Job accessibility in industrial areas

A case study in the IJmond region of spatiotemporal accessibility using a gravity model

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by

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Preface

This graduation thesis represents the final stage of my study phase at TU Delft, following the Master of Transport, Infrastructure and Logistics (TIL). During the Bachelor's program in Civil Engineering, I knew very early that I wanted to follow my passion for transport and infrastructure. Coming from a city with good public transportation, I developed an appreciation for the role that efficient and accessible transit plays in enhancing the quality of life for residents. Upon starting the TIL program, my goal was to increase my scientific knowledge within the domain of transport modelling and learn more about the different aspects of public transit. In this prologue, I would like to extend my sincere gratitude to several people who made this whole journey possible.

First, I would like to extend my gratitude to my supervisors for the constructive support they have provided me during the extended period of my master's thesis. To Niels van Oort, thank you for your holistic view, constructive feedback and for connecting me with the right people. To Matthew Bruno, thank you for your continuous feedback and motivation to keep this graduation project going. Your positivity and academic interest in inclusive mobility have been a constant source of inspiration for me. To Jan-Anne Annema, thank you for your clear feedback and for keeping me focused on a manageable research goal, especially in the beginning phase of my thesis project.

Second, I would like to thank my friends and colleagues: Abdul, Ali, Brahm, Brendan, Cuma, Ilias, Julia, Marc, Marvin, Onno, and Shaniel for the support you have given me. When times were tough and I lost my way, I was always put back on track by you guys.

I would also like to pass a heartfelt thank you to my family, especially my parents. This thesis was not possible without the love and support you have given me along the road. Lastly, a big thank you to my boyfriend Damian, for keeping me motivated to finish this graduation project.

Ruben Ranty
Delft, June 2024

Summary

This Master Thesis evaluates the accessibility of industrial areas for lower-income groups using a spatio-temporal accessibility model in the IJmond region of The Netherlands. Industrial areas are crucial for regional economic activity and their accessibility impacts employment opportunities, particularly for lower-income groups. According to Beekmans (2015), industrial areas in The Netherlands significantly impact the labour market. However, these areas have been deteriorating, making them less attractive for companies. Initially developed to separate industrial activities from residential areas, these areas often have suboptimal transit accessibility (Gommers & Wortman, 2010). This issue regarding accessibility in industrial areas is particularly pressing in the context of the IJmond region, where industrial activities are a significant employment source but are often located in areas with a heavily burdened road and public transportation system (Provincie Noord-Holland, 2021). This research aims to understand how the spatial and temporal settings of industrial areas affect accessibility for different demographic groups and transport equity.

Existing surveys, such as by Verheggen (2019), have revealed that industrial enterprises in these areas nowadays employ a more diverse workforce than before which includes students and young professionals who often do not own a car and must rely on public transportation to reach their job (CBS, 2024b). Therefore an interest is present to focus on the accessibility by transit to industrial areas. As the interest is specifically on access from the work site rather than the residential location, new research could shift focus to labour force accessibility instead of the more commonly studied job accessibility such as by Yan et al. (2022) and Chen (2015). Therefore the following Research Gap, Objective, and Questions have been formulated to have a better understanding of accessibility in industrial areas.

There is a significant research gap in understanding how the spatial configuration of industrial areas influences the accessibility for various demographic groups, especially from an employer's perspective. Previous studies have largely focused on residential accessibility to jobs, overlooking how industrial site locations affect employment opportunities for the local labour force, particularly impacting those dependent on public transit. The main research objective of this research is to evaluate the spatiotemporal accessibility of industrial job sites, particularly through transit, and to assess its impact on transport equity. This objective aims to support policymakers and urban planners in understanding how industrial sites can better serve diverse workforce needs and mitigate transport exclusion.

The main research question is as follows: How do spatio-temporal factors and socio-demographic characteristics influence transit accessibility in concentrated industrial areas, and what are the implications for transport inequality?

The corresponding sub-questions are:

1. What socio-demographic characteristics of the labour force are relevant for understanding the spatio-temporal issues of accessibility around industrial areas?

2. How do accessibility levels in industrial areas to different socio-demographic groups vary across different times of day?

3. What are the implications of these temporal and socio-demographic variations for transport policy and urban planning of industrial areas?

The research approach involves a detailed literature review followed by the application of a gravity model to analyse spatio-temporal accessibility in industrial areas. The study uses comprehensive socioeconomic data from the Central Bureau of Statistics (CBS) and geographic data regarding industrial areas from IBIS. It uses this as input for the gravity model. The results of the gravity model are then analysed and visualised with maps.

The methodology is structured in 4 steps. First, data definition and requirements are set for the accessibility analysis. The second step involves the formulation of the gravity model used to evaluate spatiotemporal accessibility. The third step concerns the formulation of further statistical analysis of the gravity model results and lastly, the case study area is defined on which the accessibility analysis will be performed. Industrial areas, a subset of business parks, focus mainly on heavy industry (Rijkswaterstaat, n.d.). Data on these industrial areas in specific is available through IBIS, applicable for spatial analysis in GIS programs as geometry is provided in the dataset (IBIS, 2022). The geometry of this data is used for the accessibility model for this study. In addition, district-level socio-economic data will be used for modelling accessibility. The required variables for this study are primarily the number of employees per district and the geometry of district locations.
The labour force consists of employees living in district areas (Dutch: wijken). This research relies on socio-economic data sourced from CBS which provides insights regarding employment trends (CBS, 2024a). The provided datasets for this research make it suitable to perform an accessibility analysis such as the usage of Gravity Model Theory. Socio-economic data from CBS provide an insight into population size per district and the data from IBIS contains the geometry of industrial area locations.

Transit skim matrices can be generated for every hour of the day whereas car skim matrices can only be computed for the whole day without accounting for different time intervals as the model assumes an uncongested road network and therefore constant travel times across the day. To account for this, the transit skim matrix for one specific hour is used, 12:00 noon, when transit accessibility levels are the highest, reflecting peak efficiency and service availability. This matrix is then utilised for the comparison of accessibility levels between car and transit. After comparing spatial accessibility levels between car and transit, the analysis is further expanded into a spatiotemporal analysis for the transit mode. Accessibility by public transport to multiple socioeconomic groups within the total working population is evaluated utilizing the z-score method. This statistical approach helps in highlighting disparities in transit accessibility among different groups.

The case study area involves the IJmond region in the province of North Holland, The Netherlands, and includes the municipalities of Beverwijk, Heemskerk and Velsen. Situated along the North Sea and split by the North Sea Canal, the area is characterised by a relatively large share of low-income households.

The evaluation of spatiotemporal accessibility in the IJmond region using the gravity model reveals several insights. By excluding the temporal factor, the analysis has shown that accessibility in these areas to the labour force is already much lower when accessed by transit compared to by car. By including temporal factors, transit accessibility levels declined even more during the nighttime hours. This is caused by the significantly longer travel times at night, making a large number of residential destinations in the case study area 'unreachable' with a travel time longer than 240 minutes. Given that non-temporal accessibility by transit is already much lower than by car and including temporal factors show that this accessibility declines even further during the night, the results of this analysis confirm existing statements made by researchers such as Gommers and Wortman (2010) that there is a troubling lack in transit services to these areas, often limited to peak hours of the day.

The implication of low-income workers living closer to industrial areas and in larger concentrations than high-income workers is that solutions for improving accessibility in industrial areas, which primarily serve low-income jobs, could be achieved on a local/regional level rather than on a national level, as the supply of employees can be found in the vicinity of industrial sites. The results show that access by transit is still challenging for these workers, especially at night which is caused by the lack of transit services during this time of the day. The latter in particular impacts shift jobs which need workers to access the workplace at irregular hours at night. Hence more attention is needed to improve this if policymakers want to motivate people to use alternative modes other than the car.
In the context of equity, it also implies that transit services need to be improved to offer low-income workers alternative means of transportation to their jobs without having to own a car. Following the egalitarian principle, access by transit in industrial areas is already much lower than by car during the day with the difference being even greater at night. This means high-income workers, who are less im-

pacted by car ownership, have greater ease of reaching these areas compared to low-income workers, whilst according to CBS, low-income workers represent the majority of the workforce in these areas (CBS, 2024b).

The case study-specific results of areas near transit hubs maintaining higher accessibility scores than a large number of other areas imply that certain areas need more attention to improve transit services. In particular, Tata Steel contributes a significant share in the number of jobs, whilst having shown severely lower transit accessibility levels, making their employees dependent on cars and Tata Steel's private transportation services consisting of touring car buses. This network of buses, however, is proprietary and not accessible for existing third parties or contractors affiliated with the factory, impacting their access to the site at night in particular ("Interview on private transport Tata Steel", 2023). Therefore the existing transport offerings are not up to standard to meet the varying supply of existing workers. As a consequence, this lack of transport alternatives limits companies such as Tata Steel from reaching potential workers in the area, despite the larger availability of low-income workers than high-income workers around industrial areas. These findings suggest a need for targeted policy interventions to improve transit accessibility, especially during nighttime hours. Enhancing transit services at night increases spatiotemporal accessibility but might not be the most ideal solution if the supply of employees (i.e. the share of workers that is willing to work at night) is much lower.

Data limitations were present in this research as group-specific data was difficult to gather. More specifically, data regarding the type of workers would provide more insights as not every worker is suited for the jobs that industrial areas provide. For example, office workers as well as catering personnel are also included in this research whilst their jobs might not be present in industrial areas. Future research could address data limitations and enhance validity through alternative computational methods. Additionally, capturing hourly transit variations could refine transit accessibility measurements Yan et al., 2022. Another limitation is the reliance on district-level data, whereas future research should consider using more detailed neighbourhood-level data if available. Challenges include insufficient insight into transit trip compositions and transfer times, warranting further research. Opportunities exist for exploring alternative computational methods and refining transit accessibility measurements.

Based on the main findings of this research, the following policy recommendations aim to improve accessibility in industrial areas. Transit services should be enhanced during the daytime to match car travel accessibility and local improvements to the infrastructure are needed to remove barriers to transit stops such as waterways and portways, though the extent of these improvements may vary per study area. Nighttime mobility solutions should align with industrial shift hours, incorporating shared mobility options to reduce car dependence. Safe, well-lit, and direct walking and cycling paths are essential to ensure reliable access for low-income workers, supporting sustainable transportation alternatives. To address study limitations, future research should consider using detailed, real-time traffic data and apply a multimodal accessibility analysis by including car and cycling travel times as well as congestion effects. Researchers should also use neighbourhood-level data to better understand where low-income workers reside and incorporate competition effects into gravity models. Implementing these recommendations will improve both the insight and the impact of accessibility, equity, and the overall attractiveness of industrial areas, fostering economic and social prosperity.

In conclusion, this research has provided an evaluation of accessibility to the labour force in industrial areas, highlighting significant disparities in accessibility levels between car and transit. The results indicate that car accessibility is higher across all industrial areas in the IJmond. By focusing on transit and considering temporal factors, the results have shown that the level of accessibility in these areas decreases significantly during the night. Taking socioeconomic characteristics into account, the results also show that low-income groups live in larger concentrations closer to industrial areas than high-income groups.

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1
Introduction

Equity and its relation to accessibility
Transport equity is a concept that has been receiving increased attention in recent academic work (Cui et al., 2019; Lucas et al., 2016; Martens & Bastiaanssen, 2019; Mladenović, 2017). It focuses on the burdens in transport environments experienced by different population groups and the standards for addressing those burdens (Martens & Bastiaanssen, 2019). Within the field of transport equity, accessibility is a key sub-topic that focuses on people's ability to reach certain destinations and (social) activities. Importantly, accessibility differs from mobility: while mobility is about the movement of goods or people through a transport network, accessibility considers the ease with which a person can reach a range of destinations. This broader concept includes transport infrastructure, spatial layout, and socio-demographic or socio-economic factors. From an equity perspective, accessibility reflects the level of options available to people within the systems available to them, significantly impacting their quality of life and social inclusion (Martens & Bastiaanssen, 2019). Within the domain of equity, the fairness of distribution of these options can be viewed through different distribution principles.

The relevance of accessibility
Contrary to accessibility, mobility is not a goal but rather a means to reach destinations and activities in the spatial setting. The PBL, a Dutch governmental institute specialising in strategic policy analysis, has stated that accessibility should be the main focus of planning and evaluation of transport policies (Bastiaanssen & Breedijk, 2022). In the often occurring case in which accessibility requires mobility, coherence between the spatial setting, the mobility system and the individual's potential are of importance (Kuiper et al., 2023). In the past, mobility has been the norm to address transportation issues and consequentially develop new policies. This shift from mobility to accessibility emphasizes the relevance of further research in the field of accessibility and exploring the possibilities to evaluate existing and design new policies.

The relevance of industrial areas
Accessibility is also important for the economic functioning of cities and regions as better connectivity increases the interactions between employees of different companies. As a consequence, this increases their innovative capability and productivity (Banister & Berechman, 2001). The PBL recommends in their report 'Brede Welvaart' to not only focus on the accessibility of urban areas such as city centres but also suburban peripheral and industrial areas, the latter of which are often situated outside the city centre (Snellen & Bastiaanssen, 2021). The general literature on location choice for businesses states that industrial areas as well as business parks in general are attractive locations for factors such as logistics and labour costs (e.g. proximity to markets and suppliers) and agglomeration benefits. As smaller companies often are unable to find appropriate commercial property in the direct vicinity, they benefit significantly from business parks (PBL, 2012). However, this is not the original motivation behind the creation of business parks. As a measure from the government, these areas were created to concentrate industrial and logistical enterprises that originally caused environmental, noise and traffic nuisances in or near residential areas on separate sites. Hence zoning required them to be concentrated in specific job sites away from areas where people lived. One of the main purposes of industrial

areas is to provide enterprises with easy access to international distribution networks through access to highways, shipping corridors and in some cases railways. This as a result can stimulate their economic activity. Easy access to these areas for employees is often a secondary concern making businesses less attractive for job seekers in the surrounding area. The attractiveness of these businesses is even lower when the mode of transport is transit, cycling or walking. According to Gommers and Wortman (2010), there are several reasons behind this problem. The first is that the location of business parks in general in the peripheral zones around large cities limits the ability of existing transit systems to facilitate the travel demand of these areas. Due to the high demand that comes with high-density zoning, most transit hubs are located in the city centers resulting in longer travel chains for people that need to travel from and to business parks. As the road infrastructure in industrial areas is already present to meet the needs of site logistics, car travel time is often much lower thus making the car a more attractive mode of transport to access these areas. The second reason is that these areas facilitate industrial enterprises where the employees work in shifts. Consequentially, the travel demand is characterized by short but intense peaks making it difficult to operate a public transit service across the day. An important third reason is that these areas often suffer from a lack of responsibility or available tools from the actors involved: Both the municipalities and businesses lack the budget to invest in better transit operations and thus view it as the national governments' task to oversee this (Gommers & Wortman, 2010). Additionally, employers are still very car-oriented which is reflected by offering higher travel allowances for the automobile and the provision of car parking spaces.

However, a study from Radboud University stated that industrial areas in The Netherlands are at risk and sometimes already are in the process of deteriorating, making them less attractive for businesses and thus resulting in lower job availability for job seekers (Beekmans, 2015). The study defines deterioration in industrial areas as the rate of technical, economic, societal as well as spatial ageing which consequentially would lead to economic sub-optimal performance and impoverishment in these areas. This is correlated to the deterioration of accessibility by road and public transportation (Beekmans, 2015; Traa & Knoben, 2009). As stated before by Gommers, they often struggle with limited transportation options, making it challenging for both employees and businesses to thrive. Insufficient public transportation links to these areas can result in employees facing longer commutes, affecting their quality of life and work-life balance. Gommers also states that providing public transport services to business parks alone is often considered too expensive due to the lack of travel demand and thus the lack of proper funds for the necessary supply (i.e. transit infrastructure).

However, according to a recent study by Verheggen (2019), there is an increasing trend in flexible working hours which has affected industrial areas as well. As a result, in the last 10 years, the workforce demographics in these areas have changed. For example: A logistical company no longer employs only forklift operators; they now also hire students to handle return shipments. In addition, diversification in these areas is present from b2b (business to business) towards b2c (business to customer) companies, which makes good public transit an important factor for these new companies. Verheggen further states that younger employees however often do not own a car and must rely on public transportation to reach their jobs. Existing research has also stated this for low-income groups in general which are overrepresented in the workforce of these areas (CBS, 2024b). Inadequate transit accessibility for employees can deter potential investors and limit the potential for further diversification and economic growth within these regions (Beekmans, 2015; Verheggen, 2019).

Despite the deterioration of existing industrial areas, an ongoing trend in The Netherlands is the increase in the total surface area of industrial areas. From 1996 to 2012, this increased by 30 %, from 649 to 841 square kilometres, and was widespread, occurring not only in major cities but also significantly in smaller municipalities (CBS, 2016). The expansion was most present in less urbanized regions, with small municipalities experiencing a 31 % increase compared to 23% in the four largest cities: Amsterdam, Rotterdam, The Hague, and Utrecht. The growth in industrial area size per municipality in The Netherlands can be seen in Figure 1.1. As industrial areas continue to expand, particularly in less urbanized regions, the relevance of evaluating labour force access to these zones is further substantiated. The increasing size of industrial areas can create significant job opportunities but also presents challenges in terms of accessibility for the local workforce.

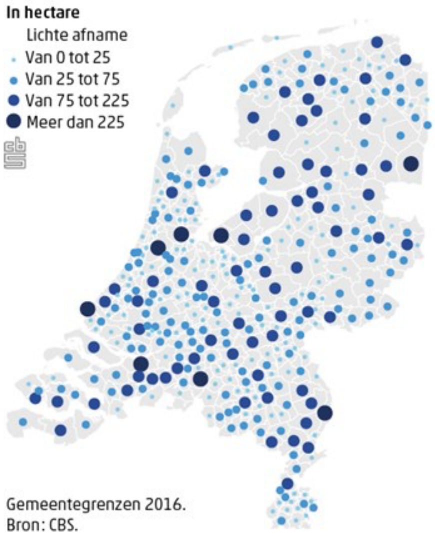


Figure 1.1: Growth of industrial areas from 1996 to 2012, the legend displays the increase per area in hectares ranging from 0 to 225

From both a societal and economic perspective, therefore, accessibility to the labour force around concentrated industrial areas is an important topic for further research. Particularly the evaluation of mixed industrial areas is of interest as they represent ninety percent of the total amount of industrial areas in The Netherlands as of 2004 (Louw et al., 2004). Designing new policies by evaluating accessibility to the labour force for mixed industrial areas is thus a research topic of special interest. There is a gap in the research on how companies in industrial areas can access the labour force that resides in the surrounding area. Previous research has primarily focused on how accessible job sites are for job seekers and whether these available jobs are eligible given the socio-economic or socio-demographic variables of the job-seekers such as income level (Cheng & Bertolini, 2013; Liu & Kwan, 2020; Wang & Chen, 2015). Spatial accessibility studies primarily focus on workers' perspectives due to their central role in using transportation systems and accessing services. By understanding and addressing the needs and barriers faced by workers, these studies contribute to the broader goal of promoting equity in terms of access to jobs, services, and opportunities, particularly for marginalized or vulnerable populations such as lower-income groups.

An evaluation of access to the labour force from a business perspective, could in return also provide new insights into job accessibility. According to Cheng and Bertolini (2013), this is because both concepts are intertwined in the relative location of houses and firms. In other words, by adopting this new perspective, deeper insights could be gained into the challenges faced by industrial areas, which are often overlooked when focusing solely on employee accessibility. This broader view allows policy-makers for a more comprehensive understanding of how to improve infrastructure and transportation systems to benefit both employers and employees in these regions. Consequentially, individual travellers could benefit from potentially greater accessibility to the jobs they seek. Further research states that industrial areas and business parks in general need to transform themselves to manage economic, environmental and social shortcomings. Therefore much is being done today to implement more sustainable business parks (Le Tellier et al., 2019). Sustainable urban planning and industrial ecology are important disciplines and key concepts related to this goal to which better accessibility could contribute.

Temporal aspects of accessibility

In addition to the lack of research in evaluating accessibility from an employer's perspective, insufficient attention has been given to the temporal component of accessibility. Existing research has neglected the impact of the transportation system, particularly concerning shift work and the consequential challenges imposed by intense travel demand peaks. Stępniak studied the spatio-temporal variations in transit services in the Polish city of Szczecin with a cumulative-based accessibility model and another similar study by Yan evaluated temporal transit accessibility for low-income workers in a set of counties in the US (Stępniak & Goliszek, 2017; Yan et al., 2022). The temporal aspect of accessibility is essential as it directly impacts the ability of workers, particularly those engaged in shift work, to reach their jobs during off-peak hours. This is where the concept of time-based exclusion becomes particularly relevant. As illustrated in red in Figure 1.2, time-based exclusion is one of the fundamental components of transport-related social exclusion as has been discussed by Luz and Portugal (2020).

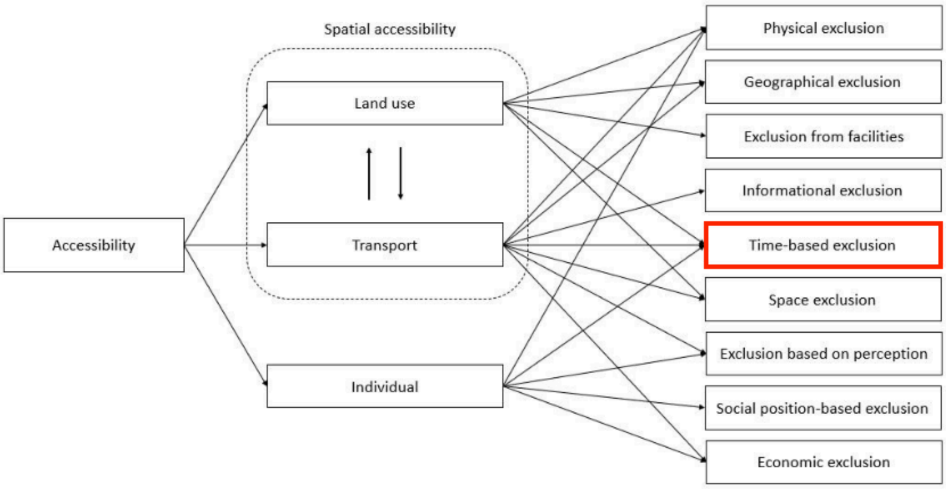


Figure 1.2: Relationship between accessibility components and transport-related social exclusion with time-based exclusion highlighted in red

Luz describes how inadequate transport frequencies or low punctuality can limit the number of opportunities for an individual, be it in the context of leisure, work or other activities. Addressing these temporal disparities is essential for creating a more equitable transportation system that accommodates the needs of all workers, regardless of their shift timings or socioeconomic background. While existing studies such as those by Yan and Stepniak have addressed temporal disparities in their studies, both have not considered the deteriorating effect that travel cost could have on job accessibility. The travel cost can either be expressed in travel time, distance or actual cost. Additionally, they view accessibility from an employee's perspective instead of through the lens of an employer. Thus the gap is a lack of understanding of how the time of day and travel cost can impact job accessibility in industrial areas from an employers' perspective.

1.1. Research Gaps

There are three research gaps in job accessibility that this thesis aims to address:

- It is unknown what the impact of different transport modes is on labour force accessibility in industrial areas.
- It is unknown what the impact of temporal factors is on accessibility to these groups from industrial areas through the lens of an employer.
- It is unclear how labour force accessibility in industrial areas is influenced by different socioeconomic variables within the working population around these areas.

It is unknown what the impact of different transport modes is on labour force accessibility in industrial areas.

It is unknown what the impact of different transport modes is on labour force accessibility in industrial areas. Comparisons have often been made between car and transit modes using a multitude of models. An example of such a model is the displacement-time factor. It is developed by the TU Delft known as the Verplaatsingstijdsfactor which has since been used by experts in the field of transport planning for decades (Bovy & Van Goeverden, 1994). The Verplaatsingstijdsfactor is the ratio between displacements possible by public transit compared to that by car. It plots this in a VF-curve with the VF factor expressed as the ratio between car and transit time on the horizontal axis and the mode share on the vertical axis. When the factor is higher than 1, the number of displacements by transit is higher by car and vice versa. In often cases, the factor is lower than 1 and declines when travel time increases. This means people prefer to use the car when the travel time is longer. The VF model developed by TU Delft relies on real-world survey data to capture the stated choice of individuals in transportation mode choices between pre-defined origin-destination pairs. It thus needs real data from surveys to determine the VF curve for a given case study. Existing VF models do not take into account the number of accessible opportunities at the destination but rather focus on the travel time or time cost imposed on actual trips. It thus is limited to the field of mobility. Its focus on choice modelling helps in understanding how people select transportation modes in different situations. Accessibility, on the other hand, is a broader concept that considers the ease with which individuals can reach various opportunities or destinations, such as employment, education, healthcare, and services. Accessibility analysis takes into account not only the transportation mode but also the spatial distribution of opportunities, the quality of transportation infrastructure, and factors that affect the ability of different socio-economic groups to reach these opportunities (Martens & Bastiaanssen, 2019). In other words, the VF model is limited to analyzing mobility rather than accessibility, hence there is a gap in understanding how different transport modes influence labour force accessibility. This gap highlights the need for an alternative approach that considers the broader aspects of accessibility.

It is unknown what the impact of temporal factors is on accessibility to these groups from industrial areas through the lens of an employer.
There is a quantitative gap regarding the understanding of what impact the time of day has on the number of accessible employees. Existing research primarily emphasizes accessibility evaluation during a single period of the day, overlooking the broader temporal aspect of accessibility, particularly when sites such as industrial areas become relevant (Yan et al., 2022). While studies acknowledge the importance of accessibility analysis, they often fail to consider the correlation between the time of day, the built environment and the ability of industrial employers to attract and retain a skilled workforce. Understanding how departure time impacts job accessibility in industrial areas from an employer's standpoint is crucial for informed decision-making, urban planning, and policies aimed at enhancing economic development, reducing congestion, and generating sustainable transportation choices. This research gap highlights the need for a comprehensive assessment of accessibility within concentrated industrial zones.

It is unclear how labour force accessibility in industrial areas is influenced by different socioeconomic variables within the working population around these areas.
It is currently unclear how accessibility to the labour force is influenced by the different socioeconomic variables of the workforce. Existing models such as the integrated land-use and transportation model TIGRIS XL simulate the interaction between land use and the transportation system on a regional level. However, TIGRIS XL is unable to model the impact on accessibility accounting for different groups based on their socio-economic characteristics. Furthermore, it is unable to model at the level of regional economic agglomerations and instead models at either a limited municipal level or a much larger macro-economic level (van Eck, 2020). This is problematic as it poses a challenge to include regional policy interventions for modelling accessibility.

