variables are determined by the stop, while others by the bus line. Since observations of different stops on the same line may share unobserved characteristics, such as the headway with other bus lines, route directness or underlying travel patterns, a conventional linear model would likely underestimate standard errors.

A multi-level model addresses this issue by introducing random effects at the line segment level, thereby separating within-line and between-line variation. More specifically, every line segment is associated with its own random intercept, which represents the base ridership for that line. All independent variables are assumed to be fixed effects, for which the coefficients are equal across line segments.

The regression equation can be written as:

$$Y_{ij} = \beta_0 + \beta_1 X_{1ij} + \beta_2 X_{2ij} + ... + \beta_k X_{kij} + u_{0j} \ + \epsilon_{ij} \tag{3.1}$$

In which:

- Y_{ij} is the observed ridership for stop i using line j.
- $\{X_1, X_2, ..., X_k\}$ denote the set of independent variables.
- X_{1ij} is the observed value for variable 1 of stop i and line j.
- $\{\beta_1, \beta_2, ..., \beta_k\}$ are the coefficients representing the change in ridership when one independent variable is changed and the others are kept constant.
- u_{0j} is the random intercept, which is a constant representing ridership not explained by the independent variables. This constant is assumed to randomly vary across bus lines.
- ϵ_{ij} is the error term, which is the difference between the observed value and the predicted value for observation at stop i, line j.

Estimating the β coefficients involves finding the values that minimise the sum of squared residuals in the error term ϵ_{ij}, thereby providing the best linear approximation of the relationship between the predictors and the dependent variable. Using the standard errors, a t-test can be conducted to conclude whether a parameter is significant.

Subsequently, the magnitude and significance of these coefficients provide insight in the effects associated with the individual independent variables. Additionally, the model fit can be assessed using the conditional and marginal R^2. The conditional R^2 calculates the ratio between the variation explained by the fixed effects only and the total variance. The marginal R^2 additionally includes the variance explained by the random intercepts.

While the regression model is the base to collecting the results to achieve the research objective, the sub-questions require some adaptations which are discussed in the following sections. The first sub-question explores the different approaches to include transfer-related variables, which is therefore discussed first.

3.2.3 Transfer to the train

To answer the sub-question *How can transfer times accurately be defined, calculated and implemented as a predictor in direct ridership models?*, three options are explored. The first method calculates a weighted average transfer time to the arrival or departure time of the bus. The second way determines the transfer time in minutes to a single selected train. The final option defines an 'attractive' transfer time window, considering a connection adequate if the transfer time to a single selected train service falls within this interval. In summary, these three approaches provide different ways to implement transfer times as a predictor in the ridership model.

The first method calculates the average transfer time per bus line, weighted according to the distribution of train passengers. More specifically, every train service is characterised by a percentage of train travellers and a corresponding departure time. For any given scheduled bus arrival time, the transfer time is calculated as the difference between the *arrival* of the bus and the *departure* of the train. All transfer times shorter than 5 minutes are increased by 30 minutes, the time to wait for the next train, since 5 minutes is the assumed minimum time needed to walk between platforms.

Collecting these layover times across all trains produces a list of transfer times. An average transfer time is then computed, weighted by the distribution of train passengers across the different train services. The scheduled bus arrival time and associated average transfer time differ per line, and are thus line-related attributes. Correspondingly, all stops served by the same bus line are assigned this transfer time in the data. The calculation is similar in the opposite case of arriving trains and departing buses, swapping the departure time with the arrival time of the train and vice versa for the bus.

Equation 3.2 shows how the average transfer time is calculated:

$$tt_{average,i} = w_{train1} tt_{train1,i} + w_{train2} tt_{train2,i} + w_{train3} tt_{train3,i} + ... \tag{3.2}$$

In which:

- $tt_{average,line1}$ is the average weighted transfer time for stops served by bus line i.
- w_{train1} is the share of all train travellers which use train service 1.
- $tt_{train1,i}$ is the transfer time between train 1 and bus line i.

The second approach avoids calculating an average and consequently the need to determine the distribution of train passengers. Instead, one or two trains are selected with a presumed high transport demand. Only the transfer times to these trains are included as a variable.

The last technique uses the same selection of trains, but instead qualifies a transfer as feasible or not. Based on design objectives of Arriva, the ideal transfer time between bus and train is between 5-12 minutes. This interval is similar to the acceptable transfer times found by Schakenbos et al. [2016], which were between 3-15 minutes. By including a dummy variable indicating whether the transfer time falls within the ideal window as defined by Arriva, the effect of the transfer opportunity can be uncovered.

These three methods are finally compared by assessing them on their accuracy and ease of implementation. The second sub-question requires comparing results from different time periods. The reason for this comparison is described in the following section.

3.2.4 Temporal patterns

During the week there is variation in transfer times due to the fact that timetables are not constant throughout the week. Because of varying running times in the off-peak hours, evenings and on weekends, the schedules are adapted accordingly. Similarly, frequencies vary throughout the week because of changes in travel demand. These dynamic schedules result in distinct transfer times and different travel behaviour in general. Accordingly, separate models are estimated for four different temporal regimes of the week. The categorization is done by checking in which time window the arrival time at the train station falls for each bus trip. In table 3.1 the specific time windows were shown that correspond to the temporal patterns.

Pattern	Day	Time window
Weekdays	Monday-Friday	7:00 - 19:00
Evenings	Monday-Sunday	19:00 - 00:00
Saturdays	Saturday	9:00 - 17:00
Sundays	Sunday	11:00 - 17:00

Table 3.1: The different temporal patterns that are treated separately in the model

3.2.5 Regional comparison

The final sub-question explores the geographic differences between networks. Since both train and bus timetables vary across locations, the transfer effect might not be equal everywhere. The second study region of Breda is studied, where a model is estimated on weekday daytime data using the same variables. The selection of lines to be included is done in such a way to most closely correspond to the Maastricht data. A more detail description of the differences is included in chapter 7.

3.3 Study areas

In this study, a selection of urban bus networks is made on each of which a separate model is estimated, using the same set of independent variables. Kerkman et al. [2015] and de Boer [2021] theorised that better results can be obtained by treating urban and regional bus routes separately. This recommendation was made due to the different user groups and corresponding travel behaviour between urban and regional transit. Of these, the choice was made to focus on within-city transit, the main motivation being the lagging recovery in passenger numbers after the COVID-19 pandemic on urban routes.

The supplier of the data, Arriva, operates urban bus networks across the Netherlands, each exhibiting varying characteristics in the context of bus-train transfers. Some transit systems contain a substantial number of routes and stops, with high-frequency corridors, while in smaller towns, the network typically consists of few short lines. In the same vein, cities located at a node in the rail network are served by multiple trains in different directions, as opposed to more excentric railway stations which might only be frequented by one intercity train per half hour. Given that these transit system traits result in varying travel patterns, multiple networks with differing characteristics are examined to capture this variation.

Another factor in network selection is data availability. One constraint in the study of bus-train transfers is the limited data on train travellers. Generally, NS (Dutch Railways) do not share detailed passenger numbers of their trains. However, Arriva operates local train services in Limburg, Gelderland, Overijssel, Friesland and Groningen, in addition to their bus operations. As a result, the sparse NS data can be supplemented by Arriva train data in these regions, leading to more reliable results.

Maastricht is one such city where Arriva runs two regional trains and one local express service, alongside the NS, which operates one intercity train every 30 minutes. The urban bus routes comprise a dense network providing a frequent connection from most parts of the city to the centre and central station. The combination of frequent bus services and less frequent train services allows for an assessment of whether buses with better connections to the trains attract more passengers than those with poorer connections. Due to the extensive urban transit system, modest train service, and data availability on regional trains, Maastricht is the first network for which passenger demand is estimated using a regression model. Further details on the local transit system and the results are presented in chapter 4.

The second study area is the urban network of Breda. This city has a similar size to Maastricht, but is served by an entirely different selection of trains. Located close to other sizeable cities such as Rotterdam and Tilburg, there are multiple important directions in which passengers travel. That said, the service is not extremely frequent, as most directions are still served only once per half hour. The comparison of two similar cities, which differ in train timetable characteristics, is predicted to give valuable insight into which networks are more sensitive to transfer optimisation.

3.4 Attribute selection

Before describing how the data was collected for the variables, it is important to clarify the selection of predictors. The starting point is the selection made by Kerkman et al. [2015], due to the relatively similar study area. However, for reasons of simplicity and practicality, not all of these variables are included in the final model of this study. This section first outlines the predictors that were excluded, followed by an overview of the variables that were retained.

Some variables were found to exhibit excessively high correlations. The most consistently used predictor in direct ridership models, the number of residents, was found to correlate with numerous other variables, which were therefore omitted. For instance, residential land use had a strong positive correlation, while industrial land use was discarded because of the negative correlation. In addition, the number of competing bus stops tended to be higher in densely populated areas, making it difficult to isolate and estimate its individual effect.

Other attributes were deemed too endogenous to be used in this model, mainly those describing the presence of stop amenities such as a shelter, a bench or dynamic information. These facilities are only likely to be placed at stops which attract a high number of passengers already, and are not assumed to substantially increase the number of riders by themselves.

Data availability was the last reason to exclude variables from the model. Job availability data was only found on the district level, which is not granular enough for the catchment areas of the bus stops, being substantially smaller than a district. Retail space is also presumed to have an effect on ridership, but there are no public sources providing such metrics. Data on the number of business location was found, but since not every business attracts the same number of bus passengers, this metric was not deemed useful. A different proposed approach is to measure the percentage of commercial land use. However, due to the high stop density, these locations where captured by multiple catchment areas, while the higher demand is expected to be present only at the stop closest to retail locations, further complicating the linking of commercial activity to bus stops.

Instead, two binary variables are proposed. The first one categorises the stops in the city centre, while the second one is assigned to local neighbourhood shopping centres.

In addition to these two binary variables, a third dummy variable is introduced that categorises the central station bus stops. The central station is the main node in the bus transport network, enabling bus-bus and bus-train transfers, thus calling for a special treatment in the model.

Variable	Description	Measurement	Data source
Dependent variable			
Bus stop ridership per line (logarithm)	Average number boarding or alighting passengers on a bus line at a bus stop during the time window	Check-ins and check-outs with the smart card system	Arriva
Transit demand			
Number of inhabitants (logarithm)	Sum of inhabitants living within the catchment area of the bus stop	Calculated using 400m buffer	CBS [2024]
Number of students (logarithm)	Number of students following a program at an educational facility served by the bus stop	Direct assignment to bus stop	DUO [2024]
% population aged 65+	% of inhabitants living in the catchment area that are older than 65	Calculate using 400m buffer	CBS [2024]
Central station (0/1)	The bus stop is the central station	Dummy variable	-
City centre (0/1)	The bus stop is a central point in the city centre and frequented by many bus routes	Dummy variable	-
Shopping centre (0/1)	The bus stop is located at a neighbourhood shopping centre	Dummy variable	-
Average income (x €1000)	The average income per person of the respective neighbourhood	Coupling of the bus stop to the neighbourhood	CBS [2021]
LU: socio-cultural facilities	% of the catchment area with socio-cultural facilities	Division of the 400m buffer	CBS [2020]
Transit supply			
Frequency (logarithm)	Total number of trips of all lines that serve the bus stop in the time window according to the timetable	Summation of trips in temporal regime	Arriva
Travel time to central station	Running time between the stop to or from the central station using the specific bus line according to the timetable	Time difference between arrival/departure time at the train station and at the specific stop	Arriva
*Transfer time (weighted average)	Average transfer time for a train traveller in the bus	Transfer time average weighted using train distribution data	Arriva, NS
*Transfer time (per train)	The transfer time of the line with one specific train service	Time difference between arrival and departure of bus and train	Arriva
*Transfer time possibilities (0/1)	The bus has an attractive connection to a specific train	The transfer time falls within the 5-12 minute window	Arriva

Table 3.2: The predictors for the direct ridership model
**only one of these variables is used at the same time*

The three dummy variables fall into the class of estimators describing transport demand at the bus stop. Other demand attributes included in the model are the number of inhabitants, number of students, proportion of elderly residents, income and finally the percentage of socio-cultural land use. Socio-cultural land use is the only land use variable retained, since it describes important locations such as hospitals and theatres, and is not correlated to other variables, as opposed to the other land use categories.

The second class of independent variables contain the level-of-service characteristics. The main indicator for a high service-level is frequency. Contrary to usual direct ridership models, the observations in this dataset each constitute one bus line serving a stop with a base frequency of two per hour. The frequency in this model thus counts how many *other* buses pass through the bus stop. The expectation is that with a higher frequency, passengers may spread themselves more across the different buses, for which this variable corrects.

The second variable is the travel time to the central station. The travel time is an indicator for the access or egress time, besides the transfer time. If the central station is far away, passengers may be less likely to travel by train altogether. Contrarily, stops in close vicinity may see less use as well, since walking or cycling to the station might be quicker. In conclusion, the travel time is an important factor in the attractiveness of the bus, and its inclusion as a predictor seems useful.

The final level-of-service variables attempt to capture the influence of transfer possibilities to the train, and its exact selection and implementation is included as a sub-research question. Consequently, the different options and corresponding metric collection methods require a more detailed description. Exploring these methods, however, first requires an understanding of the data provided and collected for the model input. For this reason, the following section first explains in detail the different data sources, and afterwards the implementation of transfer variables is discussed.

An overview of the included variables discussed in this section is presented in table 3.2.

3.5 Data collection

Based on the selected variables, data is collected from several relevant sources. These sources primarily include Arriva smart card data and CBS (Statistics Netherlands) statistics. First the variables calculated using Arriva data are described, before moving on to other data sources.

3.5.1 Ridership data

Arriva data is used for the dependent variable, *ridership per stop per line*, and for the predictors *frequency*, *travel time to central station* and transfer-related attributes. First the dependent variable is discussed, then the explanatory variables.

The explained variable, *ridership per stop per line*, is calculated using two data sources provided by the transport operator, Arriva, one for each study area. The number of registered check-ins and check-outs of the OV-Chipkaart smart card system was collected at every event of a bus passing a stop. These tap-ins and tap-outs are interpreted as boarding and alighting passengers respectively. An example of a row in the data set is shown in table 3.3.

As can be seen, both the total number of passengers boarding and alighting is shown, as well as the subset of these passengers travelling to or from the train station. The latter subset is ultimately used as input for the model, since only these passengers are assumed to be affected by differing transfer times.

Date	Line nr.	Trip nr.	Stop code	Arr.	Dept.	In	Out	From station	To station
7-1-2024	4	7042	66590120	17:59	17:59	0	4	0	2

Table 3.3: An example of a row in the dataset

Filtering is done to obtain the desired input for the model. The dataset contains only stops within the municipal borders of Maastricht and Breda respectively. In addition, days on which the so-called vacation timetable is operated, are excluded. All trip numbers are subsequently categorised according to the temporal periods listed in table 3.1, by referencing the arrival time of the bus at the train station. These time windows are chosen to minimise the variation of the timetable within one period.

For each temporal regime, the average total daily number of passengers travelling to or from the station (the last two columns in table 3.3) is calculated over the specific time window of table 3.1. The data is collected over the periods of January-February 2024 for Maastricht, and April 2025 for Breda. The argumentation for the selection of these different periods is provided in the respective case study chapters 4 and 7.

It is important to note that a single stop can only register passengers travelling either *to* or *from* the station, since a stop is located either on the line segment before, headed towards the station, or after, coming from the station. As a result a physical bus stop with two platforms, one for each direction (or one on each side of the road), will appear in the dataset as two distinct entries: one for passengers heading towards the station, and one for passengers coming from it. This distinction is clarified by table 3.4, which shows which group of passengers is counted.

The previous paragraphs described how the dependent variable is measured, but some independent variables were collected from the same dataset as well. *Frequency* is calculated by counting the total number of trips serving a stop within one of the time windows of table 3.1 for one day. One exception is the central station, for which every platform at the local bus station has a separate stop code, for which

Trip or line segment direction	Stop	Counted passengers
To train station	Central station	Alighting passengers
To train station	All other stops	Boarding passengers
From train station	Central station	Boarding passengers
From train station	All other stops	Alighting passengers

Table 3.4: The calculation of the dependent variable at each stop, for each line

a separate frequency would be calculated. Instead, the frequencies are aggregated over all platforms to calculate the total number of buses serving the train station.

The remaining predictors from the Arriva data set are all calculated using a so-called *reference time*. The reference time is defined differently depending on whether a stop is located on a line segment before or after the train station. For stops before, the reference time refers to the *arrival time* at the train station, while for stops served after the train station, the reference time is equal to the *departure time* from the train station.

The attribute *travel time to central station* is derived as follows: For stops before the train station, it is the difference between the departure time from the stop and the reference time. Conversely, for stops after the station, the difference between the arrival time at the stop and the reference time is calculated. The travel time is calculated for every stop and for every trip number. Finally, an average travel time is calculated over all trips within one time window.

All transfer-related variables are also calculated using the reference time, but since they are the main focus of this study, they were discussed in the separate section 3.2.3, which describes the comparison between these variables as well.

3.5.2 Socio-demographic and land use data

Besides data supplied by Arriva, other public sources are consulted to calculate the remaining attributes. One such source is CBS, the central statistics bureau of the Dutch government. They collect a wide array of demographic, socio-economic and geographic data. For this research, data is taken from three CBS sources, shown in table 3.5. For each data set, the most recent available edition is taken.

Dataset	Description	Variables	Reference
Postcode-5	Metrics per area delimited by the first 5 symbols of the postal code	Inhabitants, % elderly	CBS [2024]
Kerncijfers wijken en buurten	Metrics per district	Income	CBS [2021]
Bodemgebruik	Divides the area based on the land use	Land use variables	CBS [2020]

Table 3.5: The employed CBS data sources

For all stops in the Arriva dataset, a 400 m circular buffer is created and the metrics from the CBS data are calculated to reflect the values for that specific stop. 400 m emerged as the most accurate radius for the catchment area from the literature reviewed in the previous chapter.

The first data set, the postcode-5 data, segments the area based on the first five symbols of the postal code. The more granular postcode-6, which delimits the area using all six symbols of the postal code, omits a substantial proportion of the data for privacy reasons, which is why the more coarse postcode-5 is preferred. To calculate the variables *inhabitants* and *percentage of elderly residents*, the values of all postcode areas falling within one catchment area are aggregated. In cases where a postcode area only partially overlaps with the buffer zone, its values are proportionally weighted based using the percentage of overlapping area.

An example is shown in figure 3.1, where a bus stop is shown on a map. In addition, the underlying division in postal codes is shown, together with the 400 m radius catchment area.

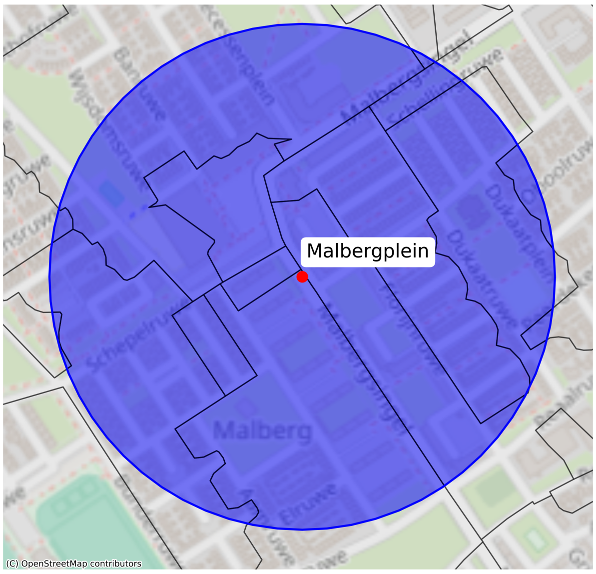


Figure 3.1: A map showing the division in postal codes, a bus stop and its catchment area

The second CBS source provides metrics at the neighbourhood level. For the *income* attribute, the average yearly income per inhabitant of a neighbourhood is directly assigned to all stops within one neighbourhood. Some neighbourhoods have no income data, since they have no inhabitants (mainly industrial zones). To prevent stops in these areas from negatively skewing the results, they are assigned the average income of the entire city of Maastricht and Breda, respectively.

The final data set divides the area in separate land use categories, of which only *socio-cultural land use* is used as a predictor. To calculate this variable, the areal percentage of the catchment area that falls under this category is determined.

3.5.3 Student data

For the *students* variable, data from DUO is used, which is the education agency of the Dutch government. They publish the amount of students enrolled in each program. In this research, the number of students is counted at educational facilities pertaining to an MBO school, HBO school or university, for which it is known that many students arrive by bus, according to Arriva. The assumption is made that students make use of the closest stop to the entrance of the building. The number of students is thus directly assigned to this closest stop and consequently included as an independent variable estimating the transport demand from the students. An overview of all identified schools and corresponding student numbers is included in appendix C.

3.5.4 Train data

The NS is the the national train operator of the Netherlands. On their website, they share some metrics concerning the daily number of passengers per station and the percentage of mode usage for access and egress transport [NS, 2024]. Only the number of passengers at Maastricht station is used, mainly to calculate the average transfer time, which will be further explained in section 3.2.3.

3.5.5 Binary variables

To account for the lack of data on commercial activity, two binary variables are introduced. For the shopping centres, the classification is based on physical observations of the location. An overview of all shopping centre stops can be found in appendix A. For the city centre stops, only the locations that serve as the main stops serving the city centre are classified as such, a list is included in appendix B.

The final dummy variable is the *central station*, which is assigned to all platforms of the bus stations located next to the central train stations.

3.6 Summary

In summary, this study applies a quantitative, cross-sectional design to estimate how bus-train transfer times affect bus stop-level ridership using a direct ridership model. Two urban networks, Maastricht and Breda, were selected based on data availability and variation in train services. Data from multiple sources, most importantly Arriva (for smart card data and timetables) and CBS (for demographic and land use data), were used to construct a dataset of observations at the stop-line level. Predictors include variables reflecting both transit demand (population, income, and land use) and supply (frequency, travel time, and transfer attributes). A multi-level linear regression model is developed to account for hierarchical data structure, allowing random intercepts per line. To address the fist sub-question, three different approaches were tested to model transfer times. Additional analyses were conducted across different time periods and across the two selected cities to assess temporal and regional variation in the transfer effect.

4 Case Study Maastricht

This chapter will discuss the characteristics and collected data of the first study area, Maastricht. To study the effect of bus-train transfers on bus ridership, insight is required in both train and bus services, and their interaction. Subsequently, a description and summary is provided of the data. In addition, patterns in the data are presented that indicate a possible interaction between transfer possibilities and passenger numbers. The model results are then presented in chapter 5. However, prior to describing the network and presenting the results, a brief description of the study area is provided to give context to the analysis.

Maastricht is the capital of the southern province Limburg of the Netherlands, located on both sides of the river *Maas* and counted 125 285 inhabitants in 2024 [Gemeente Maastricht, 2024]. Approximately 20 000 bus trips are made on an average weekday on the local Arriva bus network. The buses provide transfer possibilities at the main train station, located in the city centre and counting around 15 000 daily boarding and alighting passengers on both NS and Arriva trains [NS, 2024]. Maastricht has a wide retail offering, a university and many job opportunities, and is thus visited by many shoppers, students and workers every day [Gemeente Maastricht, 2024]. An attractive transport mode for these visitors is the train, for which the service will be extensively described in the following section.

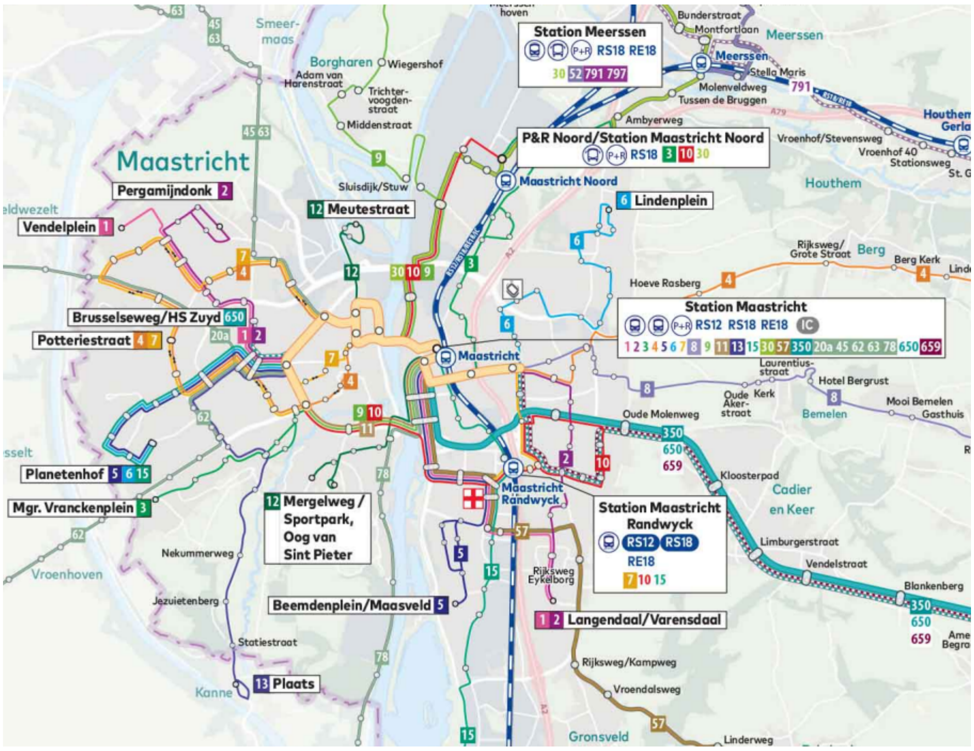


Figure 4.1: A map showing Maastricht and all its bus lines and train tracks [Arriva, 2025]

4.1 Train

Bus passengers have the option to transfer at the main Maastricht station to make a multimodal journey. At Maastricht station, trains depart in three directions, Sittard (and further north), Heerlen (and further east) and Liège (and further south). There is one intercity service every half hour connecting the city with the rest of the country, and the other directions are at least served by a regional train. An overview of the trains departing every hour and the number of average weekday passengers is included in table 4.1.