1.2. Research Objective

The objective of this research is to evaluate accessibility to the workforce for specific job sites in concentrated industrialized areas by car and transit at different times of the day. This method can then be applied to develop policy approaches for expanding the number of people able to reach these jobs. By focusing on the perspective of the enterprises situated in these industrial areas, evaluating labour force accessibility can also result in a better understanding of job accessibility.

1.3. Research Questions

The research question is as follows:

- How do spatio-temporal factors and socio-economic characteristics influence transit accessibility in industrial areas and what do they imply for transport inequality in the surrounding area?

The sub-questions that aim to help to answer the research question are:

- How does spatial accessibility in industrial areas by transit compare to accessibility by car?
- How do accessibility levels in industrial areas to different socio-economic groups vary across different times of day?
- What are the implications of these temporal and socio-economic variations for transport policy and urban planning of industrial areas?

1.4. Research Approach

This thesis starts with a definition of the problem regarding accessibility of industrial areas, followed by a literature review to better define the relationship between transport equity and accessibility and explore existing accessibility models. Next, a conceptual framework is constructed to perform the accessibility analysis. With a framework in place, data is collected from multiple (governmental) sources and prepared to be used in the accessibility model. This model is applied in several steps during the methodology phase. The case study area will also be defined in this section. The methodology of this thesis is based on transport modelling by applying a gravity model for evaluating the spatiotemporal accessibility of residential locations from industrial areas. Consecutively, the results of the spatiotemporal analysis on accessibility in industrial areas by transit are used to discuss recommendations for future researchers and policymakers.

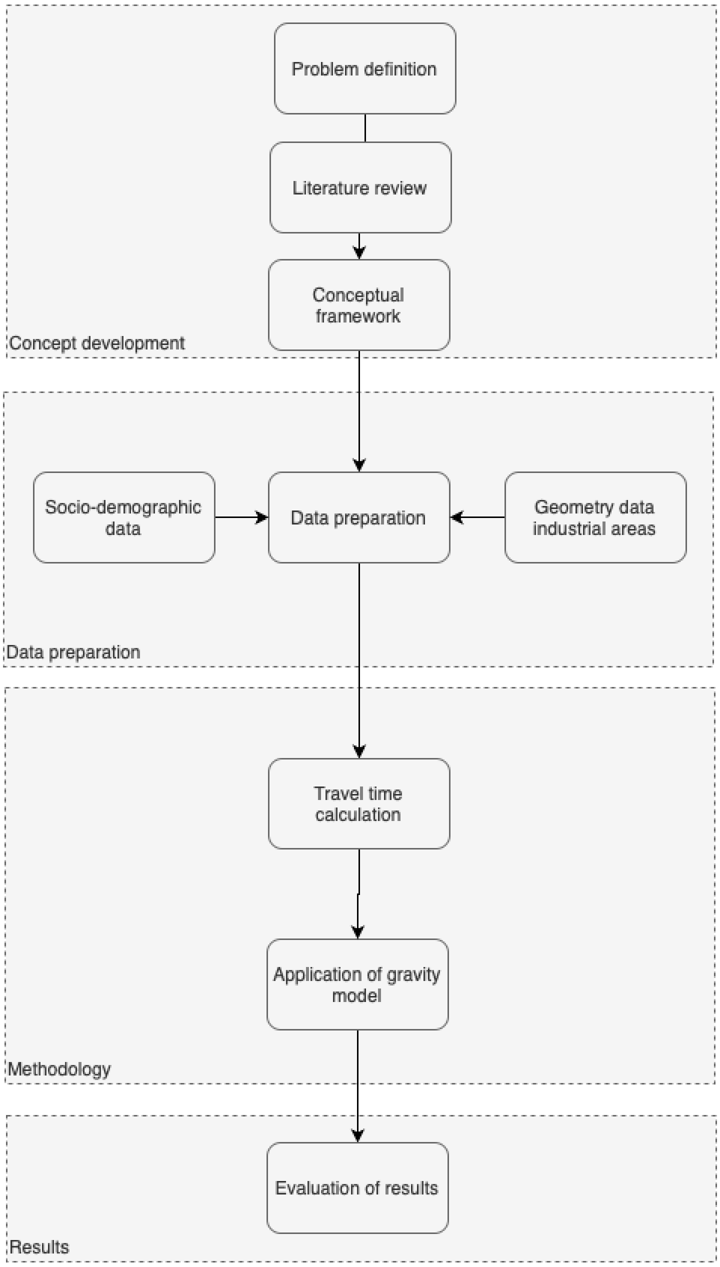


Figure 1.3: Framework for spatiotemporal accessibility analysis of industrial areas

2
Literature Review

This literature review lays out further the relationship between transport equity and accessibility and explores existing research on the impact of industrial areas on job accessibility from an employer's perspective. Furthermore, a qualitative evaluation of existing accessibility models will be discussed. In conclusion, the literature review aims to construct a clear basis for the accessibility model together with a suitable equity distribution principle and provide insights into which factors are important for constructing the methodology.

2.1. Equity definition and components

As stated in the introduction, equity focuses on the burdens in transport environments experienced by different population groups and the standards for addressing those burdens (Martens & Bastiaanssen, 2019). Equity is a concept that relates to the objective of narrowing inequalities. While it has been discussed in many studies, the concept of equity still varies among scholars (Martens et al., 2019). Equity is strongly related to other categories such as justice, fairness, accessibility and equality, of which the latter is often interchanged. Equality, however, implies that people or groups deserve the same rights. Whereas people or groups might not have the same rights or opportunities, equity implies that they should be provided differently to address these disparities. In the field of public transport, absolute equality is impractical as it implies that all groups should be provided with the same level of service. In other words, because people live in communities of different densities with different geographic characteristics it is not realistic or at times possible to develop transportation systems where every individual has a similar level of accessibility to every destination. Therefore the concept of equity is often more related to fairness and justice rather than equality.

Equity is often divided into two segments: Vertical equity and horizontal equity. Vertical equity, also known as social equity, is the broadest definition of equity and is related to the allocation of benefits among different social groups. The allocation is based on their capability or willingness to pay for a service. Horizontal equity, also defined as spatial equity, is concerned with equal treatment of social groups that have equal means (Litman, 2022; Welch & Mishra, 2013). In the field of transportation, this could mean that people with similar income and travel needs should pay similar costs or receive similar benefits. An example of horizontal equity in this case is the implementation of tolls on highways. In this example, two individuals can be considered who live in the same area, work at similar jobs, and have similar incomes. If one of these individuals uses a tolled highway for their daily commute while the other uses a route without tolls, it might be considered horizontally inequitable if the individual using the tolled highway pays a significantly higher share of their income for transportation. In this case, implementing a pricing system that charges both individuals a similar share of their income for the use of the highway could be seen as achieving horizontal equity.

Horizontal equity tries to maximize two objectives: Improving accessibility in general and achieving an equal distribution of accessibility among regions or groups (Ortega et al., 2012). It relates to the idea that individuals with different abilities to pay should be treated differently. In the context of transportation, this might involve implementing policies that provide subsidies or benefits to low-income individuals to ensure they have access to transportation services. An example of vertical equity is a city providing reduced-fare or free public transportation passes to low-income residents as it aims to reduce the transportation burden on those who are economically disadvantaged. This approach acknowledges that some individuals may need more financial assistance to access essential transportation services due to their lower income.

Martens et al. (2019) distinguishes transport equity into three key components:

- The distributed benefits and burdens;
- The populations and social groups over which they are distributed;
- The distributive principle determining the ethicality of a given distribution.

2.1.1. Benefits and burdens

The benefits and burdens can be assessed through different focal variables: Resources, opportunities, outcomes and well-being. A resource could be a thing possessed by an individual such as a car, bicycle or subsidized public transport card. Opportunities, or risks, are described as the implications enabled by possessing a certain resource. A benefit could be greater reach by owning a car. A burden could be the risk of air pollution by having more cars on the road. When an individual has successfully used certain resources and opportunities, that can best be described as outcomes. A beneficial outcome is a higher level of trips or travelled distance an individual has made. A burden could be respiratory disease from air pollution by car traffic. Well-being refers to the mental state of an individual. The mental state is a consequence of the allocation of resources, opportunities and outcomes as well as the personal characteristics of the individual.

According to Martens et al. (2019), transport equity can be further categorized into four dimensions: Mobility/accessibility, traffic-related pollution, traffic safety and health and traffic health. The topic of this research, the accessibility of industrial areas to the labour force is strongly related to the first dimension of equity. A better understanding of this relation can be provided when applying the different focal variables of the benefits and burdens in transport equity. The amount of roads, parking spaces or transit availability in the industrial area are examples of resources. Opportunities relate to the potential mobility of new job seekers and the ability of employers to reach job seekers on the other hand. An outcome could be the modal shift of work commutes in and around industrial areas. Different allocation of parking spots for cars and bicycles or different transit frequencies are also possible outcomes. The satisfaction of an employee with the number of job seekers being able to reach relates to the focal variable of well-being.

2.1.2. Populations and social groups

Identification of different populations and social groups is the second component for the assessment of equity within the transport domain. Equity analysis is motivated by evaluating how every person receives his/her fair share of the transport benefits and to what extent this person is protected from the burdens of the system. Assuming there are invariable distributions of transport benefits among populations and social groups, it can be concluded that there should be groups that experience a certain transport disadvantage. According to academic literature, low-income households and people without the ability to drive a car are particularly disadvantaged in the distribution of transport benefits. According to Martens et al. (2019), there are several distinctions of social groups that are made according to socio-economic variables: Residential location, transport mode, income, age, gender, (dis)ability and ethnicity. Employment status is also an important socio-economic factor commonly used in research (Carleton & Porter, 2018). Factors of disadvantage are usually chosen by researchers with the objective of meaningful analysis, but also due to limitations in data availability. If for example education level is not available, it might be useful to look into its correlation to other factors such as income class and use the latter as a proxy if the correlation is significant enough. Fortunately, existing data sources such as CBS do provide socio-economic information regarding income level and education level.

2.1.3. The distributive principles

The third component of an equity analysis is the application of a suitable distribution principle. There are different distribution principles for both situations as well as interventions. First, three examples of distribution principles are given. The most intuitive definition within the domain of equity is equal distribution where people have the same amount of the distributed resources and opportunities. It can be viewed as the 'default' distribution, however, this standard of equity is not always suitable as it fails to account for the complex and varied needs of different individuals and communities (Martens et al., 2019). Thus a second variation to this standard is the proportionality in which a deviation from the absolute equal distribution is allowed under the condition that these deviations are relative to the size of each population group or individual. In the case of job seekers around industrial areas, facilitating exclusive transportation for handicapped job seekers is an example of using the proportionality standard. The third variation to the standard of equity is the maximum gap standard. This variation allows inequality among population groups under the condition that this inequality is limited within a predefined range. While the proportionality standard takes a pragmatic approach to the equality of distribution, the maximum gap standard unequivocally allows inequality instead.

Rawl's Theory is perhaps the most discussed distribution principle in transport academic research. It assumes rational actors who make decisions behind a "veil of ignorance," unaware of their circumstances with equal basic liberties. It presents two principles of justice: fair equality of opportunity and the difference principle. The former demands equal access to fundamental rights, including transportation services. In the case of industrial areas, it could be the implementation of a transit line to service the area so that less advantaged groups without a car can also reach jobs. The latter principle of justice allows for inequalities but only if they benefit the least advantaged, suggesting that in transport equity, disparities should primarily aid those with limited access (Lewis et al., 2021). This draws similarities with vertical equity, discussed earlier, as it motivates to draw resources from well-advantaged groups to less-advantaged groups. Using the same case of industrial areas, it could be subsidized tickets for low-income workers. As Rawl's Theory states there should be fair equality of opportunity, similarities can be drawn with the proportionality standard discussed earlier as individuals should receive compensation proportional to their importance in office.

Utilitarianism is the second most discussed distribution principle. Over the past century, the utilitarian approach has proven to be the backbone of welfare economics and CBA analysis. This ethical framework focuses on maximizing the aggregate welfare or benefit and thus inherently minimizing the burdens on the aggregate population (Thomopoulos et al., 2009). For industrial areas, this implies that the total number of accessible jobs is acceptable, even if that means less advantaged groups such as low-income job seekers without a car cannot access the area. Therefore the principle aligns more with horizontal equity as it does not explicitly prioritize equal treatment among different social groups or address individual needs based on specific characteristics such as income or capability to pay, which are key concerns of vertical equity (Litman, 2022). Contrary to this, the egalitarian approach states that an equal level of benefits should be provided to all groups. The approach argues that individuals place different levels of value and needs on these benefits. Thus, the actual distribution of these benefits might be ethically equal without the benefits themselves being equal (Bills & Walker, 2017). In the context of horizontal and vertical equity, egalitarianism aligns with both by striving to level the playing field, ensuring that all individuals, regardless of their socio-economic characteristics, have similar access to opportunities.

When evaluating the accessibility in industrial areas to the labour market, an egalitarian approach is most suitable as it emphasizes equal access to employment opportunities for all socio-economic groups. This approach promotes fairness and inclusiveness, potentially leading to more balanced labour force participation in residential zones surrounding these industrial areas. One of the research gaps is the lack of understanding of how different socio-economic groups are impacted by the spatial setting of industrial areas. An egalitarian perspective ensures that the analysis considers the distribution of accessibility benefits across all groups, providing insights into whether these areas offer equitable access to job opportunities. By focusing on the socioeconomic characteristics of the target groups, new insights could be gained into the fairness of accessibility distributions, ensuring that no group is left behind in accessing industrial employment opportunities. Examples of target groups are low- and high-income workers and workers with either a lower or higher education level.

2.2. Accessibility definition

Accessibility is inherently related to equity. The dynamic between the two concepts in the field of transportation can be seen as how transport accessibility is equitably distributed among social groups. An egalitarian approach emphasizes providing equal access to opportunities and activities for all groups, regardless of their socio-economic status. In the context of egalitarianism, accessibility is viewed as a measure of how well different population groups can reach primary destinations and services. A lack of equitable accessibility can lead to social exclusion as earlier described by Luz and Portugal (2020), particularly for disadvantaged groups who may face barriers to reaching job opportunities, education, healthcare, and other essential services. From an egalitarian perspective, it is crucial to ensure that all groups, regardless of their socio-economic characteristics, have equal access to these opportunities, thereby promoting fairness and inclusiveness in the transportation and land-use system.

2.2.1. Accessibility perspectives

In the existing literature, accessibility is often viewed from either an empirical, theoretical, or policy perspective (Van Wee, 2022). The empirical perspective typically involves calculating differences in accessibility levels using quantitative methods, such as the gravity model, which incorporates travel time impedance functions to measure continuous accessibility. This approach assesses how many activities or opportunities can be reached within a certain time frame, providing a detailed and nuanced understanding of accessibility. The theoretical perspective involves qualitative literature reviews that explore ethical questions and moral considerations related to accessibility (Martens, 2016). An egalitarian approach in this context would focus on ensuring equal access to opportunities for all population groups, examining the implications of this principle compared to other ethical frameworks like utilitarianism. The policy perspective analyzes accessibility challenges and opportunities within existing policy plans, emphasizing the impact on different socio-economic groups. Evaluating accessibility in industrial areas for lower-income groups through an egalitarian lens would emphasize equal access to labour force opportunities and consider how current policies affect various socio-economic groups. This comprehensive approach ensures that no group is systematically disadvantaged and promotes fairness and inclusivity in transportation planning. An egalitarian approach, however, is not only theoretical but can also be applied empirically using methods such as the gravity model. This allows for a quantitative assessment of how accessibility scores are distributed among different socio-economic groups, ensuring that equal access to job opportunities is measured and evaluated in a concrete and actionable way.

2.2.2. Accessibility components

Regardless of the perspective used for accessibility analysis, academic literature acknowledges there are generally four components of accessibility: Transport, land use, individual and time (Lucas et al., 2016).

The transport component focuses on the transport system, specifically the disutility experienced by groups or individuals while travelling from an origin to a destination. Parameters that are often used are travel time, costs of travel and comfort-related variables. For industrial areas, calculating travel time for employees to these areas is an example of a transport component of accessibility.

The land-use component entails the land-use system. this consists of the amount, quality and spatial distribution of opportunities. In the case of this research, the spatial distribution of jobs and workers' households is of particular interest.

Third is the individual component which reflects the needs, abilities and opportunities of an individual. These are often based on socio-demographic (age, gender, household structure) and socioeconomic characteristics (income, education, occupation). They influence an individual's overall accessibility in terms of accessible transport modes and spatially distributed opportunities. An industrial company could perhaps struggle to reach certain job seekers with a low-income level due to high commuting costs.

The last component is the temporal component. It reflects the temporal constraints applicable to accessibility such as the availability of opportunities at different times of the day. A bus service could run only at peak hours during the day whilst some industrial enterprises with night shifts need their workers to access the site during the night, implying there are temporal constraints for both the employer and the employee willing to work at night.

The important role of the land-use component in accessibility modelling lies in its capacity to determine the spatial distribution and localization of opportunities, consequently having a direct influence on the transport infrastructure and services and thus the transport component. The land-use component serves as a fundamental determinant, shaping the geographic placement of essential opportunities, thereby establishing the spatial context in which the transport system operates (Geurs & van Wee, 2004). It may also address time restrictions (temporal component) and have a direct influence on people's opportunities (individual component). In conclusion, all these components can interact with each other in multiple directions. This implies that a disadvantage in one dimension can be compensated by an advantage in another dimension (Lucas et al., 2016). Using the research topic of industrial areas, the disadvantage of having job sites further away from households (land-use component) can be compensated by better public transport availability to these areas. In other words, the disadvantage of limited job opportunities in the land-use component can be compensated by the advantage of an efficient public transportation system from the transport component. As stated in the introduction, this public transportation system is often lacking resulting in insufficient compensation for land-use disadvantages in industrial areas (Gommers & Wortman, 2010).

For evaluating accessibility to the labour market of industrial areas, an empirical approach is most suitable to compare the weight of accessibility levels among different socio-economic groups by taking travel impedance and the size of the labour force into account. This approach highlights the importance of travel cost, either expressed in time or monetary units, and the number of opportunities at the destination side, expressed in the population size of the labour force.

2.3. Existing accessibility models

Measuring equal accessibility in the context of egalitarianism can be executed through several approaches and metrics. As mentioned in the problem statement, existing accessibility models already exist to evaluate how land-use and transportation systems improve the ability of social groups to reach activities or destinations. An example is the Lorenz Curve and Gini Coefficient as has been demonstrated by Lucas et al. (2016) in which the Lorenz curve is displayed on a graph where the number of opportunities is plotted on the y-axis and the share of the population having access to those opportunities plotted on the x-axis. The Gini Coefficient derived from the curve would indicate the level of inequality in accessibility. Two other relevant accessibility methods currently applied in the field of transport are cumulative opportunities and gravity-based measures (Cui et al., 2019). The first focuses on the number of opportunities an individual can reach within a pre-defined distance, time or cost (Geurs & van Wee, 2004). Gravity-based measures improve the cumulative opportunities method by capturing spatial friction with an impedance function. Spatial friction can be defined as a movement that leads to an undesirable loss of resources such as time or cost (Engelberg et al., 2021). Parameters of the impedance function require empirically derived data thus resulting in the model representing behavioral aspects. This results in the impedance function using an internal cost function. This cost consists of the travel time as well as the monetary cost.

The model used for evaluating accessibility in industrial areas should include the distinction between transit and car to highlight the potentially significant difference in accessibility levels between the two modes of transport. As one of the research gaps has also noted that it is unknown how temporal factors affect access to different socio-economic groups, the model should also account for time. The study by Yan et al. (2022) examined spatiotemporal job accessibility by transit and car. The focus of Yan was on job accessibility instead of access to the labour force, although his model makes use of a distinction in modes, time of day and incorporates travel time in an impedance function. These three variables are also present in the case of evaluating spatio-temporal accessibility in industrial areas to the labour force. Stępniak and Goliszek (2017) shifts the focus away from job-related activities and instead analyzes general spatiotemporal accessibility using the total population as a proxy of destination attractiveness.

Both Yan and Stepniak provide insights into how a model can be built for this research. The gravity-based Hansen model offers several advantages over other accessibility measures such as cumulative opportunity measures and the Lorenz Curve/Gini Coefficient. The Hansen model incorporates travel impedance, which allows it to account for the decreasing likelihood of accessing opportunities as travel time or cost increases. This provides a more realistic and nuanced representation of accessibility that reflects real-world conditions. Additionally, by using a decay function to weigh opportunities, the Hansen model can differentiate between destination sites that are equal in distance to the origin but vary in travel convenience due to factors such as congestion or travel time. This is particularly beneficial when evaluating accessibility in more complex urban settings, where travel times can vary significantly throughout the day.

3

Methodology

This section illustrates the method for evaluating accessibility to the labour force around industrial areas. The lack of accessibility research for these areas as well as the ambiguous term requires first to define the relevant type of industrial areas for this research. Next, the necessary data is defined that will be used for the accessibility model. Motivations will be given for why specific socio-economic variables are chosen, as well as for the scope of the spatial area. This is followed by the definition of the accessibility model itself. Finally, the case study area will be presented.

3.1. Defining Industrial Areas

As stated in the introduction, industrial areas are a type of business park created as a measure by the government. Business parks in general were created to concentrate industrial and logistical enterprises that originally caused environmental, noise and traffic nuisance in or near residential areas on separate sites (PBL, 2012). The Netherlands uses the IBIS database for storing information regarding job sites. The Dutch definition for a business park is a 'bedrijventerrein'. They are intended as a job site of a minimum gross area of 1 hectare destined for trade, commerce and industry. Additional activities such as commercial and noncommercial services can also be present, be it to a limited amount. Types of job sites that are excluded are port areas, office locations, and terrains for raw material extraction (IBIS, 2022; Rijkswaterstaat, n.d.). Within the concept of such a terrain, the term industrial area or 'industrieterrein' is used for a more specific definition of areas that primarily serve heavy industry of which commercial services and offices are excluded. The industrial area in the IJmond region in which Tata Steel Netherlands is situated can be classified as an 'industrieterrein'. This does not only apply to the establishment of large companies such as Tata Steel but also to smaller companies where industrial activity takes place (Rijkswaterstaat, n.d.).

As of 2015, a third of Dutch labour places are situated in business parks. This varies however per region in the Netherlands. In West-Brabant and the IJmond areas for example, the number of jobs is relatively high whereas in more urbanized areas such as Haarlem and Greater Amsterdam, the share is relatively low as in those areas, the sector of service jobs is significantly stronger (Renes, 2009). The same report states that, on average, over 50% of jobs in business parks are heavy industry and logistics with the IJmond area for example over 50 % solely falling under the heavy industry category due to the presence of the Tata Steel factory. The report assumes that if 50% or more of the jobs fall under heavy industry and logistics, the site will be classified as an industrial area.

In past research, the definition of business parks has been further categorized into different groups of economic activity. This can vary from factories, port facilities, financial institutions, corporate service industries as well as storage companies (CBS, 2017). Another study from the TU Delft explains that the mentioned types of activity in The Netherlands can be found in five types of business parks (Louw et al., 2004): Heavy industrial areas, seaports, mixed industrial areas high-quality business parks, distribution parks. A report by the PBL on the other hand, uses a different classification, dividing business parks into the following groups: Industrial areas, logistical areas, consumer services areas, business services areas, governmental and other services areas and lastly mixed areas (PBL, 2012).

The literature implies that there is a lack of a general classification of business parks, however, developments have been present in recent decades concerning business parks with industrial areas in particular. Weterings et al., 2008 states that employment opportunities in classic industrial areas are changing with a decreasing amount of industry and logistics jobs in the 1999-2006 period. In the same period, the share of service sector jobs has increased, in particular in the consumer, financial and business service sectors. This ongoing trend indicates that traditional industrial uses are increasingly giving way to diverse economic functions, transforming industrial areas into mixed-use zones to optimize land use. Consequently, the distinction between industrial areas and business parks is becoming less distinct. Therefore, utilizing the more general IBIS database for 'bedrijventerreinen' could be beneficial in light of this trend. Analyzing the current accessibility of these areas could inform future policymakers with policies aimed at enhancing these areas and aligning with this evolving economic environment.

This paragraph was primarily intended to define industrial areas. It is a type of business park destined for heavy industries as well as logistics, facilitating a third of the total jobs in The Netherlands. The IBIS database provides a clear definition of industrial areas as a work location with a minimum size of 1 hectare destined for trade, commerce and industry. Therefore the focus of this research is on utilizing this database. The definition by IBIS highlights the shared characteristic of industrial concentration and spatial separation from non-industrial zones.

3.2. Data Requirements

3.2.1. Socio-economic data

For this thesis, district-level (Dutch: Wijkniveau) socio-economic data will be used for modelling accessibility. A more granular level could capture localized variations of job accessibility among districts. While providing an even higher level of detail, neighbourhood-level data (Dutch: Buurtniveau) will not be considered as the granularity of this data poses a risk to the privacy of households and would increase computation times in the modelling process. Additionally and consequentially, a lot of the required variables are not available in the neighbourhood-level dataset by CBS making it impractical to consider for this research. The required variables for this study are:

- Share of low-income workers per district
- Share of low-high educated workers per district
- Total working population per district
- Geometry of residential districts

The labour force comprises employees living in district areas (Dutch: wijken). This research relies on socio-economic data from the Central Bureau of Statistics (CBS) for all of the required socio-economic variables which provide insights regarding employment trends (CBS, 2024a). Given the literature review highlighted the disparity in job accessibility between low-income households and high-income households, the focus is to compare the accessibility in industrial areas to employees from both low-income and high-income households. Due to the wide availability of data and relevance to income class, education level is also considered. The provided dataset from CBS categorizes the average personal income per household at the district level, in Dutch also known as 'Wijkniveau'. Each district has a unique 5-digit code linked to its geographical location. Income from assets and subsidies such as rent allowance and child benefits are not included in personal income calculations. In addition to the average personal income level, the dataset contains two other income classes. It categorizes the proportion of private households per district that falls within the lowest 40% of disposable income categories nationally, alongside the percentage belonging to the highest 20% income bracket in the national income distribution. In other words, if district A reflects a low-income value of 60%, it signifies that 60% of households residing in that area belong to the lowest-earning 40% as per the national income distribution. the same logic applies to the highest 20% income class. The differentiation between these income groups within the dataset fulfils the requirement to understand the accessibility differences between lower-income and higher-income employees later on in this study as a model can be built upon this data.

The primary emphasis for this research is placed on income- and education-related metrics, aiming to assess and evaluate the accessibility of job accessibility for low-income and lower-educated employees of the labour force. Specifically, the applied dataset will provide crucial insights into variables such as the share of low-income households at the district level. The provided CBS dataset, presenting income data from 2022 categorized according to the 2023 district classification, serves as an important source and will contribute to a comprehensive assessment of job accessibility for individuals in the low-income segment of the labour force.