Train	Passengers	Share	Important destinations
Intercity to Alkmaar/Enkhuizen	10719	64.5 %	Eindhoven, Utrecht, Amsterdam
RS12 to Roermond	2027	13.6 %	Sittard, Roermond
RS18 to Kerkrade Centrum	2112	13.6 %	Valkenburg, Heerlen
RE18 to Aachen	742	6.9 %	Heerlen, Aachen (express service)
RS12 to Maastricht Randwyck	126	0.7 %	Randwyck (university, hospital)
RS18 to Maastricht Randwyck	65	0.6 %	Randwyck (university, hospital)
S43 to Liège	Unknown	Unknown	Liège

Table 4.1: The trains serving Maastricht station and the total boarding + alighting passengers on an average weekday

As shown in table 4.1, most train ridership is covered by three of the seven services. Most importantly, the intercity transports almost two thirds of train passengers at Maastricht station. The RS12 and RS18 trains headed north also account for a substantial share of riders. Notably, they arrive and depart approximately at the same time, resulting in a regional train node.

Despite the insight in passenger distributions of both NS and Arriva trains, exact figures are unavailable for the S43 international Belgian train to Liège. However, since its frequency is only once per hour, and domestic trips are assumed to be much more prevalent than international journeys, the absence of data on this train is not expected to substantially affect the results. In summary, over 90 % of train travellers are distributed over three train services, of which the intercity transports the majority, and the other two (regional) trains depart and arrive simultaneously. These train users represent a potential pool of bus passengers through transfers at the train station.

4.2 Bus-train transfers

This section explains how buses can hypothetically enable transfers to the existing supply of train services at Maastricht station. Bus-train transfer times are determined by the synchronisation of their respective timetables. Both bus and train timetables operate on a fixed repeating pattern of 30 minutes. Within this cycle, the difference between bus arrival (or departure) and train departure (or arrival) calculates the layover time between bus and train. Nevertheless, not all transfers are equally feasible or attractive. For example, a bus arriving shortly before the train departs, is convenient for access transport, whereas a bus departing shortly after the train arrives, facilitates egress trips. Longer waits increase the total travel time, and are thus less attractive. Conversely, excessively short transfer times may reduce transfer quality for two reasons.

One reason is the minimum time necessary to walk between the platforms, to make the transfer physically possible. Additionally, limited service reliability and high variation in realised arrival times require a transfer time buffer in case of delays. With more service unreliability, passengers are benefitted by longer transfer times. In conclusion, the attractiveness of the transfer is defined by the duration of the wait and the feasibility is determined by the minimum walking time and the reliability margin. Considering these two reasons and after consulting local Arriva transport planners, the presumed minimum transfer time at Maastricht station is set at 5 minutes.

For the model, a metric is needed to quantify transfer attractiveness to implement it as a predictor for ridership. Three methods are tested, the first one being the calculation of an average weighted transfer time. The second manner entails selecting two important trains to transfer to, and measuring the transfer time for these two trains separately. The last approach selects the same two important trains, but instead of determining the transfer duration, a binary variable is set at 1 if the transfer is attractive, and otherwise at 0. A more extensive explanation of these three methods is provided in the following paragraphs.

4.2.1 Method 1: Weighted average transfer time

Since multiple connections exist at the transfer node of Maastricht, multiple transfer times exist for different trip chains. To express these transfer times in a single attribute, a weighted average is calculated based on the share of train travellers shown in table 4.1. This approach assumes that bus passengers are representative of the average train traveller, and thus follow the same distribution as all train passengers. For every possible bus arrival or departure time, an average transfer time can be determined, using equation 3.2 from the previous chapter. As an example, the average is calculated for a bus departing at 7 minutes past the half hour (hereafter written as :07). Table 4.2 shows the arrival times for all the trains and their specific transfer times for this specific case.

Train	Arr. time	Time difference (min)	Transfer time (min)	Share
Intercity from Alkmaar/Enkhuizen	:00	7	7	64.5 %
RS12 from Roermond	:20	17	17	13.6%
RS18 from Kerkrade Centrum	:20	17	17	13.6%
RE18 from Aachen	:09	28	28	6.9 %
RS12 from Maastricht Randwyck	:05	2	32	0.7%
RS18 from Maastricht Randwyck	:06	1	31	0.6 %

Table 4.2: An example for the transfer times of a bus departing at :07

As one can see, transfer times shorter than 5 minutes are not deemed feasible and are therefore increased by 30 minutes, the interval between two consecutive trains. Using the share of train passengers copied from table 4.1, the weighted average transfer time for a bus departing at :07 is 11.7 minutes.

Doing the same calculation for every possible arrival and departure time, the respective average transfer times are determined. Figure 4.2 displays each of these average transfer times.

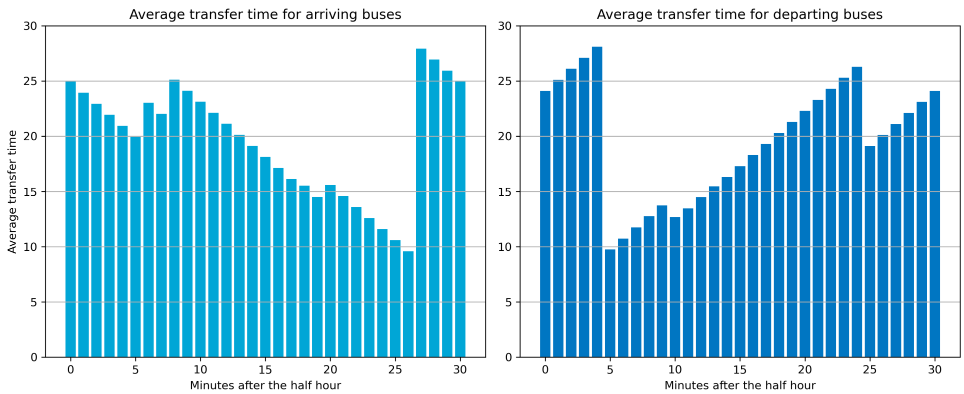


Figure 4.2: The average transfer time from the bus to the train based on the arrival of the bus (left) and the average transfer time from the train to the bus based on the departure times of the bus (right) in the 30 minute repeating pattern.

From figure 4.2 one can conclude that the optimal arrival time is :26 and the optimal departure time is :05 to minimise the average transfer time. The maximum average transfer times occur at :27 for arriving buses and :04 for departing buses, since at these times the difference with the intercity is only 4 minutes, which is too short for a feasible transfer. According to the calculation, the transfer time is then 34 minutes for 65% of bus passengers, resulting in a high average transfer times. In this case, the shorter connections with the regional trains decrease the average, resulting in a final weighted average of under 30 minutes.

The distribution shows a linear increase or decrease a each time step, with the exception of some larger shifts at specific time points, which in the right graph of figure 4.2 occur at :05, :09 and :25. These are the time stamps at which the transfer time for one of the possible trains shifts from 5 to 34 minutes due to the repeating timetable and the minimum walking time threshold.

Another observation is the symmetry between the two graphs, which is a result of the symmetry present in the timetable, where buses of the same line in opposite directions are planned to cross each other at :00 and :30. The train table is planned with the same symmetry, to ensure that the transfer time in one direction is the same as in the other direction.

4.2.2 Method 2: Transfer time per train

Instead of weighing an average transfer time, the *transfer time per train* approach selects two trains and implements the two respective transfer times each as a predictor in the model. Since over 90% of all train passengers are transported by only three train services, of which two operate simultaneously, the transfer quality for most passengers can be determined by merely calculating the transfer time for either the intercity or the regional train RS18-north (which shares the arrival and departure time with the RS12-north). By keeping both as separate variables, differences in their ability to attract bus passengers can possible be uncovered.

4.2.3 Method 3: Transfer possibility per train

Since it is unlikely that the relationship between transfer time and ridership is merely linear, a third method is tested. The transport planners at Arriva currently aim to plan the bus schedules in order for the transfer time to be with the 5-12 minute time window, since this interval is deemed reasonable for a transfer between bus and train. The last method thus includes two binary variable variables, the first assigns the value 0 or 1 based on whether the transfer to the intercity is within the 5-12 minute interval, and the second for the RS18/RS12 trains.

Having established how bus departure and arrival times shape transfer opportunities and, by extension, affect the convenience and feasibility of multimodal journeys, the different approaches to implementing transfer time can be tested to capture its influence on ridership. However, before moving on to the modelling results, it is also essential to consider the structure of the bus network. The following section therefore provides an overview to highlight how the different bus lines provide varying transfer possibilities.

4.2.4 Conclusion on the different methods

In conclusion, this section outlined three distinct approaches for incorporating transfer time into the ridership model; a weighted average transfer time, specific transfer times per train, and binary indicators for whether a good connection is available. Each method captures a different aspect of how transfer quality may influence passenger decisions. These formulations reflect both theoretical assumptions and practical scheduling strategies, such as the use of a preferred transfer window by transport planners. Before evaluating the outcomes of these modelling approaches, the following section first examines how the lines in the network are structured to enable the transfer possibilities explained in this section.

4.3 Bus network

The Maastricht urban bus network is dense, extensive and frequent on many corridors, due to many lines sharing route segments. Multiple aspects need to be considered to fully understand the functionality and use of the network. The first aspect is the timetable set-up, to assess its synchronisation with the train schedule. Secondly, the network structure and the selection of lines to be included in the model are discussed. Finally, network segments where the difference in transfer possibilities between bus lines might have a substantial effect on ridership are discussed.

4.3.1 Timetable

The Maastricht bus timetable is set up in a 30 minute repeating pattern, equal to the train schedule. The arrival and departure times (relative to the half hour) are thus constant as long as the same timetable is operated. However, to adjust to demand variations, several patterns exist during the week. The base timetable is called *weekdays daytime* and runs on weekdays from 7:00-19:00, after which the evening schedule starts. This evening pattern is also used on weekdays before 7:00, Saturday before 9:00 and on Sunday before 11:00. During the day, Saturdays and Sundays each have their own timetable patterns until 17:00, after which the evening pattern is used again. For the continuation of this chapter, all specifications are described for the weekday daytime timetable, unless stated otherwise.

In the timetable, all lines included in the model pass the station halfway, where they dwell for at least two minutes before continuing to the following line segment. This structure enables all eastern neighbourhoods to have a direct connection with the city centre, located on the west bank of the river, resulting in an eastern and western segment of the same bus line. As a consequence, one train can only connect to either (east/west) segment. For example, if the through-routed bus arrives shortly before the train departs (beneficial to access the train), it also departs shortly before the train departs (unfavourable to egressing train passengers).

Luckily, the train timetable at Maastricht station is set up such that it is possible to simultaneously connect *to* the intercity and *from* the regional trains. In practice, if a bus arrives between :23-:26 or :05-:07 and departs two minutes later, it gives connection to the intercity in one direction and to the regional trains in the other direction. For this reason, many bus lines are planned to arrive exactly within these intervals, resulting in a synchronised timetable.

To illustrate these favourable transfer connections, figure 4.3 is shown, where the x-axis represents a 30 minute time interval within a regular timetable. A yellow line indicates that the bus transfers to the intercity, while a blue line refers to connections to the regional trains. In this example, a bus line is taken that provides an intercity connection to the western segment. As one can see, the buses only dwell for two minutes at the station, and thus provide different transfer possibilities to arriving and departing bus passengers.

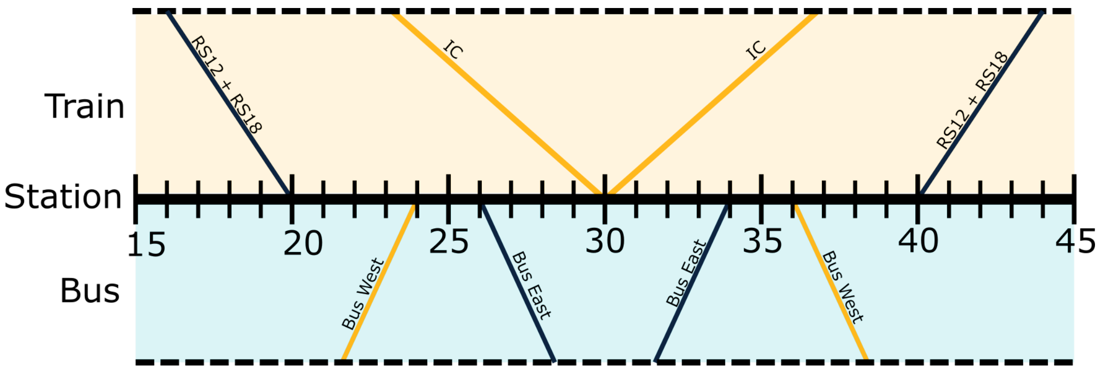


Figure 4.3: A space-time diagram of the most important train services at Maastricht station and how a bus most effectively provides transfer opportunities.

4.3.2 Bus lines

With the timetable structure defined, the next step is to analyse the specific lines that make up the network. In total 22 bus lines serve the Maastricht urban area. This research focuses on urban residents as potential travellers to access the train network. Given this context, not all lines are interesting or practical to be included in the model. To determine which lines are deemed useful, the lines are split into the following categories:

- 6 urban lines serving the station halfway (*lines 1, 2, 3, 5, 6, 7*)
- 3 mixed urban/regional lines serving the station halfway (*lines 4, 9, 15*)
- 1 short circular line (*line 11*)

- 3 regional bus lines with the station as terminus (*lines 30, 57, 350*)
- 3 bus lines operated by 8-passenger vehicles (*lines 8, 12, 13*)
- 1 urban line not serving the station (*line 10*)
- 5 international bus lines (*lines 45, 20a, 62, 63, 78*) operated by the Belgian transport operators

In this research, only the first two types are included, and only stops within the city borders are studied. The other categories are dropped because they either are used predominantly for inter-city travel, are not operated by regular buses, have a limited timetable, do not facilitate bus-train transfers, or have no available data. Besides the excluded stops and lines, the transfer possibilities are not equal across the stops on the included lines.

To optimally capture transfer-related influences, the lines have to be segmented according to their transfer opportunities. As outlined in the previous section, the bus lines pass the station halfway, and the stops served before the station have different transfer times from those served after the station. Therefore, the lines are split into both an eastern and a western segment. Additionally, a distinction is made between a bus headed to or from the station, to determine whether the transfer time is governed by the arrival or departure time of the bus at the station. In summary, every bus line is split into an eastern or western part, headed either to or from the station, to form a total of four line segments.

This practice assumes a frequency per line of two per hour for every bus line, although one exception exists within the network. More specifically, line 6 runs an additional pair of runs per hour between the city centre and its eastern terminus. Since the trains run on a frequency of two per hour, the individual bus trips provide an alternating pattern of transfer possibilities. To address this mismatch, the trips of line 6 are divided into two alternating services (designated as lines 6 and 6k), each operating at a frequency of two per hour. This adjustment ensures better alignment with the train services.

Altogether, 40 line segments are identified in the weekday daytime schedule, based on variations in their transfer characteristics. A graphic representation of the line segments included in the model is provided in figure 4.4.

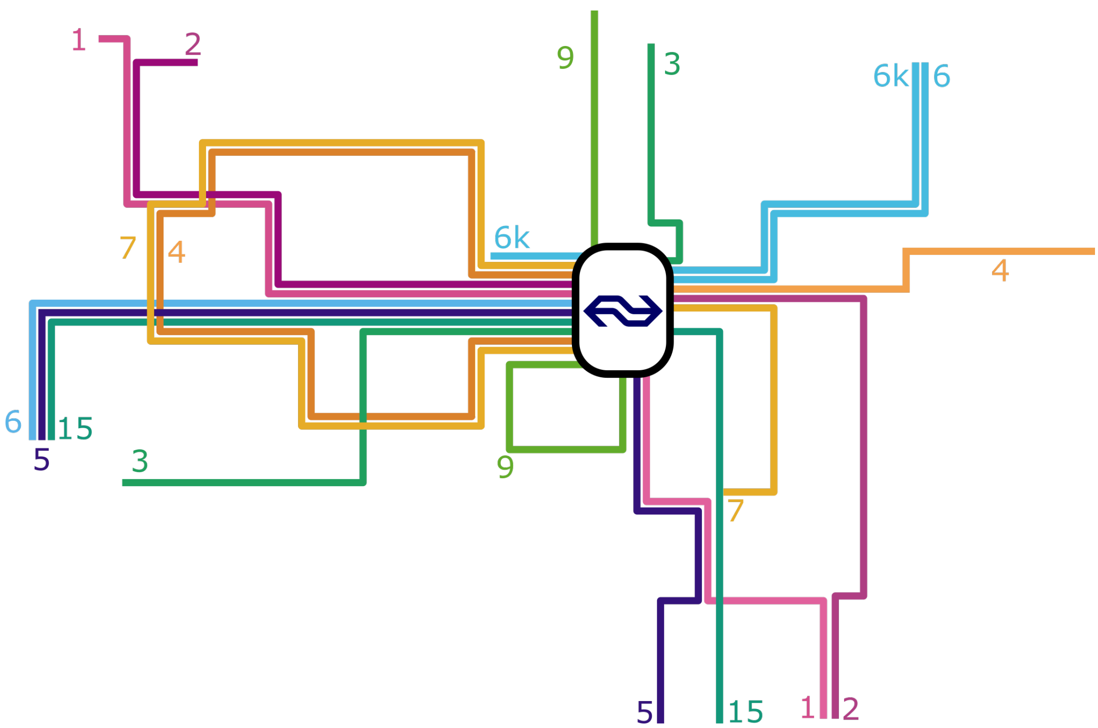


Figure 4.4: Graph showing all line segments included in the model, centred around the train station

4.3.3 Shared route segments

In addition to the through-routing of bus lines at the central station, many lines share parts of their routes or cross each other at several locations in the city. An important result of the shared route segments is that the single feature distinguishing the bus lines is the transfer time, since all other variables are determined by the location. Therefore, the difference in passenger numbers between lines serving the same segment, is possibly (partially) explained by the varying transfer time. The shared route segments thus enable capturing the effect caused by more attractive transfer possibilities, which is why they are given a more in-depth analysis in section 4.4.4.

4.4 Model data

This section presents the data collected for the model. The previously described 40 line segments serve a total of 202 platforms located at 120 different stop locations. In total, 414 unique stop-line combinations constitute the data observations for the model input. For each of these data entries, the values for the dependent and independent variables have been gathered.

To provide a clearer understanding of the dataset and the input variables, first the collection of the dependent variable is explained. Then, the descriptive statistics of both dependent and independent variables are presented, followed by a detailed discussion of the distribution of transfer-related attributes. Finally, a preliminary indication of potential transfer effects is explored by comparing ridership levels across different lines serving the same stop.

4.4.1 Dependent variable

The dependent variable is the average total number of daily passengers travelling to or from the main station at a given bus stop, using a specific bus line, within the defined time window (weekdays, 07:00–19:00).

As an example, the weekday *ridership* is 38 passengers at the stop *St. Annalaan* for line 5-west in the direction towards the station. This observation implies that 38 riders travel *from* this stop *to* the station daily between 7:00-19:00 using line 5, on average. For example, at the central station stop, a value of 187 passengers for line 5-west (heading toward the station) indicates that, on average, 187 passengers use line 5 from the western direction to access the central station daily between 07:00 and 19:00. This data is collected over the months January and February of 2024, and only includes days on which the regular weekday timetable is operated.

In total over 816 000 trips were registered within this period, of which 45% were trips to or from the station, which is the subset used as input for the model. As a result, 10 471 trips are made to or from the station, on an average weekday between 7:00-19:00. Combining the facts that a total of 15 791 passengers take the train at Maastricht station on an average weekday, and that according to NS, around 24% of train passengers use the bus to access or egress their trains [NS, 2024], an estimated 3 789 daily trips are part of a multi-modal journey of both bus and train, or 36% of all station-related trips.

While the data provides detailed metrics for the number of boarding and alighting passengers at every stop for every bus run, some irregularities persisted in the dataset. Some stops recorded almost no passengers, which was caused by diversions in bus routes due to road works. These diversions led to altered stop usage that is not representative of typical operating conditions, thereby compromising the validity of the ridership data for those cases. For this reason, all stops with less than two passengers per day were removed from the data.

4.4.2 Descriptive statistics of the model input

The descriptive statistics are shown in table 4.4 for all non-transfer-related variables. Table 4.3 shows that some variables are less evenly distributed than others. *inhabitants*, *income* and *elderly* have a relatively small standard deviation compared to their mean. On the other hand, the binary variables show a skewed distribution, which is caused by the small subset of stops actually having a value of 1 for either of these attributes. Another uneven variable is the socio-cultural land use, for which the mean is 4.76%, while for one stop the percentage increases up to 67.29%.

Compared to the input for the model by Kerkman et al. [2015], there is considerably less variation in the attributes *inhabitants* and *income*, which might make it more difficult to obtain meaningful model results for these predictors. Despite this moderate variation, the low VIF values show that there is no substantial correlation among these variables in the data, which makes any interpretations more reliable.

Variable	mean	std	min	median	max	VIF
No. of passengers (log)	2.72	1.00	1.10	2.54	5.90	-
No. of inhabitants (log)	7.80	0.48	5.01	7.94	8.46	1.59
No. of students (log)	0.46	1.85	0.00	0.00	8.62	1.29
Average income (x1000 €)	28.89	4.80	20.00	29.10	39.00	2.40
% elderly 65+	20.55	6.10	8.89	19.41	35.72	2.33
Central station (0/1)	0.10	0.30	0.00	0.00	1.00	2.69
City centre (0/1)	0.07	0.25	0.00	0.00	1.00	1.52
Local shopping centre (0/1)	0.05	0.22	0.00	0.00	1.00	1.19
% Socio-cultural land-use	8.05	12.83	0.00	4.76	67.29	1.39
Frequency (log)	4.24	0.77	3.09	4.28	5.46	1.96
Travel time to station (min)	9.62	5.75	0.00	10.00	24.00	2.75

Table 4.3: Descriptive statistics of the weekday daytime data. (VIF is variance inflation factor)

4.4.3 Transfer-related attributes

As described in the previous sections, three different methods to implement transfer-related attributes are tested. Since the effect of these variables is the main focus of this research, transfer times and transfer possibilities are analysed more in-depth. The first method is the average weighted transfer time, the second the transfer time to per individual selected train and the third the qualification of a transfer as likely or not, if the layover time falls within the interval of 5-12 minutes. An overview of their descriptive statistics is given in table 4.4. IC stands for the intercity and RS for regional sprinters, the two regional trains headed north which depart simultaneously.

Transfer attribute	mean	std	min	median	max	VIF
Average transfer time	17.94	5.44	9.79	16.21	26.29	1.03
Transfer to IC (min)	16.32	8.02	5.00	14.00	29.00	1.41
Transfer to RS (min)	20.21	8.34	6.00	20.00	34.00	1.42
Transfer to IC (0/1)	0.43	0.50	0.00	0.00	1.00	1.32
Transfer to RS (0/1)	0.22	0.41	0.00	0.00	1.00	1.31

Table 4.4: Descriptive statistics of the transfer related attributes.

These statistics show that the mean transfer times exceed the presumed convenient transfer interval of 5-12 minutes, indicating that poorly timed connections are as prevalent as efficient transfers. In addition, it is observed that 43% of stop-line combinations provide a connection with the intercity, and 22% with the regional trains, proving the planners' preference for facilitating transfers between bus and intercity train. Finally, the VIF values show that these variables do not correlate substantially.

While the descriptive statistics provide easily interpretable insight in the distribution of the binary variables, the other predictors measured in minutes require more detail to obtain a complete understanding. Therefore the distribution the average transfer time is shown in figure 4.5 and for the transfer time per train in figure 4.6.