3.2.2. Job Location Data

Job location data of industrial areas is available to evaluate the accessibility of employees necessary for these job sites. Data regarding work locations should be disaggregated into zonal data similar to the socio-economic data regarding districts. The IBIS database provides geometry data regarding the work locations in The Netherlands where paid work is performed and classifies these areas as either office (Dutch: kantorenlocaties) or industrial locations (Dutch: Bedrijventerreinen) ("IBISbedrijventerreinen", 2023). This research does not require specific job data on a district level, as the focus is on the accessibility of the labour force and not on jobs. The only limitation of this method is that competition effects amongst industrial sites are not taken into account, however, future research could explore this further.

3.3. Job Accessibility Model

Place-based accessibility is modelled both by cumulative opportunities as well as similar but more advanced gravity-based models. The benefit of gravity-based is they consider diminishing effects of more distant opportunities whereas in cumulative opportunities models, each opportunity within a certain travel time or distance threshold is weighed equally. In addition, gravity models account for population sizes as well as the number of opportunities at the destination whereas cumulative-based models do not. The provided dataset by CBS for this research makes it suitable to perform an accessibility analysis by using the Gravity Model Theory. Socio-economic data from CBS provide an insight into population size per district and the data from IBIS contains the geometry of industrial area locations.

3.3.1. Gravity model

Existing Gravity models exist based on the theory of Hansen. The formula of the gravity model by Hansen is expressed as:

$$A_i = \sum_j O_j * f(C_{ij}) \tag{3.1}$$

In Equation (3.1):

- A_i = The accessibility for industrial location i;
- O_j = Number of opportunities for residential location j;
- C_{ij} = The travel time, distance or cost for a trip from i to j;
- $f(C_{ij})$ = The impedance measuring spatial separation between i and j.

The Gravity model can capture spatial interaction between the job locations at an industrial area, represented by the accessibility for location i, and the employees, represented by the number of opportunities for location j. A higher concentration of workers at location j, would result in a higher level of accessibility for location i, while greater distance or travel time from i to j reduces the impedance and thus accessibility levels for location i.
As accessibility by both car and transit are considered for this research, Equation (3.1) can be adjusted to account for multiple modes of transport.

$$A_i^m = \sum_j O_j * f(C_{ij}^m) \tag{3.2}$$

In Equation (3.2):

- A_i^m = The accessibility for industrial location i by mode m;
- O_j = Number of opportunities for residential location j;
- C_{ij} = The travel time, distance or cost for a trip from i to j;
- $f(C_{ij}^m)$ = The impedance measuring spatial separation between i and j by mode m.

For an urban transportation system with M modes, m = 1, 2 , ..., M. Equation (3.2) has a similar characteristic as Equation (3.1) but adds context by including modes of transport.
In addition to spatial factors, a time-based measure for accessibility modelling can be incorporated to capture the dynamic nature of accessibility to the labour force around industrial areas. Time-based accessibility modelling accounts for the temporal aspect of accessibility by assuming travel times and opportunities could vary during the day, thus the gravity model can be adjusted including the time-based component:

$$A_i^{tm} = \sum_j O_j * f(C_{ij}^{tm}) \tag{3.3}$$

With t = {t1, t2, …, t24}

Equation (3.3) enables the evaluation of temporal accessibility of work location i by modelling the temporal distance decay to the surrounding areas j in the set of employee locations N. Important to notice is that the set of opportunities or employees O_j is not time-dependent as data concerning the willingness to work on specific times of the day is not available.
Regarding the gravity model, the parameter β in the impedance function represents the sensitivity of travel or interaction between locations to factors such as travel time or distance. A higher value of β indicates a greater sensitivity, implying that travel times or distances have a stronger impact on the flow of people, goods, or information between locations. Apart from variables such as masses (e.g., population, economic activity), estimating β often involves regression analysis using observed flows between origins and destinations and travel times or distances. However, in the absence of observed flows for this research, β cannot be directly estimated. Instead, this study relies on existing literature to determine plausible values for β based on similar contexts or assumptions about travel behaviour. This approach allows for informed modelling decisions and provides a basis for interpreting the results within the context of existing research and knowledge. The beta value chosen for this research is set at -0.30 and stems from research on job accessibility in the Greater London Area where this beta value applied to both low-income and high-income groups Yan et al., 2022. The Greater London Area is similar to the Metropolitan Area of Amsterdam in which IJmond is located, both being highly urbanized regions. The impedance function follows Equation (2):

$$f(C_{ij}^{tm}) = e^{\beta * C_{ij}} \tag{3.4}$$

3.3.2. Network Data

The gravity model in Equation (3.3) considers both temporal as well as spatial aspects of the environment. This study relies on two primary datasets: socio-economic data encompassing information on employees and geographical location and geographical data specific to industrial areas, indicating their locations. As the gravity model also considers travel times, it is required to perform travel time calculations with the provided datasets.
To evaluate the accessibility of job opportunities for employees through the lens of industrial areas, travel times are calculated between origins (jobs) and destinations (employees). This task is performed using Quantum GIS (QGIS), an open-source geographic information system. Within QGIS, the TravelTime (TT) plugin facilitates the computation of travel times and distances into a travel time matrix as has been described by (TravelTime Technologies Ltd., 2024).
The TravelTime plugin utilizes the Dijkstra algorithm for computing travel times. Originating from graph theory, the Dijkstra algorithm efficiently determines the shortest path between nodes in a graph. In this research, nodes represent geographical locations, and edges represent road segments connecting these locations. By implementing the Dijkstra algorithm, TravelTime identifies optimal routes based on travel time, considering factors such as road conditions, speed limits, and traffic congestion.
Additionally, TravelTime utilizes the open-source OpenStreetMap (OSM) road network data for its calculations. OSM provides a rich dataset of road networks, including information on road types, lanes, and restrictions based on mapping services by a variety of contributors such as GIS professionals, IT specialists and hobbyists (OSMF, 2024).
By using the TravelTime plugin within QGIS and utilizing the Dijkstra algorithm along with GTFS data for public transit and the OpenStreetMap road network, accurate transit travel time calculation between the locations of jobs and employee households can be achieved. The transit travel time includes access and egress by walking as well, hence the road network is included in the calculation for pedestrian routes. Access and egress travel time by walking is determined for each road segment by considering the mode restrictions corresponding to various road types and adjusting the route for walking to this. This is possible in OpenStreetMap as each road segment is tagged with several waytypes per road segment. A highway is for example tagged as 'motorway' whereas a local road in the neighbourhood or district area is tagged as 'residential'. This approach serves as the foundation of network data analysis within this research and enables further implementation in the gravity model.

3.4. Model Implementation

The implementation of the gravity model involves several key steps, including data preparation, travel time matrix computation, and the construction of the weight matrix. In this section, the process is outlined to implement the model effectively. Figure (3.1) outlines the methodological framework of the accessibility analysis.

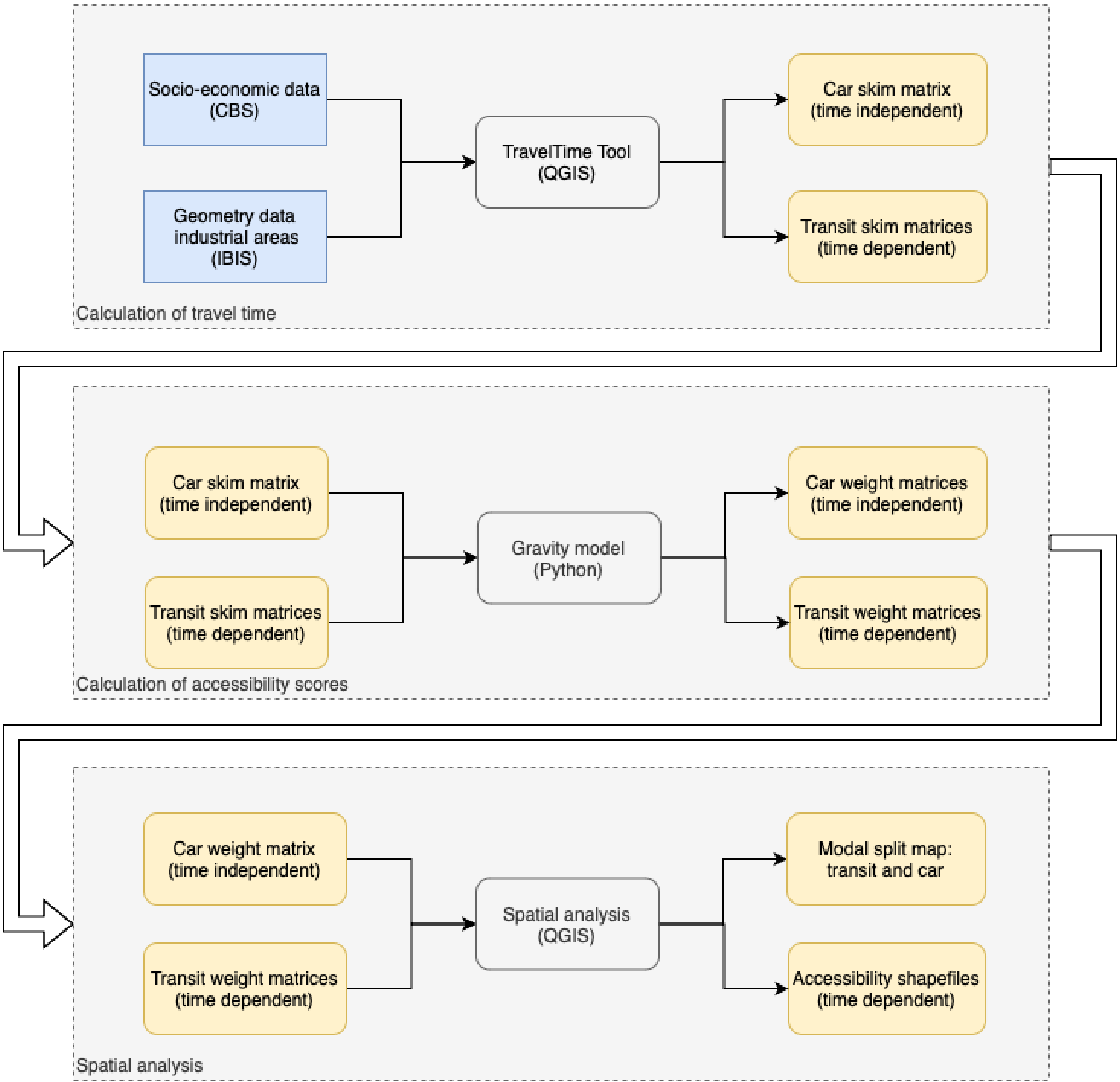


Figure 3.1: Methodological framework for accessibility analysis of industrial areas

3.4.1. Data Preparation

Initially, data preparation is carried out using Python programming language. Specifically, the dataset from IBIS containing geometry for industrial areas is reduced to the areas situated in the IJmond region. For this, Python's Pandas and Geopandas libraries are adopted. Consecutively, a new shapefile is generated to be used in QGIS. The socioeconomic data from CBS, provided as a CSV file, is reduced to only contain the districts in the Province of North Holland. The socioeconomic data based on the total working population, income and education level is appended to an existing shapefile with geometry data per district. this is needed to perform a spatial analysis. The prepared data can then be used as input for the calculation of travel times.

3.4.2. Travel Time Matrix Computation

Following data preparation, travel times in minutes are computed using the TravelTime plugin within QGIS as could be seen in Figure 3.1. The OpenStreetMap road network for the case study area is utilized through the TravelTime API for the matrix computation. The industrial area shapefile with geometry data, prior subject to manipulation in Python, serves as input data containing the origin locations of industrial areas. Meanwhile, the socio-economic household shapefile represents the destination locations of households/employees. The travel departure time is integrated into the TravelTime API, enabling the calculation of travel times for every hour of the day.

First, 24 skim matrices are computed through the API for the transit mode as a skim matrix for every hour of the day is needed. Second, a skim matrix is computed for the car mode containing the travel time regardless of the departure time. Traffic congestion is not taken into account as traffic data is not considered in the TravelTime API, thus it is obsolete to compute skim matrices at each hour of the day for the car mode. The resulting travel time skim matrices provide crucial input data for the gravity model, allowing for further analysis of accessibility to the labour force. Due to the unavailability of time-dependent travel time matrices for car travel across every hour of the day, the planned accessibility analysis comparing both transit and car modes at various times becomes limited. Consequently, the research focus will shift towards analyzing accessibility solely through the transit mode. Nevertheless, a brief comparison will be made between car and transit using the time-independent skim matrix for car travel.

Travel times are calculated for districts that are accessible within a 240-minute travel window to maintain computational efficiency. To account for the deteriorating effect of a longer trip, travel times larger than 240 minutes are not considered and are set by default at 999 minutes. This saves computation time, as a more precise value would not contribute significantly to the travel time impedance function in the gravity model. Thus the range of travel times for 'reachable' destinations is set to 0-240 minutes with unreachable destinations set at 999 minutes.

3.4.3. Weight Matrix Modelling

Subsequently, the weight matrix with accessibility scores is modelled using the gravity model in Python as can be seen in the second row of Figure 3.1. This involved importing the computed skim matrices back into the Python environment. Python's mathematical libraries, such as NumPy and statsmodels, were applied to compute the weight matrices per mode of transport and for transit: hourly time interval. The weight matrix serves as a fundamental component of the gravity model, capturing the spatiotemporal interaction between different locations within the case study area.

3.4.4. Normalization of accessibility scores:

Following the implementation of the gravity model in Python and modelling weight matrices for transit per hour of the day, an analysis of the accessibility levels between the different socioeconomic subgroups is performed. By applying the gravity model in Python as shown in the second row in Figure 3.1 to both the working population group as well as each of the socio-economic subgroups, accessibility scores for each origin i per time interval t are generated with $i = 1, ..., 22$ and $t = 1, ..., 24$. This results in matrices with accessibility scores with a dimension of 22x24. As population sizes differ across (sub)groups, scores are normalized by subtracting the minimum score value in the matrix from each accessibility score and dividing it by the range (the difference between the maximum and minimum values). This ensures fair comparison and interpretation across all economic groups as can be seen in Equation 3.5.

$$A_{i,norm}^{t} = \frac{A_i^t - min(A)}{max(A) - min(A)} \qquad \forall i \in I, \forall t \in T \tag{3.5}$$

The process for normalizing accessibility scores per population group is visualized in Figure 3.2. The model computes a total of 5 matrices with normalized accessibility scores per origin i and time interval t).

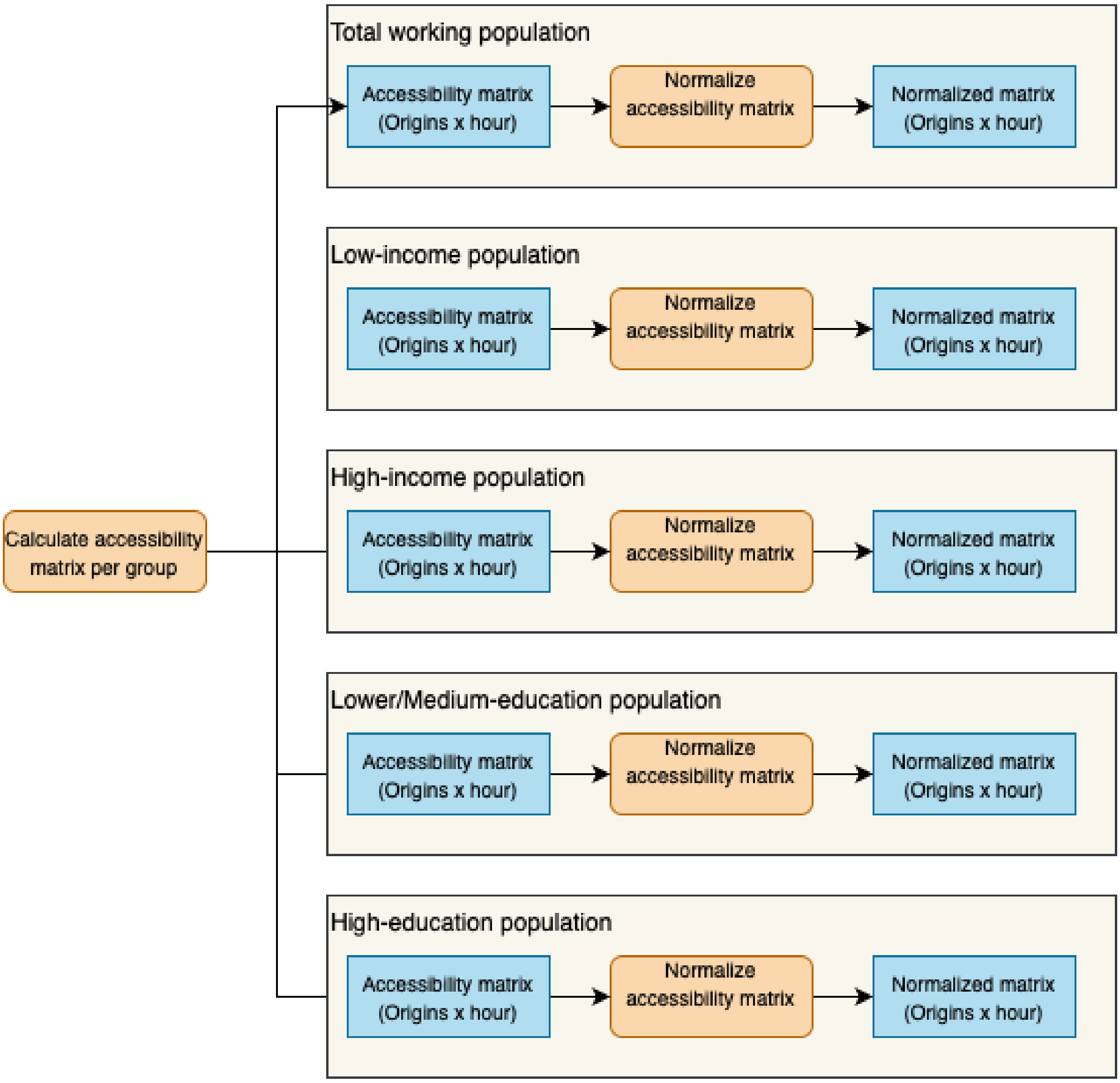


Figure 3.2: Framework of calculating normalized accessibility scores for evaluation among different socio-economic groups

By evaluating accessibility to both the total working population and the socio-economic sub-groups and providing a comparison between the different socio-economic variables, a better understanding can be provided regarding labour force accessibility from industrial areas.
The methodology of this research provides valuable data as it accounts for spatio-temporal aspects of accessibility from an employer's perspective. Instead of focusing on the journey from residential areas to job locations, the analysis looks at the accessibility of labour pools (destinations) from the perspective of employers located in industrial or employment areas (origins). By shifting the perspective, the opportunity factor is also shifted from the number of jobs towards the number of workers, distinguished by socioeconomic status. In addition, the evaluation is performed for each hour of the day, accounting for the temporal aspect of accessibility. To the author's knowledge, existing research has primarily focused on either one of these aspects.

3.4.5. Z-score generation

The z-score method allows for a comparison between groups of different proportions enabling this study to analyze how accessibility variations develop across socio-economic variables. Specifically, by calculating the z-scores for accessibility measures within each subgroup relative to the total working population, insight is provided into whether certain demographic segments experience disproportionately higher or lower accessibility levels across different time intervals.

For this, a comparison between the socio-economic subgroups and the 'total working population' group is made. Aside from the total working population, the population data from CBS is categorized according to 4 different socioeconomic variables: Low-income, High-income, Low/Medium-education and High-education. Categorization allows for an evaluation of accessibility levels between these groups when applying the method of z-scores.

The z-score represents the number of standard deviations that an individual accessibility score is from the mean of the total number of accessibility scores in the dataset. From a practical standpoint, it standardizes the accessibility score per hour in the dataset by accounting for the variability of data points, making them comparable across the different socio-economic groups. The method can transform non-normal distributions into sets of Z-scores as well. In addition, these z-scores allow us to identify hours with higher/lower accessibility scores compared to the group averages. Thus comparison among both socio-economic factors as well as time factors is possible.

It is important to verify the range of the accessibility scores calculated for each socio-economic subgroup. As all subgroups are disaggregated from the total working population and thus vary in size, normalization is necessary before applying the z-score method. Normalization is executed by adjusting the accessibility score per origin per hour relative to the range of the accessibility scores of the respective socio-economic (sub)group. The result is a normalized accessibility matrix containing values with a range from 0 to 1. The normalization step is executed for all groups, resulting in each group having its normalized accessibility matrix.

The Kruskal-Wallis test can compare three or more independent datasets, given a certain dependent variable Aljohani and Thompson, 2020. The dependent variable for this case study is the accessibility score from each origin i per time interval t. To study how each socio-economic variable has an impact on the labour force accessibility from industrial areas, The Kruskal Wallis test is performed by ranking each dataset's observations from lowest to highest, followed by a calculation of test statistic 'H'. This statistic measures the degree of difference between certain population groups. A larger value for H indicates a greater difference between the two groups. The Kruskal-Wallis test uses a null hypothesis as well as an alternative hypothesis to test the significance of the median of each population group.

The generation of skim matrices for both transit and car, as well as the gravity model, can be further explored in Appendix B.

3.5. Case study area

For this research, the IJmond region is chosen as the case study area. It is located in the province of North Holland in The Netherlands, west of the metropolitan area of Amsterdam as can be seen in Figure 3.3. It encompasses an area along the North Sea coast and boasts a significant amount of economic activity facilitating the seaport of IJmuiden along which the steel factory of Tata Steel. The North Sea Canal (Dutch: Noordzeekanaal) crosses the area and functions as an artificial waterway for the transportation of goods by cargo ship to and from the Amsterdam port area. The IJmond is a regional administrative power consisting of the municipalities Heemskerk, Beverwijk and Velsen and is listed as COROP area 20 by CBS (CBS, 2024c).

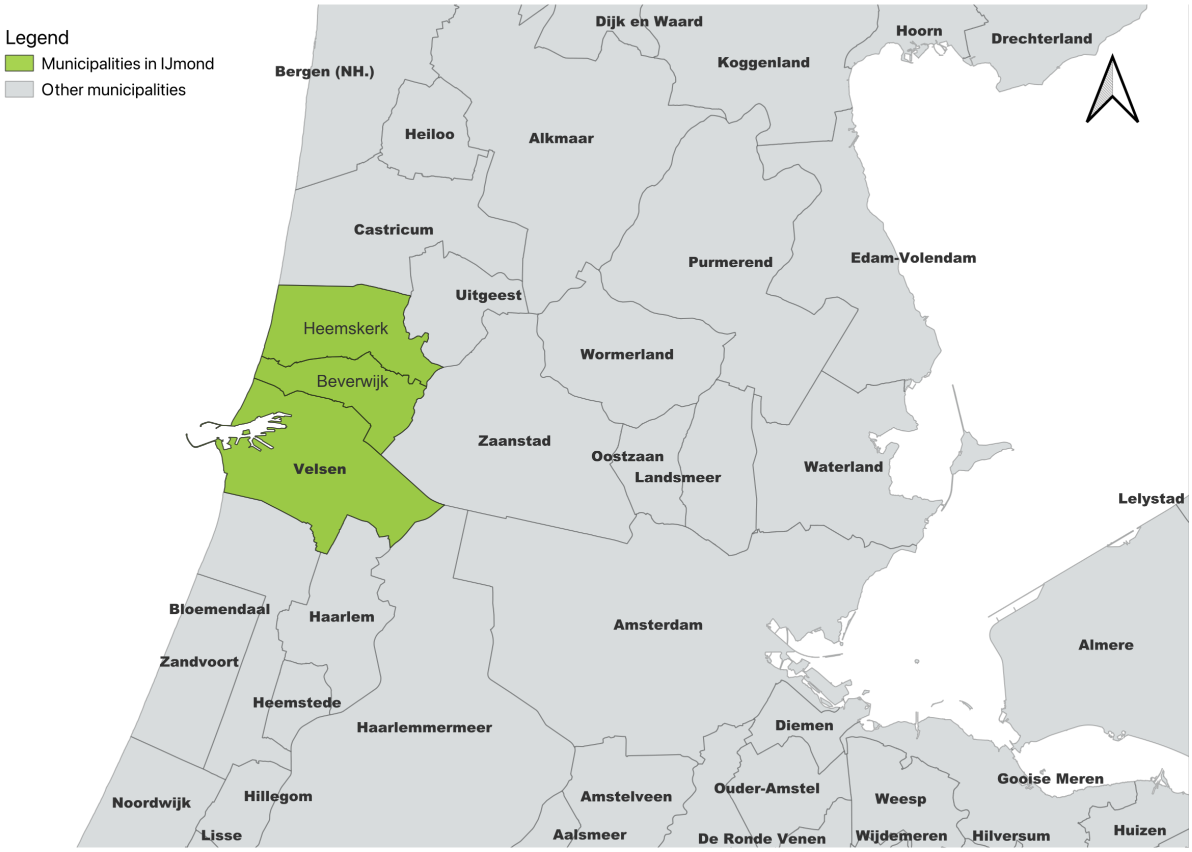


Figure 3.3: Map of the IJmond region to be used as the case study area

According to the Province North Holland, the IJmond is further characterized by peak traffic intensities by both car and train due to the geographical proximity to other economic powerhouses such as Schiphol, the city of Amsterdam the ports along the North Sea Canal. Additionally, the region serves as an important link to the north (Alkmaar region) and the south (Leiden/The Hague), making both the highway A9 and Kennemerrailway line important corridors (Provincie Noord-Holland, 2021).

3.5.1. Industrial areas

The industrial areas (Dutch: Bedrijventerreinen) of the IJmond region are classified according to the IBIS database in which each area is identified by a unique RIN number and categorized by COROP area as well as municipality IBIS, 2022. The RIN number varies in length from 4 to 6 digits, due to it being a countrywide standard therefore accounting for all industrial areas in The Netherlands. The dataset is provided as a shapefile containing polygon geometry for all 3800 industrial areas in The Netherlands. The dataset is provided as a shapefile containing polygon geometries for all 3,800 industrial areas in the country. From this dataset, areas tagged with one of the municipalities of the IJmond region were extracted. For ease of analysis, the original RIN numbers for these 22 areas were replaced with new identifiers with smaller numbers ranging from 1 to 22. A map of all industrial sites in the IJmond region is visualized in figure 3.4 coloured in red with the surrounding residential district coloured in grey.

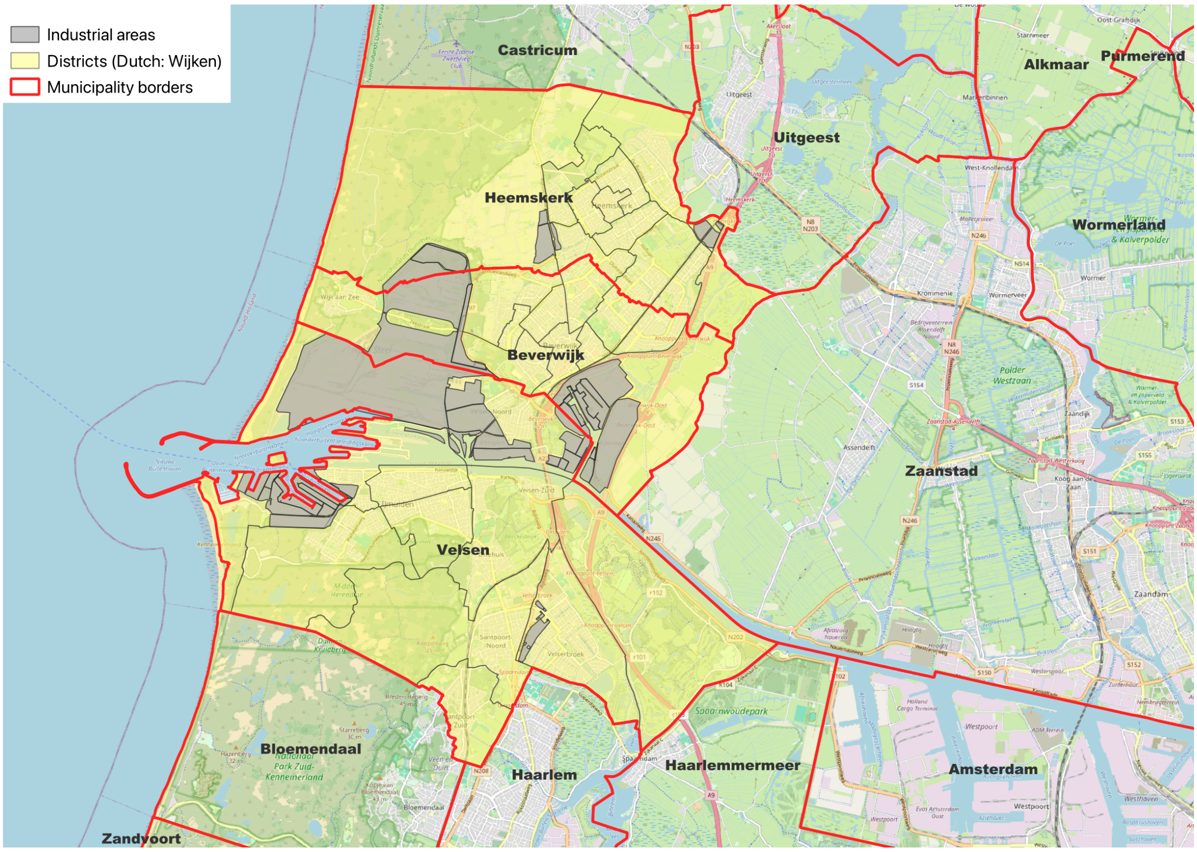


Figure 3.4: Map of the IJmond region to be used as the case study area

As can be seen from the figure, a significant number of areas are located around the town centre of Beverwijk. Using the OpenStreetMap map data as a base layer, the spatial impact of the North Sea Canal is visible with the canal starting from the east in Amsterdam westwards towards the North Sea, dividing the IJmond land area in two parts. It functions as a border between the towns of Beverwijk and Velsen, although the municipality boundaries of Velsen stretch further north of the canal as indicated by the red municipality border on the map. The large grey industrial area crossing all three municipalities of Velsen, Beverwijk and Heemskerk represents the steel factory Tata Steel facilitating over 9,000 jobs Tata Steel, 2024. Other notable areas are the port of IJmuiden, west of the town of Velsen as well as smaller industrial sites around Heemskerk.
A total of 22 industrial sites of the IJmond region with a unique RIN number are grouped in the following areas:

- De Trompen & Houtwegen (Municipality Heemskerk)
- De Pijp & Noordwijkermeer (Municipalities Beverwijk & Velsen)
- Tata Steel IJmuiden (Municipalities Beverwijk & Heemskerk & Velsen)
- Grote Hout (Municipality Velsen)
- IJmuider Delta (Municipality Velsen)
- Broekerwerf (Municipality Velsen)

Several companies situated in these areas facilitate jobs requiring shift work. Schavemaker Logistics is an example that runs trucks during the night hours as well as Tata Steel running 3 consecutive shifts of 8 hours in 24 hours Tata Steel, 2024. In light of this, it is crucial to consider accessibility not only in terms of location but also over time. These varied schedules highlight the need to examine how companies have access to the labour force during the day as well as at night. Inversely, this could give more insights as well as how workers can access these workplaces at different times of the day. This aspect is essential for having a comprehensive understanding of workforce accessibility in these industrial areas.

3.5.2. Socio-economic data

The dataset kerncijfers Wijken-en-Buurten from CBS provides socio-economic information for the province of North Holland (CBS, 2022). A total of 471 districts (Dutch: Wijken) are present in de province for which several variables will be used for the accessibility evaluation of industrial areas. The area with green boundaries represents the municipalities of the IJmond, outlining the three municipalities of Beverwijk, Heemskerk and Velsen where the industrial sites are situated. As the main focus of this research is evaluating accessibility by transit, the main railway lines are visualized as well with the stations indicated with a dot icon. All depicted railway lines support public transit operations, enhancing regional connectivity.

Population density:

The population density levels are relatively high in the Amsterdam area as well as Haarlem and Alkmaar as can be seen in Figure 3.5. Population density is defined as the number of residents per hectare area functioning as a measure of how many people live in an area. Density is in particular high along the railway lines. The Kennemer railway line from Haarlem towards Alkmaar for example traverses several districts with high population density. Many of these districts are part of the IJmond region.

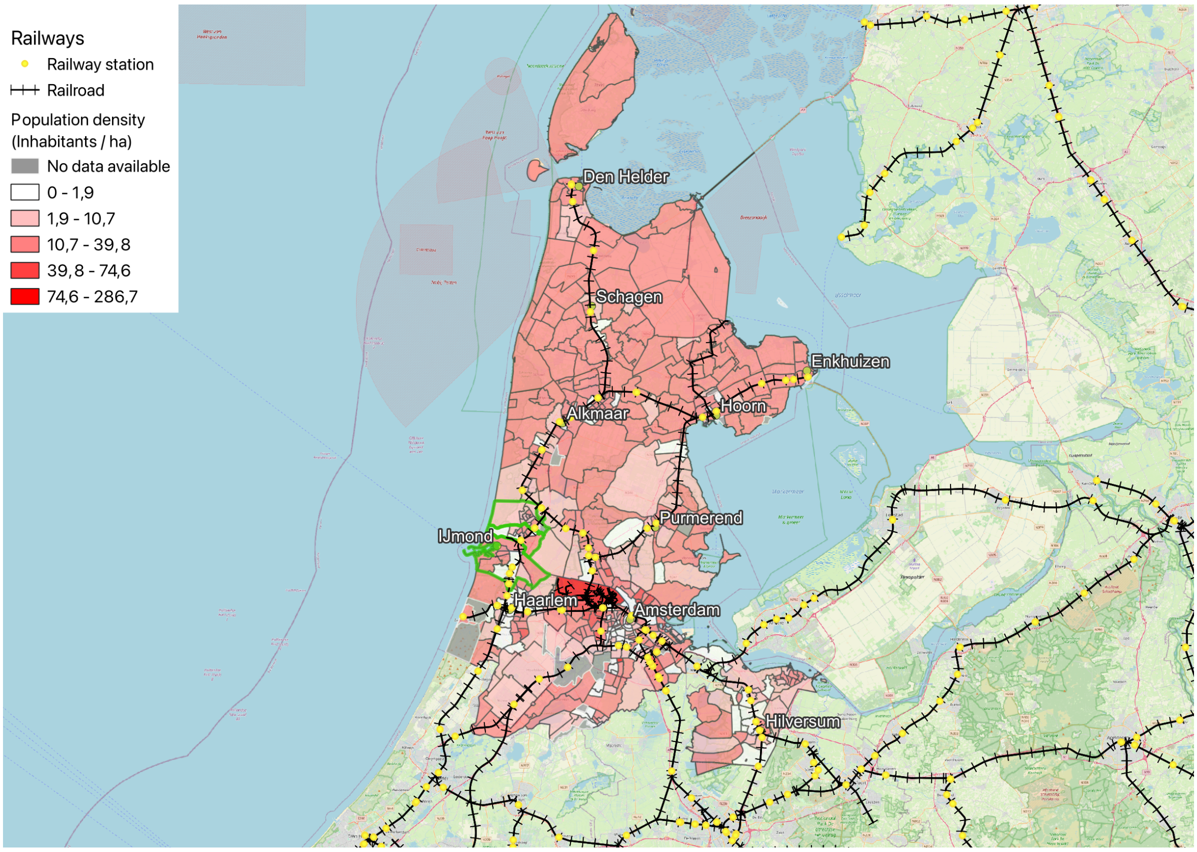


Figure 3.5: Population density per district in the Province North Holland

Share of groups with a low-income:
As stated before in Section 3.4.1, low-income groups are categorized as the proportion of income recipients per district that fall within the lowest 40% of disposable income categories nationally. The share of low-income individuals per district in North Holland is presented in Figure 3.7. The share of low-income residents is particularly high in the northern part of the province (Dutch: Kop van Noord Holland) where population density is relatively low. Several districts in the periphery of Amsterdam show similar results. Outliers are either heavily industrialized areas such as the port of Amsterdam with a low-income share of 84.9% and student campuses such as Uilenstede in Amstelveen with a low-income share of 77,4%. Overall the mean share of low-income individuals is 36,8% which is below the national average of 40%. Despite the lower-than-average value, income disparity remains visible from the map.

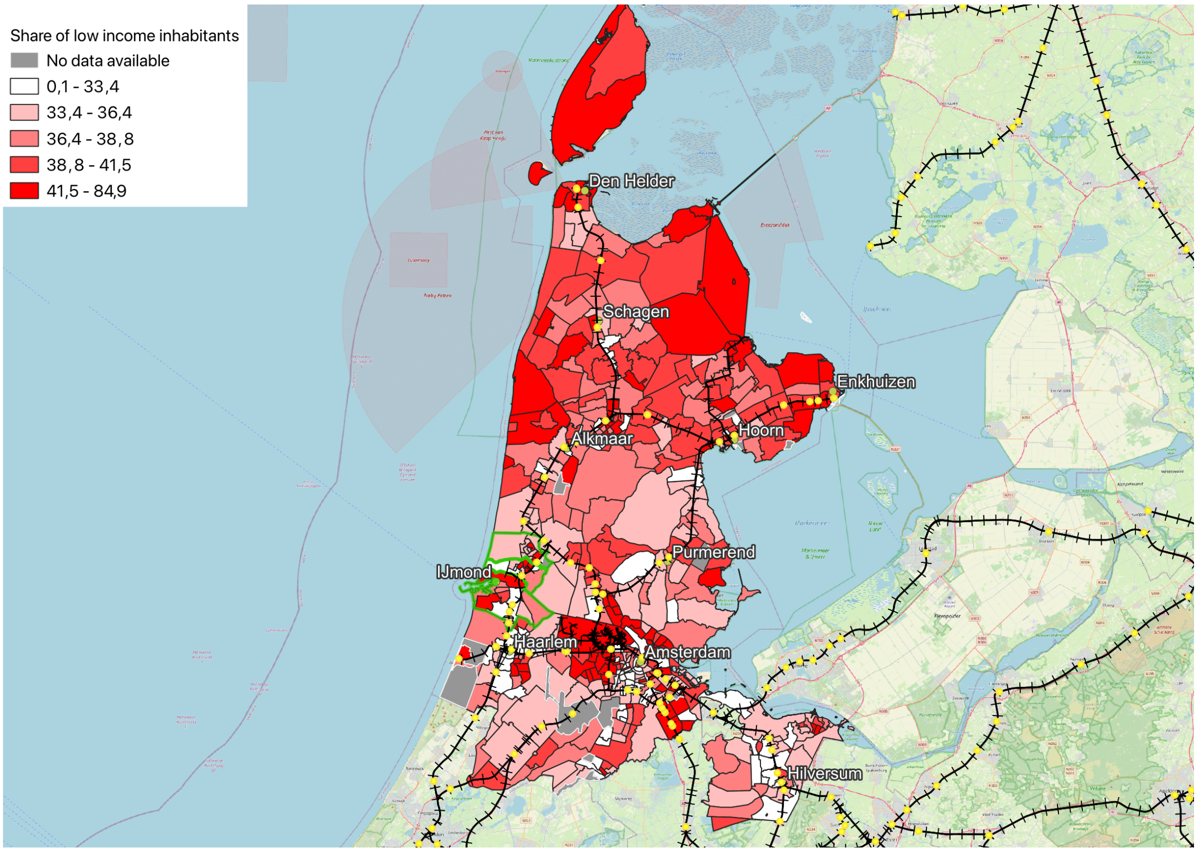


Figure 3.6: Share of inhabitants with a low-income per district in the Province North Holland

Share of groups with low/medium education level:
Areas such as Alkmaar, Schagen, Hoorn, and parts surrounding Amsterdam show a higher share of inhabitants with lower or medium-level education backgrounds as well as rural areas, as indicated by the darker red colour. With a share of 94%, the rural district Kreileroord relatively has the most amount of inhabitants with a low/mid education background. In contrast, the IJmond region and city centres of Amsterdam and Haarlem display a lower share of this demographic. The Houthavens district in Amsterdam relatively has the least amount of residents with a low/mid education background.

It is important to consider the social and economic implications of such a distribution. Regions with a higher proportion of lower education levels often seem to be situated further away from large cities and suffer from low population density. Conversely, areas with higher education levels seem to correlate with high-density districts.

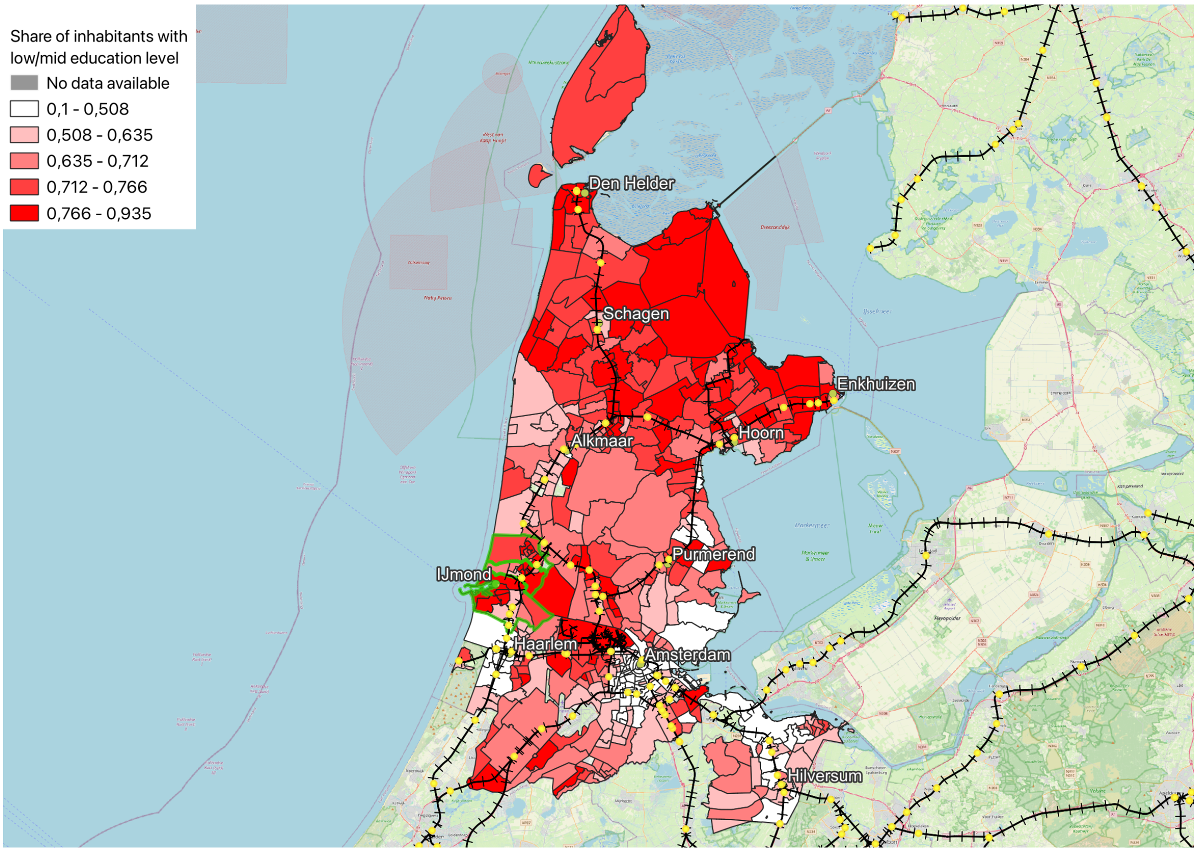


Figure 3.7: Share of inhabitants with a low/mid education level per district in the Province North Holland

4 Results

In this chapter, the methods for evaluating spatio-temporal accessibility using a gravity model are applied to the industrial areas in the IJmond region. The chapter explains how the usage of the TravelTime API and gravity model resulted in the observation that the mean accessibility scores in industrial areas by car are significantly higher than by transit. This is followed by an explanation of how a significant share of the 478 residential districts becomes ‘unreachable’ during the night-time hours, as their travel time exceeds the 240-minute threshold of the TravelTime plugin. Moreover, the remaining share of reachable destinations also experiences longer travel times during the night. A consecutive section focuses on the result that industrial areas such as De Houtwegen and De Waterwegen in Heemskerk, which are situated along transit (bus) stops, have significantly higher mean accessibility over all hours of the day. In contrast, areas with low accessibility levels include Tata Steel and the IJmond Haven, which are located further from transit stops suffer from lower accessibility levels during all hours of the day. Then, an explanation will be provided on how the model shows that larger groups of low/medium-education and low-income individuals live closer to industrial areas compared to high-education and high-income groups. These findings structure the subsequent sections of this chapter, where each key result will be discussed, providing a deeper understanding of spatiotemporal accessibility in the IJmond region.

Accessibility to the total working population group:
Evaluation of the accessibility to the labour force is composed of an analysis of the total working population over 24 hours, focusing specifically on the time intervals of 00:00, 3:00, 7:00, 12:00, 17:00 and 21:00. This analysis provides insights into accessibility dynamics at key time intervals throughout the day, offering an understanding of accessibility levels to each destination zone. The accessibility scores from each origin to the working population in the destination zones are calculated using the gravity model.

Accessibility to different socio-economic population groups:
Subsequently, an analysis examines different target groups within the working population based on income and education levels. The disaggregation into these groups allows for an understanding of accessibility levels among different socioeconomic variables. Similarly to the working population, accessibility scores from each origin to each socio-economic group in the destination zones are calculated using the gravity model. The population data from CBS is categorized according to 4 different socio-economic variables: Low-income, High-income, Low/Medium-education and High-education as can be seen in Table 4.1. The accessibility scores of these 4 groups will be compared to the aggregated accessibility scores of the entire workforce, hence the variable for the total working population is included in the table.

The sizes of both the low-income and high-income populations are not available in the CBS dataset. Instead, ratios are provided for each variable per district/destination zone (j. In other words, a value of 0.37 for a low-income group, would indicate 37% of the working population in that zone has a low income. Accounting for consistency in the population sizes for all groups, the data of the total working population was utilized to calculate the group sizes for both low-income and high-income population groups per destination zone j. The number of people with a low/medium- or high-education level is readily available from CBS and thus does not require this step. It is important to note that the total sum of the people having an education level is not equal to the total working population. More specific data on the education level amongst the working population was not available, hence these alternatives are used as an estimate.

Table 4.1: Fixed-width columns.

Population groups	Description	CBS dataset variable
Entire workforce	Total number of employed people receiving an income out of work	'a_inkont'
Low-income	The share of low-income individuals corresponding to the bottom 40% of the national income distribution	'p_ink_li'
High-income	The share of high-income individuals corresponding to the top 20% of the national income distribution	'p_ink_hi'
Low/Medium-education	Number of individuals with low or medium educational level	'a_opl_lg & a_opl_md'
High-education	Number of individuals with high educational level	'a_opl_hg'

4.1. Transit and car accessibility

The first analysis entails a comparison of the accessibility scores between car and transit modes. As mentioned in the methodology, the accessibility scores are a product of the impedance function, based on travel time, and the working population size. As the travel time matrix for the car is based on an uncongested network assignment, travel times remain constant during all hours. Thus the results in Figure 4.1 display the accessibility scores to the total working population for both modes without accounting for the temporal accessibility component. The transit accessibility scores used for the comparison are generated for t=12:00 (noon). The average transit accessibility is the highest during this time of the day, reflecting peak efficiency and service availability. This approach ensures a balanced evaluation of transit and car accessibility, despite the discrepancy in the availability of hourly car travel time data. The horizontal axis represents each of the industrial areas in the IJmond region and the vertical axis displays the accessibility index score generated by the gravity model in Equation 3.2.

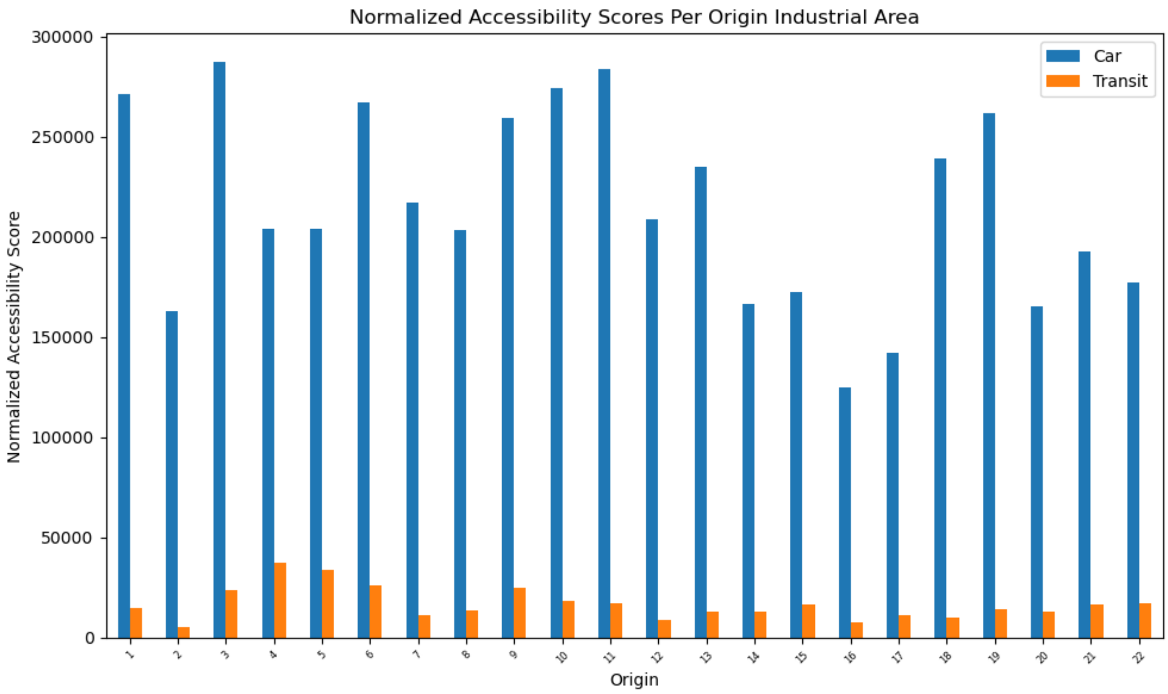


Figure 4.1: Acessibility scores per industrial area i by both car and transit. The scores are a product of the population size and travel impedance function.

Based on the scores in Figure 4.1, it can be concluded that there are significant differences in accessibility levels between the two modes of transport. The figure implies that all industrial sites in the case study area have better access to the working population by car compared to transit. For spatial analysis, Figure 4.2 displays the accessibility scores by transit from Figure 4.1 relative to the scores by car: The ratio of 'transit vs car'.

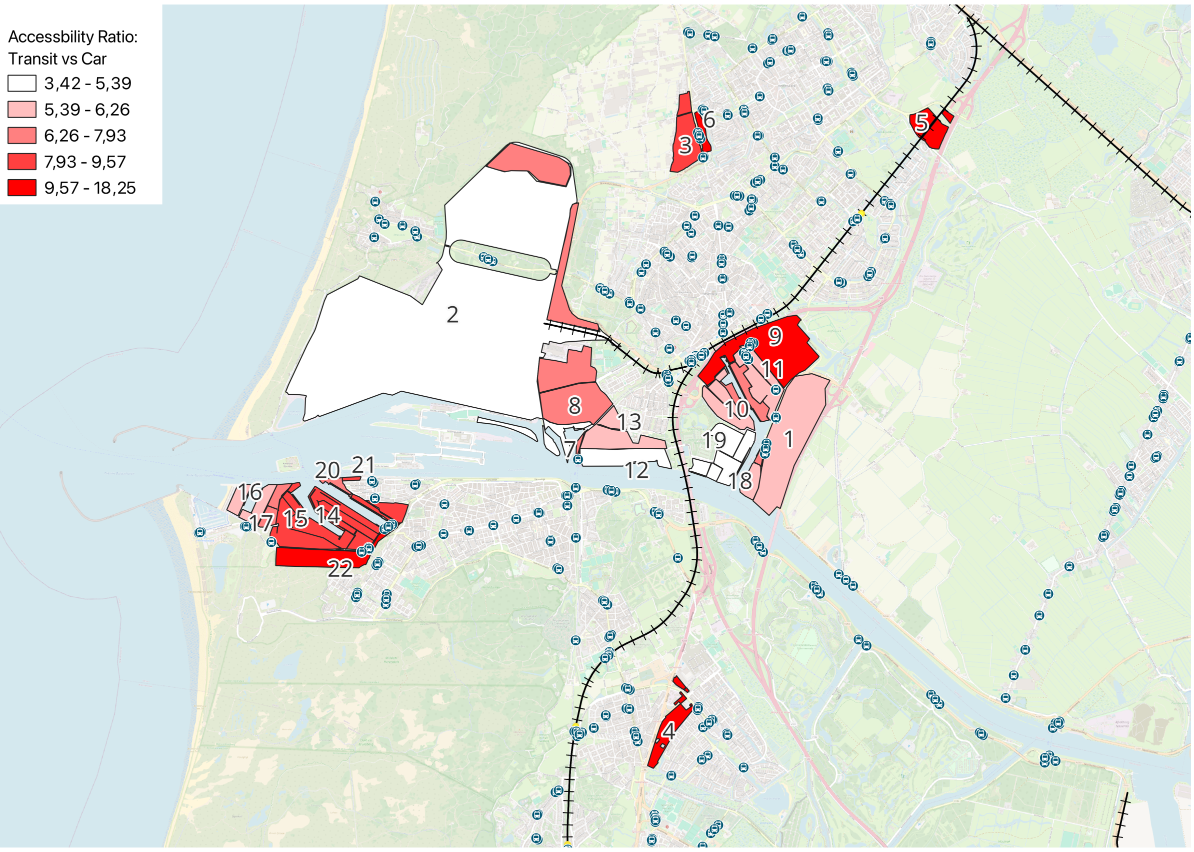


Figure 4.2: Accessibility score by transit per industrial area i, relative to the score by car. The numbers on the map represent the area number. The ratio is visualized with a colour gradient.