In figure 4.5, two peaks arise in the average transfer time distribution around 10 and 23 min. This distribution is a direct result of planning the arrival and departure of buses in the most desirable time intervals, which are :23-:26 and :05-:07, as described in section 4.3.1. Using the previously shown graph from figure 4.2, one can derive that these intervals provide an average transfer time of around 10 minutes for arriving passengers and around 23 minutes for departing passengers, or vice versa.

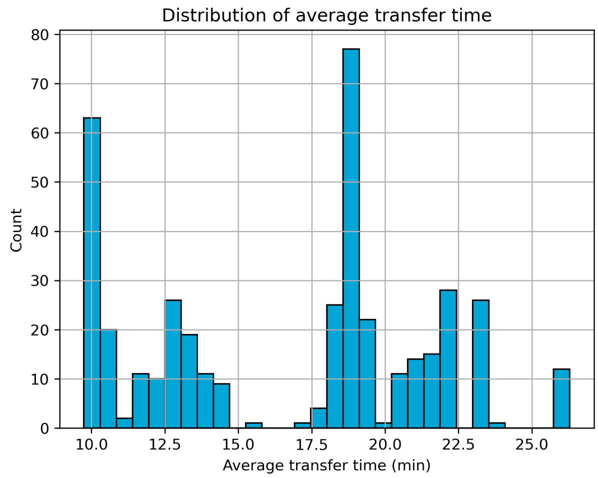


Figure 4.5: The distribution of average transfer times

Figure 4.5 also shows the consequence of through-routing bus lines at the train station. While one segment provides attractive connections, the other is automatically dealt long wait times for transferring passengers, as was explained in section 4.3.1.

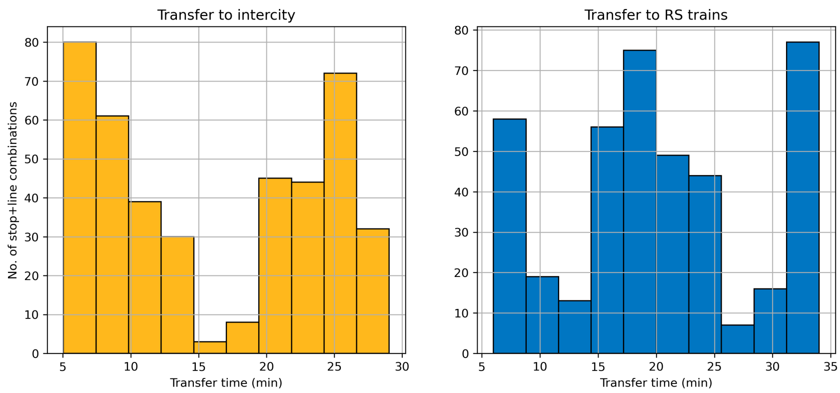


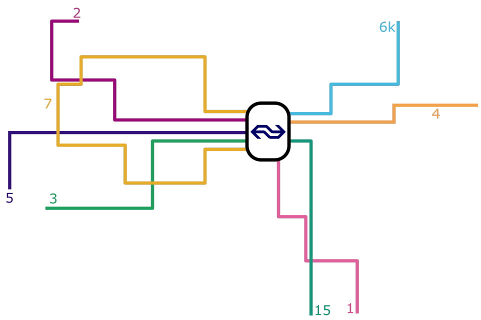
Figure 4.6: Distribution of transfer time in minutes for the intercity and the regional trains

Using a weighted average to represent transfer time offers both practical advantages and limitations One benefit is that it introduces only one additional variable in the model. In addition, this type of variable can theoretically be computed for any transport network centred around a train station, as long as there is data available. Nevertheless, it relies on the assumption that a bus passenger reflects the average distribution of train passengers, which may not hold in cases where specific trains attract more transferring bus riders than others.

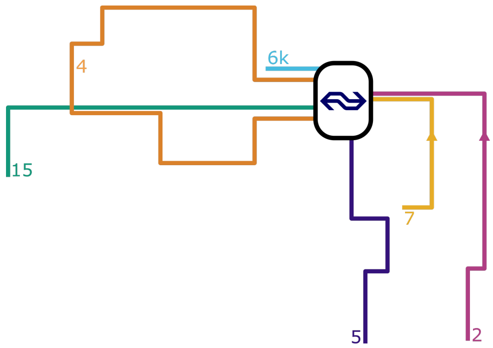
To resolve this shortcoming, the second approach includes transfer time to two different trains separately in two different variables. The first variable is the time difference between arrival/departure of the bus and the intercity. The second selected variable is the transfer time to the regional train RS18 in the northern direction, which operates on the same schedule as the RS12. Therefore, this one *regional* *train* variable captures the transfer time to both trains. A distribution of the transfer time to these trains is provided in figure 4.6.

This figure again shows two peaks for the intercity trains, while for the RS trains a third peak arises for buses that provide a worst possible transfer time of 34 minutes. This last observation is due to a planned time difference of 4 minutes between the regional trains and some bus lines. 4 minutes is below the threshold for a feasible transfer of 5 minutes, which is why its transfer time is increased by 30 minutes.

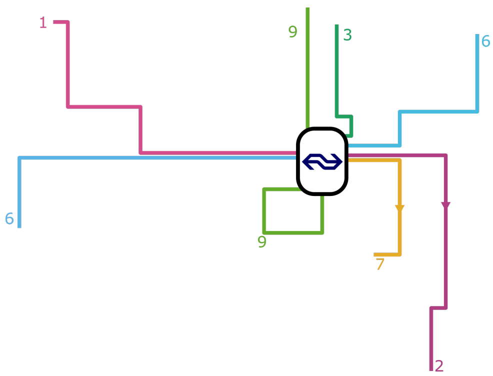
The final method selects the same trains as the previous approach, assigning a binary value (0 or 1) to the variable depending on whether the transfer time falls within the 'attractive' interval of 5 to 12 minutes. A visual representation of which bus lines connect to which trains is provided in figure 4.7. This figure shows that most areas of the city offer adequate feeder connections to the intercity service. In contrast, transfer opportunities to regional trains are more limited. Notably, lines 2 and 7 east display differing transfer possibilities depending on the direction of travel (towards or away from the station).



(a) Line segments with connection to the IC



(b) Line segments with connection to the RS trains



(c) The different line segments, categorised by transfer possibilities

Figure 4.7: The different line segments, categorised by transfer possibilities

Having provided a clear overview of the different feeder opportunities of the bus network, an initial insight in possible transfer effects can be obtained by comparing the ridership numbers at stops located on shared route segments as defined in section 4.3.3.

4.4.4 Ridership comparison at shared stops

Many stops within the network are served by multiple bus lines, resulting in a separate data entry for each stop–line combination. For these entries, most independent variables are identical, with the notable exception of the transfer-related attributes, which differ due to variations in the arrival and departure times of the respective line services at the station. Comparing the number of passengers across these lines at the same stop allows for the identification of potential effects stemming from scheduling differences.

The first example is the eastern section of line 6 and its subset of trips defined as line 6k in subsection 4.3.2. The trips of lines 6 and 6k have a headway of 15 minutes and connect the neighbourhoods of Wittevrouwenveld and Amby in the northeast with the train station. The line 6 runs arrive at :09/:39 at the station, and thus provide an average transfer time of 25 minutes. In contrast, line 6k arrives at :24/:54, 6 minutes before the departure of the intercity train, resulting in an average transfer time of 12 minutes. According to the better transfer possibilities provided by line 6k, the number of boarding passengers at each stop is expected to be higher. In fact, when observing figure 4.8, line 6k indeed shows higher ridership at all stops.

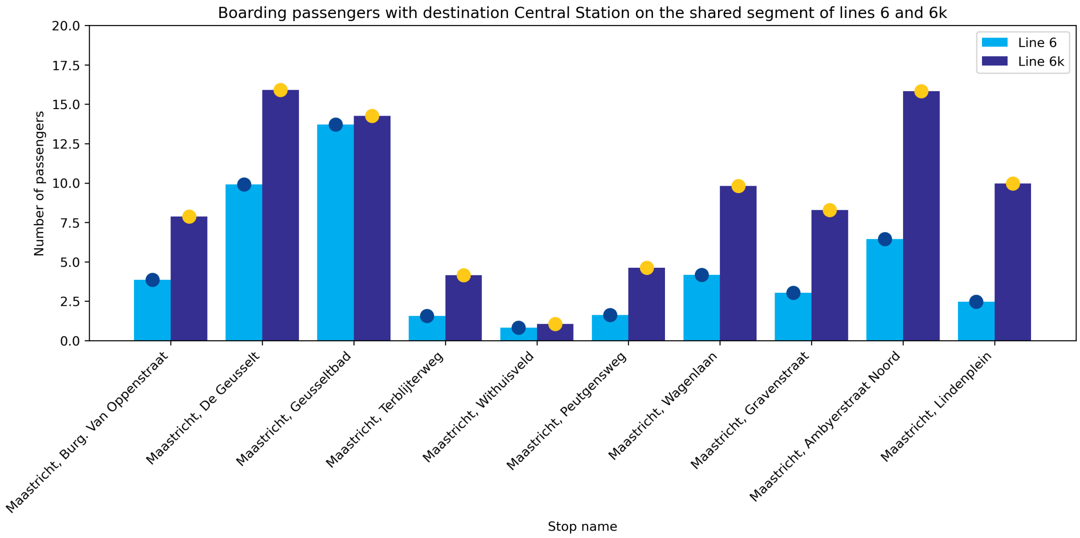


Figure 4.8: Comparison of passenger numbers to the station on shared line segment of lines 6 and 6k. A yellow dot represents a connection to the IC, a blue dot to the RS trains.

Figure 4.8 shows that the 6k trips attract about twice as many passengers at each stop. One notable exception is the stop Geusseltbad. Interestingly, this stop is located near an international school that attracts many students. The observation that this stop attracts relatively more passengers for line 6 than others may indicate that students from this school are more likely to travel by regional train. Another reason could be that line 6 is the first bus that passes the school after the school day ending time. In conclusion, the variation in ridership numbers may also depend on existing underlying travel patterns or school hours.

A similar effect can be measured on the western section of lines 1 and 2 between Via Regia and Malbergplein for the access trips to the train station. Line 1 arrives at :10/:40 at the station, while line 2 arrives at :22/:52, the latter being more attractive when transferring to the intercity train. Again, the line connecting to the intercity, line 2, attracts more passengers, as can be seen in figure 4.9.

In figure 4.9, line 2 attracts on average twice as many passengers at each stop. The exception is the stop Via Regia/Brusselse Poort, which is located very close to a stop that is served by five other lines, indicating that the competition between stops and lines also influences the relative popularity of the lines. Specifically for this case, line 2 probably experiences more competition than line 1, resulting in a different distribution when comparing to the other stops.

Despite the popularity of line 2 in the access direction (travelling to the station), the same pattern does not emerge in the egress direction. Figure 4.10 shows that line 1, despite not providing any useful train connections, attracts substantially more egressing passengers than line 2, except at the stop Brusselseweg/Zuyd Hogeschool. Notably, this stop serves a higher education institution, which may indicate that students are either more sensitive to transfer time compared to other passengers in the area, or that students are more likely to travel by intercity trains. Again, underlying travel patterns seemingly influence the passenger distribution across lines, indicating that facilitating feasible transfers does not result in an even increase in passengers at all locations..

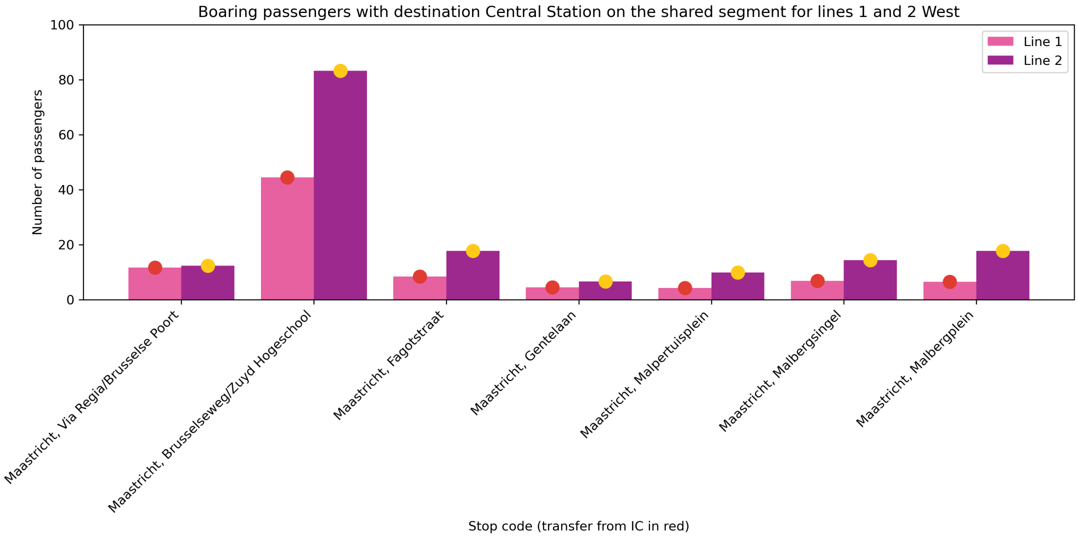


Figure 4.9: Comparison of passenger numbers to the station on shared line segment of lines 1 and 2. A yellow dot represents a connection to the IC, a red dot no connections.

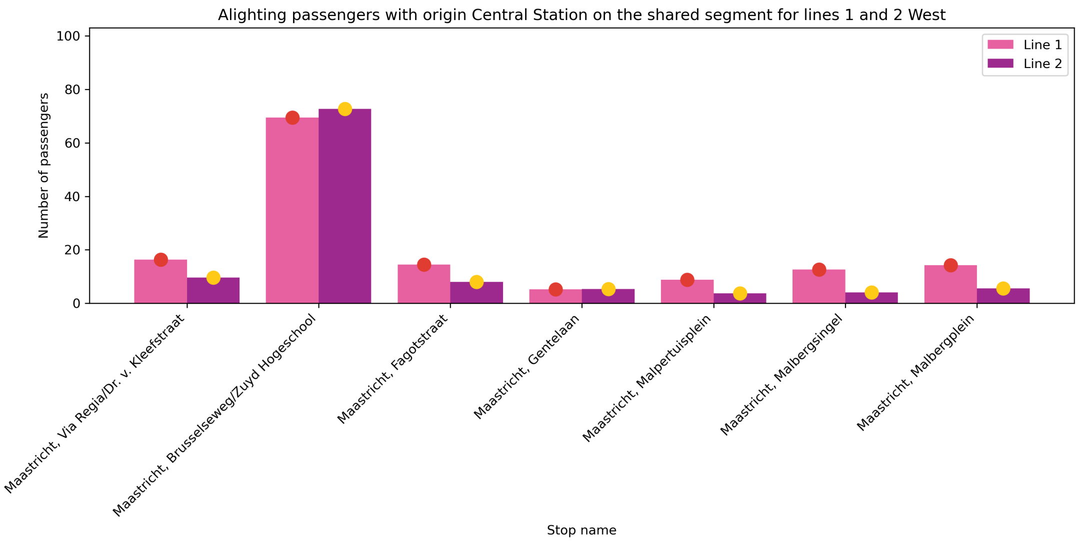


Figure 4.10: Comparison of passenger numbers from the station on shared line segment of lines 1 and 2.A yellow dot represents a connection to the IC, a red dot no connections.

While students may show different travel behaviour from the residents in this neighbourhood, the difference in most popular line between the access and egress directions might also be caused by the existence of another competing line at some of the stops on this corridor. This competing service is line 7, which also serves the stops Malbergsingel and Malbergplein, albeit via a different route. In the egress direction, line 7 offers slightly better transfer times than line 2. Conversely, in the access direction, line 2 provides the best transfer opportunities, explaining why line 2 is more popular only in the direction towards the station.

One final considered shared segment is the corridor served by lines 5, 6, and 15 in the western half of the network. This segment is unique in that it operates at a combined frequency of six buses per hour. Line 5 connects to the intercity service, line 15 to the regional trains, and line 6 operates in between to maintain an approximate 10-minute headway.

Figure 4.11 displays the number of daily boarding passengers travelling to the station along this segment. Notably, the most popular line varies per location, suggesting that the distribution of transferring passengers is not uniform at each bus stop. One possible explanation is that, due to the shorter headways, passengers may not select the bus line with the shortest transfer, increasing their transfer time

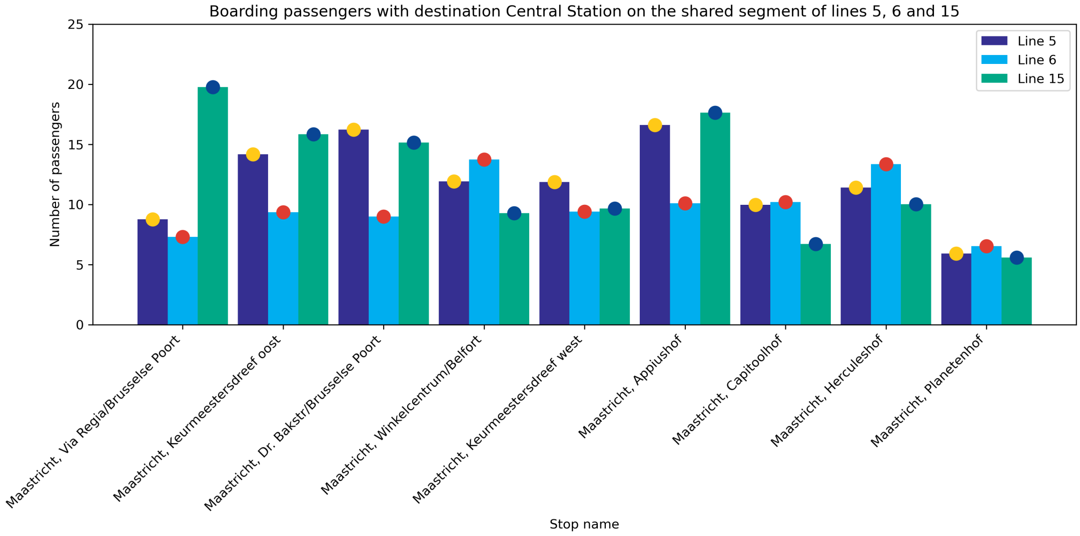


Figure 4.11: Comparison of passenger numbers to the station on shared line segment of lines 5, 6 and 15. A yellow dot represents a connection to the IC, a blue dot a connection to the RS trains and a red dot no connections.

for additional reliability. Another reason could be that bus passengers from these neighbourhoods are simply less likely to transfer to the train altogether. These observations indicate, on this high-frequency corridor, a clear transfer effect is less easily observed.

To summarise, there are indications that a connection to the intercity train may positively influence bus ridership. Several examples show that bus lines offering better train connections attract more passengers; however, counterexamples also exist, suggesting that the relationship may not be consistent across all contexts. Other factors determining the popularity of bus lines can be school hours, relative headways, competing bus lines and stops and underlying travel patterns. The relative importance of bus lines is not equal across all stops, which shows that transfer time alone cannot explain all variance in ridership at these stops. Nevertheless, to formally assess whether there is a significance relationship between transfer time and ridership, a multilevel regression analysis is conducted. The results of this analysis are presented in the following chapter.

5 Comparison of transfer-related attributes

Now that the train service, bus network, and their interaction have been fully described, along with the data used for the model, the three proposed methods for examining the relationship between transfer opportunities and bus ridership can be applied, to answer the first sub-question. The results are presented in table 5.1, containing parameter estimates, standardised coefficients, t-values, and the significance levels denoted by asterisks.

Since the effect of transfer mechanics is the main focus of this research, the associated variables will be discussed first by comparing the three model outcomes. The other predictors will be commented after by examining the magnitude and significance of their parameters.

	Average transfer time			Per train (min)			Per train (0/1)		
Variable	Coef.	Std. β	t-value	Coef.	Std. β	t-value	Coef.	Std. β	t-value
intercept	2.272	0.00	3.68***	2.311	0.02	3.77***	1.660	0.00	2.69***
Population (log)	0.155	0.07	2.22**	0.158	0.08	2.27**	0.158	0.08	2.27**
Students (log)	0.155	0.29	10.34***	0.155	0.29	10.35***	0.154	0.29	10.31***
% elderly	-0.031	-0.19	-5.05***	-0.032	-0.19	-5.10***	-0.032	-0.19	-5.07***
Income	0.000	0.00	0.05	0.000	0.00	-0.01	0.000	0.00	-0.05
Station (0/1)	2.343	0.69	16.66***	2.345	0.69	16.73***	2.352	0.69	16.74***
City centre (0/1)	0.723	0.18	5.80***	0.714	0.18	5.75***	0.721	0.18	5.80***
Shopping centre (0/1)	0.623	0.14	5.20***	0.621	0.14	5.17***	0.623	0.14	5.19***
% LU Socio-cultural	0.006	0.07	2.376**	0.006	0.07	2.34**	0.005	0.07	2.27**
Frequency (log)	-0.026	-0.03	-0.54	-0.025	-0.02	-0.52	-0.020	-0.02	-0.41
Travel time to station	-0.006	-0.01	-0.73	-0.005	-0.03	-0.68	-0.004	-0.03	-0.62
Avg. transfer time	-0.023	-0.12	-2.75***						
Transfer to IC				-0.013	-0.11	-2.45**	0.305	0.15	3.09***
Transfer to RS				-0.012	-0.10	-2.38**	0.170	0.07	1.44
Random intercept σ^2	0.24			0.24			0.24		
Intra-class correlation (ICC)	0.18			0.16			0.17		
Marginal R^2	0.721			0.726			0.724		
Conditional R^2	0.771			0.771			0.771		

Table 5.1: Coefficients for the multi-level model. (*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$)

Table 5.1 shows that most variables turned to be out significant, including many transfer-related variables. In addition, all three models show a high and roughly equal model-fit. The marginal R^2 represents the percentage of variance that is explained by the fixed effects, which in this model correspond to all the independent variable parameters. For each method, approximately 72% is explained by these variables. The conditional R^2 also includes the random effects, which in this model represent the random intercepts for every line segment. The random effects explain additional variance, resulting in 77.1% of variance explained for all three models.

The estimated variance of the random intercept at the line-segment level was 0.24, indicating that there is meaningful variation in baseline ridership between bus line segments. The intra-class correlation (ICC) value shows the proportion of variance explained by differences between line segments. The IC value of around 0.17 justifies the use of a multi-level model grouping the route segments. With the choice of regression method justified, the model fit can be assessed.

In previous research conducted in the Netherlands, direct ridership models were estimated using the OLS-regression method and produced an R^2-value of 77.2% by Kerkman et al. [2015] and 70.2% by de Boer [2021]. These values can, however, not directly be compared to the results in this study due to other variables being used and the different structuring of the model and the data. Despite the model fit not being comparable with previous research, the model is deemed accurate enough for further interpretation of the contribution of transfer-related attributes.

5.1 Average transfer time

The average weighted transfer time is a highly significant variable, with a negative influence on passenger numbers. For every additional minute, a bus line sees a decrease of 2.3% passengers per stop, which for a shift of 15 minutes would result in 29.5% fewer riders travelling to the station. Its relative influence can be assessed by comparing the standardised coefficients. The transfer time has a standardised coefficient of -0.12, indicating a stronger effect, in absolute terms, than the number of residents (0.07), but a weaker effect than the presence of a shopping centre (0.14). In summary, higher average transfer times substantially reduce trips made to or from the train station.

5.2 Transfer time per train

For the second approach, the transfer times in minutes to both intercity and regional trains emerge as significant predictors, each showing a similarly negative effect on patronage. However, the magnitude of these effects is more modest compared to the average weighted transfer time. Specifically, an additional minute of waiting time to connect to either train, decreases trips to or from the station by 1.2-1.3%.

This similarity in effect size is counter-intuitive, since the intercity transports twice as many passengers as the regional trains combined. A possible explanation lies in the inherent coupling of the arrival and departure times of both trains in the timetable. The intercity consistently departs 10 minutes before, and arrives 10 minutes after the regional trains. A transfer time of 6 minutes from the bus to the intercity train thus automatically means a transfer time of 16 minutes to the regional trains. Shifting the bus arrival time by one minute, simultaneously increases both transfer times to 7 and 17 minutes, respectively.

Although the two variables were not found to correlate as a whole, there are specific times for which the fixed timetable offset results in multicollinearity. In these cases, changes to one transfer variable are mechanically linked to changes in the other, making it difficult for the model to disentangle their separate effects, explaining the implausibly similar coefficients despite the clear difference in importance of each train type.

5.3 Transfer possibility per train

In contrast, the third method estimates more distinct coefficients for the different train services, suggesting that this approach is less affected by the coupling of arrival and departure times and therefore more reliable. In this specification, only a feasible transfer possibility to the intercity, defined as a connection within the 5–12 minute interval, has a statistically significant positive effect on ridership. Stops offering such a connection to the intercity train service see a 36% increase in estimated passenger numbers. Although a similarly positive effect is observed for regional trains, the associated standard error is too large to confirm statistical significance.