Decimal values for the accessibility ratio per industrial area can be found in Appendix A. The results in Figure 4.2 show that the areas that see significantly lower levels of access to workers are 2, 7, 12, 18 and 19. These areas represent Tata Steel, Grote Hout and Noordwijkermeerpolder. This means that industries in these zones have more difficulties attracting job seekers by mode of transit if travel time and population size are the main deciding factors. Noticeable is that these areas are located further away from important public transport hubs such as train stations and bordered by waterways such as the North Sea Canal. The density of bus stops is also lower in these areas compared to other industrial sites. IJmuiden Haven represents a collection of these other areas, labelled on the map with numbers 14, 15, 16, 17, 20, 21 and 22. A reason for this could be that IJmuiden Haven is serviced by high-frequency R-NET bus services 283 and 385 operated by the transport company Connexxion whereas Tata Steel and Grote Hout do not see any transit services at all (Connexxion, 2024). The bus stops going through the middle of area 2 (Tata Steel) do not serve the industrial site as it is surrounded by fences. Tata Steel has a central gate at the southern side, close to the North Sea Canal, where no bus stops are present. This explains the low ratio for this specific factory. Industrial sites 9 and 11 show high ratios which is caused by the proximity to the train station of Beverwijk. High values for sites 3 and 6 can be explained similarly due to the location directly along a bus stop. Area 5 shows a high ratio as well while no train station or bus stop serves this location. The lack of large waterways and the presence of neighbourhoods in all directions likely explains the high score for Area 5. Area 4 shows similar characteristics, being located in the centre of the town of Velserbroek whilst also benefitting from multiple bus stops and the train station of Driehuis.

With this spatial analysis, the results show that areas close to the North Sea Canal show a lower competitiveness of transit with the car compared to other areas. Given the absence of time-based skim matrices for the car mode, the following results in this Chapter will focus on the spatiotemporal analysis of transit accessibility to the total working population and across different socio-economic groups in the working population. The significantly lower accessibility levels by transit, regardless of temporal aspects, give enough reason to study transit accessibility further.

4.2. Accessibility to the total working population

This section starts with an explanation of how the mean travel time influences accessibility levels across all industrial areas across all hours of the day. The resulting accessibility scores are further visualized in graphs displaying the accessibility scores A_i per origin industrial area i developing over a time interval t, normalized for comparison. Consecutively, a set of maps presents the spatial dimension of accessibility scores across industrial areas in the IJmond region across different time intervals.

4.2.1. Mean Travel Time

The results of generating the mean travel time to the destination set of residential districts from each origin industrial area i for each time interval t by transit are displayed in Figure 4.3. As can be seen, the travel time starts increasing from 00:00 towards 01:00 at night to almost 1000 minutes followed by a sharp decrease to 250 minutes. It increases steadily again from 16:00 reaching the same peak of nearly 1000 minutes during the night at 01:00. Given that the mean travel time reaches a minimum of 250 minutes, which translates to over 4 hours, it is essential to interpret these results relatively, focusing on the trends and patterns in the graph rather than the absolute travel time values as it is not realistic to view a minimum travel time of 4 hours as accessible. This relative interpretation is particularly important as the set of residential districts spans the entire Province of North Holland. Therefore, these travel times should not be considered as definitive measures of feasibility but rather as intermediate results to be utilized in the gravity model, which factors in both the size of the labour force and travel impedance.

Returning the focus to the trend of the mean travel time, the peak during the night can be attributed to the distinction between 'reachable' and 'unreachable' residential districts in the model as has been explained in Section 3.4.2. A mean travel time significantly higher than 240 minutes indicates a high number of 'unreachable' destinations. Table 4.2 shows the number of unreachable districts per hour of the day with the largest number of unreachable districts being 386 at 01:00 which is 81.9% of the total set of destinations. This implies that at night, less than a fifth of the working population is accessible within a 240-minute travel time window from industrial areas in the IJmond. During the day, the number of unreachable destinations declines to 79 which is 16.7% of the total number of destinations. These numbers confirm the results of Figure 4.3 and imply transit services are lowest during the night.

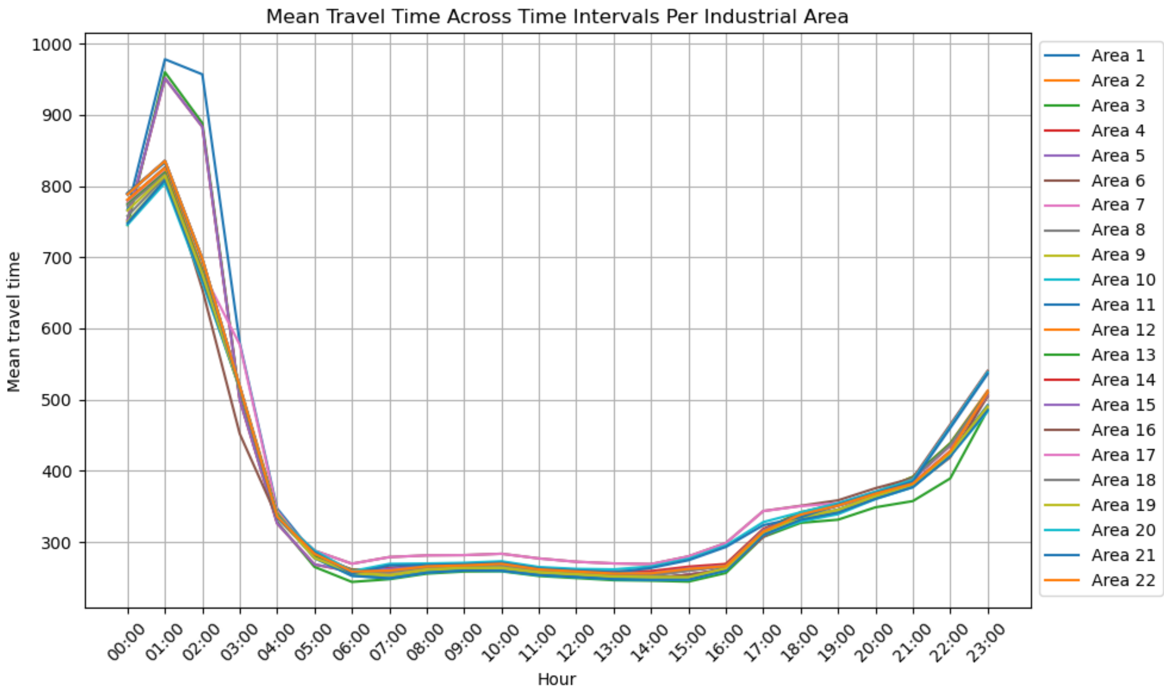


Figure 4.3: Mean travel time per industrial area location i per time interval t

Table 4.2: Number of unreachable destinations per hour according to the TravelTime API

Hour	Number of unreachable locations
00:00	350
01:00	386
02:00	308
03:00	187
04:00	94
05:00	83
06:00	81
07:00	81
08:00	84
09:00	85
10:00	85
11:00	81
12:00	79
13:00	78
14:00	78
15:00	81
16:00	87
17:00	114
18:00	124
19:00	129
20:00	138
21:00	147
22:00	176
23:00	216

To achieve a better understanding of the mean travel time for the remaining set of 'reachable' destinations, Figure 4.4 displays the mean travel times from the aggregated set of industrial areas to all residential districts within a 240-minute travel time. Noticeable is that for these remaining districts, the travel time increases as well during the night with the highest travel times between 01:00 and 02:00 with a mean duration of 200 minutes. It decreases towards 110 minutes from 06:00 onwards. Contrary to the original mean, a further decrease to 90 minutes at 23:00 is present. It should be noted that the number of reachable destinations fluctuates over time as has been shown in Table 4.2. However, the results of both Figures 4.4 and 4.2 indicate that travel time increases significantly during the night regardless of their classification as reachable or unreachable.

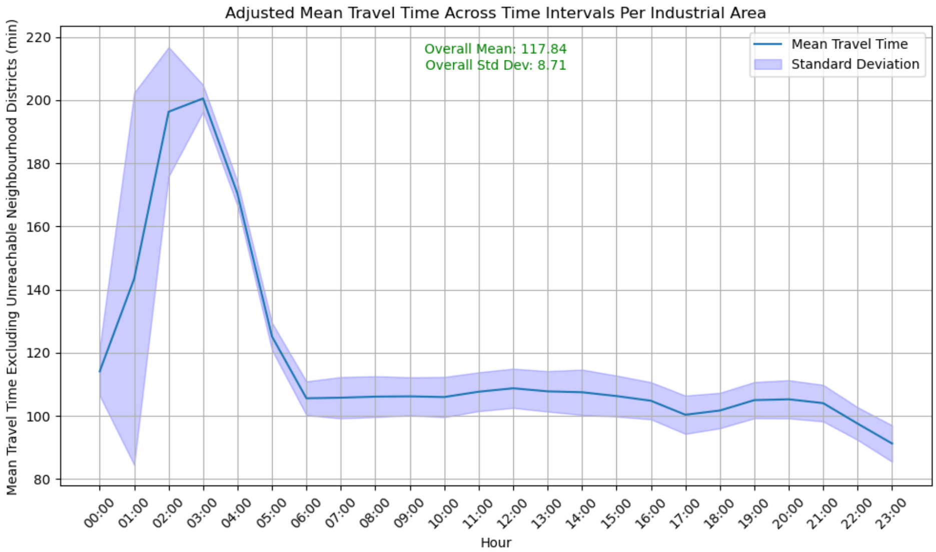


Figure 4.4: Adjusted mean travel time per industrial area location i per time interval t

4.2.2. Temporal Variability

While the results of the mean travel time imply significantly longer transit travel times during the night and evening, it provides a limited understanding in the context of accessibility as it does not account for the size of opportunities which, in the case of this research, is represented by the size of the working population. For a more comprehensive understanding, the results of generating normalized accessibility scores for each hour of the day by utilizing time-dependent transit skim matrices in a gravity model in Python are visualized in Figures 4.5. The horizontal axis displays the time of day in intervals of an hour and the vertical axis represents the normalized accessibility scores A_i. Scores for each of the 22 industrial areas are present in the Figure. These results show a decrease in accessibility levels during the night at 03:00 for all areas, indicating access to the total working population by transit is lowest during the night. As both the Dutch railway operator NS and bus operator Connexxion do not operate any buses and trains during the night in the IJmond region, this is to be expected (Connexxion, 2024; Nederlandse Spoorwegen, 2024). Noticeable is the decline for A_i between 00:00 and 06:00 for all origin zones i with the index scores remaining relatively constant from 06:00 to 22:00. Contrary to the results of the mean travel time in Figure 4.3, a short increase in the accessibility index score in Figure 4.5 is present at 18:00 and 23:00 for certain areas. The results of both Figures together thus imply that the working population remains relatively well-served throughout the day, despite the increasing mean travel time and increasing number of 'unreachable' districts starting from 16:00 onwards.

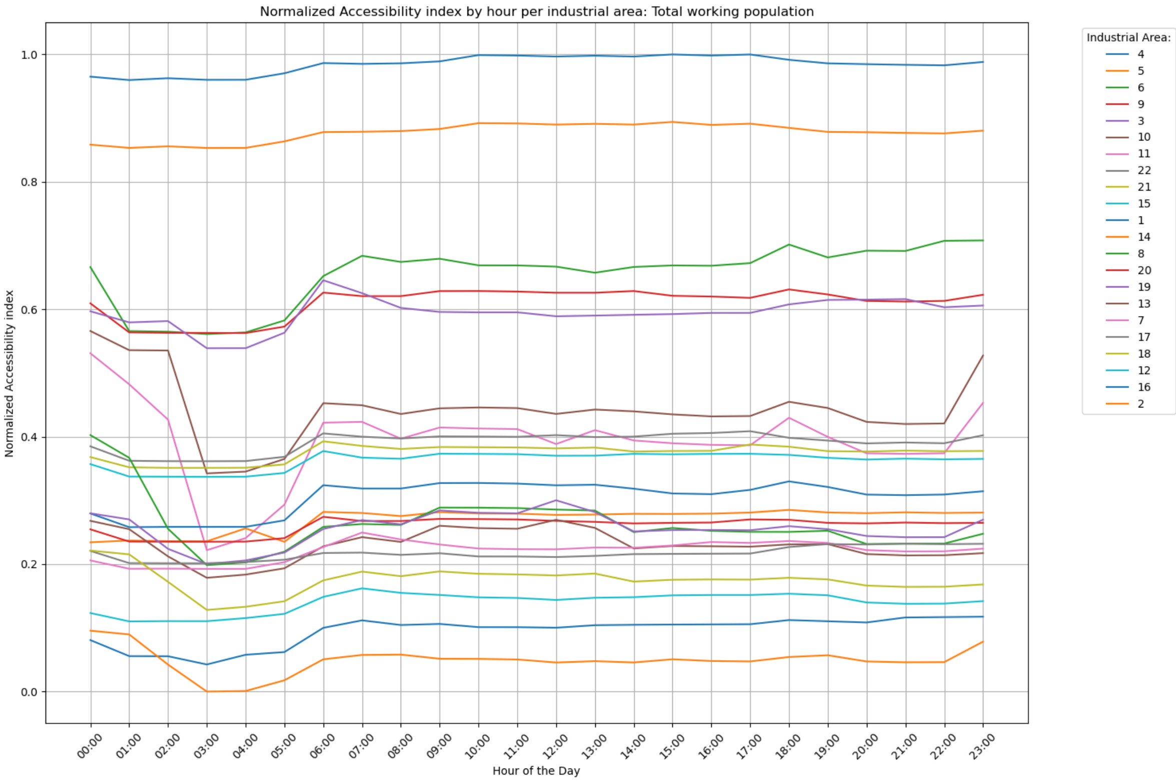


Figure 4.5: Accessibility index per industrial site per time interval for the total working population in North Holland

According to the timetables of the IJmond region, there is no indication of higher route frequencies at this time of the day, meaning no increase in accessibility should be expected Connexxion, 2024. The local peaks in accessibility level at 18:00 and 23:00 can therefore be interpreted as a result of a calculation anomaly of the TravelTime plugin.

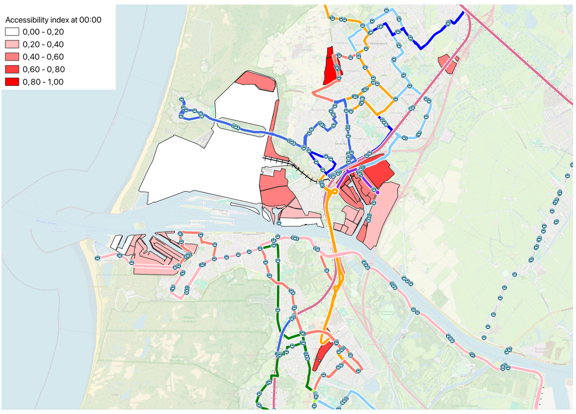
4.2.3. Spatiotemporal Accessibility

A spatiotemporal visualization of the results in Figure 4.5 can be seen in Figure 4.6. It displays the normalized accessibility scores for t=03:00, t=07:00, t=12:00, t=17:00 and t=21:00. These time intervals represent the level of transit services during the middle of the night (t=03:00), the morning peak (t=07:00), midday (t=12:00), the afternoon peak (t=17:00) and the early evening (t=21:00) as used in previous research (Yan et al., 2022). Additionally, the transit lines, derived from the GTFS dataset, are also visible in the visualization, showing the train and bus routes serving these areas.

The visualization shows that industrial areas 3 (De Houtwegen) and 6 (De Waterwegen) in Heemskerk have significantly higher accessibility scores at all 6 time intervals. These areas are further characterized by the proximity of the residential districts belonging to Beverwijk and Heemskerk. As a reminder, the result of the gravity model in 1 is determined by an opportunity factor O_j (population size) and travel impedance function (travel time).

Since Figure 4.3 has shown that the mean travel time from Areas 3 and 6 is significantly higher at night, the accessibility levels in Figure 4.5 are primarily impacted by a combination of larger population sizes per district and smaller travel times. The gravity model assigns less weight to population centres with larger travel times in the total accessibility calculation, which explains why these do not contribute to the high accessibility levels of these industrial areas. Therefore, it can be stated that areas 3 and 6 maintain high accessibility scores primarily due to their larger population sizes and favourable travel times during peak transit service hours.

It is also noticeable that other areas display significantly lower accessibility scores over time. Area 2 (Tata Steel) and areas 12, 16 and 18 show a decrease in accessibility levels with a minimum at t=03:00 with scores ranging from 0 to 0.15. Transit services in this area are almost non-existent with no trains operating at this hour of the day while at night only one hourly Nightline bus, N80, operates between IJmuiden and Amsterdam (Connexxion, 2024). These areas are further characterized by their greater distance to residential districts compared to the areas 3 and 6 discussed before. The accessibility level increases again at t=07:00 which corresponds to the returned presence of transit services based on the timetable (Connexxion, 2024). During daytime, the scores remain relatively constant across all areas as can be seen in the subfigures for the consecutive time intervals t=12:00, t=17:00 and t=21:00 indicating little temporal variation in accessibility levels in these industrial areas.



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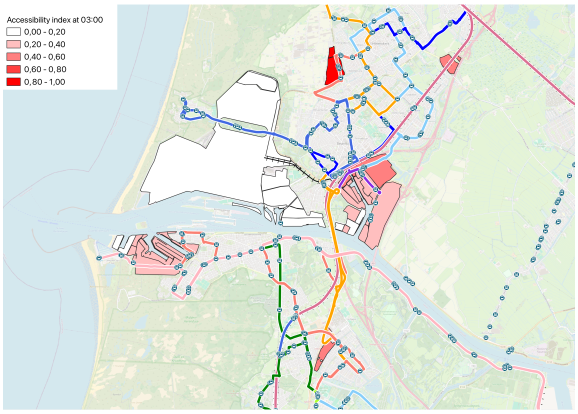

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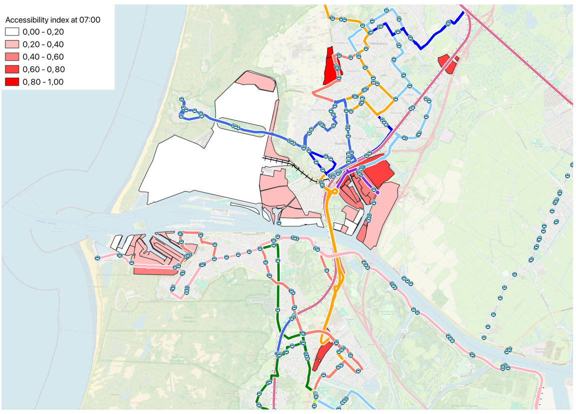

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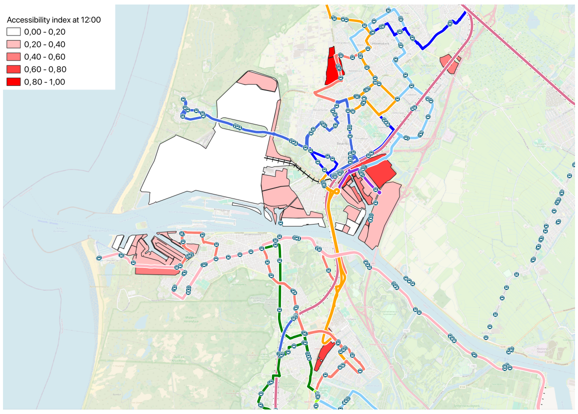

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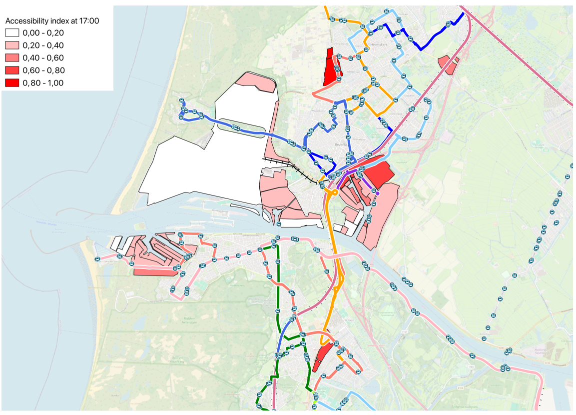
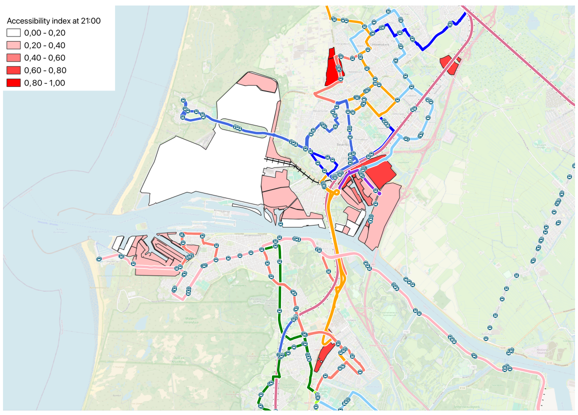


(e)



(f)

Figure 4.6: Normalized accessibility scores per industrial area at 6 time intervals

The results for evaluating the accessibility to the total working population from industrial areas suggest significant spatiotemporal variation during the night hours with zones adjacent to the Tata Steel factory seeing lower accessibility levels at t=03:00 while other industrial areas located in the vicinity of transit stops and residential districts are relatively less affected by the time of the day. Having evaluated spatiotemporal effects on accessibility to the total working population, a consecutive approach focuses on the variation among different socio-economic sub-groups within the working population.

4.3. Accessibility to socioeconomic population groups

With the spatiotemporal variations in accessibility levels to the working population now evaluated, this section focuses on the results of evaluating accessibility to subgroups of the total working population. An overview of the mean accessibility index for each socio-economic group is visualized with a graph containing the index score over a time series of 24 hours aggregated over all origin locations i. To further confirm the model is working correctly, the results of a statistical analysis with a Kruskal-Wallis test followed by Dunn's Post Hoc test are presented.

4.3.1. Spatiotemporal Accessibility

The mean accessibility index per sub-group is visualized in Figure 4.7, where each mean is computed across all origins i (industrial zones) and aggregated per time interval t (hour), resulting in 24 mean values for each group with the normalized values of the accessibility scores plotted on the y-axis and the time intervals on the x-axis. Normalization was performed for each subgroup across the hours. As both the income and education groups are subgroups of the total working population and thus use the same travel time matrices, the trend for each subgroup displays identical patterns differing only in vertical y-intercepts.

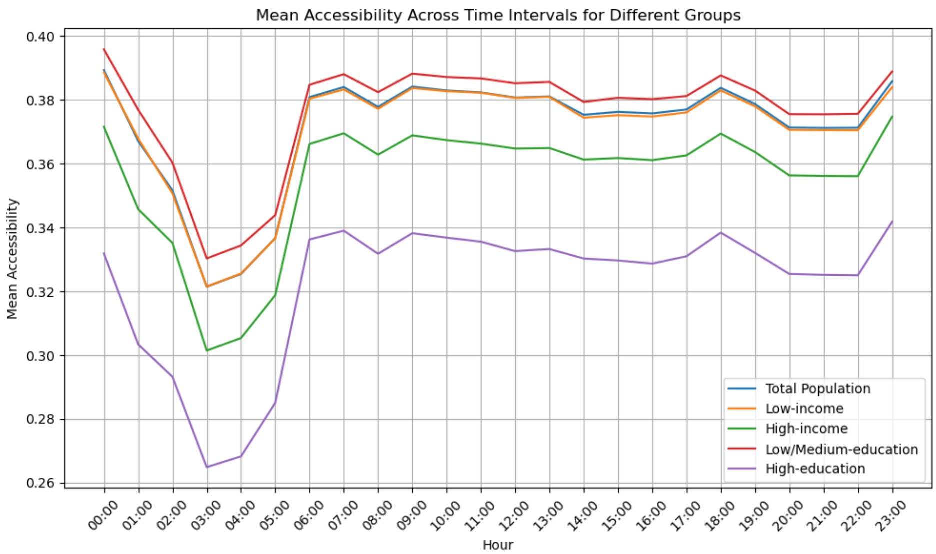


Figure 4.7: Mean normalized accessibility index per socio-economic group per time interval

The mean accessibility across time intervals however does not account for the different group sizes within the total working population. Therefore the evaluation is further expanded with the results of applying the z-scores method from Section 3.4.5 on the accessibility scores for each subgroup. The results of performing a z-score test using these matrices as input can be seen in Table 4.3 and are further visualised in Figure 4.8. The columns in Table 4.3 display each subgroup whereas the rows represent an hour of the day. The values represent how many standard deviations the subgroup's accessibility score is from that of the total working population. Figure 4.8 shows the same subgroup's accessibility scores along a time axis to better visualize the development of the z-scores along the different hours.