The finding that intercity connections have a stronger influence aligns more closely with expectations, given the intercity's higher ridership relative to the regional services.

5.4 Conclusion to sub-question 1

In conclusion, all three methods demonstrate that transfer-related attributes have a measurable effect on station-related bus ridership. To answer the first sub-question: *"How can transfer times accurately be defined, calculated and implemented as a predictor in direct ridership models?"*, the three approaches need to be examined on their accuracy and ease of calculation and implementation.

The weighted average variable, while capturing the effect in a single variable, depends heavily on assumptions made on train passenger distribution. In addition, detailed train data is required that may not be readily available for other regions, making it difficult to calculate accurately.

The transfer time in minutes per train avoids the need for train passenger data, but is sensitive to coupling effects introduced by the fixed train timetable. Besides, this approach assumes a strictly linear relationship between transfer time and ridership. Given that both excessively short and long transfer times are generally undesirable, this assumption is unlikely to hold.

The inclusion of binary variables addresses this shortcoming, and produced the more logical result of the intercity being more influential than the regional trains. For these two reasons, the inclusion of binary transfer variables, indicating whether a bus line offers an attractive transfer or not, is considered the most accurate approach for explaining ridership variation in this study. Now that the most promising method has been established, it can be used to obtain model results to answer the second sub-question, but before moving on to the second analysis, the remaining attributes are discussed to be able to reflect on the model to compare findings with previous research.

5.5 Remaining attributes

A notable observation in table 5.1 is that all non-transfer related estimators show nearly the same results in coefficient values and significance levels in all three model outcomes.

Most non-transfer related attributes show a significant influence on ridership, the exceptions are income, frequency and travel time to the station. First the positive effects will be discussed, then the negative coefficients and finally the non-significant predictors.

5.5.1 Positive effects

Positive parameter values are estimated for population, number of students, the central station, city centre, shopping centre and socio-cultural land use. The largest effect is observed for the central station dummy variable, where the estimated ridership is $e^{2.35} = 10.4$ times higher than at other stops. This result is logical, since only trips are measured to and from the station, and thus every data entry contains at least one passenger boarding or alighting at the station. Other substantial effects are observed for the number of students, as well as for the binary variables representing the city centre and shopping centres, for which a 106% and 86% increase in riders is estimated. These outcomes align with expectations, given that the data pertain exclusively to weekday daytime periods, when these facilities operate.

The population variable has a standardised coefficient of 0.07, which is lower than most other variables, but similar to the value of 0.091 found by Kerkman et al. [2015] for potential travellers. The land use variable also shows a similarly small effect, which could be due to schools falling under socio-cultural facilities, for which the higher ridership is rather explained by the *students* attribute. Remaining socio-cultural facilities include hospitals, libraries and theatres, which show a less strong passenger attraction effect.

5.5.2 Negative effects

The percentage of elderly residents is the only remaining significant attribute, and the only predictor with a negative standardised coefficient, valued -0.19. This result suggests that areas with a higher share of elderly residents tend to have lower bus ridership, potentially due to higher rates of car ownership in this demographic. A similar effect was observed by de Boer [2021], who estimated a coefficient of -0.15 for elderly residents.

A summary of all coefficient interpretations is listed in table 5.2, based on the binary transfer indicator method.

Change in variable	Change in ridership
1% increase in population	+0.16%
1% increase in students	+0.16%
1 percentage point increase in elderly	-3%
€1000 increase in yearly income	0%
Stop located at the central station	+951%
Stop located in the city centre	+106%
Stop located next to local shopping centre	+86%
1 percentage point increase in socio-cultural land use	+0.5%
1% increase in total number of passing buses	-0.02%
1 additional minute travel time to central station	+0.04%

Table 5.2: Interpretation of the other variables

5.5.3 Insignificant attributes

Three attributes showed no significant relationship with ridership; *income*, *frequency* and *travel time to station*. While Kerkman et al. [2015] found a small but negative effect of income on public transport use, de Boer [2021] did not observe a significant relationship, suggesting that the effect of income is inconsistent across different areas in the Netherlands. The lack of an observed significant effect in the Maastricht study could be due to limited variation in income levels across the study area, or it may indicate that higher-income neighbourhoods do not attract fewer public transport users for the subset of trips to the train station. A final explanation is that lower-income neighbourhoods are possibly served by a greater number of bus lines, due to a presumed higher travel demand, such that the increase in ridership is reflected by a greater number of data entries per stop, and consequently a higher total when aggregating across lines, rather than increased ridership per line at each stop.

Frequency is the most remarkable attribute for which no significant effect is observed. For both Kerkman et al. [2015] and de Boer [2021] this variable was the most influential with a standardised coefficient of 0.39 and 0.58 respectively. The divergence from previous studies arises from the way the data is structured in this research. Each data entry represents a specific bus line operating at a frequency of two trips per hour, and the frequency variable reflects the number of *additional* lines serving the same stop. As such, higher total service frequency at a stop is modelled indirectly through the presence of multiple lines.

In this context, this parameter captures whether the presence of more lines at a stop leads to passenger dispersion, resulting in lower ridership per line, or whether increased service frequency continues to attract higher ridership per line, despite being shared across multiple services. Since the predictor is insignificant, no conclusion can be drawn on which of these effects dominates.

Finally, the variable *travel time to station* did not yield a statistically significant result. One explanation is the non-linear relationship between this variable and ridership. Specifically, stops located closer to the station face greater competition from walking and cycling, which may reduce bus ridership. However, longer travel times may also be unattractive due to the increased total journey time, suggesting that the effect of this variable is likely non-linear. Previous research has not reached a consensus either. de Boer [2021] reported a positive relationship between ridership and distance to the station, while Kerkman et al. [2015] observed a negative relationship with the distance of a bus stop to the urban centre.

An alternative reasoning is that, while stops located farther from the station may generally attract more passengers, certain high-demand stops, such as those serving the city centre and the university, are located relatively close to the station and may distort the overall relationship.

With all variables discussed, a conclusion can be drawn on which approach is the most suitable to include transfer-related attributes in a direct ridership model.

6 Comparison of different times of the day and week

Since the model input consists of specific stop–line combinations tied to a fixed timetable, data from periods with a different schedule cannot be included in the same model. This segmentation, based on the distinct timetables operated during different times of the week, raises the question whether the effects of the predictors remain consistent across these temporal regimes. To explore this question, the model is also applied to data from evening, Saturday, and Sunday services, each of which follows a different timetable structure.

The results of these three time periods are combined in table 6.1, using the binary transfer variables. Table 6.1 shows both the unstandardised and standardised coefficient estimates of the multi-level regression models that were separately estimated on the three different time windows. The significance levels are represented by asterisks, showing that most variables are significant, especially for the Saturday results. Meanwhile in the evenings, fewer significant effects were observed, notably for the transfer variables. First the model fit will be commented, after which the influence of offering transfer connections to the trains will be compared across temporal windows. Finally, the changes in non-transfer-related parameters will be discussed.

	Evenings			Saturdays			Sundays		
Variable	Coef.	β	t-value	Coef.	β	t-value	Coef.	β	t-value
intercept	1.288	0.00	1.59	0.778	0.00	1.23	0.119	0.00	0.18
Population (log)	0.163	0.08	1.783*	0.158	0.16	2.18**	0.169	0.09	2.25**
Students (log)	0.019	0.04	1.05	-0.007	-0.02	-0.48	-0.023	-0.05	-1.61
% elderly	-0.060	-0.35	-7.98***	-0.046	-0.31	-3.14***	-0.041	-0.29	-6.39***
Income	-0.010	-0.05	-0.97	-0.011	-0.06	-1.20	-0.008	-0.04	-0.84
Station (0/1)	2.196	0.65	13.30***	2.262	0.76	16.18***	2.040	0.76	14.40***
City centre (0/1)	0.608	0.14	3.90***	0.684	0.18	5.42***	0.461	0.14	3.78***
Shopping centre (0/1)	0.386	0.08	2.67***	0.471	0.12	3.83***	0.411	0.11	3.47***
% LU Socio-cultural	0.000	0.01	0.14	0.005	0.07	2.11**	0.002	0.03	0.88
Frequency (log)	0.102	-0.03	1.73*	0.097	0.09	1.82*	0.144	0.13	2.71***
Travel time to station	0.027	0.14	2.45**	0.026	0.17	3.14***	0.029	0.20	3.43***
Transfer to IC	0.297	0.14	1.41	0.361	0.19	-2.76***	0.503	0.29	3.57***
Transfer to RS	-0.153	-0.06	-0.54	0.178	0.08	1.13	0.258	0.12	1.50
Random intercept σ^2	0.26			0.20			0.18		
Intra-class correlation (ICC)	0.55			0.29			0.38		
Marginal R^2	0.548			0.675			0.656		
Conditional R^2	0.793			0.769			0.786		

Table 6.1: Coefficients for the multi-level model across different schedules. (*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$)

Judging by the conditional R^2, all models exhibit a similarly high level of fit compared to the daytime results. However, the marginal R^2 values are lower, particularly for the evening period, indicating that a greater share of the explained variance is attributable to the random intercepts, which vary across line segments. This conclusion can also be drawn from the higher ICC values for all three outcomes. Nevertheless, the consistently high conditional R^2 suggests that the models offer a reliable basis for interpreting the effects of the various predictors.

6.1 Effect of transfer possibilities

The most relevant observation is that the effect of an attractive transfer opportunity varies across time periods. During the evening, neither transfer variable shows a statistically significant effect. One possible explanation is that the proportion of egress trips from the station is substantially higher in the evening compared to access trips, which is also reflected in the high ICC-value. As a result, buses *arriving* at the station, despite offering good connections to the intercity, likely experience lower passenger volumes than buses *departing* from the station. This imbalance makes it more difficult to detect a clear effect of the transfer variables.

On Saturdays, the results are comparable to those observed during weekday daytime, with an estimated ridership increase of 43% at stops offering a good connection to the intercity service. Meanwhile, Sundays exhibit the most pronounced effect, where an attractive intercity transfer is associated with a 65% increase in passenger numbers. The relative increase in passengers on trips connecting to the intercity train may be attributed to students returning home at the end of the weekend. Students living in student housing often travel to their home-towns during the weekend, for which they are likely to travel by the intercity train.

It is important to note that the frequency on many corridors is lower in these time windows, which results in fewer competition between lines. This reduced competition can result in connecting bus lines being more important, since there is also less variation in transfer possibilities.

6.2 Conclusion to sub-question 2

In summary, the analysis shows that the effects of transfer-related attributes vary across time periods. To answer the second sub-question *"To what extent is there variation between the different times of the day and week in the effect of transfer time on bus ridership?"*, the parameter estimates for the transfer-related variables were compared across temporal regimes. The conclusion can de drawn that the effect of transfer opportunities on bus ridership varies across different times of the day and week. More specifically, the influence appears to be lowest during the evening, increases on Saturdays, and is strongest on Sundays.

Underlying transfer patterns seem to be responsible for these differences. In the evening, more passengers travel away from the station than to the station, while on Sundays more intercity travel is expected due to the students returning home for the week. In addition, the lower frequencies in these time windows might also increase the relative importance of lines facilitating train transfers.

6.3 Remaining attributes

Variation was also observed for the other predictors. Many estimators showed changes in significance levels, most of which align with expectations. For example, the number of students no longer had a significant effect in these three time periods, which is consistent with the fact that schools are closed during during evenings and weekends. A similar explanation applies to the socio-cultural land-use variable.

In contrast, two predictors that were previously insignificant, *frequency* and *travel time to the station*, now exhibit significant effects. Stops that are served more frequently show higher ridership during evenings and weekends. In contrast, low frequency stops did not show substantially fewer passengers during the week. This result aligns with previous research [Kerkman et al., 2015; de Boer, 2021], but can still be attributed to endogeneity.

The same change in significance occurs for stops located farther from the train station, which experience increased passenger numbers for these periods. An explanation is the absence of high-demand stops serving schools located near the station.

In addition to changes in statistical significance, several variables also showed shifts in the magnitude of their estimated effects. The influence of local shopping centres is reduced during evening and weekend periods. A similar decline is observed for the city centre on Sundays, these changes reflect that these destinations are less popular to reach by bus during these time periods. Meanwhile, the negative effect associated with stops serving a high proportion of elderly residents becomes more pronounced during evening hours, which indicates that elderly passengers are less likely to travel at night. Finally, the parameter estimates for *population* and *station* remained relatively stable across all temporal regimes, which is logical since no temporal effects can be associated with these variables.

Now that the all variables have been discussed and the second sub-question has been answered, the third analysis can be introduced. The third analysis involves the introduction of another network, which is therefore thoroughly discussed in the next chapter to understand the transfer mechanics.

7 Case Study Breda

Breda is a city in the southern province of North-Brabant in the Netherlands, counting 189 000 inhabitants in 2024 [Gemeente Breda, 2024]. The main Breda station is used by 36 131 passengers every day [NS, 2024], making it more than twice as busy as the Maastricht station, of these, 30 442 have Breda as the origin or destination. NS estimate the share of train passengers using the bus as an access mode at 23%, and 20% for egress, which theoretically means that of the 16 363 average total weekday trips to and from the station by bus, 40% transfer to or from the train . To outline the transfer possibilities, the train service is first described, followed by the ways in which bus services connect to these trains, and finally the structure of the bus network itself. A map of Breda depicting the bus network is shown in figure 7.1.

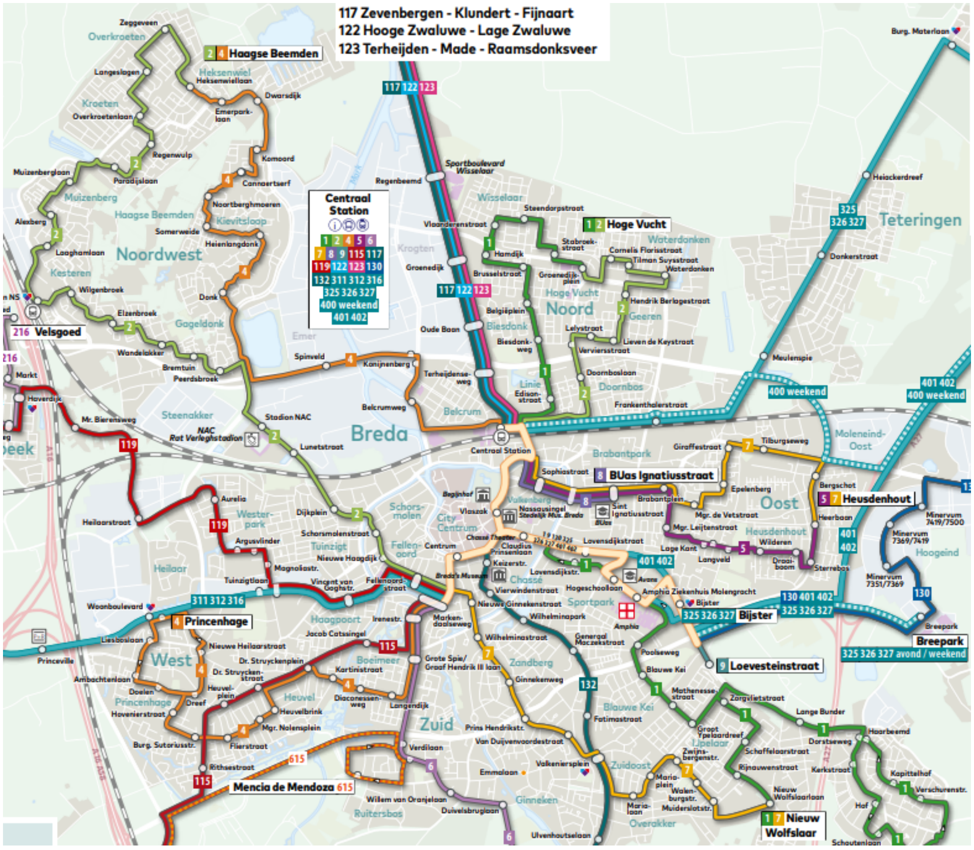


Figure 7.1: A map of the Breda bus network [Arriva, 2025]

7.1 Train services

Breda station is frequented by three intercity services, one sprinter (regional train) service, and one international service, all headed for one of four possible directions. An overview of the different arrival and departure times is included in table 7.1. Notably, all trains depart and arrive within a 16 minute interval (:07-:23), when excluding the international train. There is even a narrower interval, :15-:23, in which trains depart in all three important national directions, north, east and west.

One limitation in this study area is the lack of available data on the distribution of passengers across the individual trains, but according to Arriva planners, the IC-1100 train headed north (to Rotterdam) transports the largest share. There are several planning tactics to optimally schedule the arrival and departure times to facilitate attractive transfers between bus and train, which are discussed in the following section.

Train service	Direction	Arrival	Departure	Freq. (per hour)	Important destinations
IC-1100	North	:07	:23	2	Rotterdam, The Hague
IC-900	North	:15	:15	2	Rotterdam, Amsterdam
IC-9200	North	:34	:26	1	Rotterdam
SP-6600	North	:21	:08	2	Dordrecht
IC-3600	East	:10	:20	2	Tilburg, 's-Hertogenbosch
IC-1100	East	:21	:08	2	Tilburg, Eindhoven
SP-6600	East	:07	:23	2	Tilburg University, Tilburg
IC-9200	South	:18	:42	1	Antwerp, Brussels
IC-3600	West	:15	:15	2	Roosendaal

Table 7.1: Train timetable at Breda station

7.2 Bus-train transfers

While the train timetable in Breda does not contain one dominant train as in Maastricht, some points in time exist which provide better transfer possibilities than others. Since all trains depart within a 16-minute interval, the time windows in between of 14 minutes are more quiet for train passengers. Exactly arriving when the quiet interval begins (:23), is therefore less beneficial. In contrast, arriving at the beginning of the high-traffic interval (:07) provides more possibilities.

In practice, most bus lines are scheduled to arrive at or depart from the station around :15 or :30. These times correspond to the symmetry points of the Dutch railway timetable. To ensure equal transfer opportunities in all directions, bus services must align with this same :15/:30 symmetry. A :15/:30 symmetry implies that vehicles operating on the same route but in opposite directions cross each other at these fixed times.

Most urban bus lines in Breda are through-routed via the station, and as a result the separate line segments have different transfer opportunities, like in Maastricht. However, both line segments can be provided similar transfer times if the buses of both directions arrive and depart simultaneously at the station, which implies planning around the :15 and :30 symmetry times.

These nodes differ in transfer possibilities. Arriving at :15 provides connections to Tilburg and its university, 's-Hertogenbosch and its transfer possibilities to Utrecht, Rotterdam, Delft and the Hague. Meanwhile, arriving at :30 is only beneficial for passengers in the direction of Tilburg, Eindhoven and Dordrecht.

To illustrate these connections, figure 7.2 is shown. Here, the green lines indicate trains or buses in the :15 node, while the red lines are part of the :30 node. If a bus and train have the same shade, then they connect to each other. As one can see, buses serving the station around :15 have more transfer possibilities.

In summary, transfer possibilities can be grouped into two categories: those associated with arrival or departure times around either :15 or :30. The :15 group is assumed to offer better connections, making it particularly relevant to investigate whether bus lines falling into this category attract relatively more passengers. Before presenting the results, an overview of the bus lines comprising the network is provided.

7.3 Bus network

The Breda station is frequented by both urban and regional bus lines. Compared to Maastricht, the share of regional bus lines is higher. However, this scope of this study is limited to urban routes, of which 5 are present in the network, lines 1, 2, 4, 5 and 7. They form a set of 5 loops, served in both

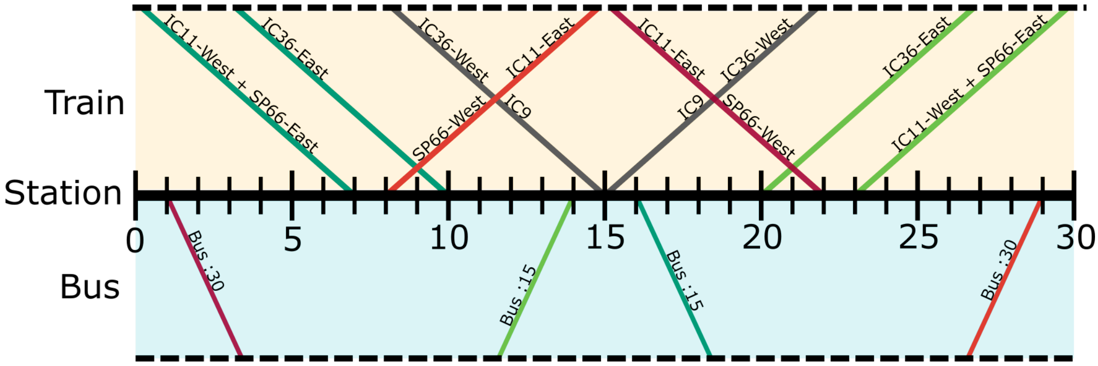


Figure 7.2: A space time diagram of the train and bus connections at Breda station.

directions, resulting in most stops having two connections to the station, one direct and one with a detour. As in Maastricht, most bus lines pass the station halfway (through-routed), in order to provide the northern neighbourhoods a direct connection with the city centre, located south of the station.

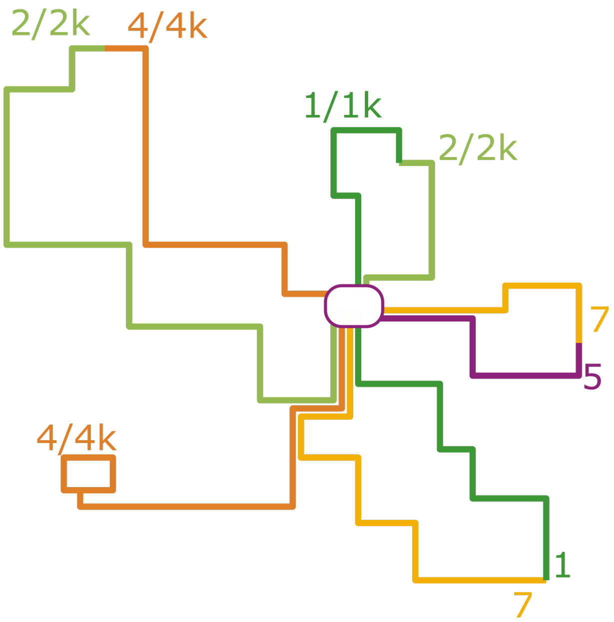


Figure 7.3: The network of lines included in the model

While the higher share of regional services is a motivation to include them in the model, they do not operate under the standard frequency of two per hour, and consequently do not align with the train schedule consistently. Some run less frequently, others more frequently, but only at set hours. In addition, there are shuttle services to the institutes of higher education which run up to 12 times per hour during peak moments. To most closely correspond to the data in the Maastricht model, only the lines which run twice or four times per hour the entire day can be selected.

In Breda, these are the urban lines 1, 2, 4, 5 and 7, most of which are through-routed at the station and split into four segments; north/south and to/from the station. For the reasons explained in section 4.3.2, all lines with a frequency of four per hour are split into two lines. In Breda these are the lines 1-north, 2 and 4, for which all trips serving the station around :15 are categorised in lines 1k-north, 2k or 4k. To obtain a visual impression of the network, a diagram consisting of the lines included in the network is presented in figure 7.3, where the square in the middle represents the train station. These simplifications mean that a smaller subset of trips is modelled, but this approach enables the results to be compared as fairly as possible with the outcomes of the Maastricht study.

7.4 Model data

For the Breda study two adaptations were made to the model. The first change is the time frame over which the data is collected. Secondly, the transfer-related variables are adjusted to the train timetable at Breda station, since the two stations are served by different trains.

The Breda data counts an average of 16 363 station-related trips per day. Combined with NS data saying that around 22% of all 30 442 boarding and alighting train passengers at Breda station use the bus as the first- or last-mile mode, 41% of the trips included in the model are approximately part of a multimodal bus-train journey, which is slightly higher than in Maastricht.

7.4.1 Time period

Data was collected on trips made to and from the central station on weekdays between 7:00-19:00 during April 2025, counting the boarding and alighting passengers per stop. This time frame is different from the Maastricht study, which used data from January-February 2024. The reasoning for selecting a different period lies in the modification of the Breda timetable in January 2025.

Prior to this change, a limited service was operated due to driver shortages. This reduced schedule showed less variety in transfer times across bus lines, complicating the analysis. To accurately capture the effect of transfers on ridership, the arrival and departure times of the buses at the station are ideally heterogenous. For this reason, data from a period during which the regular timetable was in effect was selected. April 2025 was ultimately chosen to ensure that travel behaviour had time to adapt following the schedule change.

7.4.2 Transfer-related attributes

To answer the third sub-question, the transfer effects within the Breda network have to be estimated and compared with the outcomes of the Maastricht study. Chapter 5 concluded that including binary variables is the most useful method. The binary variables indicate whether a bus line provides an attractive connection to a train that is presumed to attract intermodal transferring passengers.

In the previous section, the ideal arrival and departure times for buses with respect to bus-train transfers were outlined, either categorising the possibilities around the :15 or the :30 node. Consequently, the train 3600-East is selected as the first train for which a transfer variable is included in the model, pertaining to the :15 node. This train connects Breda with the cities of Tilburg and 's-Hertogenbosch (where transfers to Utrecht can be made). This train departs shortly before two other trains, which are also expected to attract many travellers (departing at :23 and arriving at :07). The first of these trains is the 1100-West, providing connections to Rotterdam and The Hague. The second is the regional train 6600-East, for which the most important destination is Tilburg University. In conclusion, a transfer from the bus to the 3600-East is automatically also an attractive connection to many other destinations.

The second node is centred around :30, for which the buses provide an attractive transfer to the train 1100-East, with destinations Tilburg and Eindhoven. Associating the second transfer variable with this train gives the most complete insight in the transfer mechanics in passenger distributions at the Breda station, capturing both the :15 and the :30 nodes. In summary, the two binary variables are *transfer to 3600-East* and *transfer to 1100-East*.

7.4.3 Descriptive statistics

With the time frame and transfer-related variables now clarified, an overview of the dataset is presented. The 28 line segments present in the dataset serve 113 stops at 207 platforms, forming a total of 372 unique stop-line combinations. The attribute values of these data rows are summarised in table 7.2.

Variable	mean	std	min	median	max	VIF
No. of passengers	2.70	1.04	1.10	2.50	6.05	-
No. of inhabitants (log)	7.78	0.59	3.80	7.91	8.37	1.32
No. of students (log)	0.60	2.04	0.00	0.00	9.55	1.79
Average income (x1000 €)	29.16	4.81	20.05	29.14	42.30	1.43
% elderly 65+	17.25	5.63	4.47	16.90	40.00	1.70
Central station (0/1)	0.08	0.26	0.00	0.00	1.00	1.74
City centre (0/1)	0.03	0.16	0.00	0.00	1.00	1.57
Local shopping centre (0/1)	0.11	0.32	0.00	0.00	1.00	1.13
% Socio-cultural land-use	3.88	7.24	0.00	0.08	48.95	1.75
Frequency (log)	4.65	0.47	3.14	4.53	6.36	1.47
Travel time to station (min)	12.01	7.32	0.00	11.63	36.50	1.63
Transfer to 3600-East (0/1)	0.46	0.50	0.00	0.00	1.00	1.86
Transfer to 1100-East (0/1)	0.32	0.47	0.00	0.00	1.00	1.73

Table 7.2: Descriptive statistics of the Breda weekday daytime data

Compared to Maastricht, there are three variables for which the statistics are remarkably different. First is the number of students, for which the mean of the log-transformed values in Breda is higher (0.60 vs. 0.46). Second is the percentage of elderly, which in Maastricht is higher (21% vs. 17%) Last is the travel time to station, where the most notable difference is the maximum travel time, which in Breda is over 36 minutes, while in Maastricht no one lives farther than a 24 minute bus ride away from the station. On average, Breda passengers similarly take longer to reach the station (12.0 minutes vs. 9.6 minutes).

These differences suggest that public transport in Breda is more oriented toward students, and that longer in-vehicle travel times are an additional factor alongside transfer times in selecting the bus as first- or last-mile transport. In addition, the low VIF values indicate that the variables are uncorrelated and therefore apt to be included in the model. Following the clarification of the transfer interactions at Breda station and the summary of the the input data, the modelling results are presented in the next chapter.

8 Comparison of different networks

The multi-level regression analysis is conducted in the exact same manner as for Maastricht. The analysis is only done on weekday daytime data, since that time period transports the most substantial proportion of all passengers. The parameter estimates and significance levels are listed in table 8.1. First the model fit and transfer effects will be discussed, after which the other estimators will be compared with the Maastricht study. Finally, this chapter will conclude with an answer to the third sub-question *"Are there regional differences between bus networks in the effect of transfer time on bus ridership?"*.

Variable	Coef.	β	t-value
intercept	3.885	0.00	8.02***
Population (log)	0.035	0.02	0.71
Students (log)	0.162	0.32	9.74***
% elderly	-0.002	-0.01	-0.26
Income	-0.010	-0.05	-1.36
Station (0/1)	2.626	0.67	20.68***
City centre (0/1)	0.445	0.07	2.28**
Shopping centre (0/1)	0.923	0.28	10.80***
% LU Socio-cultural	0.006	0.04	1.23
Frequency (log)	-0.283	-0.13	-4.05***
Travel time to station	-0.036	-0.25	-7.21***
Transfer to 3600-East	0.211	0.10	2.21**
Transfer to 1100-East	0.114	0.04	1.15
Random intercept σ^2	0.24		
Intra-class correlation (ICC)	0.07		
Marginal R^2	0.764		
Conditional R^2	0.781		

Table 8.1: Coefficients for the multi-level model applied on the Breda network
(*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$)

Table 8.1 shows the parameter estimates for the multi-level regression model to estimate the number of passenger per stop per line. Many parameters show a significant effect, of which the transfer to the 3600-East train is the most important with respect to the research objective.

Compared to the Maastricht result, the model fit is slightly higher, but the intra-class correlation is lower. A lower intra-class correlation means that there is less correlation between stops on the same line, suggesting that ridership patterns are less clustered per line. As a result, the marginal R^2 is higher for Breda than for Maastricht, indicating that a greater proportion of the variation in ridership is explained by the fixed effects alone. Despite these observations, the random intercept variance remains roughly equal, which indicates there is more variation within line segments than between segments.

8.1 Effect of transfer possibilities

The two transfer variables in this model are the binary variables for the attractive transfer to the 3600-East and 1100-East trains. Of these, only the attractive transfer connection to the 3600-East train is significant. It is estimated that bus lines connecting to this train attract 23% more passengers at each stop. Compared to Maastricht, the significant transfer possibility variable in Breda shows a smaller effect and a lower significance level.

The lower parameter estimate can be attributed to the lower relative importance of the 3600-East train. Although a connection to this train simultaneously enables transfers to another intercity train with high passenger volumes (train 1100-West), the total proportion of train passengers benefiting from these transfer opportunities is presumably lower than in the Maastricht intercity case, where a single train transported 65% of all travellers. Connecting to the 3600-East train automatically prevents attractive transfer times to other important train services, explaining the lower relative importance.

The lower significance level is likely related to these dispersed transfer possibilities. Whereas Maastricht has a single domestic intercity connection, resulting in a clear focal point in the timetable, Breda is served by five intercity services. Consequently, the influence of transfer opportunities on ridership is likely more diffuse across stops and bus lines. The effects that the transfer possibilities have on ridership are therefore more varied over the stops and lines and less pronounced, resulting in a less confident result.

8.2 Remaining attributes

Compared to the Maastricht results, some variables that were previously insignificant now show a significant effect, while others that were significant no longer do. In addition, most predictors saw a shift in parameter magnitude. Meanwhile, three variables stayed relatively equal; *central station*, *students* and *income*.

Factors that do not significantly influence ridership in Breda are *population*, *elderly* and *socio-cultural land use*. Of these, *population* is the most remarkable, since it is expected that densely populated catchment areas supply relatively more transit passengers. This change in significance level can be explained by other attributes being more important. For example, a stop located in a densely populated area may still experience low ridership if it is served by a line with a slow connection to the central station and poor transfer opportunities, despite the high underlying demand potential.

The lack of a statistically meaningful effect in the percentage of elderly residents suggests that older demographics do not show different travel behaviour from other age groups in Breda. For *socio-cultural land use* an explanation can be found in most socio-cultural facilities being located at stops in the city centre or next to local shopping centres, meaning that an increase in ridership is already explained by those variables.

The estimators that now yield significant parameter estimates, while they did not in Maastricht, are the frequency and the travel time to the station. The negative parameter for frequency indicates that stops served by multiple bus lines have a lower ridership *per bus line*. This observation suggests that passengers are dispersed over the higher supply of bus services at high-frequency stops. Nevertheless, other justifications can be found as well.

The first is the presence of competing regional bus lines. While there are fewer shared segments in Breda than in Maastricht, the shared trajectories that do exist in Breda are often also shared with regional bus lines, which mean that the actual dispersion is even higher than explained by the observations in this model, since the regional lines are not included. Such an effect would be less prevalent in Maastricht, where there are much fewer regional services.

Another explanation is the looped structure of the network, which means that the termini of the bus lines have twice as many travel possibilities to the station as the other stops on the line. These terminal stops are not necessarily situated in areas with high travel demand, which results in stops with higher frequency showing a decrease in ridership. These two factors offer a reasonable explanation for why frequency has a significant negative effect in Breda but not in Maastricht.

The other attribute newly demonstrating both a substantial effect and statistical significance is the travel time to the station. For every additional minute of travel time, a decrease of 3.5% in passengers is estimated. This observation can be attributed to stops located beyond the distance passengers are typically willing to travel by bus to reach the station in Breda. In Maastricht, the longest travel time to the station was 24 minutes, whereas in Breda, it extends up to 37 minutes, suggesting that such an upper limit exists between these two durations.

Finally the two binary variables indicating the presence of the city centre or the shopping centre are discussed, due to a noticeable shift in their parameter estimates. The city centre stops exhibit a smaller

Change in variable	Change in ridership
1% increase in population	+0.04%
1% increase in students	+0.16%
1 percentage point increase in elderly	-0.20%
€1000 increase in yearly income	-1%
Stop located at the central station	+1281%
Stop located in the city centre	+56%
Stop located next to local shopping centre	+125%
1 percentage point increase in socio-cultural land use	+0.62%
1% increase in total number of passing buses	-0.32%
1 additional minute travel time to central station	-3.41%
Transfer possibility to the 3600-East train	+23%
Transfer possibility to the 1100-East train	+12%

Table 8.2: Interpretation of the coefficients

effect on ridership compared to Maastricht, which can be attributed to the closer proximity of the train station to the city centre, which makes it less likely for people to travel between the city centre and the station by bus.

The higher ridership observed at local shopping centres in Breda may be caused by a presence of additional passenger-attracting facilities at these locations, which were possibly absent in Maastricht. Alternatively, these stops may serve more populated catchment areas, which could also explain why the *population* variable itself was not statistically significant.

In summary, although the model yielded different coefficient estimates and is therefore not directly generalisable to other areas, the selected parameters still produce a comparable model fit and provide meaningful insights, showing potential for applying this method in other areas as well. An overview of coefficient interpretations is presented in table 8.2.

8.3 Conclusion to sub-question 3

These outcomes can now be interpreted to form an answer to the third sub-question *"Are there regional differences between bus networks in the effect of transfer time on ridership?"*. Regional differences were certainly observable for both the transfer-related attribute and the other predictors. This variation is inherent for the transfer variables specifically, due to the different train schedule in Breda. In detail, the influence of transfer possibilities is weaker in Breda than in Maastricht, which can be attributed to the more diffuse train connections. An overview of these important characteristics is included in table 8.3.

Table 8.3 shows that transfer coordination is more important in scheduling for networks where the transport flows are less equally distributed across trains. Nevertheless, a clear positive effect is observed for at least one bus-train transfer relationship in both cases, where improved layover opportunities are associated with increased bus ridership. This finding confirms the presence of a synergistic relationship between train and bus use.

Aspect	Maastricht	Breda	Comparison
Number of train services	7, of which only 3 transport over 90% of passengers	9, of which most serve important destinations	Breda has more trains of relatively equal importance, while in Maastricht the passenger flows are centred around one train.
Number of intercity services	1	6	Breda is served by many intercities in many directions, whereas Maastricht only by one
Train timetable	Intercity departures and arrivals occur simultaneously	The train arrivals and departure are more spread out, but within a 15 minute interval	In Maastricht there is one important time stamp to connect to, while in Breda there are more options.
Interval attracting most passengers	:05-:12 (departing buses) or :19-:26 (arriving buses)	:15-:22 (departing buses) or :08-:15 (arriving buses)	In Breda the intervals for arriving and departing buses almost overlap. In Maastricht there is no overlap at all.
Associated increase in passengers	36%	23%	In Maastricht the increase associated with attractive transfers is higher.

Table 8.3: An overview of the most important differences between the Maastricht and Breda situations.

9 Practical application of the model

To show how the model can be used in network redesign, two planned route alterations are assessed using the results of this research; one for Maastricht and one for Breda. In Maastricht, a new line 11 will be introduced in August 2025, which connects stops that were previously only served by a mini-bus or the P+R-shuttle to the central station. In Breda, two line sections are combined into a single line to provide faster connections to the train station. First the expected ridership in Maastricht is estimated and subsequently the predictions for Breda are presented.

9.1 Maastricht: introduction of line 11

The current line 11 in Maastricht is a short circular line only serving parts of the city centre, which are not visited by other lines. The number of passengers on this line is relatively small, because there is only one stop uniquely served by the current line 11, and the other nine stops are located on the city centre corridor, where there is strong competition from other bus lines.

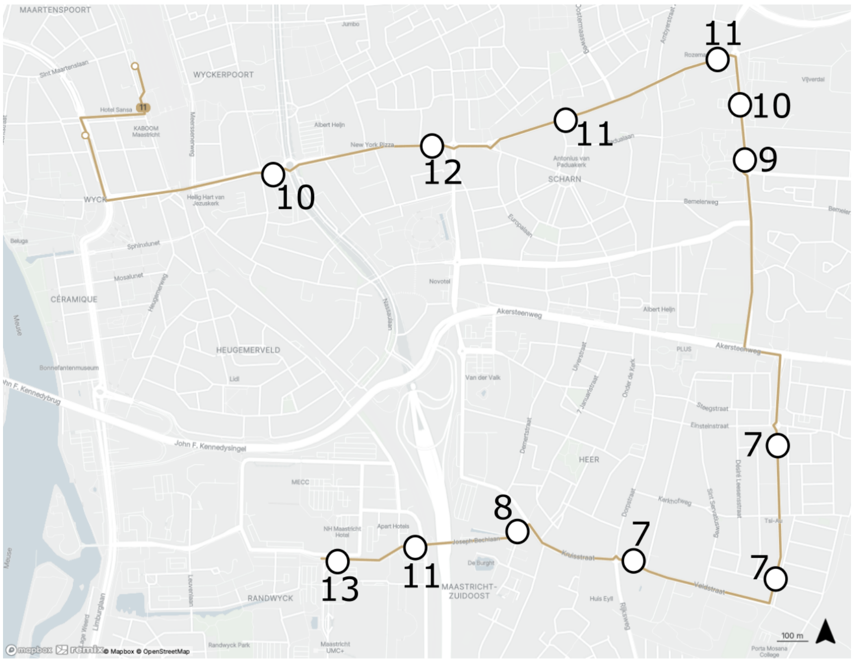


Figure 9.1: Ridership prediction for line 11 in Maastricht. Next to each stop the number of passengers travelling to the train station is predicted for weekdays between 7:00-19:00.

To more effectively use the operating resources, an entirely different line 11 is proposed. Currently in the residential eastern neighbourhood *Heer*, there are bus stops which are only served by line 10, which is a shuttle bus connecting the city centre with a P+R-facility. As a result, these stops are currently not connected to the train station, making the bus an unattractive option for local residents to access the train network. The proposed line 11 will drastically decrease the travel time to the station, and eliminate the need to transfer.

Additionally, the new bus line will pass stops which are now only served by line 8, which is a mini-bus with a very limited timetable. The introduction of a regular bus service is therefore also a service-level improvement for the residents around these stops.

Interestingly, line 11 provides an attractive transfer to the intercity train of 5 minutes. Therefore, line 11 is a good alternative for line 2-East, which also serves these neighbourhoods via a different route. Line 2-East, however, has very poor connections to the train.

Figure 9.1 shows the route of line 11, the stops that it will serve and the predicted number of passengers per stop that travel from the station on weekdays between 7:00-19:00. The method using the binary indicators for a transfer is used, and for the random intercept, the value of line 7-East is used, due to the similar service-level and route characteristics. The total number of attracted riders is 115, which is more than the 78 daily passengers that the current line 11 attracts. In the new situation, these 78 passengers can distribute themselves over the other lines, since the current line 11 almost completely overlaps with other lines. The single stop uniquely served by line 11 currently, will be taken over by line 3, whose route will therefore be slightly adjusted.

In conclusion, few passengers are expected to be lost by this network change. The predicted number of new riders is 115, making this adjustment logical and favourable for the transport operator. The model results help in justifying this choice.

9.2 Breda: combining sections of line 2 and 4 into a new line 3

Starting from July 2025, the northern Breda district *Haagse Beemden* will see a change in bus service. Where currently two lines serve the neighbourhood, line 2 the slow route through the city centre and line 4 the more direct option, in the new situation three lines will transport passengers from the Haagse Beemden to the train station, lines 2, 3 and 4, each with an adjusted itinerary.

The current line 2 is the longest route in the network, with up to 37 minutes necessary to reach the station. In the new situation, the connection between the train station and the current stops on line 2 is accelerated by taking over a section of the current route of line 4. The new route is called line 3, and the stops which are skipped by this route acceleration, are instead served by a different, new line 2.

(a) The current lines 2 and 4, with the ridership numbers for the stops that will be served by the new line 3

(b) The predicted ridership numbers for the new line 3

Figure 9.2: Current and predicted number of passengers travelling to the station on weekdays between 7:00-19:00

Figure 9.2 shows the current and new situations. Most stops see an increase in ridership, attributable to the shorter travel time to the train station. The transfer possibilities remain unchanged. Compared to the current situation, 70 more passengers will use the stops on line 3. In total, the new line 3 is expected to attract 130 passengers travelling to the station. This number is less than for the current line 2, which is used by 164 passengers, despite almost all stops expecting a surge in passenger numbers.

This discrepancy is caused by the eight stops of the current line 2 which will be skipped by line 3. These stops serve important locations, such as the city centre. As a replacement, the new line 2 will still pass by these stops, meaning that there is effectively no deterioration in service-level for station-related travel.

While the bus line itself will become less crowded, the ridership per stop is predicted to increase. Due to the benefit for riders, a positive recommendation can be given for this network adjustment. The introduction of this new line 3 is associated with 70 more passengers, which can be compared with additional resources required to operate this additional service.

10 Discussion

This study was lead by the objective of increasing bus ridership on urban bus networks by studying the potential of improving bus-train connections at the train station. The research question formulated to address this objective is *"What is the influence of train-bus transfer times on bus ridership?"*. Since this influence can be broken down into multiple aspects, three sub-questions are defined, for which the main findings will be summarised first before moving on to the reflection and final conclusion.

10.1 Main Findings

10.1.1 Sub-question 1: transfer time implementation in the model

The first sub-question is *"How can transfer times accurately be defined, calculated and implemented as a predictor in a direct ridership model?"*. The transfer time is *defined* as the scheduled time difference between arrival of the bus and departure of the train (or vice versa), as long as this difference exceeds five minutes, which is seen as the lower time limit for a feasible transfer. The *calculation* of the transfer time requires collecting the standard timetable arrival and departure times of both bus and train. To *implement* the transfer time in a direct ridership model, a train with a high presumed passenger volume is selected. Consequently, a given bus line is assigned a binary variable, valued 1 if the transfer time with the selected train falls within the time interval of 5-12 minutes, and 0 otherwise. This variable represents the existence of an attractive connection between bus and train.

This method is appealing due to its applicability across different networks and the consistency of its results with theoretical expectations. To *apply* this method to different networks, the necessary steps involve identifying a train service with high travel demand, and analysing the synchronisation of the bus schedule with that specific train. Subsequently, the implemented binary variable associated with the most important train, showed a significant positive effect on bus ridership, in line with expectations. Facilitating a connection between bus and train of 5-12 minutes is therefore suggested to increase the number of passengers in the bus, which is *consistent* with the intuitive appeal of short and convenient transfers. These two reasons make this approach favourable over the alternative tested methods, which used an average transfer time or the transfer time in minutes for each train separately.

10.1.2 Sub-question 2: comparison of time windows

After identifying the most useful approach to implementing transfer time as a predictor in a direct ridership model, this model was applied to data pertaining to varying times of the week. This comparison enables understanding whether the transfer effect is constant across all time periods. The sub-question guiding this component is *"To what extent is there variation between the different times of the day and week in the effect of transfer time on bus ridership?"*. The compared temporal regimes are daytime, evenings, Saturdays and Sundays.

Variation was observed between all periods. Whereas the increase in passengers associated with a connection to the intercity train was estimated at 36% for weekdays during daytime, in the evening no statistically meaningful effect was observed. Saturdays showed an increase of 43%, which is comparable to weekdays, but Sundays experience a sharp increase of 65% more bus passengers for lines providing an attractive connection to the intercity trains. These results indicate that the potential to increase bus ridership by improving bus-train transfers is not uniform across all times of the day and week.

10.1.3 Sub-question 3: comparison of study areas

Since changes in transfer effects were observed across different time periods, the point is raised whether their influence also differs across different networks, leading to the final sub-question: *"Are there regional differences between bus networks in the effect of transfer time on bus ridership?"*. The comparison of study areas yielded a similar relationship, despite the differing magnitude of the effect.

In both Breda and Maastricht, a positive influence was observed for buses connecting to a heavily used train. However, the estimated increase was lower in Breda (23%) than in Maastricht (36%). This disparity is likely explained by a greater dispersion of passengers across the diverse train services in Breda, indicating that the effect is also influenced by the train scheduling at a station.

The comparison of the two study informs that transfer effects are more pronounced in networks where the transport flows across train is less evenly distributed and where there is less variation in departure and arrival times of trains.

In conclusion, although the specific influence of transfer possibilities on bus patronage appears to be location-specific, the general pattern is clear; desirable transfer times (between 5-12 minutes) are associated with increased ridership.

10.1.4 Answer to the research question

This study examined the influence of train-bus transfer times on bus ridership, guided by the research question *"What is the influence of train-bus transfer times on bus ridership?"*. The analysis concluded that a positive effect is observed for transfer times falling in the 5-12 minute interval on passengers travelling to and from the station. However, this effect was not equal across all time periods and the two studied networks. These findings collectively indicate that **enabling convenient transfers between bus and train is essential in attracting bus riders travelling to or from the train station**, despite the temporal and regional variations.

This conclusion confirms the findings by Schakenbos et al. [2016] and Bovy and Hoogendoorn-Lanser [2005], who state that passengers are more likely to choose the bus when the transfer time is attractive. While these previous studies used stated choice survey data to come to their conclusion, this research observed a similar effect using data of actual travel patterns.

10.2 Implications

From these findings both scientific and practical implications can be drawn. The first scientific implication is that separately modelling bus lines at each stop, specifically using multi-level regression, enables the explanation of ridership using relatively few variables. In addition, endogenous variables like frequency and stop amenities can be excluded, while still maintaining adequate performance.

Second, this approach enables the inclusion of detailed timetable-dependent attributes, like transfer time. These predictors were found to have a significant effect, and therefore provide insight in the varying appeal between bus lines.

Third, transfer time was not the only factor explaining variation in the number of passengers travelling to or from the stations, implying that other aspects of access or egress travel can be influential as well. In-vehicle travel time was found to be significant in some instances. Besides, walking time to the stop, price and convenient access to the train platforms must be considered when aiming to attract more accessing and egressing train passengers to the bus.

This last implication can be of importance to a transport operator, like Arriva. A few additional practical inferences can be drawn from the results of this study. Most importantly, the higher ridership associated with bus lines with good train connections implies that providing appealing transfers is important in attracting passengers.

Despite the importance of appealing transfers, it is important to note that only a subset of all riders are potentially benefitted by improved coordination. The share of passengers using the train station as origin or destination was 45% in Maastricht and 69% in Breda. The remaining share trips, those made entirely within the city with no possibility of transferring to the train, are not modelled in this research.

Presumably, this group of riders is influenced by other service level characteristics to travel by bus. As a result, schedule adaptations in favour of better train connections, should be assessed on their associated benefit for non-station-related travel. If better train connections result in longer travel times to the city centre or a transfer required to reach important locations, more passengers might be lost than gained.

The exact increase in passengers associated with transfer possibilities differed per location. In Maastricht, the transfer effect was stronger than in Breda, which was explained by the dominance of one train service in Maastricht as opposed to the more diffuse train connections in Breda, implying that transfer-focused planning is more useful in some cities than others. For the networks operated by Arriva, the cities Heerlen, Enschede, Hengelo and Almelo have the most similar transit characteristics to Maastricht in terms of train services.

10.3 Practical recommendations

The previously stated implications can be translated into practical recommendations for transport operators and transport authorities. The recommendations are divided into general and more case-specific public transport-related measures.

10.3.1 General recommendations for transport operators

The established synergy between train and bus ridership emphasises the importance of establishing transfer connections with a duration between 5 and 12 minutes. At each of the two studied train stations, one train was identified that had the highest potential in attracting passengers. Buses should therefore be scheduled in such a way to maximally connect to the most important train at a station.