Table 4.3: Z-Score Results for Different socio-economic groups per hour

Hour	Low-income	High-income	Low/Medium-education	High-education
00:00	-0.00	-0.07	0.03	-0.24
01:00	0.00	-0.09	0.04	-0.27
02:00	-0.00	-0.07	0.04	-0.24
03:00	0.00	-0.08	0.04	-0.23
04:00	0.00	-0.08	0.04	-0.24
05:00	-0.00	-0.07	0.03	-0.21
06:00	-0.00	-0.06	0.02	-0.18
07:00	-0.00	-0.06	0.02	-0.19
08:00	-0.00	-0.06	0.02	-0.19
09:00	-0.00	-0.06	0.02	-0.19
10:00	-0.00	-0.06	0.02	-0.19
11:00	-0.00	-0.07	0.02	-0.19
12:00	-0.00	-0.07	0.02	-0.20
13:00	-0.00	-0.07	0.02	-0.20
14:00	-0.00	-0.06	0.02	-0.18
15:00	-0.00	-0.06	0.02	-0.19
16:00	-0.00	-0.06	0.02	-0.19
17:00	-0.00	-0.06	0.02	-0.19
18:00	-0.00	-0.06	0.02	-0.19
19:00	-0.00	-0.06	0.02	-0.19
20:00	-0.00	-0.06	0.02	-0.19
21:00	-0.00	-0.06	0.02	-0.19
22:00	-0.00	-0.06	0.02	-0.19
23:00	-0.01	-0.05	0.01	-0.18

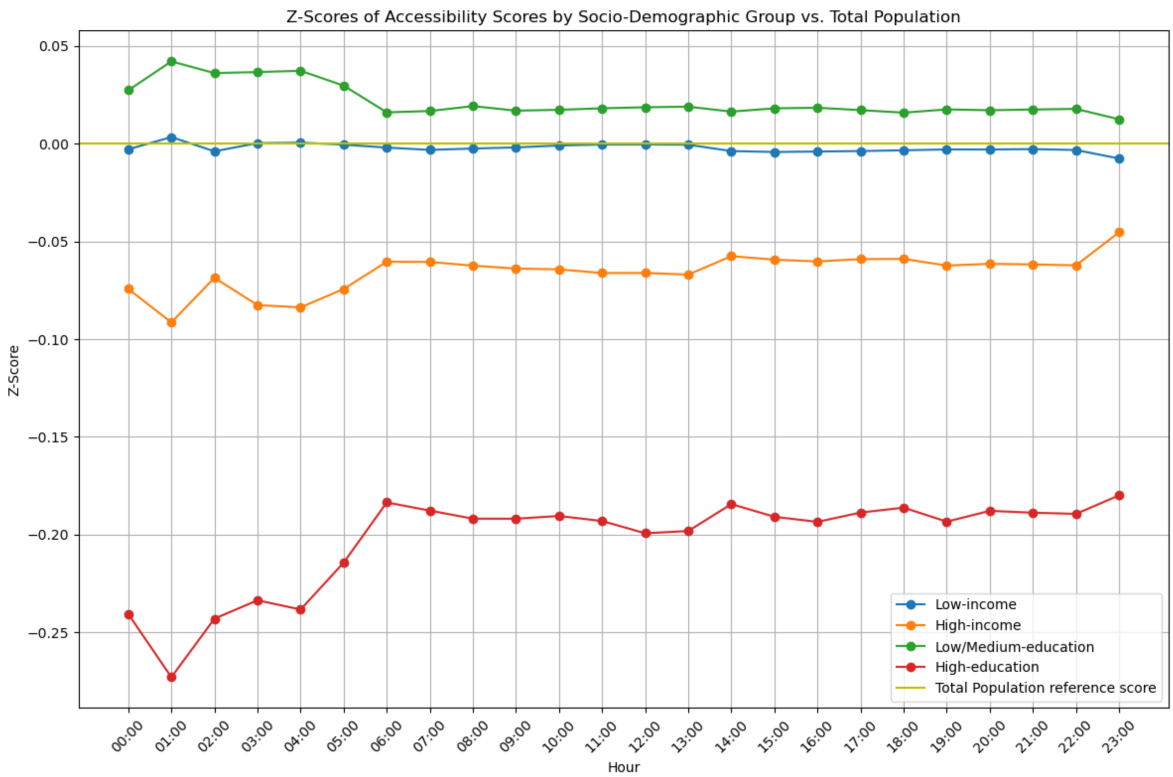


Figure 4.8: Graph displaying the development of the z-score per socio-economic subgroup per hour, based on the normalized accessibility scores per subgroup. A positive score indicates a larger deviation from the normalized accessibility scores of the total working population.

The results from both Table 4.3 and Figure 4.8 show that accessibility decreases between 00:00 and 06:00 for the high-income and high-education groups with in particular the high-income group having a z-score of -0.27. This implies that the accessibility score of the high-income group at 01:00 at night is a factor of 0.27 standard deviations below the mean of the total working population. However, accessibility remains relatively constant for both low/medium education groups and low-income groups. Noticeable is that the low-income group sees a higher z-score during the night than the total working population. This implies that industrial areas are subject to above-average accessibility to low-income employees during nighttime hours, indicating that their relative ease of access to this group of workers is better than that of the overall working population during these hours. The difference becomes even more pronounced when compared to groups with higher income and education levels. It is known that the travel time from an industrial area to each residential district is not dependent on the type of socioeconomic subgroup as they use the same road network and public transit services. The remaining variable in the gravity model, the size of the population, is the determinant factor that explains the differences in accessibility among these subgroups. Therefore, these results indicate that workers with either a low income or low/medium education live in larger concentrations in proximity to industrial areas in the IJmond compared to workers with a high income or higher education level.

The positive normalized z-scores for low-income and low/medium-education during the night indicate that the accessibility scores at night for these subgroups are higher than that of the total population. As the travel time between each origin industrial area i and destination residential district j is independent of the socio-economic variable, the scores can be explained by the different low/high income/education ratios per district. Thus, the results of the z-score analysis imply that relatively more low-income workers with a low/medium education level live closer to industrial areas than high-income workers with a high education level. When focusing on the trend in accessibility level for the low-income and low/medium-education group, during nighttime, accessibility scores remained constant despite public transportation services being almost nonexistent at this time. This means that nighttime public transportation travel times used in the travel impedance function for the gravity model were entirely composed of access and egress times. Thus walking is the primary factor behind these scores at night.

4.3.2. Statistical analysis

To evaluate the reliability of the calculated accessibility results of the gravity model for each socio-economic group, a statistical analysis has been performed to assess the relation between the accessibility levels and the socio-economic characteristics of the labour force. For this, the following null hypothesis and alternative hypothesis are formulated:

The null hypothesis H_0 states that: There are no differences in the median of the normalized accessibility scores across the socio-economic groups (low-income, high-income, low-education, high-education), suggesting that socio-economic characteristics do not have an impact on labour force accessibility from industrial areas.

The alternative hypothesis H_1 states that: At least one of the median of the socio-economic groups has a different median in normalized accessibility score compared to the other groups, suggesting that socio-economic characteristics have an impact on labour force accessibility from industrial areas.

The core step of the Kruskal-Wallis test is the comparison of the test statistic 'H' to a critical value from the chi-square distribution with k-1 degrees of freedom. As there are 4 socio-economic groups for this research, the resulting degree of freedom equals 3. An 'H' greater than the critical value results in the rejection of the null hypothesis, indicating that at least one of the socio-economic groups differs from the others.

Table 4.5 displays the results of the Kruskal-Wallis test conducted in Python to evaluate differences in accessibility scores across various socio-economic groups at different hours of the day. For this, the original accessibility scores were used as the goal here is to conclude whether they are significantly different based on these accessibility scores. Thus comparison to the total working population would yield no useful results, as this population group represents the aggregate of the two income groups and the aggregate of the two education groups. The H-statistic and corresponding p-values are also provided for each hour. The results indicate statistically significant differences between the groups for every hour, as shown by the consistently high H-statistics and extremely low p-values (reported as 0.00 due to rounding, but implying $p < 0.05$). These values suggest that the accessibility scores of the respective socio-economic groups are not statistically equivalent at any hour of the day, pointing to disparities between the groups that vary significantly over time.

This consistent pattern of significance across all hours emphasizes the need for further research to determine the specific group differences. For this, Dunn's post hoc test is conducted. This analysis is often performed when the initial test such as the Kruskal Wallis test applied here indicates that there are significant differences among the socio-economic groups but does not identify which groups specifically differ from each other. Since the data from the Kruskal Wallis test is not normally distributed, the Dunns Post Hoc test will be performed to determine pairwise differences between groups.

Table 4.4: Dunn's Post-hoc Test Results for the different socio-economic groups

	High-education	High-income	Low-income	Low/Medium-education
High-education	-	1.000	0.02929	1.424×10^{-7}
High-income	1.000	-	0.002001	1.247×10^{-9}
Low-income	0.02929	0.002001	-	0.03388
Lowm/Medium-education	1.424×10^{-7}	1.247×10^{-9}	0.03388	-

Table 4.5: DKruskal-Wallis Test Results for the different socio-economic groups

Hour	H-statistic	p-value
00:00	50.30	0.00
01:00	51.04	0.00
02:00	47.60	0.00
03:00	46.11	0.00
04:00	47.36	0.00
05:00	47.59	0.00
06:00	49.21	0.00
07:00	50.07	0.00
08:00	50.12	0.00
09:00	50.31	0.00
10:00	49.77	0.00
11:00	49.62	0.00
12:00	49.60	0.00
13:00	49.96	0.00
14:00	48.64	0.00
15:00	49.31	0.00
16:00	49.28	0.00
17:00	49.36	0.00
18:00	49.04	0.00
19:00	49.28	0.00
20:00	48.45	0.00
21:00	48.62	0.00
22:00	48.43	0.00
23:00	48.87	0.00

Table 4.4 displays the p-values after applying the Dunn Post Hoc statistical test. The process was applied using Python and resulted in p-values between the different socio-economic groups. The test has found no statistical difference between the high-education and high-income groups as its p-value is 1, indicating a perfect correlation. Significant disparities are observed between high-education and low/medium-education groups, indicating that high-education groups are better accessible from industrial areas than lower/medium-education groups.

Applying the gravity model to the IJmond area revealed several key findings. The mean accessibility level across all hours of the day is higher by car than by transit in industrial areas. A significant portion of the 478 residential districts becomes unreachable during nighttime, with travel times exceeding the 240-minute threshold, peaking at 81% at 01:00 and dropping to 16.3% at 13:00. Industrial areas such as De Houtwegen and De Waterwegen in Heemskerk, which are near bus stops, exhibit significantly higher accessibility throughout the day, whereas Tata Steel and IJmond Haven, further from transit stops, show lower accessibility levels. The model also indicates that low-income workers, who have higher normalized accessibility scores, tend to live closer and in larger groups to industrial areas compared to high-income workers. Additionally, similar accessibility scores between low-income and low/medium education groups, as well as between high-income and high-education groups, align with existing literature, confirming the model's accuracy.

Therefore the main findings of this research indicate that accessibility in industrial areas in the IJmond region is significantly influenced by the proximity to transit stops, the time of day, and the socio-economic status of the workforce. Overall, these findings underscore there is a need for improved alternatives to the car to accommodate the more diverse supply of jobs in industrial areas, particularly during nighttime for shift jobs as the results indicate that the current transit system does not support relatively high levels of accessibility.

5 Discussion & Conclusion

Chapter 4 concluded with the key findings of this research by stating that the mean accessibility level across all hours of the day is higher by car than by transit in industrial areas. A significant portion of the residential districts becomes unreachable during nighttime and industrial areas near bus stops exhibiting significantly higher accessibility throughout the day than those further from transit stops. Low-income workers, who have higher normalized accessibility scores, tend to live in larger groups and closer to industrial areas compared to high-income workers. Having reiterated the key findings of Chapter 4, this Chapter discusses further implications of these findings within existing literature while also discussing methodological limitations. Finally, recommendations for future research and policymakers are discussed.

5.1. Implications

In this section, the implications of the key findings of the study are further discussed, using both previous research and existing policies. The results of the accessibility analysis address the research gaps presented in Chapter 1 which were as follows:

- It is unknown what the impact of different transport modes is on labour force accessibility in industrial areas.
- It is unknown what the impact of temporal factors is on accessibility to the labour force from industrial areas through the lens of an employer.
- It is unclear how labour force accessibility in industrial areas is influenced by different socioeconomic variables within the working population around these areas.

In Section 4.1 it has already been mentioned that transit accessibility is lacking severely compared to cars, making these industrial areas much more attractive for workers and job seekers who already own a car. It can therefore be stated that the car mode has a larger impact on access to workers from these areas than transit, thus addressing the first research gap. Industrial areas today attract a diverse range of workers beyond traditional roles of plumbers, construction workers, or distribution centre staff as has been stated by Verheggen (2019). Increasingly, these areas also appeal to students seeking part-time employment alongside their studies, as well as office workers. This shift is partly due to the evolving nature of businesses in industrial zones, which are now partly more oriented towards direct consumer interactions (B2C) rather than solely business-to-business (B2B) transactions. This development broadens and diversifies the traditional definition of industrial areas. The diversification of the required workforce in industrial areas reflects broader economic trends where industrial areas are becoming hubs not only for manufacturing and logistics but also for retail, services, and administrative functions (Verheggen, 2019). As a result, the types of jobs available in these areas have expanded to accommodate a more varied demographic of workers, ranging from students seeking flexible hours to young professionals looking for office-based roles within industrial settings. A significant share of these groups often have a driver's license but do not own a car (CBS, 2019). According to CBS, the low car ownership for students is that they often are not financially strong enough to own an automobile and are further burdened by student debt.

Aside from lower accessibility levels for certain industrial areas, the results had shown that accessibility for all industrial areas in the IJmond region decreases significantly during the night. Therefore the results have shown that temporal factors have a significant influence on accessibility to workers from these areas, addressing the second research gap. The model generated the accessibility scores making a distinction between residential areas with a travel time of equal to or less than 240 minutes, and destinations with a travel time beyond that, set by default at 999 minutes. 84% of these residential areas had a travel time from industrial areas set at 999 minutes at 03:00 at night, which impacted the accessibility scores during this time of the day. However, this also means that 16% of the residential districts remain 'accessible' from industrial areas, though it should be noted that an individual would unlikely accept a travel time of 240 minutes to their job location. In addition, these 'reachable' residential locations also saw higher mean travel times, compared to the time intervals during the middle of the day when transit was present. However, the benefit of applying a gravity model for this thesis is that it inherently accounts for travel impedance already, using the travel time. In the model used for this research, both a 240-minute trip and a 999-minute trip are unattractive and are assigned low accessibility scores due to the nature of the travel impedance function of the gravity model. Using the beta of -0.30, the travel impedance for a travel time of 30 minutes would be $1.23 * 10^{-4}$ and 240 minutes already yields $5.38 * 10^{-32}$. While the model may consider locations within a 240-minute travel time, the accessibility scores are already significantly lower for those further away, reflecting the decreasing likelihood of individuals accepting longer travel times. This justifies not having to calculate the exact travel times for destinations beyond the 240 threshold, as this would have no significant impact on the impedance factor. The number of unreachable residential districts might also seem too high, as these are better served by alternative industrial areas within the province of North Holland that are beyond the scope of the case study area for this research. With the results showing an average travel time by transit of 375 minutes from industrial sites in the case study area, job accessibility in the IJmond region only benefits on a local level from transit services. Therefore workers living in the municipalities of Heemskerk, Beverwijk and Velsen would benefit the most. For the larger region of North Holland, workers living further away, the car becomes a much more attractive alternative, if travel time is the deciding factor.

In particular access from areas such as Tata Steel and IJmuiden Haven decreased significantly during the night hours. By focusing on transit, the maps visualizing the transit accessibility scores indicate that these industrial areas are further away from the districts where the working population resides whilst also being bounded by the NorthSea Canal waterway, despite being well connected by the Kennemer railway line as well as multiple bus services operated by Connexxion. The North Sea Canal waterway limits access to districts in IJmuiden, Velsen and beyond. Therefore these lower accessibility scores were to be expected given the spatial layout of the area. The lack of public transportation during the night hours also further contributes to the observed lower levels of accessibility. It should be noted that these factors are specific to the local context of these industrial areas. They may differ significantly in other industrial zones or regions such for example the Rijnmond region in South Holland or Eemshaven in Groningen. However, the effect of lower access by transit compared to car would likely remain in other case study areas as well, given the characteristics of industrial sites being concentrated in certain locations and closed off from residential areas.

With the results of this research underlining transit being an underperforming mode of transport compared to the car, the impact of this is affecting shift work in particular. As Tata Steel operates 24 hours a day, shift work is part of the company's daily operations (Tata Steel, 2024) with the company needing to attract workers able to reach the factory at night as well. Research by Breedveld, 1998 shows that shift work is often performed by workers with a lower/medium education level compared to workers with a higher education level. It is reported that low/medium-educated workers have less control over their working hours due to the nature of the jobs they occupy. The production of a factory can often not be adjusted to the flexibility of an individual worker, as multiple people need to operate on a job site at the same time. Similar results of shift work being primarily presented by low/medium-education groups are also present in more recent research (RIVM, 2012). The need for good accessibility to these industrial areas for shift workers with a lower/medium education background, emphasizes the need to make industrial job sites situated further away from transit stations and residential districts better accessible during all hours of the day. However, it should be noted that the results of lower accessibility levels around Tata Steel and other industrial areas in the IJmond could be case study-specific and not apply to other regions with a different geographic setting.

Having discussed that there is a need for low-income workers by Tata Steel, the result of this research stating that the low-income population shows higher accessibility scores compared to the high-income group, further implies that the surrounding residential districts meet this requirement. However, these higher scores are relative to the high-income population and do not provide clarity on accessibility on a more general level. For instance, existing studies have repeatedly found that high-income workers are more likely to own a car compared to their lower-income counterparts, enabling them to access a job site more easily as they are less dependent on alternative modes of transport which would limit their radius of job opportunities (CBS, 2018; Dalla Longa, 2024; Shen, 1998). In addition, there is an ongoing trend of increasing electric car ownership, particularly among high-income households. According to CBS, electric cars are predominantly owned by higher-income groups, which further enhances their mobility and access to employment locations that may not be well-served by public transport (CBS, 2023). This trend further accelerates the disparity between low and high-income accessibility, as low-income workers remain more reliant on public transportation and other alternative modes of transport, of which the former is often less available, especially during off-peak hours. Therefore, policymakers and companies must focus on improving existing public transportation options and providing alternative mobility solutions to ensure that low-income workers can reliably access industrial job sites. This is further emphasized in Section 5.3.2. Addressing these disparities is essential for attracting and retaining a diverse workforce in industrial areas and ensuring transport equity for all socioeconomic groups.

The results of the gravity model in this research imply that companies in industrial areas can reach low-income workers better than high-income workers due to their size and proximity to these areas, addressing the research gap on how different socioeconomic variables influence spatiotemporal labour force accessibility in industrial areas. Previous research by Bon et al. (2023) has stated that income is strongly correlated with car ownership and together influence the rate at which certain groups of people have access to opportunities by mode of transit. It states that income is the most significant socioeconomic indicator for transport poverty. Having used income in this research on industrial areas, it was expected that low-income workers would be less accessible by transit compared to high-income workers. However, the results of the gravity model imply that low-income workers are less challenging to access compared to high-income workers, given that travel time and (sub)population size are the determinant factors and that both groups need to be accessed by transit rather than car. The study by Bon focused on the Amsterdam Metropolitan Area and included multiple modes of transport including transit and car whereas this study focuses on a peripheral region within the Amsterdam metropolitan area, IJmond, with its main focus on transit. Therefore the unexpected outcome of higher transit accessibility from industrial sites to low-income workers in the IJmond could be the result of these lower-income groups being more dependent on public transport and policymakers thus having the transport network adapted to this. However, it is important to consider several additional factors. These include the quality and frequency of public transit services, the availability and affordability of housing near industrial zones, and potential barriers to transit use such as safety or convenience. Additionally, other socioeconomic factors, such as actual employment opportunities and availability of social services, might also play significant roles in accessibility outcomes. By considering these additional factors, a more general understanding of accessibility in industrial areas can be achieved.

5.2. Methodological Limitations

The implications of the results are accompanied by several limitations that must be considered. These limitations do not invalidate the research but rather provide a foundation for understanding how future studies can be improved. The model resulted in higher accessibility scores from industrial areas by car compared to transit. The model was limited to the usage of a single travel time matrix for the car and an averaged travel time matrix for transit. To enhance the model with the temporal component, computing car travel times for each hour of the day would allow for a more comprehensive accessibility analysis across multiple modes of transport. Additionally, including traffic data would be essential to achieve this improvement as it takes congestion effects into account. The computed transit skim matrices provide an insight into the aggregated transit travel time, which includes access to and egress from transit stops by walking. Decomposition of the trip chain would yield more detailed results and enable a deeper analysis (bus, metro, train, or walking). As the travel time calculation involves finding the shortest (time) path within the transit network using both GTFS data as well as street network data, it assumes an uncongested network assignment. Similar to the limitation of the single travel time matrix for the car, congestion effects and dwelling times could result in longer transit travel times as well, reducing the accessibility scores in industrial areas even further. In addition, the model now assumes a seamless transfer between walking and public transport, whereas, in practice, transfer times between different modes should be considered.

In addition to not accounting for congestion effects, the gravity model primarily addresses potential mobility by indicating the opportunity to travel or reach workers. This differs from travel behaviour studies, which focus on the actual trips made, and choice modelling, which considers the willingness to travel or reach a destination and attempts to predict individuals' choices among a set of travel alternatives, often from the perspective of an employee. This means that the gravity model does not account for variations in travel preferences in the same manner as other methods using travel behaviour or choice modelling. It assumes that all individuals or a given group of individuals experience the same travel impedance based on their travel time or cost. This could be altered by adding more variables to the travel impedance functions, although this would remain group-specific rather than geared towards the individual. The results of this study therefore should be viewed in the context of labour force opportunities rather than actual travel behaviour, as the gravity model's assumptions provide a generalized picture of accessibility that might not capture the complexities of individual travel decisions and preferences.

The results also show a significant share of 'unreachable' residential districts at night, which affected industrial areas such as Tata Steel and IJmond Haven in particular. These locations were situated far away from bus stops and important transit hubs such as the train station of Beverwijk. A limitation of the model is that these results primarily focus on the IJmond area, which makes the implications of these results case study-specific. Other regional areas might not be bordered by the North Sea or waterways and thus could display different results. Additionally, other regions with industrial areas in the province of North Holland also compete for the same group of workers, which could result in lower accessibility levels for the industrial sites in the IJmond region. Accounting for competition effects in the gravity model results in longer computation times and would thus require better processing power, especially as these competition effects would need to be calculated 24 times to account for the temporal aspect of this research.

The model showed that low-education/income groups live in larger sizes near industrial areas than their counterparts. According to a study by CBS, these groups often rely more heavily on public transport due to lower car ownership rates (CBS, 2018). The study indicates that 45.9% of Dutch people in the lowest income bracket do not own a car, which is significantly higher than the 5.9% of people with a high income. In the future, low-income people who do own a car will be financially impacted further compared to high-income people, as current government policy promotes the costly transition to environmentally friendly electric vehicles. Due to their proximity to industrial areas, compared to high-income groups, policymakers could focus on enhancing alternative modes of transport on a local to regional level. Alternatives could be improving bicycle infrastructure in industrial areas and providing residential districts with shared mobility options such as shared bicycles or cars. Low-income employees who work primarily night shifts and are situated further away from industrial areas should be given the option to sign a lease car contract under multiple employers. This approach would allow a single car to be leased by a household but used by both partners within that household, even if they work for different companies. For instance, a couple where one partner works night shifts at an industrial site and the other works daytime shifts at a school or retail job could share one lease car. This system would reduce the financial burden of owning multiple cars, thus providing a practical transportation solution for households with varying work schedules. Such shared lease programs would enhance overall accessibility and mobility, benefiting both employees and in particular low-income employers by increasing mobility to destinations further away from industrial areas and reducing the financial impact of car ownership for the employees. To provide policymakers with more detailed results on where low-income people reside around industrial areas, utilizing neighbourhood-level (Dutch: Buurtniveau) data instead of district-level (Dutch: Wijkniveau) data would contribute to a better understanding of accessibility to workers in these neighbourhoods. However, this would require stronger processing power and longer computation times as well. The North-Holland area contains 478 districts (Dutch: Wijken). Disaggregating to the neighborhood level would yield 1962 neighborhoods (Dutch: Buurten) which quadruples the number of destinations compared to the current model using district-level data. Existing travel time tools such as Open Route Service and TravelTime provide a limited number of matrix calculations within their API, posing difficulties in performing travel time calculations using neighbourhood-level data.

5.3. Recommendations

5.3.1. Recommendations for Future Research

These limitations highlight important areas for future research. More comprehensive data collection, supported by more powerful computational capabilities to manage more detailed data granularity, could provide a better understanding of labour force accessibility in industrial areas. Expanding the scope to include car accessibility by incorporating real-time traffic data and disaggregating transit travel time into the different access and egress trips would offer a more complete picture of the spatiotemporal dynamics of urban labour force accessibility.

To enhance the model with a fair multimode analysis, computing car travel times for each hour of the day would allow for a more comprehensive accessibility analysis across multiple modes of transport. Cycling should also be considered as a mode of transport in this analysis as bicycle travel time can vary depending on the presence of traffic lights on cycling routes. Including traffic data for these modes would be essential to achieve this improvement as it takes congestion effects into account. Decomposition of the public transport trip chain would yield more detailed results and enable a deeper analysis (bus, metro, train, cycling or walking).

Furthermore, accounting for competition effects in the gravity model results in longer computation times and would thus require better processing power, especially as these competition effects would need to be calculated 24 times to account for the temporal aspect of this research. To provide policymakers with more detailed results on where low-income people reside around industrial areas, researchers utilizing neighbourhood-level (Dutch: Buurtniveau) data instead of district-level (Dutch: Wijkniveau) data would enable a more granular analysis. Higher-resolution data can reveal specific accessibility challenges and opportunities within smaller geographic units such as 'wijken', providing a broader understanding of the local labour market dynamics.

The results of this research stating that certain industrial areas face lower accessibility levels due to their distance from transit stops and being surrounded by barriers is case study specific. Nonetheless, the general patterns observed in this study can provide valuable insights into other industrial areas both within and outside of the Netherlands. For example, similar industrial setups in the United States of America or China could face similar challenges regarding transit accessibility, particularly during off-peak hours. The spatial layout of industrial areas is common across regions in the world as they are often located in the periphery, outside city centres. Existing studies abroad have also highlighted the lack of transit and the presence of cars in these areas. Therefore future studies should explore areas with similar spatial characteristics to further validate the findings in this research.

Furthermore, future research on workforce accessibility could explore how employers aim to reach specific groups and their willingness to provide subsidised transportation for these groups, thus incorporating elements of choice modelling to offer a more comprehensive understanding of labour force accessibility. Researchers should also recognize that the supply of services does not automatically translate into usage. Behavioural aspects, such as the willingness of workers to use alternative modes of transport for night shifts, should be considered. This may involve conducting surveys or pilot programs to better understand the potential usage of proposed alternative mode solutions.

5.3.2. Recommendations for Policymakers

The research highlights significant gaps in transit accessibility compared to car accessibility, particularly affecting workers at night. Addressing these disparities is essential for creating equitable transportation solutions that benefit all socioeconomic groups. Therefore, there are four main recommendations that policymakers should consider based on the existing results.

The first key policy recommendation is to increase accessibility by transit to reach levels closer to that of car accessibility. This includes evaluating and modifying local infrastructure to remove barriers that impede access to transit stops. For instance, fences may need to be adjusted or removed, and waterways should be bridged, as they currently form significant obstacles to accessing existing transit stops as was found in this research. It is important however to note that the results of this research are context-specific. Policymakers should assess whether their areas face similar issues before implementing these recommendations. Conducting a local accessibility study can help determine the specific barriers and needs within their regions, ensuring that any improvements are tailored to the unique characteristics of the area and effectively address local accessibility challenges.

The second recommendation is to offer tailor-made solutions at night that align with the working hours of industrial companies in these areas, public transport could become an attractive option for shift workers, benefiting low-income and low/medium education groups the most, as these groups represent a relatively large share of shift workers. According to the Dutch Social Cultural Planning Agency, only 1 out of 8 workers experienced shift work at night in 2018, indicating that the demand for transit at night is significantly lower (Putman, 2020). Policymakers need to consider this when improving the public transport system by offering solutions on a smaller scale. Merely increasing the availability of overnight public transport does not guarantee its usage. Policymakers should implement further studies that investigate the actual demand for such services among workers in industrial areas, ensuring that the supply aligns with the needs of the labour market. Shared mobility could function as an access and egress mode for the train, or even replace the entire transit trip if the distance between residential districts and industrial sites is small enough. In return, this would make industrial areas more attractive for companies and make workers less dependent on cars.

Based on the finding that accessibility levels for low-income and low/medium-education workers at night remain constant and are primarily composed of the access and egress mode 'walking' due to the absence of transit services at this time, policymakers should consider improving pedestrian and cycling routes to industrial areas. The larger size and proximity to industrial areas of these groups compared to high-income and education groups further underscore the importance of this. Enhancing these routes will provide reliable and safe access for low-income workers who rely on walking during hours when public transportation is not available. This approach not only addresses the immediate need for better accessibility but also supports sustainable transportation alternatives. Investments in well-lit, safe, and direct walking and cycling paths can significantly improve the overall accessibility of industrial areas for these workers, thereby supporting economic activities.

5.4. Conclusion

This study has provided an evaluation of accessibility to the labour force in industrial areas, highlighting significant disparities between car and transit accessibility. The findings indicate that car accessibility is generally higher than transit accessibility for all industrial areas in the IJmond. Many industrial areas in The Netherlands, such as the IJmond, and industrial sites in other countries are often located on the periphery of urban regions, which can influence the accessibility dynamics for different socioeconomic groups. These peripheral locations typically have limited public transport options and are more dependent on the car mode. The spatiotemporal analysis of transit accessibility has shown that particularly during off-peak hours levels of accessibility in these areas decrease significantly, which has implications for workers reliant on public transport. The results have further confirmed existing literature that industrial areas are poorly accessible by public transit. In addition to existing literature, this research has further highlighted the significantly lower rate of accessibility at night by transit. Furthermore, the evaluation of different socio-economic groups with the z-score analysis implies that low-income groups live in larger concentrations closer to industrial areas than high-income groups. As the travel time by transit at night is mainly represented by the walking mode due to the absence of public transport services, these low-income groups are mainly dependent on walking to reach a job at an industrial site. Furthermore, the number of 'unreachable' residential districts at night underscores the need for improved mobility options during these hours, especially when night shift work is considered. Policymakers need to evaluate how alternative modes of transport outside of the traditional modes of car and public transit, can accommodate the lack of accessibility during these hours of the day.

Several methodological limitations were identified, including the use of a single travel time matrix for cars and assuming an absence of competition from other job sites for the same working population. Addressing these limitations by incorporating temporal components and real-time traffic data could significantly enhance the model's accuracy. It should be noted, however, that this could result in longer computation times as more detailed and complex data are processed. Furthermore, by using job data for industrial areas, the number of reachable employees or potential workers from the origin location can be weighed by the number of accessible jobs at the destination side. This would yield more accurate results by better reflecting the true job availability and competition effects within industrial areas. A higher number of jobs would mean more demand for workers and therefore lower accessibility and vice versa. by including competition effects, the expectation is that absolute accessibility levels in industrial areas would decrease, though differences between areas would be more accurately captured, highlighting specific regional differences and local accessibility challenges.

Despite the methodological limitations, this study shifted the focus from the traditional concept of job accessibility in existing studies to the accessibility of the labour force, providing a new perspective on how employers can reach their existing and potential workers. By evaluating the accessibility of workers from the employers' perspective, particularly in industrial areas which are characterized by a high density of employment opportunities, this approach highlights the significant role that the location of industrial areas has in influencing accessibility levels. Understanding how various factors affect the ability of workers to reach jobs in these areas is relevant for developing effective transportation and employment policies.

Shift work is present in industrial areas, highlighting the need for employers to reach a share of the labour force that is willing to work at night. As this share is significantly smaller than the working population during the day, policy recommendations should focus on increasing night-time accessibility to industrial areas by alternative modes of transport. This is particularly applicable for low-income and low-education groups who are more dependent on public transport as well as companies in industrial areas in general as they accommodate primarily low-wage jobs compared to other job sites such as central business districts. Given the ongoing trend in diversification in industrial areas in which a more diverse workforce is present, policymakers should consider attracting students and young professionals as well. Particularly students are dependent on public transport or cycling as they often do not own a car. Improving walking and cycling routes as well as offering alternative sustainable mobility options at night accounting for the lower demand such as providing shared mobility options could mitigate some of the identified accessibility issues. More studies focused on travel behaviour are needed to understand whether in practice there is a willingness among workers to use these services and among employers to provide them.

In conclusion, while this study has highlighted key transit accessibility challenges in industrial areas, addressing these issues requires more extensive efforts from policymakers, urban planners, and researchers. By offering alternative mobility solutions and incorporating more detailed data into accessibility models, a more equitable urban environment for all workers and employers can be created. Moreover, these efforts will not only address current accessibility issues but will also increase the attractiveness and functionality of industrial areas, contributing positively to their economic vitality.

A
Accessibility ratio

Table A.1: Relative accessibility of transit compared to car, per industrial area

Search_id	Relative accessibility
1	5.47
2	3.42
3	8.24
4	18.25
5	16.51
6	9.82
7	5.29
8	6.68
9	9.59
10	6.77
11	5.98
12	4.24
13	5.54
14	7.98
15	9.48
16	5.92
17	7.81
18	4.23
19	5.37
20	7.85
21	8.69
22	9.86

B
Python code

```
import os
import numpy as np
import pandas as pd
import geopandas as gpd
import matplotlib.pyplot as plt
from scipy.optimize import minimize
from shapely.geometry import Polygon
from IPython.display import FileLink

base_path = "Input data/skims transit"
dest_path = "Input data/skims transit/pivot tables"

for hour in range(24):
    # Construct the file name based on the hour
    filename = f"skim_transit_{hour:02}00.gpkg"
    gpkg_path = os.path.join(base_path, filename)
    if not os.path.exists(gpkg_path):
        print(f"File does not exist: {gpkg_path}")
        continue

    # Load the geopackage file
    travel_time_gdf = gpd.read_file(gpkg_path)
    travel_time_gdf['prop_travel_time'] = pd.to_numeric(travel_time_gdf['prop_travel_time'
    ]/60, errors='coerce')

    # Group by 'search_id' and 'gwb_code_1', then calculate mean 'prop_travel_time'
    aggregated_travel_time = travel_time_gdf.groupby(['search_id', 'gwb_code_1']).
    prop_travel_time.mean().reset_index()
    pivot_table = aggregated_travel_time.pivot(index='search_id', columns='gwb_code_1',
    values='prop_travel_time')
    pivot_table.fillna(999, inplace=True)
    pivot_table = pivot_table.astype(float)

    output_path = os.path.join(dest_path, f"pivot_table_{hour:02}00.csv")
    pivot_table.to_csv(output_path, float_format='%.1f')
```

Listing B.1: Transit skim matrix generation

```
# Car
base_path = "Input data/skims car"
dest_path = "Input data/skims car/pivot tables"

filename = f"skim_car.gpkg"
gpkg_path = os.path.join(base_path, filename)

if not os.path.exists(gpkg_path):
    print(f"File does not exist: {gpkg_path}")

# Load the geopackage file
travel_time_gdf = gpd.read_file(gpkg_path)
```

```
travel_time_gdf['prop_travel_time'] = pd.to_numeric(travel_time_gdf['prop_travel_time'],
    errors='coerce')
travel_time_gdf['prop_travel_time'] = travel_time_gdf['prop_travel_time']/60

# Group by 'search_id' and 'gwb_code_1', then calculate mean 'prop_travel_time'
aggregated_travel_time = travel_time_gdf.groupby(['search_id', 'gwb_code_1']).
    prop_travel_time.mean().reset_index()
pivot_table = aggregated_travel_time.pivot(index='search_id', columns='gwb_code_1', values='
    prop_travel_time')
pivot_table.fillna(999, inplace=True)
pivot_table = pivot_table.astype(float)

output_path = os.path.join(dest_path, f"pivot_table.csv")
pivot_table.to_csv(output_path, float_format='%.1f')
```

Listing B.2: Car skim matrix generation

```
# Socioeconomic data
df = pd.read_excel("Input data/kwb-2022.xlsx")
df = df[df['gwb_code_10'].str.startswith("WK")]

# Make list with minipality names to filter on for IJmond
df_gemeenten = pd.read_excel("Input data/Gemeenten alfabetisch 2023.xlsx")
gemeenten_noord_holland = df_gemeenten[df_gemeenten['Provincienaam'] == 'Noord-Holland']
gemeenten_filter = gemeenten_noord_holland['Gemeentenaam'].tolist()

gefilterde_df = df[df['gm_naam'].isin(gemeenten_filter)]
gefilterde_df.to_excel("Prepared data/gefilterde_kwb-2022.xlsx", index=False)

gdf_wijken = gpd.read_file("Input data/wijken_2022_v2.shp")
columns_to_include = ["gwb_code_10", "gm_naam", "a_inw","a_hh","a_opl_lg","a_opl_md","
    a_opl_hg","p_arb_pp","a_inkont","p_ink_li","p_ink_hi","p_hh_li","p_hh_hi","p_hh_lkk","
    a_pau","g_pau_hh"]
df_kwb = pd.read_excel("Prepared data/gefilterde_kwb-2022.xlsx",usecols=columns_to_include,
    decimal=",")
df_kwb.replace(".", "0", inplace=True)

# Convert numeric columns to float
numeric_columns = ["a_inw","a_hh","a_opl_lg","a_opl_md","a_opl_hg","p_arb_pp","a_inkont","
    p_ink_li","p_ink_hi","p_hh_li","p_hh_hi","p_hh_lkk","a_pau","g_pau_hh"]
df_kwb[numeric_columns] = df_kwb[numeric_columns].astype(float)
gdf_wijken_compleet = gpd.read_file("Input data/wijken_2022_v2.shp")
columns_to_include_shp = ["WK_CODE","OPP_LAND","Shape_Leng","Shape_Area","geometry"]
gdf_wijken = gdf_wijken_compleet[columns_to_include_shp]

# Add geometry based on district code
socio_demographic_data = pd.merge(df_kwb, gdf_wijken, left_on="gwb_code_10", right_on="
    WK_CODE", how="left")
gdf_socio_demographic = gpd.GeoDataFrame(socio_demographic_data)

# Export dataframe as shapefile
gdf_socio_demographic.to_file("Prepared data/Socio_demographic_data.shp")
gdf_socio_demographic_point = gdf_socio_demographic.copy()
gdf_socio_demographic_point['geometry'] = gdf_socio_demographic_point['geometry'].centroid
gdf_socio_demographic_point.to_file("Prepared data/Socio_demographic_data_with_point.shp")
```

Listing B.3: Socioeconomic data preparation

```
# Industrial area data

# Read csv and append to shapefile
banen_csv = 'Input data/LISA_banen_IJmond.csv'
IJmond_shp = '/Users/rubenranty/Library/CloudStorage/OneDrive-Persoonlijk/Documenten/Msc TIL/
    Year2/TIL-5060 Thesis/Job accessibility/QGIS werkmap/QGIS/BuurtenNH/ibis_IJmond.shp'

banen_per_regio = gpd.read_file(banen_csv)
bedrijventerreinen_df = gpd.read_file(IJmond_shp)

gemeenten = banen_per_regio.iloc[:3]['Gemeente'].unique()
totaal_banen_per_gemeente_list = []

```

```
for gemeente in gemeenten:
    banen_in_gemeente = banen_per_regio[banen_per_regio['Gemeente'] == gemeente]['Banen totaal'].sum()
    totaal_banen_per_gemeente_list.append({'Gemeente': gemeente, 'BANEN_TOTAAL': banen_in_gemeente})

totaal_banen_per_gemeente_df = pd.DataFrame(totaal_banen_per_gemeente_list)
totaal_banen_per_gemeente_df['Gemeente'] = totaal_banen_per_gemeente_df['Gemeente'].str.upper()
totaal_banen_per_gemeente_df['BANEN_TOTAAL'] = pd.to_numeric(totaal_banen_per_gemeente_df['BANEN_TOTAAL'], errors='coerce')

# Calculate jobs per industrial area
bedrijventerreinen_df['oppervlakte'] = bedrijventerreinen_df.geometry.area
oppervlakte_per_gemeente = bedrijventerreinen_df.groupby('TER_BEHEER')['oppervlakte'].sum()
bedrijventerreinen_df['relatief_aandeel'] = bedrijventerreinen_df.apply(
    lambda x: x['oppervlakte'] / oppervlakte_per_gemeente[x['TER_BEHEER']], axis=1)
bedrijventerreinen_df['banen_per_terrein'] = bedrijventerreinen_df['BANEN_TOTAAL'] * bedrijventerreinen_df['relatief_aandeel']

gdf_bedrijventerreinen = gpd.GeoDataFrame(bedrijventerreinen_df, geometry='geometry')
output_shapefile_path = "/Users/rubenranty/Library/CloudStorage/OneDrive-Persoonlijk/Documenten/Msc TIL/Year2/TIL-5060 Thesis/Job accessibility/QGIS werkmap/Gravity_model_python/Prepared data/bedrijventerreinen_banen.shp"
gdf_bedrijventerreinen.to_file(output_shapefile_path)
```

Listing B.4: Industrial area data preparation

```
# Gravity model

# Load input files
population_shapefile_path = 'Prepared data/Socio_demographic_data_with_point.shp'
jobs_shapefile_path = 'Prepared data/bedrijventerreinen_banen.shp'

population_df = gpd.read_file(population_shapefile_path)[['gwb_code_1', 'a_inw']]
jobs_df = gpd.read_file(jobs_shapefile_path)[['RIN_NUMMER', 'banen_per_']]

jobs_dict = jobs_df.set_index('RIN_NUMMER')['banen_per_'].to_dict()
population_dict = population_df.set_index('gwb_code_1')[ 'a_inw'].to_dict()

base2_path = "Input data/skims transit/pivot tables"
dest2_path = "Output data/Weight_matrices_transit/Base/Total population test"

# Defining impedance function
def impedance_function(C, beta):
    return np.exp(beta * C)
beta = -0.3

combined_accessibility_scores = pd.DataFrame()
pd.set_option('display.float_format', '{:.10f}'.format)

for hour in range(24):
    # Load the skim matrix with travel time for current hour
    pivot_path = f"{base2_path}/pivot_table_{hour:02}00.csv"
    travel_time_matrix = pd.read_csv(pivot_path, index_col=0)
    accessibility_scores = pd.DataFrame(index=travel_time_matrix.index, columns=[f'{hour:02}:00'])

    # Calculate A_i for each origin i
    for i in travel_time_matrix.index:
        A_i = sum(population_dict.get(j, 0) * impedance_function(travel_time_matrix.loc[i, j], beta)
                  for j in travel_time_matrix.columns if not pd.isna(travel_time_matrix.loc[i, j]))
        accessibility_scores.at[i, f'{hour:02}:00'] = A_i

    combined_accessibility_scores = pd.concat([combined_accessibility_scores, accessibility_scores], axis=1)

# Export accessibility matrix for each hour
output_path = f"{dest2_path}/A_i_base_TotPop.csv"
```

```
combined_accessibility_scores.to_csv(output_path)
print('Calculation of accessibility scores A_i has been finished')

# Normalisation
global_min = combined_accessibility_scores.min().min()
global_max = combined_accessibility_scores.max().max()
normalized_accessibility_scores = (combined_accessibility_scores - global_min) / (global_max - global_min)

# Export normalized accessibility matrix for all hours
output_path = f"{dest2_path}/A_i_base_TotPop_norm.csv"
normalized_accessibility_scores.to_csv(output_path)
print('Normalization of accessibility scores has been finished')

import warnings
warnings.filterwarnings("ignore", message="Column names longer than 10 characters will be truncated when saved to ESRI Shapefile.")

# Import existing shapefiles
base_csv_path = "Output data/Weight_matrices_transit/Base/Total population"
dest_gpkg_path = "Output data/Weight_matrices_transit/Base/Accessibility shapefiles"
jobs_shapefile_path = 'Prepared data/bedrijventerreinen_banen.shp'

# Load the base shapefile
base_shapefile = gpd.read_file(jobs_shapefile_path)
base_shapefile['RIN_NUMMER'] = base_shapefile['RIN_NUMMER'].astype(str)

csv_file = f"{base_csv_path}/A_i_base_Totpop_norm.csv"
csv_data = pd.read_csv(csv_file)

# Convert RIN numbers to numbers
base_shapefile['RIN_NUMMER'] = range(1, len(base_shapefile) + 1)
csv_data['search_id'] = range(1, len(csv_data) + 1)

hour_columns = [col for col in csv_data.columns if ':' in col]

# Only iterate over hour columns, assuming they are formatted as HH:MM
for hour in hour_columns:
    safe_hour = hour.replace(':', '')
    temp_data = csv_data[['search_id', hour]]
    merged_data = base_shapefile.merge(temp_data, left_on="RIN_NUMMER", right_on="search_id", how="left")
    output_file = f"{dest_gpkg_path}/A_i_Base_Totpop_norm_{safe_hour}.gpkg"
    merged_data.to_file(output_file, driver="GPKG")

print('geopackage file export has finished')
```

Listing B.5: Gravity model

```
# Mean travel time
directory = skim_data
all_hours_averages = pd.DataFrame()

# Loop through each hour
for hour in range(24):
    filename = f"pivot_table_{hour:02d}00.csv"
    file_path = os.path.join(directory, filename)
    pivot_table = pd.read_csv(file_path, index_col=0)

    # Calculating mean travel time for each search_id
    average_travel_time = pivot_table.mean(axis=1)
    all_hours_averages[f'{hour:02d}:00'] = average_travel_time

all_hours_averages['search_id'] = range(1, len(all_hours_averages) + 1)

plt.figure(figsize=(10, 6))

# Plot each search_id's average travel time across the 24 hours
for search_id in all_hours_averages.index:
    plt.plot(all_hours_averages.columns[:-1], all_hours_averages.loc[search_id, all_hours_averages.columns[:-1]], label=f'Search ID {int(all_hours_averages.loc[search_id
```

```
    , "search_id"])}')

plt.xlabel('Hour')
plt.ylabel('Mean travel time')
plt.title('Mean Travel Time Across Time Intervals Per Industrial Area')
plt.xticks(rotation=45)
plt.legend()
plt.grid(True)
plt.legend(loc='upper left', bbox_to_anchor=(1, 1))
plt.tight_layout()
plt.savefig('Output data/Figures/Mean_travel_time')
plt.show()
```

Listing B.6: Mean travel time

```
# Accessibiltiy comparison between car and transit
dest3_path = "Output data/Weight_matrices_car/Base/Total population/A_i_base_TotPop.csv"
dest4_path = "Output data/Weight_matrices_transit/Base/Total population/A_i_base_TotPop.csv"

df = pd.read_csv(dest3_path)
df2 = pd.read_csv(dest4_path, usecols=['search_id', '12:00'])

# Transform 'searchid' column to a normal sequence in both dataframes, skipping the RIN
    numbers
df['search_id'] = range(1, len(df) + 1)
df2['search_id'] = range(1, len(df2) + 1)

# Merge the two dataframes on 'search_id'
merged_df = df.merge(df2, on='search_id')

plt.figure(figsize=(10, 6))
merged_df.set_index('search_id').plot(kind='bar', figsize=(10, 6))

plt.xlabel('Origin')
plt.ylabel('Normalized Accessibility Score')
plt.title('Normalized Accessibility Scores Per Origin Industrial Area')
plt.xticks(rotation=45, fontsize=6)
plt.legend(["Car", "Transit"])
plt.tight_layout()
plt.savefig('Output data/Figures/A_i_car_vs_transit')
plt.show()
```

Listing B.7: Comparison accessibility between car and transit

```
# Mean travel time
pd.set_option('display.max_columns', None)
pd.set_option('display.expand_frame_repr', False)

file_paths = {
    "Total Population": 'Output data/Weight_matrices_transit/Base/Total population/
    A_i_base_TotPop_norm.csv',
    "Low-income": 'Output data/Weight_matrices_transit/Base/Low-income/A_i_base_LowInc_norm.
    csv',
    "High-income": 'Output data/Weight_matrices_transit/Base/High-income/
    A_i_base_HighInc_norm.csv',
    "Low/Medium-education":"Output data/Weight_matrices_transit/Base/LowMid-education/
    A_i_base_LowMidEdu_norm.csv",
    "High-education":"Output data/Weight_matrices_transit/Base/High-education/
    A_i_base_HighEdu_norm.csv"
}

mean_dfs = []
for key, path in file_paths.items():
    df = pd.read_csv(path, index_col=0)
    mean_data = df.mean(axis=0)
    mean_df = pd.DataFrame(mean_data, columns=[key])
    mean_dfs.append(mean_df)

# Concatenate all mean dataframes into one
combined_df = pd.concat(mean_dfs, axis=1)
print(combined_df)
```

```python

plt.figure(figsize=(10, 6))
for column in combined_df.columns:
    plt.plot(combined_df.index, combined_df[column], label=column)

plt.xlabel('Hour')
plt.ylabel('Mean Accessibility')
plt.title('Mean Accessibility Across Time Intervals for Different Groups')
plt.xticks(rotation=45)  # Rotate x-axis labels for better readability if needed
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.savefig('Output data/Figures/A_i_base_mean_groups')
plt.show()
```

Listing B.8: Mean travel time to socioeconomic subgroups

```python
# z-score method
import matplotlib.pyplot as plt

# Calculate mean and standard deviation for each group for each hour
total_pop_mean = total_pop_data.mean()
low_inc_mean = low_income_data.mean()
high_inc_mean = high_income_data.mean()
lowmed_edu_mean = lowmid_edu_data.mean()
high_edu_mean = high_edu_data.mean()
total_pop_std = total_pop_data.std()
low_inc_std = low_income_data.std()
high_inc_std = high_income_data.std()
lowmed_edu_std = lowmid_edu_data.std()
high_edu_std = high_edu_data.std()

# Create DataFrame for the mean data
mean_data = pd.DataFrame({
    'Total Population': total_pop_mean,
    'Low-income': low_inc_mean,
    'High-income': high_inc_mean,
    'Low/Medium-education': lowmed_edu_mean,
    'High-education': high_edu_mean
})

# Calculate z-scores
z_scores = pd.DataFrame()
for group in mean_data.columns[1:]:
    z_scores[f'Z-score {group}'] = (mean_data[group] - mean_data['Total Population']) /
     total_pop_std
z_scores = z_scores.reset_index()
z_scores.rename(columns={'index': 'Hour'}, inplace=True)

latex_table = z_scores.to_latex(index=False, header=True, column_format='lcccc', float_format
    ="{:0.2f}".format)
print(latex_table)

plt.figure(figsize=(12, 8))
plt.plot(z_scores['Hour'], z_scores['Z-score Low-income'], label='Low-income', marker='o')
plt.plot(z_scores['Hour'], z_scores['Z-score High-income'], label='High-income', marker='o')
plt.plot(z_scores['Hour'], z_scores['Z-score Low/Medium-education'], label='Low/Medium-
    education', marker='o')
plt.plot(z_scores['Hour'], z_scores['Z-score High-education'], label='High-education', marker
    ='o')
plt.axhline(y=0.0, label='Total Population reference score', color='y', linestyle='-')

plt.title('Z-Scores of Accessibility Scores by Socio-Demographic Group vs. Total Population')
plt.xlabel('Hour')
plt.ylabel('Z-Score')
plt.xticks(rotation=45)
plt.grid(True)
plt.legend()

plt.tight_layout()
plt.savefig('Output data/Figures/z-scores_graph.png')
```

```
plt.show()
```

Listing B.9: Z-Score method comparing socioeconomic groups

```
# Statistical analysis
kruskal_results = []
for hour in low_income_data.columns:
    result = kruskal(
        low_income_data[hour],
        high_income_data[hour],
        lowmid_edu_data[hour],
        high_edu_data[hour]
    )
    kruskal_results.append({
        "Hour": hour,
        "H-statistic": result.statistic,
        "p-value": result.pvalue
    }
    )

results_df = pd.DataFrame(kruskal_results)

latex_table = results_df.to_latex(index=False, header=True, column_format='lcc', float_format
    ="{:0.2f}".format)
print(latex_table)

groups = ['Low-income', 'High-income', 'Lowmid-edu', 'High-edu']

low_income_data2 = pd.read_csv(file_paths['Low-income'])
high_income_data2 = pd.read_csv(file_paths['High-income'])
lowmid_edu_data2 = pd.read_csv(file_paths['Lowmid-edu'])
high_edu_data2 = pd.read_csv(file_paths['High-edu'])

# Melt dataframe to convert to long format
low_income_long = low_income_data2.melt(id_vars='search_id', var_name='Hour', value_name='
    Score', ignore_index=True)
high_income_long = high_income_data2.melt(id_vars='search_id', var_name='Hour', value_name='
    Score', ignore_index=True)
lowmid_edu_long = lowmid_edu_data2.melt(id_vars='search_id', var_name='Hour', value_name='
    Score', ignore_index=True)
high_edu_long = high_edu_data2.melt(id_vars='search_id', var_name='Hour', value_name='Score',
     ignore_index=True)

combined_data = pd.concat([low_income_long, high_income_long, lowmid_edu_long, high_edu_long
    ],keys=groups, names=['Group', 'ID']).reset_index()

# Example to perform Dunn's test for one hour: "00:00"
test_data = combined_data[combined_data['Hour'] == '00:00']

# Perform Dunn's test using the Kruskal-Wallis test as a follow-up
p_values = sp.posthoc_dunn(test_data, val_col='Score', group_col='Group', p_adjust='
    bonferroni')
print(p_values)
```

Listing B.10: Statistical analysis of accessibility levels between subgroups

C
Scientific paper

Job Accessibility in Industrial Areas

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This research evaluates the accessibility in industrial areas to the labour force by applying a spatio-temporal accessibility model in the IJmond region, located in The Netherlands. Industrial areas are crucial for regional economic activity, impacting employment opportunities for the labour force, especially those with lower incomes. This research aims to understand how the spatiotemporal configuration of industrial areas affects accessibility for different demographic groups and its implications for transport equity. The study shifts focus from job accessibility for workers to workforce accessibility from the employers' perspective, highlighting challenges faced by industrial areas regarding public transport. A gravity model is built to analyse spatiotemporal accessibility using socio-demographic data from CBS and geographic data from IBIS. Findings indicate significant disparities in non-spatiotemporal accessibility levels between car and public transit, with car accessibility generally higher. Focusing on spatio-temporal accessibility for transit has shown that levels decrease further during the night. Many industrial areas become 'unreachable' by public transit during nighttime hours with those that remain reachable, facing significantly longer travel times. In addition, it has been found that low-income workers tend to live closer to industrial areas and in higher concentrations compared to high-income workers. Recommendations include developing alternative transport solutions that will primarily support shift workers during nighttime, enhancing pedestrian and cycling routes, and utilizing more detailed neighbourhood-level data for future studies that aim to improve accessibility and gain more insights into equity in industrial areas.