The developed method can additionally be used for data-driven decision making in network redesigns, as was shown in the practical applications of the previous chapter. The modelled change in passengers can be used in a cost-benefit analysis to decide whether the cost associated with service level improvements pays out in higher ridership. Conversely, efficiency improvements which harm transfer opportunities can be compared to the expected ridership decrease. Additionally, the use of externally available factors enables the transport operator to model travel behaviour in areas where detailed origin-destination data is unavailable. This insight can subsequently aid in proposing new routes and schedules for tender bids.

Another recommendation includes identifying competition between bus lines using the model. If two bus lines are found to be more substituting than supplementary to each other, resources are used inefficiently. Discovering such instances therefore helps in planning a more efficient schedule and network.

10.3.2 General recommendations for transport authorities

Transport authorities can also aid in ensuring attractive bus services for train travellers. By demanding guaranteed connections from the transit operators, train passengers can more reliably depend on the bus for their first- and last-mile transport. A guaranteed connection entails forcing the buses to wait a limited amount of time in case the train is delayed.

Authorities can also guide the improvement of transfer quality in general. Station layout, way-finding and information supply is not the responsibility of the transport operator solely. For these aspects, governmental agencies can enforce enhancements benefitting the public transit traveller by means of convenient transfers.

A final recommendation addresses the pricing of public transport. In the Netherlands a base fare is charged for a trip. When transferring bus-bus or train-train, this boarding fare is not charged twice, as opposed to bus-train transfers. Integrating the tariff systems of both networks can make it more appealing to use the bus as first- or last-mile transport.

10.3.3 Case-specific recommendations for Breda and Maastricht

This section provides practical recommendations for both Maastricht and Breda, based on the analysis of transfer connections and the current timetables.

When studying the 45% share of passengers with the train station as origin or destination in Maastricht, a strong transfer effect is observed. However, when considering all passengers, buses with weak transfer connections are not less crowded in general, as can be seen in appendix D. In the current timetable, the buses with no transfer opportunities have the important function of increasing frequency on corridors with high travel demand. Adapting the schedule so these lines connect as well, would cause redundancy and lower frequency on these corridors.

Only two main residential areas currently lack a good connection to the intercity, Scharn and Heugem. However, rerouting services to improve their access would interfere with existing vehicle charging schedules and with transfer connections at other points in the network. As such, improving station connections would likely require increasing service frequency, which entails deploying additional vehicles.

Given the relatively small proportion of train passengers among total bus users in Maastricht, it is not recommended to implement major changes to the current network configuration. Nevertheless, this relative small share might indicate that there is untapped potential in attracting more train passengers. Other measures to attract train passengers to the bus besides improving transfers would be tariff integration, guaranteed connections in the case of delays or more direct routes to the most prevalent origins and destinations of train passengers within the city of Maastricht

In Breda, the consistently high bus frequencies generally ensure that a transfer opportunity to the train is always available, reducing the need for schedule adaptations. However, on many bus lines frequencies are halved during holidays and weekends. Based on the current findings, if service reductions are necessary, it is advisable to maintain the trips that offer a connection to train service 3600-East, as these appear to provide the most meaningful transfer utility.

10.4 Model reflection

While these recommendations are promising for transport operators and authorities, reflections upon the model are necessary to uncover any directions of improvement. The reflection is done by comparing the model in this research to similar applications in previous literature.

This study employed an approach, where ridership was modelled separately for each line at the same stop, instead of all ridership at one stop combined. This method has previously been used in Buffalo, United States by Wang and Park [2024], however, their model did not account for scheduling variables and intermodal connectivity. The omission of such variables may partly explain the substantial difference in pseudo-R^2 values between this study and theirs (0.77 vs. 0.25, respectively).

Nonetheless, such a large discrepancy is likely also attributable to other factors, including geographic context and methodological differences. The high R^2-value in this study is mainly attributable to the high importance of the station variable, which is unsurprising due to the focus on train transfers. Other explanations are the lack of any socio-demographic variables in the study by Wang and Park [2024], underlining the need to include both geographic and service-level variables.

Two advantages were identified for modelling each line separately. First is the small number of variables necessary to produce significant results. In this study twelve predictors were included in the model, of which not all where significant in every context. In contrast, the similar study by Kerkman et al. [2015] used eighteen independent variables.

Another advantage to modelling ridership at the stop-line level, is the reduced influence of the endogenous variable *frequency*. In traditional models, the high explaining power of this variable is attributable to the two-way relationship between ridership and frequency. As a result, predicting demand on new or hypothetical lines becomes inaccurate, since such feedback loops do not yet exist.

In this model, all observations had a frequency of two buses per hour, reducing this endogeneity concern. However, it remains unclear how the presence of multiple observations at the same stop reflects ridership. In some cases, it might increase, due to the appeal of the combined high frequency. On the other hand, travellers distributing themselves across the multiple available services decreased the passengers per line. Whether either of these effects apply, is likely dependent on the underlying travel demand.

The underlying travel patterns also play a role in estimating the transfer effect altogether, most visibly in the *evening* model. Later in the day, egress travel is more predominant due to passengers returning home. Transfer times for outbound buses from the station are therefore presumed to play a more influential role in the evening. However, the current model does not differentiate for the varying travel flows during the day, and is therefore not equipped to understand the transfer effects equally well for all time periods.

Besides these strengths and weaknesses, there is also some ambiguity in interpreting the model outcomes that should be considered. Due to the absence of data measuring the precise number of passengers transferring between a specific bus and train, it remains unclear whether the additional passengers, associated with improved transfer connections, indeed originate from or are destined for the train. Given the synchronised timetables, the periods surrounding train arrivals and departures tend to be the busiest at stations, which also increases the likelihood of passengers transferring between bus lines rather than between bus and train.

10.5 Limitations & further research

Still, some limitations were observed that provide leads for further research and improvements. The constraints are mainly related to the accurate estimation of passenger numbers, a more detailed understanding of transfer mechanics and the generalisability of this research to other study areas.

10.5.1 Model improvement

There were several instances in which the model failed to fully explain ridership. To apply this approach to make predictions for network redesigns, it is desirable to most accurately predict changes in passenger numbers. For this reason, a few shortcomings are listed together with possible ways to solve them.

The first constraint was the lack of data on retail spaces and job opportunities, which is why binary variables were introduced for shopping centres and the city centre. However, not every shopping centre has the same pull factor, which can be dependent on the size of the stores or their quantity. Working locations such as offices and industrial zones may also attract passengers, but the exact number remains unknown.

Despite this lack of data, from a network development standpoint, the current approach provides enough insight. Clearly, the shopping centres and city centres attract more passengers, underpinning the importance to serve them by bus. How many passengers they attract exactly is less important, as long as they remain accessible.

While this lack of data on commercial spaces mainly relates to transit demand, transit supply can also be described in greater detail to improve the model. Transfer opportunities often provided a logical explanation for differences in ridership between bus lines, but several line sections showed unexpected travel behaviour. These anomalies suggest that other attributes may affect the attractiveness of a specific bus line relative to others, such as punctuality or headway.

Relative headway can serve as a replacement to the *frequency attribute*. If two buses drive shortly behind one another, the second bus is likely to serve fewer passengers, since there is less time for additional passengers to gather at the stop. This difference in headway might also explain variation in ridership on for example 10/20-minute interval corridors, where the first bus after the longer interval likely attracts more riders.

In addition to the competition between bus lines, the individual bus stops are also expected to compete with each other due to overlapping catchment areas. This overlap results in certain residents being counted multiple times if they fall within the catchment zones of more than one stop. While this issue could be addressed by assuming that individuals always walk to their nearest bus stop, such an assumption may not reflect actual behaviour. In reality, passengers may choose to walk farther if doing so leads to a shorter overall travel time, by walking to a stop with more favourable transfer connections, or a shorter in-vehicle travel time.

In summary, the choice of bus stop and line is also important in ridership modelling, which is why it has been included in transport models before [Brands et al., 2014]. A possible research direction is exploring the extension of direct ridership models to account for this competition between stops and lines.

More accurately estimating travel demand around a bus stop can be done in more ways than only accounting for the overlapping catchment areas. Following the street network to shape the catchment area would reflect more accurate walking times [Montero-Lamas et al., 2024]. Similarly, distance-decay effects may also be present in the popularity of a bus stop [Gutiérrez et al., 2011]. Finally, the catchment radius may also be dependent on the service level of the bus stop [Brand et al., 2017]. Developing a sub-model to more accurately define the catchment areas can therefore be a promising improvement.

The previous suggestions mostly discussed the selection and collection of attributes. A different direction of further research could be the exploration of other statistical methods. While the influence of possibly endogenous variables was reduced in this modelling approach of this research, it cannot be stated with absolute certainty that endogeneity has been eliminated.

Still, frequency continued to show some explaining power, for which the alternative variable relative headway was previously proposed. In addition, the transfer variables might be subject to some levels of endogeneity as well. For a transport operator, ensuring that favourable connections are provided for at least the high-demand services seems as a logical planning principle. That said, high-demand corridors are often also served more frequently, for which this model corrects and distinguishes the separate bus lines.

These arguments show that it is inconclusive whether there is bias in the results stemming from endogeneity. Therefore, it might be useful to test whether models designed to resolve endogeneity, such as the two-stage least square regression method shows any improvements. Aston et al. [2021] encountered issues in determining suitable instrument variables. Similarly, there is not an obvious choice for an attribute that is correlated with transfer time but exogenous with respect to ridership.

An option would be, when studying daytime ridership data, to use the transfer times from a different schedule (such as evening or weekend) as an instrument. While transfer times vary during the week, some key planning principles ensure that the variation for many lines is negligible, resulting in high correlation between daytime and evening transfer times. Therefore, if daytime riders do not base their mode choice on evening or weekend transfer times, they can be used as an instrument in a two-step least square model.

Together, these suggestions for other variables, different catchment area calculations and more complex statistical methods provide various directions for further research and improvements in the applicability of the model.

10.5.2 Improved insight in transfer mechanics

One demonstrated use of the model is to explain passenger numbers. In addition, the relationship between transfer time and ridership was determined. For Maastricht, the resulting effects were -2.3% riders for every additional minute of average transfer time or a 36% increase in case the transfer time with the intercity train was within the 5-12 minute interval. While these numbers are a useful indication of the influence of train connections on ridership statistics, there are reasons to suspect that the precise relationship is more complex.

One of these reasons is the non-linear effect that Schakenbos et al. [2016] established between transfer time and travel utility on one hand. The other is the possible dependence of the precise duration of the feasible interval on other factors.

Schakenbos et al. [2016] found that the optimal transfer time between train and bus is 8 minutes. In addition, decreasing utility was observed for shorter times up to 3 minutes, and for longer times up to 15 minutes. While this observation means that a similar pattern is to be expected in ridership numbers, the limited variation in arrival and departure times in the data set made it difficult to uncover the precise relationship. This lack of variation is a result of the planned synchronisation in the timetable, which is why a flat interval of 5-12 minutes was chosen. Further research could investigate the non-linearity of the relationship between transfer times and bus ridership, to study any differences between a transfer of, for example, 5, 8 or 12 minutes.

Besides, the exact limits of this time window can also be studied in greater detail, since they can be dependent on contextual factors. The lower limit is partially influenced by the arrival punctuality of the first mode [Lee et al., 2014]. In the Maastricht case, many buses had a 4 minute transfer time to the regional trains, which based on the 5-12 minute assumption are considered infeasible. However, if these trains run reliably and punctually, such short connections may be more viable than presumed.

The feasibility of short transfers is additionally influenced by passenger demographics. More mobile travellers may find brief transfers manageable, while others, such as elderly passengers, are likely to prefer longer layover times to accommodate their walking pace and comfort.

Not only is the minimum transfer time context-dependent, the maximum time might vary as well. For example, travel purpose is a factor in transfer-related travel utility [Schakenbos et al., 2016]. Similarly, Nielsen et al. [2021] and Arentze and Molin [2013] concluded that it is important in access/egress mode choice as well. For a daily trip to work, efficiency is valued more as opposed to a recreational journey, where a more relaxed pace is preferred.

A final variation in acceptable transfer times can be linked to the total travel time of the journey. Krygsman et al. [2004] state that the maximum access and egress time is determined by the duration of the main leg of the trip. Specifically, long-distance travellers are more willing to accept longer transfer times.

In parallel, temporal variation in travel behaviour presents further opportunities to refine the understanding of transfer mechanics. This study only distinguished between weekday daytime, evenings, Saturdays and Sundays, yet a more segmented approach might provide insight in differences between peak and off-peak, and across the different business days. However, the practical benefit of these detailed insight must be balanced against operational feasibility, as adapting timetables to account for every small temporal variation results in irregular schedules which may reduce overall passenger satisfaction.

These contextual factors do not merely pertain to the traveller's preferences or service performance. Geographic specificity was also found to be important in the validity of the results. For this reasons, the generalisability of the method in this research is discussed in the following paragraphs.

10.5.3 Generalisability

This research studied two mid-sized Dutch cities with one central station facilitating transfers between the bus and train network. Other more sizeable cities can have multiple intercity stations, where transfers are possible at different locations. In such cases, the design of transfer-related variables would be more complex, and travel patterns on a more regional level should be accounted for, which is difficult in direct ridership modelling. Nevertheless, Arriva mostly operates in cities with a single intercity station. These cities are often also serve by smaller suburban stations, which are assumed to affect ridership negligibly, due to the very limited transfer possibilities. Given the networks that Arriva operates in the Netherlands, the model remains applicable to various other urban bus networks operated by the commissioning company of this study.

An extension of this method would be to estimate ridership on regional lines as well. While the influential attributes are presumably different for stops in more peripheral regions, the disutility of long transfer times likely persists. One remark is that studying a study area on a larger scale requires more closely examining travel patterns.

For example, suppose village A is served by two regional bus lines; one bus to city B and another bus to city C. In addition, cities B and C are connected with each other by train. In that case, it is not necessary for the bus to city B to transfer to a train towards city C, since passengers from village A can directly take the bus to city C. These connections on the higher regional level therefore pose additional difficulties.

While there are several instances in which the method of this research can be applied as well, the generalisability is restricted by the required repeating invariant timetable. In the Netherlands, all trains have a base frequency of 2 per hour, and most buses follow that pattern to optimally accommodate transfers. In regions where train and bus services are less frequent, such transfer mechanics might be absent altogether, limiting the benefit of including transfer-related variables in ridership modelling.

On the other hand, in major urban centres where transit services are highly frequent, transfer times might have reduced explaining power as well. In high service networks, transfer times are consistently short and the willingness to transfer is rather influenced by other factors, such as station amenities and information supply [Nielsen et al., 2021].

In conclusion, generalisability is constrained by the presence of a single transferring node in the network, moderately frequent transit services and invariant repeating timetables.

11 Conclusion

This study was conducted to explore the effect of train-bus transfer time on bus ridership in urban multimodal networks, to explore the potential in increasing bus ridership by improving connections to the train. By applying a multi-level regression model to two Dutch cities, Maastricht and Breda, it examined how the convenience of transfers influences the number of passengers boarding urban bus lines.

The findings demonstrate that attractive transfer times are associated with higher ridership, confirming the importance of well-coordinated multimodal connections. Among three tested methods to include transfer time in the model, a binary indicator setting a transfer as attractive when the transfer time falls within a 5-12 minute time window, proved to be the most useful. This method allowed transfer quality to be easily assessed across time periods and locations.

Applying this method revealed a temporal variation: transfer times had a stronger impact on weekends than during weekday daytime. For evenings, the model was unable to capture a transfer effect due to the inability of the model to account for common travel patterns. This comparison suggests that planning objectives may vary over the time periods.

Lastly, comparing the two networks showed that while train-bus synergy was observed at both locations, the strength of its influence varied. These differences underline the importance of local context in focusing bus scheduling around train connections. Stations which are served less frequently by train require a more synchronised bus schedule to maximally attract passengers.

Two practical applications of the model showed that proposed network adjustments in the study areas are expected to increase ridership, supporting the usefulness of direct ridership modelling in public transport planning,

In summary, this research confirms that train-bus transfer time is a significant and previously underexplored factor in influencing urban bus ridership in networks centred around a train station. Ensuring favourable connections to the train improves multimodal integration and attracts more passengers to public transport.

A Shopping centre stops

Stop name	lines
Roserije	1, 2
Herculeshof	5, 6, 15
Malbergplein	1, 2, 4
Dr. Bakstr./Brusselse Poort	4, 5, 6, 15
Clavecymbelstr./Prestantstr	7

Table A.1: All stops serving a local shopping centre in Maastricht

Stop name	lines
Dr. Struyckenplein	4
Heksenwiellaan	2, 4
Heerbaan	5, 7
Stadion NAC	2
Valkeniersplein	7
Groenedijkplein	1, 2
Alexberg	2
Groot IJpelaardreef	1
Brabantplein	5, 7
Donk	4

Table A.2: All stops serving a local shopping centre in Breda

B City centre stops

Stop name	Stop code	lines
Boschstraat/Markt	66590130	all
Mosae Forum/Centrum	66590440	all
Koningin Emmaplein	66590320	1, 2, 3, 5, 6, 9, 15

Table B.1: All stops serving the city centre in Maastricht

Stop name	Stop code	lines
Centrum	72005580	2, 4, 7
Centrum	72005570	2, 4, 7

Table B.2: All stops serving the city centre in Breda

C Student data

Stop name	School	No. of students
MUMC	Maastricht University faculty of Health, Medicine and Life Sciences	4914
Endepolsdomein	Maastricht faculty of Science and Engineering, faculty of Psychology and Neuroscience	5515
Sibemaweg	VISTA college	1433
Scharnerweg	VISTA college	1433
Brusselsweg/Zuyd Hogeschool	Zuyd Hogeschool	4850

Table C.1: Stops serving institutes of higher education, with number of students taken from DUO [2024].

Stop name	School	No. of students
Fellenoordstraat	De Rooi Pannen	1610
Centrum	Curio	297
Nassausingel	Curio	1616
Lelystraat	Curio	758
Lovendijksstraat	Avans	14040
Biesdonkweg	Curio	3283
Verviersstraat	Curio	758
St. Ignatiusstraat (to station)	BUAS & Curio	8616
St. Ignatiusstraat (from station)	BUAS	7000

Table C.2: Stops serving institutes of higher education, with number of students taken from DUO [2024].

D Boarding passengers per line Maastricht

Line segment	No. of passengers	Transfer to IC
15 West	1088	No
1 West	986	No
5 West	985	Yes
2 West	932	Yes
1 East	861	Yes
6 West	836	No
4 West	817	No
15 East	788	Yes
5 East	705	No
2 East	645	No
7 West	618	Yes
6k East	539	Yes
4 East	523	Yes
7 East	498	No
3 West	443	Yes
6 East	376	No
3 East	324	No
6k West	157	No
9 East	146	No
9 West	121	No

Table D.1: The average total number of boarding passengers per line between 7:00-19:00 in Maastricht, also counting non-station-related travel

E Scientific article

Filling buses with train passengers: How train connections influence bus ridership

Kristian Terlien[a]

[a]*Delft University of Technology, Netherlands*

Abstract

This study investigates how transfer times between bus and train affect bus ridership in urban networks, with the aim of identifying strategies to increase bus use through optimised intermodal connections. Using a multi-level direct ridership model applied to two Dutch cities, Maastricht and Breda, the research examines three aspects: optimal implementation of transfer time in models, variation across time periods, and regional differences. A binary variable indicating whether the transfer time to a high-demand train fell within a 5–12 minute window was found to be the most effective predictor, significantly correlating with increased ridership. The transfer effect varied by time period, and differed between cities, likely due to differences in bus frequency and underlying travel patterns. The modelling approach addresses endogeneity concerns by fixing bus frequency and focusing on less demand-responsive variables describing multimodal transfer quality. While the method offers valuable insights using limited data, its generalisability is constrained to contexts with regular, repeating timetables and networks centred on a single transfer hub. The findings emphasise the importance of transfer coordination in attracting bus passengers and provide a structure for evaluating schedule or network changes.

Keywords: bus ridership, transfer time, bus-train transfer,

1. Introduction

Urban public transport plays a vital role in ensuring accessibility, sustainability, and efficient urban mobility. In the Netherlands, around 1.2 million bus trips are made each day (CROW, 2024). Buses help reduce car dependency and support equitable, environmentally friendly travel (van Oort et al., 2017). However, full and well-occupied buses are crucial for maintaining both cost-effectiveness and the societal benefits of the bus network. In recent years, urban bus ridership has been slow to recover to its pre-pandemic levels in the Netherlands (de Haas, 2023; Arriva, 2023), partly due to competition from cycling, particularly in cities where distances are short (Ton and van den Heuvel, 2023).

One opportunity in drawing more passengers lies in making it more attractive for a train passenger to travel to or from the train station by bus. Train passengers already depend on public transport, so they are presumably predisposed to using it for the first/last mile as well. In addition, most urban networks are mainly planned around a train station, resulting in bus riders being naturally funnelled to the train station, making the bus a logical and attractive choice for access and egress transport, even more so than for other types of bus trips. For these train travellers, transfer time can be a crucial factor in choosing the bus as first- or last-mile transport (Schakenbos et al., 2016). Still, it remains unclear to transport operators whether better alignment between buses and trains truly leads to more passengers. To obtain insight into this relationship, variables describing transfer quality should be used to explain bus ridership.

Many studies have previously attempted to model bus ridership, identifying key factors such as population density, service frequency, and land use (Chu, 2004; Dill et al., 2013; Kerkman et al., 2015). However, a common challenge in these studies is endogeneity, since service quality is often a response to high demand, rather than a pure explanatory variable. This issue makes it difficult to interpret the true effect of service-related factors in conventional regression models that aggregate ridership at the stop level.

One way to address this endogeneity issue is by incorporating variables that are less likely to be adjusted in response to demand, but still reflect service quality from the passenger's perspective. Transfer time between train and bus is one such variable. It captures the quality of multimodal coordination and may help explain ridership patterns without being directly influenced by demand. Additionally, since transfer times vary between individual bus lines serving the same stop, using this variable warrants a disaggregated modelling approach, estimating ridership at the line-per-stop level rather than aggregating frequency across all lines. This adjustment enables the uncovering of any transfer-related effect on ridership between lines, and the estimation of the explanatory power of service-related factors beyond frequency alone.

While various service and land-use variables have been studied, intermodal factors, such as transfer times between bus and train, are largely absent from ridership models. This absence may be caused by the difficulty of defining transfer quality in a consistent way as a single variable. Other complications include the dependency on fluctuating bus and train timetables, and variation in available transfer options between different stations and regions. These three challenges complicate the incorporation of specific transfer variables in direct ridership models.

To address this gap, this study introduces transfer time as a key variable in a direct ridership model, using a multilevel regression framework. By modelling ridership at the line-per-stop level, the model accounts for variation in transfer opportunities across bus lines and avoids some of the endogeneity issues associated with frequency. The multilevel structure also accounts for the hierarchical nature of the data, where observations from the same bus line segment are correlated.

While previous research has established that longer transfer times negatively affect travel utility (Bovy and Hoogendoorn-Lanser, 2005; Schakenbos et al., 2016), their quantitative impact on bus ridership has not yet been studied in detail. Longer transfer times increase perceived inconvenience and total travel time, which reduces the overall attractiveness of multimodal journeys involving buses. As a result, passengers may avoid itineraries that involve long bus-train transfers, leading to lower ridership on bus lines with poor connections to the train. To evaluate the validity of this assumption, this study analyses how transfer time affects the number of boarding passengers at bus stops in urban networks where trains and buses interact.

To do so, two urban networks in the Netherlands, pertaining to the cities of Maastricht and Breda, are analysed. In Maastricht, three different methods of modelling transfer time are tested to determine the most effective way to incorporate it into ridership models. This optimal method is then applied across four distinct time periods (weekday daytime, evening, Saturday, and Sunday) to assess temporal variation. Finally, the results from Maastricht are compared with findings from Breda to explore whether the effect of transfer time is region-specific. Together, these analyses provide insight into how better transfer coordination may contribute to restoring urban bus ridership.

2. Review of ridership models and transfer penalties

To investigate the effect of transfer times on bus ridership, it is important to gain understanding on transfer times and on the factors attracting passengers to bus. Previous literature has studied both topics in great detail. Therefore first a review is presented of the various ways in which bus ridership is modelled, followed by the findings on the effect of intermodal transfers on travel behaviour.

2.1. Ridership modelling

Understanding how to model bus ridership begins with an overview of previously used methods in transport studies. One of the more elaborated approaches is the 4-step transport model, which consists of trip generation, trip distribution, mode choice, and route assignment (Brands et al., 2014). While this method provides a detailed insight in travel demand, it often requires detailed survey data describing full travel chains, which limits its applicability when only stop-level data is available.

Another way to understand ridership is through the concept of elasticity, which describes how demand responds to changes in service level or price. van Oort et al. (2015) and De Lanoy (2019) have estimated elasticities of ridership with respect to frequency, showing how service improvements can lead to increases in demand. However, these approaches are typically suited for before-and-after studies and require previous network adaptations, which can subsequently be analysed. Since the bus-train connections have not significantly changed in recent years in the study areas, an elasticity-based approach is less suitable.

This study instead employs a direct ridership modelling (DRM) approach, which estimates the number of passengers at the stop level using externally observed attributes. DRM allows for the incorporation of new explanatory variables, such as transfer time, without requiring detailed trip chain data. As such, it forms a practical basis for the analysis conducted in this study.

2.2. Direct Ridership Models

Direct ridership models rely on statistical regression to predict passenger numbers based on variables such as land use, population, and service quality. Early studies used Poisson regression to account for the count nature of ridership data (Chu, 2004), but OLS regression gained popularity for its simplicity and interpretability (Ryan and Frank, 2009; Dill et al., 2013; Kerkman et al., 2015). In addition, log-transformations of the dependent variable were introduced to improve model fit (Dill et al., 2013; Kerkman et al., 2015).

Despite its advantages, OLS regression has some limitations. One major issue is endogeneity, where service variables like frequency are a result of high demand, instead of the assumed one-way relationship of high demand being purely a result of high frequency. Techniques like two-stage least squares (2SLS) regression can address this by using instrumental variables (Taylor et al., 2009; Estupiñán and Rodríguez, 2008), though identifying valid instrument variables, necessary for 2SLS, has proven to be difficult (Aston et al., 2021).

For this study, endogeneity is less of a concern, as the focus lies on transfer time, a variable less likely to be directly adjusted based on observed demand. Therefore, OLS remains a suitable method, although the required separate observations of lines at the same stop introduces dependency between observations. To address this possible source of correlation, a multi-level regression model is employed, similar to the study by Wang and Park (2024). The line-level variable transfer time is separated from the other stop-level attributes to prevent the underestimation of standard errors and overstated statistical significance of the line-level variable.

2.3. Determinants of ridership

Ridership determinants are generally grouped into three categories: socio-demographics, the built environment, and level of service. These variables are measured within a stop's catchment area, typically defined by a 400-meter buffer, which corresponds to the average walking distance accepted by passengers (Pulugurtha and Agurla, 2012; Kerkman et al., 2015). Though more catchment areas can be drawn based on the street pattern, studies show limited improvement unless significant barriers are present (Montero-Lamas et al., 2024).

Socio-demographic factors include population density, age, income, car ownership, and employment. Of these, variables counting the population in the catchment area are the most consistent strong predictor of ridership (Chu, 2004; Dill et al., 2013; Kerkman et al., 2015). In addition, low-income and car-free households are more likely to use public transport (Chu, 2004; Ryan and Frank, 2009).

The built environment affects ridership through land use and street design. Residential and commercial areas are positively associated with bus use, while industrial zones have a negative impact (Pulugurtha and Agurla, 2012; Kerkman et al., 2015). Distance to the city centre, and walkability are also important factors (Dill et al., 2013; Ryan and Frank, 2009; Kerkman et al., 2015).

Level-of-service variables measure the quality and convenience of the bus service. These include frequency, headway, number of directions, and stop amenities like benches and real-time information displays (Kerkman et al., 2015; de Boer, 2021). However, a key lapse in the literature is the lack of variables capturing intermodal transfer quality, such as the time required to transfer between bus and train.

Direct ridership models have proven effective in explaining bus passenger volumes, particularly at the local scale. However, their applicability is often context-specific, requiring tailored models for different areas (Kerkman et al., 2015; de Boer, 2021). The main knowledge gap lies in the omission of intermodal transfer quality as a predictor. The next section explores why transfer time may be a critical missing link in ridership modelling.

2.4. Intermodal Transfers

Research shows that access and egress components of a multimodal trip are perceived as disproportionately unfavourable by travellers. This aversion is captured through the concept of transfer penalties, which represent the additional perceived cost of switching modes. Wait time is weighted more heavily than in-vehicle travel time in utility functions (Wardman and Hine, 2000). For example, Bovy and Hoogendoorn-Lanser (2005) found that waiting time contributes 2.2 times more to perceived disutility than in-vehicle travel time.

Quantifying the disutility of transfers in extra perceived minutes has been done for various modes. Arentze and Molin (2013) and De Keizer et al. (2012) found penalties of over 20 minutes for train-train transfers. Yap et al. (2024) reported that bus-to-metro transfers in London carried a penalty exceeding 10 minutes, significantly higher than metro-to-metro transfers. For Dutch bus-train transfers, Schakenbos et al. (2016) found penalties ranging from 5 to 9 minutes depending on the frequency of the connecting mode. Schakenbos et al. (2016) also determined that the optimal transfer time between train and bus is 8 minutes. Shorter times are less appealing due to the lack of buffer in case of low punctuality. In the same vein, longer times deter passengers due to the large influence on total travel time.

However, while the behavioural effects of transfer penalties are well documented, their quantitative impact on bus ridership has not been explored in detail. Transfer time plays a key role in perceived travel utility and, by extension, in mode choice. Longer transfer times reduce utility and are therefore expected to reduce the likelihood that a passenger will choose the bus as an access or egress mode. This relationship suggests that transfer time may directly affect bus ridership levels, yet this effect has not been demonstrated by using transfer times as a predictor in ridership models. The next section explores how transfer quality might be incorporated into direct ridership models as an explanatory variable.

2.5. Incorporating transfer variables in direct ridership models

A straightforward approach is to include average transfer time as a single explanatory variable in the ridership model. The average can be calculated by collecting the transfer times of all possible bus-train connections, and weighing them by the share of passengers making a specific interchange. This method assumes that the average across all connections captures the disutility, and that there is a linear relationship between average transfer time and ridership. While simple, this approach may overlook the fact that some trains may be more sensitive in attracting bus passengers than others,

Alternatively, transfer time can be decomposed into multiple indicators, each representing the transfer time to one of the available train services at the train station. While this method can hypothetically capture any differences between train services, it still assumes a linearly dependent relationship.

A previous study suggests that transfer time exhibits a non-linear relationship with travel utility. Schakenbos et al. (2016) found that between a layover time of 3-8 minutes, utility increases, while from 8-15 minutes a decrease was observed. The effect on ridership might be similar as on travel utility, raising doubts whether representing transfer quality in minutes is the best option. A possible solution is to include binary variables for time windows representing feasible transfers to represent this non-linearity.

3. Methodology and data

3.1. Study areas

The two urban bus networks of the cities of Maastricht and Breda are studied. Both networks are operated by Arriva and compose extensive networks with high stop density. In terms of bus-train transfers, the main difference between the cities is that Maastricht is only served by one intercity train per half hour, connecting the capital of the southern province of Limburg to the rest of the country. Conversely, Breda is frequented by over six intercity services, since other large urban centres are located nearby in all directions. The most important similarities and differences are presented in table 1.

A notable observation in table 1 is relative popularity of the bus in Maastricht, when comparing to the number of train passengers. While Breda has around a third more inhabitants and about double the number of train travellers, the total bus ridership is roughly equal. In Maastricht, there are also more than twice as many urban bus lines. However, the high line density in Maastricht number is caused by lines sharing the same corridor, but having separate termini. Meanwhile, the Breda network has fewer lines with higher frequency, supplemented by regional lines serving parts of the city. As a result, the number of stops does not differ substantially between study areas.

	Maastricht	Breda	Source
No. of inhabitants	125,000	180 000	(Maastricht, 2024; Breda, 2024)
No. of train passengers	15,000	30,000	(NS)
No. of bus passengers	20,000	23,000	Arriva
No. of bus lines	18	7	Arriva
No. of bus stops	120	113	Arriva
No. of stop-line combinations	414	372	Arriva
No. of train services	1 intercity, 5 local	6 intercity, 2 local	–
Passenger distribution across trains	1 intercity transports 65% of all passengers	No dominance of a single train	–
Distribution of train arrivals/departures	Intercity arrives and departs simultaneously	More varied arrivals and departures, but all within a 15-minute window	–
Distribution of bus arrivals/departures	One node for passengers accessing the intercity, another node for egressing passengers	One node around :15 and another around :30	–

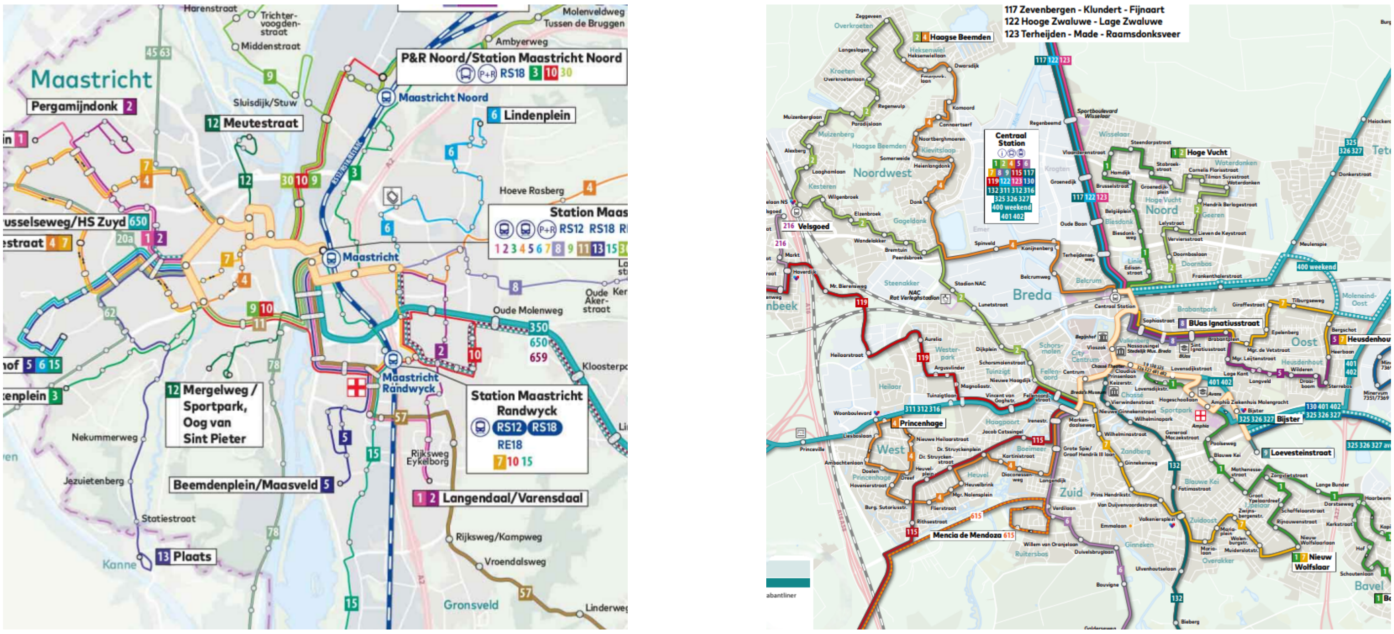
Table 1: Comparison of key attributes describing the two study areas

Only urban bus lines with a base frequency of two trips per hour are included in the model. For services operating at four trips per hour, the data is split into two separate lines, each representing a 30-minute frequency. This standardisation is necessary because trains in the Netherlands operate on a fixed 30-minute timetable pattern. As a result, only the alignment within this repeating half-hour window needs to be analysed to determine transfer characteristics. By ensuring that all observations reflect services recurring every 30 minutes, transfer patterns become comparable across all cases.

The train schedules show important differences. In Maastricht, the dominant train service transporting more than half of passengers arrives and departs simultaneously. For efficient access/egress transport, a bus should arrive shortly before this time point and depart shortly after. In Breda, there is a more varied choice of train destinations, but since they all depart within a 15-minute window, a bus arriving and departing within this same window is more favourable.

While certain times are more beneficial for bus-train transferring, in practice it is impossible to connect each bus line to all trains. In fact, bus lines are through-routed at the stations in both cities, meaning that the train station is not one of the termini but rather a stop along the way. This route design enables all neighbourhoods to reach the city centre without transfer. However, this configuration complicates the provision of attractive interchanges.

The issues are best understood by presenting a space-time diagram of the arrival and departures of buses and trains, shown in

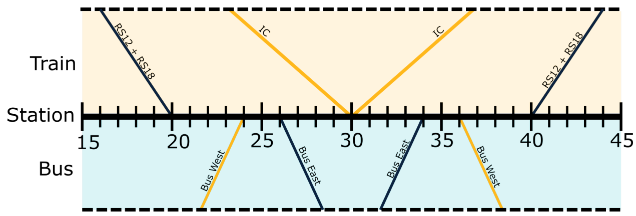


(a) Maastricht

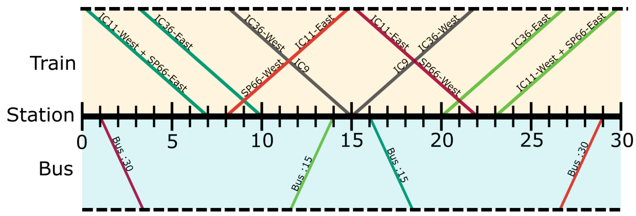
(b) Breda

Figure 1: Maps showing the bus networks of the two study areas (Arriva, 2025)

figure 2. In these figures, the same colour represents a transfer possibility existing between train and bus. Figure 2a shows that in Maastricht, the two segments of a bus line (one before station arrival and the other after station departure) have different transfer possibilities. On the other hand, in Breda it is possible for both line segments to have similar train connections.



(a) Maastricht



(b) Breda

Figure 2: Space-time diagrams depicting the transfer possibilities between bus and train.

Pattern	Day	Time window
Weekdays	Monday-Friday	7:00 - 19:00
Evenings	Monday-Sunday	19:00 - 00:00
Saturdays	Saturday	9:00 - 17:00
Sundays	Sunday	11:00 - 17:00

Table 2: The different temporal patterns that are treated separately in the model

3.2. Data

The dependent variable in the model is the number of passengers per line per stop. Only trips made to or from the train station are counted, since only these are assumed to be influenced by transfer possibilities. The data is collected by the smartcard system, registering a tap-in or tap-out as a boarding or alighting passenger respectively. For Maastricht, the data is collected in the period of January-February 2024, and for Breda in April 2025. Different time periods are chosen since in Breda until recently a limited schedule was operated due to staff shortages.

For the independent variables, data sources include the Dutch national statistics bureau (CBS), Dutch railways (NS) and the government executive agency for education (DUO). Table 3 shows an overview of the independent variables and the corresponding data source. Due to a lack of data on commercial activity, binary variables are introduced to indicate whether a stop is located next to a local shopping centre or in the city centre.

In the review three methods were proposed to include transfer quality as a predictor. Each of these methods is tested, and the corresponding variables are listed in table 4.

3.3. Analysis

To evaluate how transfer time can be incorporated into direct ridership models, three different methods are tested using data from the urban bus network in Maastricht. These methods include: the average transfer time weighted by estimated passenger shares, the transfer time to a specific train, and a binary indicator of whether a transfer falls within an attractive time window to a specific train. For the last two methods based on a specific train connection, two different reference trains were selected: the single intercity service and the regional train service RS18 heading north. The comparison enables the assessment of the methods on their accurateness and ease of implementation.

Using the best-performing transfer variable identified in the first step, the analysis further examines whether the effect of transfer time differs across time periods. To this end, the Maastricht dataset was segmented into four distinct time windows: weekday daytime, evenings, Saturdays, and Sundays. These time windows each follow a different timetable structure, resulting in variations in both transfer opportunities and passenger travel behaviour. The specific time limits defining each period are provided in table 2.

Finally, to compare whether the findings in Maastricht also apply across different urban contexts, a separate model was estimated for the city of Breda. This comparison focuses on weekday daytime travel only, as this period reflects the bulk of passenger transport. By applying the same modelling approach to both cities, potential similarities or differences in the effect of transfer time on bus ridership can be identified. The binary indicator method was used in this comparison, where for Maastricht again the intercity and RS18-north train were taken, while for Breda the intercity services 1100-east and 3600-east were selected, since these trains are the farthest apart in the schedule and expected to transport a large share of passengers.

4. Results

4.1. Comparison of transfer time implementation

The results of the three models, each incorporating a different method for representing transfer time, are summarised in table 5. The table presents coefficient estimates, standardised coefficients, t-values, and significance levels for each predictor. All models include the same set of non-transfer-related variables to ensure comparability, and most predictors show consistent significance and effects that are consistent in sign and align with theoretical expectations. Notably, all three methods for capturing transfer opportunities produced a significant result for at least one transfer-related variable.

All three models display strong model fit, with marginal R^2 values of approximately 0.72 and conditional R^2 values of around 0.77. These figures indicate that both fixed and random effects explain a substantial portion of the variation in bus ridership. While not directly comparable to previous OLS-based studies due to differences in data structure and variable selection, the model fit is sufficiently high to justify further interpretation. Additionally, the intra-class correlation (ICC) of around 0.17 and a random intercept variance of 0.24 support the use of

Variable	Description	Measurement	Data source
Dependent variable			
Bus stop ridership per line (logarithm)	Average number boarding or alighting passengers on a bus line at a bus stop during the time window	Check-ins and check-outs with the smart card system	Arriva
Independent variables			
Number of inhabitants (logarithm)	Sum of inhabitants living within the catchment area of the bus stop	Calculated using 400m buffer	CBS (b)
Number of students (logarithm)	Number of students following a program at an educational facility served by the bus stop	Direct assignment to bus stop	DUO (2024)
% population aged 65+	% of inhabitants living in the catchment area that are older than 65	Calculate using 400m buffer	CBS (b)
Central station (0/1)	The bus stop is the central station	Dummy variable	-
City centre (0/1)	The bus stop is a central point in the city centre and frequented by many bus routes	Dummy variable	-
Shopping centre (0/1)	The bus stop is located at a neighbourhood shopping centre	Dummy variable	-
Average income (x €1000)	The average income per person of the respective neighbourhood	Coupling of the bus stop to the neighbourhood	CBS (c)
LU: socio-cultural facilities	% of the catchment area with socio-cultural facilities	Division of the 400m buffer	CBS (a)
Frequency (logarithm)	Total number of trips of all lines that serve the bus stop in the time window according to the timetable	Summation of trips in temporal regime	Arriva
Travel time to central station	Running time between the stop to or from the central station using the specific bus line according to the timetable	Time difference between arrival/departure time at the train station and at the specific stop	Arriva

Table 3: The predictors for the direct ridership model excluding the transfer-related variables

Method	Calculation
Average transfer time	the average of the transfer times of all possible connections, weighted against the share of travellers on the connecting service.
Transfer time per train	Time difference between arrival and departure of a specific previously selected train.
Transfer possibility binary indicator	The time difference between arrival and departure of a specific previously selected train falls within the 5-12 minute interval.

Table 4: The three proposed methods to include transfer variables in the direct ridership model

a multi-level model to account for variation between bus line segments.

Despite using different transfer-related variables, all three models produce broadly similar results for the non-transfer-related predictors, with minimal changes in magnitude or significance. The primary distinction between the results is the effect of the transfer variables. The average transfer time variable shows a strong and significant negative effect on ridership. The per-train transfer time model also yields negative coefficients, though these are smaller in magnitude and somewhat counter-intuitive, since the effect per train is equal, despite the intercity transporting more than twice as many passengers. This anomaly is likely due to multicollinearity between the intercity and regional train transfer times, due to the set timing offset between their arrivals and departures in the schedule. In contrast, the binary indicator method provides more distinct effects, with only the intercity connection being statistically significant, aligning better with expectations based on train usage patterns.

Interpreting the transfer variables reveals that unfavourable transfer times indeed decrease ridership. The average transfer time method captures a clear and substantial negative effect, wehere each minute of additional waiting reduces ridership by 2.3%. The per-train method shows smaller and unexpectedly similar coefficients for both train types, indicating a decrease in ridership of 1.1% for every additional minute of transfer time of both the intercity and the regional train. In many cases, a one-minute shift in bus arrival or departure time increases the transfer time to both the intercity and regional trains by the

	Average transfer time			Per train (min)			Per train (0/1)		
Variable	Coef.	Std. β	t-value	Coef.	Std. β	t-value	Coef.	Std. β	t-value
intercept	2.272	0.00	3.68***	2.311	0.02	3.77***	1.660	0.00	2.69***
Population (log)	0.155	0.07	2.22**	0.158	0.08	2.27**	0.158	0.08	2.27**
Students (log)	0.155	0.29	10.34***	0.155	0.29	10.35***	0.154	0.29	10.31***
% elderly	-0.031	-0.19	-5.05***	-0.032	-0.19	-5.10***	-0.032	-0.19	-5.07***
Income	0.000	0.00	0.05	0.000	0.00	-0.01	0.000	0.00	-0.05
Station (0/1)	2.343	0.69	16.66***	2.345	0.69	16.73***	2.352	0.69	16.74***
City centre (0/1)	0.723	0.18	5.80***	0.714	0.18	5.75***	0.721	0.18	5.80***
Shopping centre (0/1)	0.623	0.14	5.20***	0.621	0.14	5.17***	0.623	0.14	5.19***
% LU Socio-cultural	0.006	0.07	2.376**	0.006	0.07	2.34**	0.005	0.07	2.27**
Frequency (log)	-0.026	-0.03	-0.54	-0.025	-0.02	-0.52	-0.020	-0.02	-0.41
Travel time to station	-0.006	-0.01	-0.73	-0.005	-0.03	-0.68	-0.004	-0.03	-0.62
Avg. transfer time	-0.023	-0.12	-2.75***						
Transfer to IC				-0.013	-0.11	-2.45**	0.305	0.15	3.09***
Transfer to RS				-0.012	-0.10	-2.38**	0.170	0.07	1.44
Random intercept σ^2	0.24			0.24			0.24		
Intra-class correlation (ICC)	0.18			0.16			0.17		
Marginal R^2	0.721			0.726			0.724		
Conditional R^2	0.771			0.771			0.771		

Table 5: Coefficients for the multi-level model. (*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$)

same amount. As a result, the model attributes the effect to both transfer variables, even though the actual decrease in ridership is unlikely to be equally caused by both train services. The binary indicator method appears more reliable, showing a strong positive effect (+36%) for stops with an attractive intercity transfer, while the regional train effect remains statistically insignificant.

All three methods confirm the importance of transfer time, but they differ in accuracy and ease of implementation. The average transfer time method requires assumptions about passenger distribution and access to detailed train data, limiting its applicability. The per-train method avoids these assumptions but suffers from hidden collinearity due to coupling in the timetable and assumes a linear effect of time, which may not reflect actual preferences. The binary indicator method is simple to interpret, accounts for non-linearity, and aligns well with expected passenger behaviour, making it the most consistent and practical approach for inclusion in direct ridership models.

4.2. Comparison of time windows

To assess temporal variation in the effect of transfer opportunities, the model was applied separately to evening, Saturday, and Sunday data, each following a different timetable. Table 6 presents the coefficients for these time windows using binary transfer variables. All models show strong fit, with conditional R^2 values around 0.77–0.79. However, marginal R^2 values are notably lower, particularly for the evening model, indicating a greater contribution of random effects. High ICC values, especially in the evening, suggest that ridership is more dependent on differences between line segments during these periods.

The significance and effect of transfer opportunities vary by time window. In the evening, neither the intercity nor regional transfer variable is statistically significant, possibly due to the dominance of egress trips and reduced demand for accessing trains. On Saturdays, the intercity transfer variable is significant, with a 43% increase in ridership at well-connected stops. The strongest effect is seen on Sundays, where the presence of an attractive intercity connection corresponds to a 65% increase in passenger numbers, which can presumably be attributed to students returning home at the end of the weekend.

These results suggest that underlying travel behaviour explains much of the variation. Evening trips primarily involve passengers leaving the station, making transfers from bus to train less relevant than from train to bus. In contrast, weekend travel shows a stronger synergy with rail ridership. The reduced number of lines operating during these off-peak periods likely limits transfer options, further increasing the impact of bus–train coordination. As a result, the influence of transfer quality on ridership is dependent on the time of the week and corresponding travel patterns.

Several non-transfer variables also show temporal variation. Student numbers and socio-cultural land use lose significance in evenings and weekends, consistent with the closure of schools and institutions during these times. Conversely, frequency and travel time to the station become significant predictors, where they previously were not. For travel time, this change can be explained by popular bus-stops located close to the train station which see high usage during the day but not on weekends. The frequency is positively related to ridership, similar to previous ridership studies (Dill et al., 2013; Kerkman et al., 2015).

During the week, this relationship was not observed, likely due to a dispersion effect of many lines serving the same stop. Since each observation represents a single line at a stop, a higher frequency resulted in a lower ridership per line. In the other time windows, frequencies are lower, resulting in the absence of this dispersion effect and a positive coefficient.