Key words: job accessibility, labour force, industrial areas, gravity model, transit, qgis

Introduction

This research evaluates the accessibility of industrial areas for lower-income groups by applying a spatio-temporal accessibility model in the IJmond region in The Netherlands. As industrial areas play a crucial role in regional economic activity, their accessibility significantly impacts the inclusion and employment opportunities of the labour force, particularly for those with lower incomes. This research aims to bridge the gap in understanding how the spatiotemporal setting of industrial areas affects the accessibility of different demographic groups within the labour force and the subsequent effects on transport equity.

According to Beekmans (2015), industrial areas in The Netherlands have a critical role in regional economies and a strong impact on the labour market. However, through recent years these areas have been deteriorating and thus are less attractive for companies to settle in. A further study into how accessible these areas currently are for the workforce could yield insight into how it can be improved. Initially, these areas were developed by the government to locate industrial companies away from neighbourhoods due to noise and sound pollution factors. Whilst this resulted in a higher concentration of industries and thus optimizing the road and waterway infrastructure for logistics to and from these areas, transportation by transit was often a secondary concern for these areas (Gommers & Wortman, 2010). Existing research has primarily focused on job accessibility for workers, but research is lacking regarding the accessibility to the workforce in these industrial areas. In other words, previous studies have failed to shift the perspective from the employee towards the employer. By adopting this new perspective, deeper insights could be gained into the challenges faced by industrial areas, which are often overlooked when focusing solely on employee accessibility. This broader view allows policymakers for a more comprehensive understanding of how to improve infrastructure and transportation systems to benefit both employers and employees in these regions.

Logistics companies no longer employ only forklift operators; they now also hire students to handle return processing. Younger employees often do not own a car and must rely on public transportation.
This issue regarding accessibility in industrial areas is particularly pressing in the context of the IJmond region, where industrial activities are a significant employment source but are often located in areas with a heavily burdened road and public transportation system. According to the Province North Holland, the IJmond region serves as a crucial corridor for travel between outer origins and major destinations such as Amsterdam and Schiphol, which affects accessibility challenges for local job locations within the region itself (Provincie Noord-Holland, 2021).

The following Research Gap, Objective, and Questions have been formulated to have a better understanding of accessibility in industrial areas.

Research Gap
The research identifies a significant gap in understanding how the spatial configuration of industrial areas influences the accessibility for various demographic groups, especially from an employer's perspective. Previous studies have largely focused on residential accessibility to jobs, overlooking how industrial site locations affect employment opportunities for the local labour force, particularly impacting those dependent on public transit.

Research Objective
The main objective of this research is to develop a methodological framework that evaluates the spatiotemporal accessibility of industrial job sites, particularly through transit, and to assess its impact on transport equity. This framework aims to aid policymakers and urban planners in crafting interventions that enhance accessibility.

Research Questions
Main Question: How do spatio-temporal factors and socio-demographic characteristics influence transit accessibility in concentrated industrial areas, and what are the implications for transport inequality? Subquestions:

1. What socio-demographic characteristics of the labour force are relevant for understanding the spatio-temporal issues of accessibility around industrial areas?

2. How do accessibility levels in industrial areas to different socio-demographic groups vary across different times of day?

3. What are the implications of these temporal and socio-demographic variations for transport policy and urban planning of industrial areas?

Research Approach
The approach involves a detailed literature review followed by the application of a gravity model to analyze spatio-temporal accessibility in industrial areas. The study uses comprehensive socioeconomic from CBS and geographic data regarding industrial areas from IBIS. It uses this as input for the gravity model. The results of the gravity model are then analyzed and visualized with maps.

Methodology

The methodology is structured in 4 steps. First, data definition and requirements are set for the accessibility analysis. The second step involves the formulation of the gravity model used to evaluate spatiotemporal accessibility. The third step concerns the formulation of further statical analysis of the gravity model results and lastly, the case study area is defined on which the accessibility analysis will be performed.

Business parks, termed 'bedrijventerrein' in Dutch, are job sites primarily for trade, commerce, and industry, excluding commercial services and offices. Industrial areas, a subset of business parks, focus mainly on heavy industry (Rijkswaterstaat, n.d.). In the Netherlands, around one-third of job sites are in business parks, with regional variations, such as West-Brabant and the IJmond areas, having a high concentration of jobs, particularly in heavy industry and logistics, exemplified by Tata Steel's presence (Renes, 2009). Research categorizes business parks into various economic activity groups, such as factories, port facilities, financial institutions, corporate service industries, and storage companies (CBS, 2017). Different studies propose classifications based on types of activities, such as heavy industrial areas, seaports, mixed industrial areas, high-quality business parks, and distribution parks (Louw et al., 2004; PBL, 2012). Recent studies note changes in employment opportunities within industrial areas, shifting from traditional industrial to service sector jobs. Defining industrial areas remains a challenge due to inconsistent terminology, but they are characterized by the concentration of heavy industries and logistics (Weterings et al., 2008). Data on these industrial areas in specific is available through IBIS, applicable for spatial analysis in GIS programs as geometry is provided in the dataset (IBIS, 2022). The geometry of this data is used for the accessibility model for this study.

In addition, district-level socio-economic data will be used for modelling accessibility. A more granular level could capture localized variations of job accessibility among districts. While providing an even higher level of detail, 'buurtniveau' or neighbourhood-level data will not be considered as the granularity of this data is not available and would require much longer computation times. Additionally and consequentially, a lot of the required variables are not available on the neighbourhood level making it impractical to consider for this research. The required variables for this study are:

- Share of low-income households per district (at wijkniveau, CBS)
- Number of employees per district (CBS)
- Vehicle ownership per district (CBS)
- Geometry of district locations

The labour force consists of employees living in district areas (Dutch: wijken). This research relies on socio-economic data sourced from the Central Bureau of Statistics (CBS) which provides insights regarding employment trends (CBS, 2024a). The provided datasets for this research make it suitable to perform an accessibility analysis such as the usage of Gravity Model Theory. Socio-economic data from CBS provide an insight into population size per district and the data from IBIS contains the geometry of industrial area locations. Using this data, the gravity model can be formulated as follows:

$$A_i^{tm} = \sum_j O_j * f(C_{ij}^{tm}) \tag{1}$$

In Equation (1):

- A_i^{tm} = The accessibility for job location i per time t by mode m;
- O_j = Number of opportunities for residential district location j;
- $f(C_{ij}^{t}m)$ = The impedance measuring spatial separation between i and j.

The impedance function can be described as:

$$f(C_{ij}^{tm}) = e^{\beta * C_{ij}} \tag{2}$$

In Equation (2):

- β = Impedance function parameter;
- C_{ij} = The travel time, distance or cost for a trip from i to j per time t by mode m;

Equation (1) enables the evaluation of temporal accessibility of work location $\imath$ by modelling the temporal distance decay to the surrounding residential areas $\jmath$ in the set of employee locations N. It is important to notice that the set of opportunities or employees $_j$ is not time-dependent as data concerning the willingness to work at specific times of the day is not available. The impedance function describes the impedance or travel time decay function between i and j. The group-specific parameter β is based on existing research on the Greater London Area and set at -0.30 (Giannotti et al., 2022).

Transit skim matrices can be generated for every hour of the day whereas car skim matrices can only be computed for the whole day without accounting for different time intervals as the model assumes an uncongested road network and therefore constant travel times across the day. To account for this, the transit skim matrix for one specific hour is used, 12:00 noon, when transit accessibility levels are the highest, reflecting peak efficiency and service availability. This matrix is then utilized for the comparison of accessibility levels between car and transit. The framework for the methodology is visualized in Figure 1.

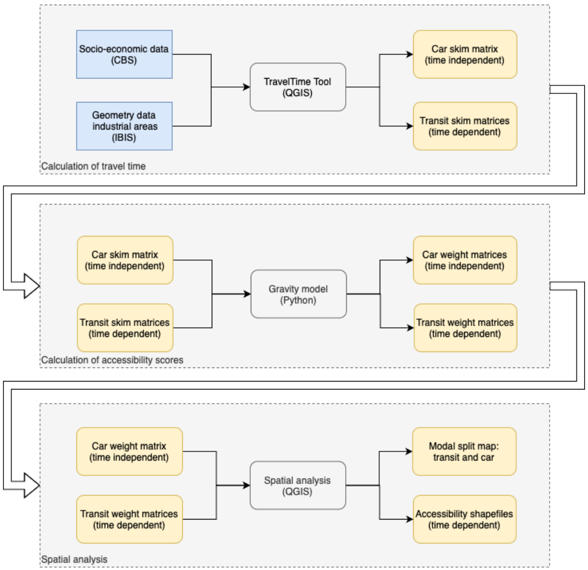


Figure 1: Methodological framework for accessibility analysis of industrial areas

After comparing spatial accessibility levels between car and transit, the analysis is further expanded into a spatiotemporal analysis for the transit mode. Accessibility by public transport to multiple socioeconomic groups within the total working population is evaluated utilizing the z-score method. The z-score method accounts for the varying group sizes by indicating the number of standard deviations a particular group's accessibility measure is from the overall mean accessibility measure. Applying the z-score method allows for the study to identify areas where specific socioeconomic groups experience significantly higher or lower accessibility compared to the average. This statistical approach helps in highlighting disparities in transit accessibility among different groups.

Case Study Area

The case study area involves the IJmond region in the province of North Holland, The Netherlands, and consists of the municipalities of Beverwijk, Heemskerk and Velsen. Situated along the North Sea and split by the North Sea Canal, the area facilitates a relatively high number of industrial jobs with Tata Steel as its main provider with 9000 jobs (Tata Steel, 2024). Transit to, from and within the IJmond is provided with train services operated by the Dutch National Railways (NS) on the Kennermer railway line and buses operated by Connexxion.

Results

Applying the gravity model to the IJmond area has resulted in the following main findings:

- Calculating the mean accessibility of all hours of the day combined, the accessibility level in industrial areas by car is higher than by transit.
- A significant share of the 478 residential districts becomes 'unreachable' during the night time hours, which means their travel time is longer than the threshold value of 240 minutes that the model considers. This share reaches its peak of 81 % at 01:00 at night and is the lowest at 13:00 with 16.3 %. It is observed that the remaining share of reachable destinations also sees longer travel times during the night.
- It is observed that industrial areas of De Houtwegen and De Waterwegen in Heemskerk, situated along a transit (bus) stop, have a significantly higher accessibility mean over all hours of the day. Areas with lower accessibility levels are Tata Steel and the IJmond Haven, located further from transit stops.
- Because the normalised accessibility scores in industrial areas show higher scores for low-income workers than high-income workers with both groups being subject to the same travel time between origin and destination zones, the gravity model shows that larger groups of low-income workers live closer to industrial areas than groups with high-education workers.
- There are similar accessibility scores observed between low-income and low/medium education groups as well as between high-income and high-education groups, corresponding to existing literature and confirming the model works as expected.

These results represent a thorough analysis of the accessibility patterns observed in the IJmond region. First, the mean accessibility index is observed to be higher by car than by transit as can be seen in Figure 2. The Figure displays the scores for accessibility to the total working population by both modes without accounting for the temporal component. The transit accessibility scores used for the comparison are generated for t=12:00 (noon). Transit accessibility is the highest during this hour of the day, reflecting peak efficiency and service availability. The higher accessibility score for car in Figure 2 is directly caused by higher travel times by transit compared to by car. A higher travel time results in a larger impedance and thus lower accessibility scores in the gravity model. As the total working population represents the opportunity component in the gravity model and remains constant over time, the only factor that contributes to the difference in accessibility scores for both modes is the travel time.

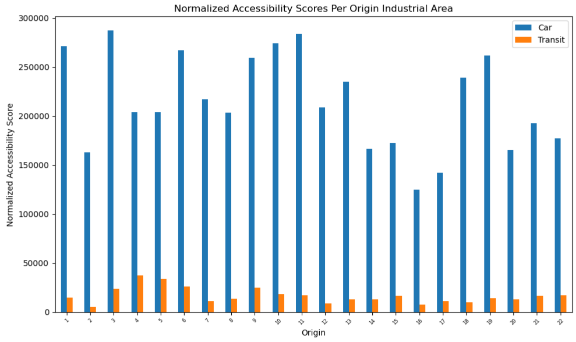


Figure 2: Accessibility scores per industrial area i for both car and transit

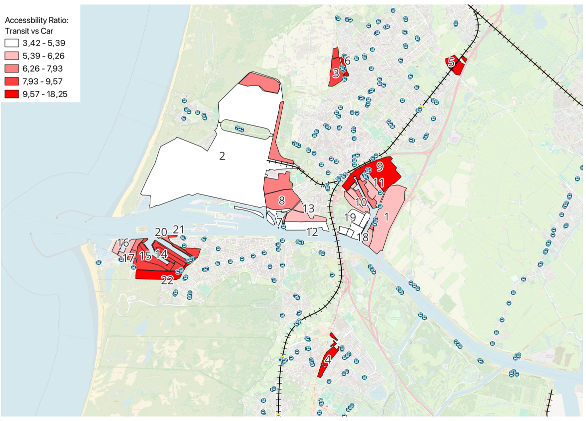


Figure 3: Accessibility score by transit per industrial area i, relative to the score by car. The numbers on the map represent the area number. The ratio is visualized with a colour gradient.

Focusing on transit and applying temporal factors to the gravity model, the hourly travel time skim matrices generated through the TravelTime plugin indicate that a significant share of the 478 residential districts becomes ‘unreachable’ during the night time hours, which means their travel time is longer than the threshold value of 240 minutes that the TravelTime plugin considers. This share of unreachable destinations reaches its peak of 81 % at 01:00 at night and is the lowest at 13:00 with 16.3 %. indicated transit services from industrial areas are best during the early afternoon. It is observed that the remaining share of reachable destinations also sees longer travel times during the night. No transit services are present during the night, however, 19 % of residential destinations do have transit travel times lower than 240 minutes at 01:00. This is due to the fact the transit mode also includes walking as an access and egress mode using the pedestrian street network. In the absence of any public transport services at night, walking routes are utilized for finding the shortest path between industrial areas and residential districts. It should be noted, however, that an individual would likely not choose to walk 240 minutes to work. For the gravity model analysis, ’unreachable’ destinations are set to 999 minutes to reduce their accessibility weight to near 0. To visualise how travel time develops during the day, Figure 4 shows the ratio between the accessibility score by transit and by car for all industrial areas.

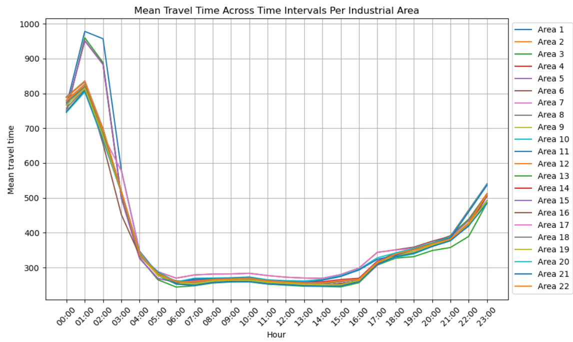


Figure 4: Mean travel time per industrial area location i per time interval t

Figure 5 displays the accessibility scores per industrial area per hour of the day, generated by the spatiotemporal gravity model. The horizontal axis represents the time of day whereas the vertical axis shows the normalized accessibility score per industrial area. These results show that certain industrial areas have significantly higher accessibility scores over all hours of the day.

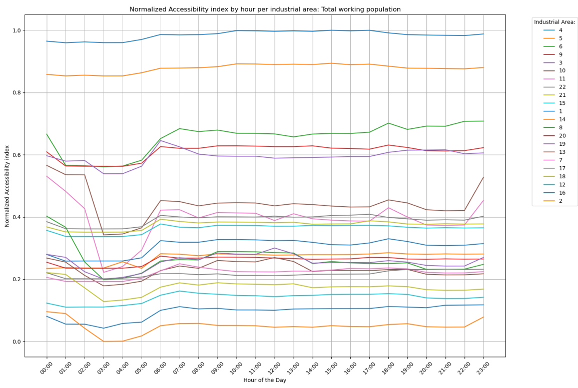


Figure 5: Accessibility index per industrial site per time interval for the total working population in North Holland

Figure **??** visualizes the spatiotemporal distribution of the accessibility scores using 6 intervals over 24 hours. The results for evaluating the accessibility to the total working population from industrial areas suggest significant spatiotemporal variation during the night hours with zones adjacent to the Tata Steel factory suffering from lower accessibility levels at 03:00 while other industrial areas located in the vicinity of transit stops are relatively less affected by the time of the day.

Aside from the total working population, 4 socio-economic variables are considered to analyse accessibility to different subgroups within the total working population: Low-income, high-income, lower/medium-education and high-education. The sum of the two income groups and the sum of the education groups is equal to the total working population. Using the normalization and z-score method to compare the accessibility scores between different socio-economic subgroups and the total working population, the results show that accessibility scores are higher for low-income and low/medium-education groups compared to their counterparts. Figure 6 displays the z-score of each subgroup over the period. Noticeable is the lower score for high-income and high-education groups, indicating it is more challenging for industrial areas to reach these groups and vice versa.

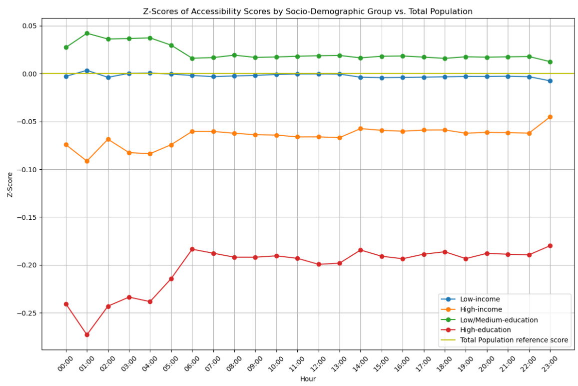


Figure 6: Graph displaying the development of the z-score per socio-economic subgroup per hour, based on the normalized accessibility scores per subgroup. A positive score indicates a larger deviation from the normalized accessibility scores of the total working population.

The normalised accessibility score, which is a product of travel impedance (based on travel time) and population size, indicates higher accessibility scores for lower-income workers. Given that travel time is independent of socioeconomic variables, the remaining variance is attributable to population size. Since normalization for population size has been applied, this suggests that lower-income workers live in larger numbers closer to industrial areas. Also noticeable is the level is higher during all time intervals, including the night. Transit is almost nonexistent at night, meaning these travel times are primarily composed of the transit access and egress mode 'walking'. The increase in accessibility at night from industrial areas to low-income workers relative to that of the total working population indicates that these groups are relatively more accessible by walking than other groups.

Limitations

This study has examined spatiotemporal accessibility from an employer's viewpoint, focusing on labour force accessibility instead of job accessibility. The results of the z-score test indicate higher transit accessibility for low-income groups, which indicates that larger concentrations of these groups live in closer proximity to industrial areas than their counterparts. Future research could address data limitations and enhance validity through alternative computational methods. Data limitations were present in this research as group-specific data was difficult to gather. More specifically, data regarding the type of workers would provide more insights as not every worker is suited for the jobs that industrial areas provide. For example, office workers as well as catering personnel are also included in this research whilst their jobs might not be present in industrial areas. Additionally, capturing hourly transit variations could refine transit accessibility measurements (Yan et al., 2022). The current method relied on travel time skim matrices computed by the TravelTime API, not accounting for different departure times within an hour. Another limitation is the reliance on district-level data, suggesting potential insights with more detailed neighbourhood-level data (Liu & Kwan, 2020). Challenges include insufficient insight into transit trip compositions and transfer times, warranting further research. Opportunities exist for exploring alternative computational methods and refining transit accessibility measurements.

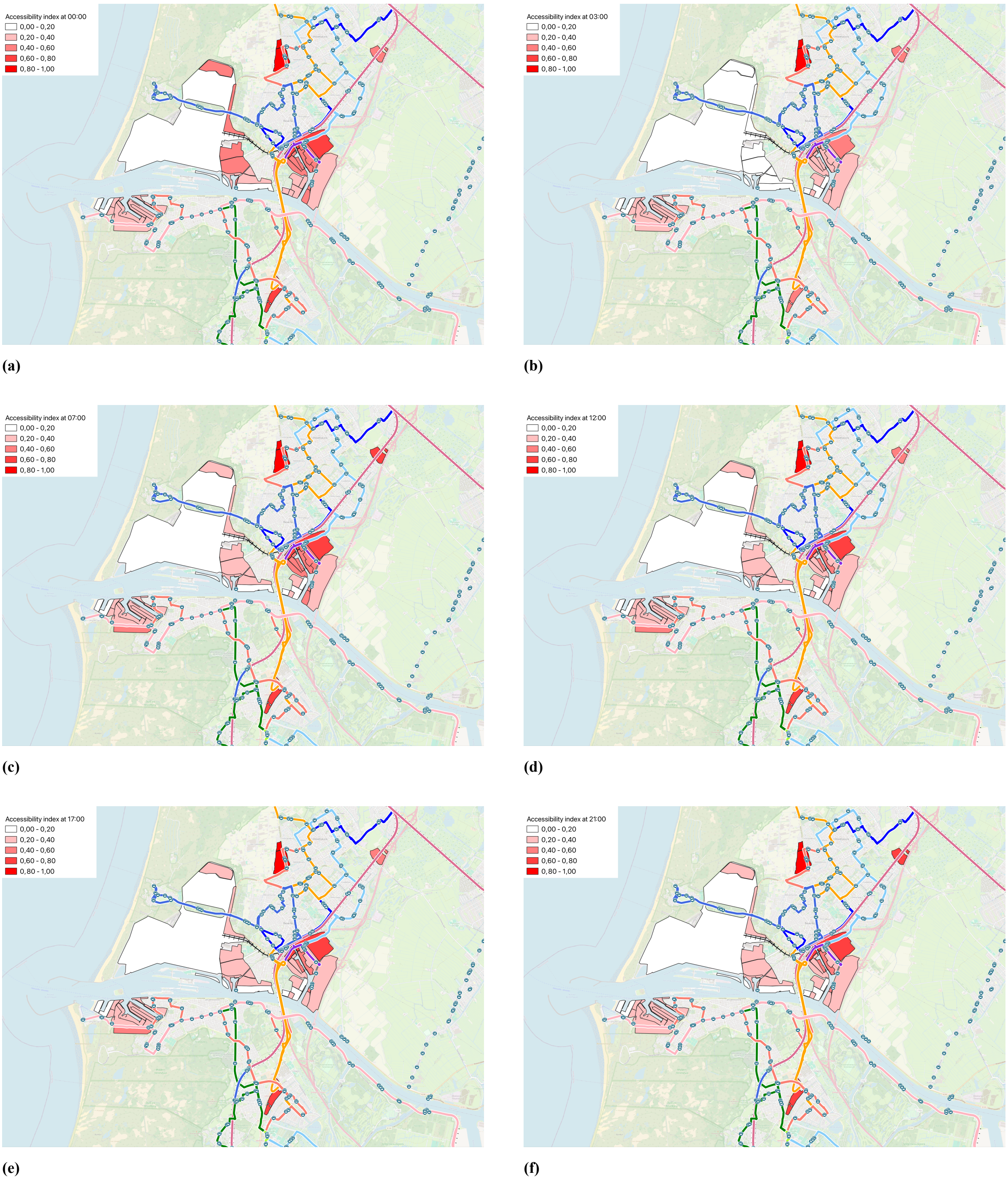
Recommendations

Based on the main findings of this research, the following policy recommendations are given to improve accessibility in industrial areas:

- Increase Transit Accessibility: Transit services should be improved during the daytime to achieve accessibility levels closer to car travel. Policymakers should analyse the context of their area and modify local infrastructure to remove barriers such as fences and bridge waterways to enhance access to transit stops.

- Enhance Nighttime Mobility: Adapted nighttime mobility solutions aligned with industrial shift hours should be provided, benefiting low-income and low/medium-education groups. Policymakers should consider shared mobility options to complement or even replace public transport and reduce dependence on cars.

- Improve Pedestrian and Cycling Routes: Investments in safe, well-lit, and direct walking and cycling paths to industrial areas are necessary to en-



(a) (b) (c) (d) (e) (f)

Figure 7: Normalized accessibility scores per industrial area at 6 time intervals

sure these routes provide reliable access for low-income workers during hours when public transport is unavailable, supporting sustainable transportation alternatives.

Considering the identified limitations of this study, the following research recommendations are proposed:

- Comprehensive Data Collection: More detailed data granularity and real-time traffic data should be utilized to improve the understanding of labour force accessibility in industrial areas.
- Multimodal Accessibility Analysis: Car travel times for each hour of the day should be computed and cycling should be included as a mode of transport in the analysis. The usage of traffic data to account for congestion effects and decomposing public transport trips for detailed multi-modal spatiotemporal analysis is deemed neces-

sary for this.

- Neighborhood-Level Data: Future researchers should utilize neighbourhood-level data to better understand where low-income workers reside around industrial areas. Competition effects should be incorporated in the gravity model for a more accurate representation, requiring stronger processing power and longer computation times.

By addressing these recommendations, policymakers can improve accessibility in industrial areas and create more equitable and enhance the attractiveness and functionality of industrial areas, contributing to their economic and social prosperity. Future research including temporal factors for multiple modes and incorporating more granular data will further refine these models, supporting informed decision-making.

Conclusion

In conclusion, this research has provided an evaluation of accessibility to the labour force in industrial areas, highlighting significant disparities in accessibility levels between car and transit. The results indicate that car accessibility is higher across all industrial areas in the IJmond. By focusing on transit and considering temporal factors, the results have shown that the level of accessibility in these areas decreases significantly during the night. Taking socioeconomic characteristics into account, the results also show that low-income groups live in larger concentrations closer to industrial areas than high-income groups.

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