In addition to service-related factors like frequency, the influence of demographic variables also changes across time pe-

	Evenings			Saturdays			Sundays		
Variable	Coef.	β	t-value	Coef.	β	t-value	Coef.	β	t-value
intercept	1.288	0.00	1.59	0.778	0.00	1.23	0.119	0.00	0.18
Population (log)	0.163	0.08	1.783*	0.158	0.16	2.18**	0.169	0.09	2.25**
Students (log)	0.019	0.04	1.05	-0.007	-0.02	-0.48	-0.023	-0.05	-1.61
% elderly	-0.060	-0.35	-7.98***	-0.046	-0.31	-3.14***	-0.041	-0.29	-6.39***
Income	-0.010	-0.05	-0.97	-0.011	-0.06	-1.20	-0.008	-0.04	-0.84
Station (0/1)	2.196	0.65	13.30***	2.262	0.76	16.18***	2.040	0.76	14.40***
City centre (0/1)	0.608	0.14	3.90***	0.684	0.18	5.42***	0.461	0.14	3.78***
Shopping centre (0/1)	0.386	0.08	2.67***	0.471	0.12	3.83***	0.411	0.11	3.47***
% LU Socio-cultural	0.000	0.01	0.14	0.005	0.07	2.11**	0.002	0.03	0.88
Frequency (log)	0.102	-0.03	1.73*	0.097	0.09	1.82*	0.144	0.13	2.71***
Travel time to station	0.027	0.14	2.45**	0.026	0.17	3.14***	0.029	0.20	3.43***
Transfer to IC	0.297	0.14	1.41	0.361	0.19	-2.76***	0.503	0.29	3.57***
Transfer to RS	-0.153	-0.06	-0.54	0.178	0.08	1.13	0.258	0.12	1.50
Random intercept σ^2	0.26			0.20			0.18		
Intra-class correlation (ICC)	0.55			0.29			0.38		
Marginal R^2	0.548			0.675			0.656		
Conditional R^2	0.793			0.769			0.786		

Table 6: Coefficients for the multi-level model across different schedules. (*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$)

riods. The negative association of elderly population increases in the evening, indicating that this demographic is less likely to travel by night. Meanwhile, the effects of population size and station location remain stable, showing no clear temporal sensitivity.

4.3. Comparison of study areas

Table 7 presents the multi-level regression results for the city of Breda, based on weekday daytime data. This time window captures the majority of travel activity and therefore provides a suitable basis for comparison with Maastricht. The table includes coefficient estimates, standardised betas, and t-values for each predictor. The model shows strong performance, with a marginal R^2 of 0.76 and conditional R^2 of 0.78. These values are slightly higher than in Maastricht, indicating that fixed effects alone explain more variation in Breda. The lower intra-class correlation suggests less variation between bus lines, which may point to a more evenly spread passenger demand over the bus routes.

In terms of transfer-related predictors, only the binary variable for connections to the 3600-east intercity service shows a significant positive effect. Lines offering such a connection see a 23% increase in ridership per stop. Compared to Maastricht, where the estimated effect was 36% for the most popular train, this impact is smaller and shows a less reliable statistical effect. This reduced effect is likely due to the broader distribution of passenger flows across multiple intercity services in Breda, making any single transfer opportunity less dominant.

The difference in the importance of transfer opportunities can be explained by the structure of each city's train timetable. Maastricht is served by one dominant intercity train that carries a large share of all passengers, making connections to it critical for ridership. In Breda, multiple intercity services operate in different directions with more evenly distributed passenger volumes. These diffuse connections create multiple potential transfer windows and makes the schedule less focused around one time point. Table 8 summarises the key structural differences between the two networks, showing how Breda's timetable results in more dispersed transfer patterns and lower associated ridership increases. Aside from transfer effects, other predictors also show notable differences between the two cities. In Breda, frequency and travel time to the station are both significant with negative signs. The negative sign for frequency can be attributed to the regional lines not included in the model. These lines share many of the high-frequency stops on urban lines, increasing the dispersion of passengers across lines. The negative effect of travel time in Breda can likely be explained by the presence of longer travel durations to the station. While all stops in Maastricht are located within a 24-minute bus ride, travel times in Breda reach up to 37 minutes, which potentially exceeds the threshold beyond which passengers are no longer willing to use the bus for access or egress to the station.

Variable	Coef.	β	t-value
intercept	3.885	0.00	8.02***
Population (log)	0.035	0.02	0.71
Students (log)	0.162	0.32	9.74***
% elderly	-0.002	-0.01	-0.26
Income	-0.010	-0.05	-1.36
Station (0/1)	2.626	0.67	20.68***
City centre (0/1)	0.445	0.07	2.28**
Shopping centre (0/1)	0.923	0.28	10.80***
% LU Socio-cultural	0.006	0.04	1.23
Frequency (log)	-0.283	-0.13	-4.05***
Travel time to station	-0.036	-0.25	-7.21***
Transfer to 3600-East	0.211	0.10	2.21**
Transfer to 1100-East	0.114	0.04	1.15
Random intercept σ^2	0.24		
Intra-class correlation (ICC)	0.07		
Marginal R^2	0.764		
Conditional R^2	0.781		

Table 7: Coefficients for the multi-level model applied on the Breda network (*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$)

Aspect	Maastricht	Breda	Comparison
Number of train services	7, of which only 3 transport over 90% of passengers	9, of which most serve important destinations	Breda has more trains of relatively equal importance, while in Maastricht the passenger flows are centred around one train.
Number of intercity services	1	6	Breda is served by many intercities in many directions, whereas Maastricht only by one
Train timetable	Intercity departures and arrivals occur simultaneously	The train arrivals and departure are more spread out, but within a 15 minute interval	In Maastricht there is one important time stamp to connect to, while in Breda there are more options.
Interval attracting most passengers	:05-:12 (departing buses) or :19-:26 (arriving buses)	:15-:22 (departing buses) or :08-:15 (arriving buses)	In Breda the intervals for arriving and departing buses almost overlap. In Maastricht there is no overlap at all.
Associated increase in passengers	36%	23%	In Maastricht the increase associated with attractive transfers is higher.

Table 8: A synthesis of the results produced by the comparison of study areas.

In contrast, other commonly used socio-demographic predictors such as population size and elderly share do not exhibit significant effects in Breda, possibly due to other variables being relatively more important in explaining ridership. The effects of student populations, the city centre and local shopping centres remain consistently positive and significant, reinforcing their strong influence on bus ridership.

5. Conclusion and discussion

This research was conducted to investigate how train connections influence bus ridership in urban transit networks, with the goal of exploring the value of improving train connections to increase bus patronage. Using a direct ridership model with multi-level regression, it focused on how transfer time between bus and train services contributes to passenger numbers. To account for the difficulties inherent in examining transfer times, three separate analyses were performed concerning model implementation, temporal variation, and regional differences. Each revealed key insights about the role of transfers in bus ridership.

First, the analysis tested three methods to incorporate transfer time into a direct ridership model. The most effective approach was a binary indicator identifying whether a specific bus line provided a feasible transfer, defined as having a transfer time within a 5 to 12-minute interval, to a high-demand train. This variable proved significant and positively associated with ridership, suggesting that facilitating such connections can raise the number of passengers. Compared to methods using average or continuous transfer times, the binary method was more aligned better with expected rider behaviour, in addition to accounting for the non-linear relationship between transfer time and ridership. However, a limitation of this binary approach is that it does not capture differences within or outside the 5–12 minute interval, for example, whether a 4-minute or a 11-minute transfer has a different impact. Exploring these more detailed effects could be a valuable direction for future research.

Second, applying the model to different time periods revealed that the transfer effect is not uniform throughout the week. During weekday daytime and Saturdays, strong positive effects were found, while in the evening, no significant effect was observed. On Sundays, the transfer effect was considerably larger than on weekdays. These findings suggest that transfer quality matters most during periods with lower operating frequency and varies depending on the underlying travel patterns. For instance, evening travel is more oriented toward returning home, which may increase the relevance of transfer times from bus to train.

Third, a comparison between Maastricht and Breda showed regional differences. While both cities showed a positive transfer effect, the magnitude was larger in Maastricht. This difference is likely explained by the more dominant presence of a single train connection in Maastricht, versus a a larger variation of train services in Breda. This observation implies that the effectiveness of transfer-focused improvements may depend on the structure of the train schedule and how well buses can be synchronised with the available train services.

Endogeneity, a common issue in ridership modelling, was addressed by fixing the frequency at two buses per hour across observations and focusing on transfer variables that are less demand-responsive. This approach decreased the explaining power of the endogenous variable frequency. Still, some potential endogeneity remains in the transfer variables, as operators might naturally align schedules for high-demand services. Further research could explore more complex methods to resolve this remaing endogeneity by using the two-stage-least-squares method.

The added value of this modelling framework lies in its ability to explain ridership per line per stop using detailed service level variables, like transfer time, and relatively few additional variables. In addition, the necessary metrics can be obtained relatively easily and do not rely on detailed passenger data. It offers a means to understand expected changes in ridership from improving transfer coordination and route alterations. Though results may be context-dependent, the findings underline that optimising transfers between bus and train is a meaningful intervention for increasing ridership in urban bus networks.

While the modelling approach proved to be effective in the studied context, its applicability to other settings may be limited. The method was designed for urban networks structured around a single central train station, where transfer opportunities between bus and train are concentrated. Additionally, the approach relies on regular, repeating timetables, which is common in the Dutch public transport network with train frequencies of at least two per hour. In higher-frequency networks, such as in dense metropolitan areas, transfer times are often short by default and thus become less decisive in influencing travel behaviour. Conversely, in regions with lower service frequencies or irregular schedules, transfer-based modelling may not yield meaningful results. For these reasons, the generalisability of the findings is strongest in contexts with moderately frequent, but coordinated transit systems, and weaker in settings with either very high or very low service levels.

References

Arentze, T.A., Molin, E.J.E., 2013. Travelers' preferences in multimodal networks: Design and results of a comprehensive series of choice experiments. Transportation Research Part A: Policy and Practice 58, 15–28. doi:10.1016/j.tra.2013.10.005.

Arriva, 2023. Exploitatieplan 2023 West-Brabant. Technical Report. Provincie Noord-Brabant.

Arriva, 2025. Lijnennetkaart Zuid-Limburg. https://www.arriva.nl/plan-je-reis/dienstregeling/geplande-dienstregeling/?regio=Limburg. Lijnennetkaart Zuid-Limburg.

Aston, L., Currie, G., Kamruzzaman, M., Delbosc, A., Brands, T., van Oort, N., Teller, D., 2021. Multi-city exploration of built environment and transit mode use: Comparison of Melbourne, Amsterdam and Boston. Journal of Transport Geography 95. doi:10.1016/j.jtrangeo.2021.103136.

de Boer, S., 2021. Predicting bus ridership in the Netherlands. Master's thesis. TU Delft.

Bovy, P.H.L., Hoogendoorn-Lanser, S., 2005. Modelling route choice behaviour in multi-modal transport networks. Transportation 32, 341–368. doi:10.1007/s11116-004-7963-2.

Brands, T., de Romph, E., Veitch, T., Cook, J., 2014. Modelling public transport route choice, with multiple access and egress modes. Transportation Research Procedia 1, 12–23. doi:10.1016/j.trpro.2014.07.003.

Breda, 2024. Breda in cijfers. https://breda.incijfers.nl/dashboard/bevolking/.

CBS, 2020a. Bestand bodemgebruik. https://www.cbs.nl/nl-nl/dossier/nederland-regionaal/geografische-data/bestand-bodemgebruik.

CBS, 2021c. Kerncijfers wijken en buurten. https://www.cbs.nl/nl-nl/reeksen/publicatie/kerncijfers-wijken-en-buurten.

CBS, 2024b. Gegevens per postcode. https://www.cbs.nl/nl-nl/dossier/nederland-regionaal/geografische-data/gegevens-per-postcode.

Chu, X., 2004. Transit Ridership Models at the Stop Level. Report CUTR-NCTR-RR-2002-10. National Center for Transit Research. doi:https://doi.org/10.5038/CUTR-NCTR-RR-2002-10.

CROW, 2024. Staat van het ov. https://www.staatvanhetov.nl/mosaic/staat-van-het-ov/gebruik-van-openbaar-vervoer/. Staat van het OV.

De Keizer, B., Geurs, K.T., Haarsman, G., 2012. Interchanges in timetable design of railways: A closer look at customer resistance to interchange between trains, in: European Transport Conference.

De Lanoy, J., 2019. Predicting bus ridership. Master's thesis. TU Delft.

Dill, J., Schlossberg, M., Ma, L., Meyer, C., 2013. Predicting transit ridership at stop level: Role of service and urban form. Transportation Research Board .

DUO, 2024. DUO open onderwijsdata. https://duo.nl/open_onderwijsdata.

Estupiñán, N., Rodríguez, D.A., 2008. The relationship between urban form and station boardings for Bogotá's BRT. Transportation Research Part A: Policy and Practice 42, 296–306. doi:https://doi.org/10.1016/j.tra.2007.10.006.

de Haas, M., 2023. Waar is de OV-reiziger gebleven? Technical Report. Kennisinstituut voor Mobiliteitsbeleid.

Kerkman, K., Martens, K., Meurs, H., 2015. Factors Influencing Stop-Level Transit Ridership in Arnhem–Nijmegen City Region, Netherlands. Transportation Research Record: Journal of the Transportation Research Board 2537, 23–32. doi:10.3141/2537-03.

Maastricht, 2024. Maastricht in cijfers. https://www.maastrichtincijfers.nl/.

Montero-Lamas, Y., Fernández-Casal, R., Varela-García, F.A., Orro, A., Novales, M., 2024. A spatial statistical approach to estimate bus stop demand using GIS-processed data. Journal of Transport Geography 118. doi:10.1016/j.jtrangeo.2024.103906.

NS, 2024. NS dashboard reizigersgedrag 2024. https://dashboards.nsjaarverslag.nl/reizigersgedrag/.

Pulugurtha, S., Agurla, M., 2012. Assessment of models to estimate bus-stop level transit ridership using spatial modeling methods. Journal of Public Transportation 15, 33–52. doi:10.5038/2375-0901.15.1.3.

Ryan, S., Frank, L., 2009. Pedestrian environments and transit ridership. Journal of Public Transportation 12, 39–57. doi:10.5038/2375-0901.12.1.3.

Schakenbos, R., Paix, L.L., Nijenstein, S., Geurs, K.T., 2016. Valuation of a transfer in a multimodal public transport trip. Transport Policy 46, 72–81. doi:10.1016/j.tranpol.2015.11.008.

Taylor, B.D., Miller, D., Iseki, H., Fink, C., 2009. Nature and/or nurture? analyzing the determinants of transit ridership across us urbanized areas. Transportation Research Part A: Policy and Practice 43, 60–77. doi:https://doi.org/10.1016/j.tra.2008.06.007.

Ton, D., van den Heuvel, J., 2023. Trends in access and egress transportation to and from train stations in The Netherlands, in: European Transport Conference 2023.

van Oort, N., Brands, T., de Romph, E., 2015. Short term ridership prediction in public transport by processing smart card data, in: Proceedings of the Transportation Research Board 94th annual meeting, Transportation Research Board (TRB). pp. 1–14.

van Oort, N., van der Bijl, R., Verhoof, F., 2017. The wider benefits of high quality public transport for cities, in: European Transport Conference 2017.

Wang, C., Park, J., 2024. A Multi-Level Analysis of Bus Ridership in Buffalo, New York. ISPRS International Journal of Geo-Information 13. doi:10.3390/ijgi13120443.

Wardman, M., Hine, J., 2000. Costs of interchange: A review of the literature. .

Yap, M., Wong, H., Cats, O., 2024. Passenger valuation of interchanges in urban public transport. Journal of Public Transportation 26. doi:10.1016/j.jpubtr.2024.100089.

Bibliography

Arentze, T. A. and Molin, E. J. E. (2013). Travelers' preferences in multimodal networks: Design and results of a comprehensive series of choice experiments. *Transportation Research Part A: Policy and Practice*, 58:15–28.

Arriva (2023). Exploitatieplan 2023 west-brabant. Technical report, Provincie Noord-Brabant.

Arriva (2025). Lijnennetkaart Zuid-Limburg. `https://www.arriva.nl/plan-je-reis/dienstregeling/geplande-dienstregeling/?regio=Limburg`. Lijnennetkaart Zuid-Limburg.

Aston, L., Currie, G., Kamruzzaman, M., Delbosc, A., Brands, T., van Oort, N., and Teller, D. (2021). Multi-city exploration of built environment and transit mode use: Comparison of Melbourne, Amsterdam and Boston. *Journal of Transport Geography*, 95.

Bakker, P. and Zwaneveld, P. (2009). Het belang van openbaar vervoer: De maatschappelijke effecten op een rij. Technical report, Centraal Planbureau and Kennisinstituut voor Mobiliteitsbeleid.

Bovy, P. H. L. and Hoogendoorn-Lanser, S. (2005). Modelling route choice behaviour in multi-modal transport networks. *Transportation*, 32(4):341–368.

Brand, J., Hoogendoorn, S., Oort, N., and Schalkwijk, B. (2017). Modelling multimodal transit networks integration of bus networks with walking and cycling. In *2017 5th IEEE International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS)*, pages 750–755.

Brands, T., de Romph, E., Veitch, T., and Cook, J. (2014). Modelling public transport route choice, with multiple access and egress modes. *Transportation Research Procedia*, 1(1):12–23.

CBS (2020). Bestand bodemgebruik. `https://www.cbs.nl/nl-nl/dossier/nederland-regionaal/geografische-data/bestand-bodemgebruik`.

CBS (2021). Kerncijfers wijken en buurten. `https://www.cbs.nl/nl-nl/reeksen/publicatie/kerncijfers-wijken-en-buurten`.

CBS (2024). Gegevens per postcode. `https://www.cbs.nl/nl-nl/dossier/nederland-regionaal/geografische-data/gegevens-per-postcode`.

Cervero, R., Murakami, J., and Miller, M. (2010). Direct Ridership Model of Bus Rapid Transit in Los Angeles County, California. *Transportation Research Record: Journal of the Transportation Research Board*, 2145(1):1–7.

Chu, X. (2004). Transit ridership models at the stop level. Report CUTR-NCTR-RR-2002-10, National Center for Transit Research.

CROW (2024). Staat van het ov. `https://www.staatvanhetov.nl/mosaic/staat-van-het-ov/gebruik-van-openbaar-vervoer/`. Staat van het OV.

de Boer, S. (2021). Predicting bus ridership in the Netherlands. Master's thesis, TU Delft.

de Haas, M. (2023). Waar is de ov-reiziger gebleven? Technical report, Kennisinstituut voor Mobiliteitsbeleid.

De Keizer, B., Geurs, K. T., and Haarsman, G. (2012). Interchanges in timetable design of railways: A closer look at customer resistance to interchange between trains. In *European Transport Conference*.

De Lanoy, J. (2019). Predicting bus ridership. Master's thesis, TU Delft.

Dill, J., Schlossberg, M., Ma, L., and Meyer, C. (2013). Predicting transit ridership at stop level: Role of service and urban form. *Transportation Research Board*.

DUO (2024). DUO open onderwijsdata. https://duo.nl/open_onderwijsdata.

Estupiñán, N. and Rodríguez, D. A. (2008). The relationship between urban form and station boardings for Bogotá's BRT. *Transportation Research Part A: Policy and Practice*, 42(2):296–306.

Gemeente Breda (2024). Breda in cijfers. https://breda.incijfers.nl/dashboard/bevolking/.

Gemeente Maastricht (2024). Maastricht in cijfers. https://www.maastrichtincijfers.nl/.

Guo, R. and Huang, Z. (2020). Mass Rapid Transit Ridership Forecast Based on Direct Ridership Models: A Case Study in Wuhan, China. *Journal of Advanced Transportation*, 2020:1–19.

Gutiérrez, J., Cardozo, O. D., and García-Palomares, J. C. (2011). Transit ridership forecasting at station level: an approach based on distance-decay weighted regression. *Journal of Transport Geography*, 19(6):1081–1092.

Kerkman, K., Martens, K., and Meurs, H. (2015). Factors Influencing Stop-Level Transit Ridership in Arnhem–Nijmegen City Region, Netherlands. *Transportation Research Record: Journal of the Transportation Research Board*, 2537(1):23–32.

Kerkman, K., Martens, K., and Meurs, H. (2017). A multilevel spatial interaction model of transit flows incorporating spatial and network autocorrelation. *Journal of Transport Geography*, 60:155–166.

Kholodov, Y., Jenelius, E., Cats, O., van Oort, N., Mouter, N., Cebecauer, M., and Vermeulen, A. (2021). Public transport fare elasticities from smartcard data: Evidence from a natural experiment. *Transport Policy*, 105:35–43.

KiM (2023). Mobiliteitsbeeld 2023.

Krygsman, S., Dijst, M., and Arentze, T. (2004). Multimodal public transport: an analysis of travel time elements and the interconnectivity ratio. *Transport Policy*, 11(3):265–275.

Lee, A., van Oort, N., and van Nes, R. (2014). Service reliability in a network context. *Transportation Research Record: Journal of the Transportation Research Board*, 2417(1):18–26.

Liu, T., Cats, O., and Gkiotsalitis, K. (2021). A review of public transport transfer coordination at the tactical planning phase. *Transportation Research Part C: Emerging Technologies*, 133.

Marques, S. d. F. and Pitombo, C. S. (2022). Transit ridership modeling at the bus stop level: Comparison of approaches focusing on count and spatially dependent data. *Applied Spatial Analysis and Policy*, 16(1):277–313.

Martens, K. (2004). The bicycle as a feedering mode: experiences from three European countries. *Transportation Research Part D: Transport and Environment*, 9(4):281–294.

Montero-Lamas, Y., Fernández-Casal, R., Varela-García, F.-A., Orro, A., and Novales, M. (2024). A spatial statistical approach to estimate bus stop demand using GIS-processed data. *Journal of Transport Geography*, 118.

Nielsen, O. A., Eltved, M., Anderson, M. K., and Prato, C. G. (2021). Relevance of detailed transfer attributes in large-scale multimodal route choice models for metropolitan public transport passengers. *Transportation Research Part A: Policy and Practice*, 147:76–92.

NS (2024). NS dashboard reizigersgedrag 2023. https://dashboards.nsjaarverslag.nl/reizigersgedrag/breda.

Pulugurtha, S. and Agurla, M. (2012). Assessment of models to estimate bus-stop level transit ridership using spatial modeling methods. *Journal of Public Transportation*, 15(1):33–52.

Rijkswaterstaat (2020). Factsheet: fietsparkeren. https://www.rijkswaterstaat.nl/zakelijk/zakendoen-met-rijkswaterstaat/werkwijzen/werkwijze-in-gww/communicatie-bij-werkzaamheden/werkwijzer-hinderaanpak/toolbox-slim-reizen/factsheet-fietsparkeren.

Ryan, S. and Frank, L. (2009). Pedestrian environments and transit ridership. *Journal of Public Transportation*, 12(1):39–57.

Schakenbos, R., Paix, L. L., Nijenstein, S., and Geurs, K. T. (2016). Valuation of a transfer in a multimodal public transport trip. *Transport Policy*, 46:72–81.

Stam, B., van Oort, N., van Strijp-Harms, H. J., van der Spek, S. C., and Hoogendoorn, S. P. (2021). Travellers' preferences towards existing and emerging means of first/last mile transport: a case study for the Almere centrum railway station in the Netherlands. *European Transport Research Review*, 13(1).

Taylor, B. D., Miller, D., Iseki, H., and Fink, C. (2009). Nature and/or nurture? analyzing the determinants of transit ridership across us urbanized areas. *Transportation Research Part A: Policy and Practice*, 43(1):60–77.

Ton, D., Shelat, S., Nijënstein, S., Rijsman, L., van Oort, N., and Hoogendoorn, S. (2020). Understanding the role of cycling to urban transit stations through a simultaneous access mode and station choice model. *Transportation Research Record: Journal of the Transportation Research Board*, 2674(8):823–835.

Ton, D. and van den Heuvel, J. (2023). Trends in access and egress transportation to and from train stations in The Netherlands. In *European Transport Conference 2023*.

Van Oort, N. (2016). Data driven enhancement of public transport planning and operations: service reliability improvements and ridership predictions. In *European Transport Research Conference*.

van Oort, N., Brands, T., and de Romph, E. (2015). Short term ridership prediction in public transport by processing smart card data. In *Proceedings of the Transportation Research Board 94th annual meeting*, pages 1–14. Transportation Research Board (TRB).

van Oort, N., van der Bijl, R., and Verhoof, F. (2017). The wider benefits of high quality public transport for cities. In *European Transport Conference 2017*.

Wang, C. and Park, J. (2024). A Multi-Level Analysis of Bus Ridership in Buffalo, New York. *ISPRS International Journal of Geo-Information*, 13(12).

Wardman, M. and Hine, J. (2000). Costs of interchange: A review of the literature.

Yap, M., Wong, H., and Cats, O. (2024). Passenger valuation of interchanges in urban public transport. *Journal of Public Transportation*, 26.

AI-statement

For this thesis, artificial intelligence was used to help with rephrasing sentences, finding synonyms, structuring chapters and debugging code.